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Automatic segmentation of arteries in CT scan data of
patients with peripheral arterial diseases

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Abstract

Peripheral artery disease, if left untreated, can cause serious cardiovascular complications and limb amputation. The diagnosis often relies on advanced imaging techniques such as computed tomography, followed by detailed vascular analysis. However, accurate segmentation of the peripheral artery remains challenging due to its small size, intricate anatomy, class imbalance, and variability in imaging protocols.

To address these challenges, this study proposes a framework for peripheral artery segmentation from three-dimensional computed tomography scans. The approach begins with a YOLOv8 network to detect and isolate the region of interest from full-body scans, significantly reducing computational load and processing time. The extracted region of interest is analyzed using an isolated learning approach that employs the proposed Single-Depth Vascular Network - SDVN for precise segmentation of the peripheral artery. Furthermore, the approach is compared with a transfer learning strategy that leverages pre-trained models on pulmonary and coronary arteries.

In addition, peripheral arteries visualization is improved using planar curve reformation and cluster-based techniques, providing clear and interpretable representations of vascular structures. Experimental results demonstrate that the proposed framework achieves improved segmentation accuracy and efficiency compared to existing methods, providing a reliable tool to support automated diagnosis and assessment of peripheral artery disease in clinical practice.

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Abstrakt

Choroba tętnic obwodowych, jeśli pozostaje nieleczone, może prowadzić do poważnych powikłań sercowo-naczyniowych oraz amputacji kończyn. Diagnostyka często opiera się na zaawansowanych technikach obrazowania, takich jak tomografia komputerowa, a następnie na szczegółowej analizie naczyń. Jednym z elementów oceny jest dokładna segmentacja tętnic obwodowych, która pozostaje wyzwaniem ze względu na ich niewielki rozmiar, złożoną anatomię, nie zrównoważenie klas oraz zmienność protokołów obrazowania.

Aby sprostać tym wyzwaniom, w niniejszej pracy zaproponowano metodę segmentacji tętnic obwodowych z trójwymiarowych skanów tomografii. Podejście bazuje na zastosowaniu sieci YOLOv8 do wykrywania i izolowania regionu zainteresowania z pełnych skanów ciała, co znacząco zmniejsza obciążenie obliczeniowe i czas przetwarzania. Wyodrębniony obszar zainteresowania jest następnie analizowany przy użyciu podejścia opartego na izolowanym uczeniu, które wykorzystuje zaproponowaną sieć SVDN do precyzyjnej segmentacji tętnic obwodowych. Ponadto podejście to porównano ze strategią uczenia transferowego, wykorzystującą modele wstępnie wytrenowane na tętnicach płucnych i wieńcowych.

Dodatkowo, wizualizacja tętnic obwodowych została usprawniona dzięki zastosowaniu rekonstrukcji struktur anatomicznych w formie wyprostowanej oraz klasteryzacji, co pozwala na uzyskanie przejrzystych i interpretowalnych reprezentacji struktur naczyniowych. Wyniki eksperymentalne wykazują, że zaproponowane podejście zapewnia wyższą dokładność i efektywność segmentacji w porównaniu z istniejącymi metodami, stanowiąc narzędzie wspierające automatyczną diagnostykę i ocenę choroby tętnic obwodowych w praktyce klinicznej.

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List of Abbreviations

ABI	Ankle-Brachial Index
BCE	Binary Cross Entropy
CIP	Cumulative Intensity Projection
CNN	Convolutional Neural Network
CPR	Curved Planar Reformation
CRFs	Conditional Random Fields
CA	Coronary Artery
CLI	Critical Limb Ischemia
CAD	Coronary Artery Disease
CT	Computed Tomography
DL	Deep Learning
DRU-Net	Dense Residual U-Net
DSC	Dice Similarity Coefficient
FCNs	Fully Convolutional Networks
HD	Hausdorff Distance
HD95	95th percentile Hausdorff Distance
LCA	Left Coronary Artery
LMIC	low- and middle-income countries
ML	Machine Learning
MR	Mixed Reality

MRA	Magnetic Resonance Angiography
OCT	Optical Coherence Tomography
PA	Peripheral Artery
PAD	Peripheral Artery Disease
PulA	Pulmonary artery
RCA	Right Coronary Artery
RNN	Recurrent Neural Networks
SAM	Segment Anything Model
SAM-Med	Segment Anything Model for Medical Imaging
SDVN	Single-Deep Vascular Network
ViTs	Vision Transformers
VR	Virtual Reality
YOLO	You Only Look Once

Chapter 1

Introduction

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1.1	Challenges in Peripheral Artery Segmentation	2
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The peripheral artery (PA) originates in the aorta and ensures the blood supply to the lower extremities. When these arteries constrict or become obstructed, it can significantly impact a person’s mobility, a condition known as peripheral artery disease (PAD) [1]. Preventing the progression of PAD is crucial to avoid reduced blood flow, ischemia, tissue necrosis, and potential cardiac complications [2].

In clinical practice, PAs are assessed using different imaging modalities, including computed tomography (CT) and magnetic resonance angiography (MRA). These non-invasive modalities have largely supplanted traditional diagnostic arteriography and are now considered first-line approaches to evaluate PAD [3]. For an accurate diagnosis, PA including vessels such as the common iliac, femoral, and tibial arteries must be segmented from surrounding anatomical structures such as bone and soft tissue [4]. However, the task is challenging due to the intricate arterial branching, narrow vessel diameters, and patient-specific morphological differences [2]. In addition, human visual assessment has limitations and requires significant expertise and analytical precision.

Traditional methods, including thresholding, region growing, level-set models, and model-based approaches, rely on prior assumptions about vessel intensity, shape, and

connectivity [1]. While these methods can be effective for segmenting large, high-contrast vessels, they often struggle with small, partially occluded, or calcified arteries, where intensity variations and structural complexity challenge their robustness and accuracy [4].

However, deep learning (DL) based segmentation models offer a robust approach for the precise delineation of peripheral artery (PA) structures, effectively addressing the inherent complexity and variability of PA anatomy. Accurate segmentation enables a wide range of downstream applications, including computational modeling of blood flow, simulation of interventional procedures, and longitudinal assessment of arterial morphology. Additionally, DL-based approaches provide consistent and reproducible analyses over time, facilitating detailed evaluation of vascular changes [4].

Despite these advancements, accurately segmenting peripheral arteries still poses a significant challenge. Several factors contribute to these difficulties, which are discussed in the following section.

1.1 Challenges in Peripheral Artery Segmentation

PA segmentation remains highly challenging due to several factors. These include limited data availability, low image contrast, and artifacts introduced by hospital-grade imaging equipment. Additionally, anatomical variability among patients and dataset heterogeneity further complicate model generalization [4]. The PA itself exhibits a wide variation in diameter, length, curvature, and branching patterns [2]. In addition, small arteries are often intertwined with veins, muscles, and adipose tissue, making boundary delineation particularly difficult [1].

As shown in Figure 1.1, these challenges can be broadly categorized as follows.

- Limited spatial coverage: CT scans often encompass large anatomical regions, whereas PAs occupy only a small portion of the volume. This results in class imbalance, where arterial voxels are significantly underrepresented, posing challenges for accurate segmentation [5].
- Variability in contrast and scanner protocols: Factors such as contrast timing, distribution, scanner model, and reconstruction method impact PA visibility. These

variations introduce heterogeneity between datasets and reduce the robustness of segmentation algorithms [6].

- Vessel geometry and anatomical variability: Irregular diameters, complex branching patterns and shapes make accurate segmentation difficult and pose significant challenges to algorithm generalization [7].
- Low contrast with surrounding tissues: Arteries often exhibit intensity values similar to those of muscles, adipose tissue, and connective structures. When combined with a limited spatial resolution, this similarity complicates the detection and segmentation of small vessels [8].

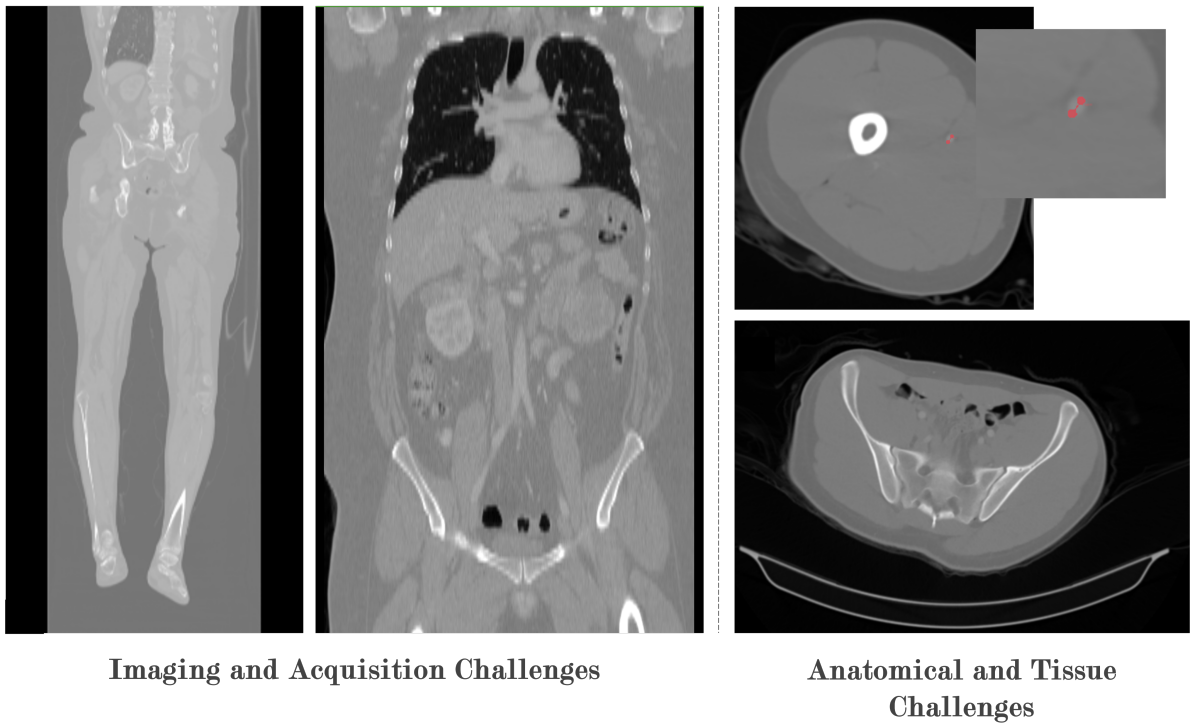


Figure 1.1: Overview of major challenges in segmenting PA, including imaging and acquisition issues, small vessel diameter (highlighted in red), and anatomical and tissue-related complexities.

1.2 Motivation

PAD is increasing globally, with projections that estimate more than 360 million cases by 2050 due to aging populations and metabolic risk factors [9]. Despite this growing

prevalence, limited attention has been paid to automated segmentation of PAs, particularly in three-dimensional (3D) imaging. Existing studies rarely address DL models specifically designed for clinical 3D imaging of vascular structures. The aim of this thesis is to develop a DL-based approach to achieve accurate PA segmentation.

The approach involves two primary stages: localization of the region of interest (ROI) and segmentation of the PA structures.

Stage 1: ROI Localization with YOLOv8

Whole-body CT scans include extensive anatomical structures, many of which are irrelevant to PA evaluation. The first stage focuses on extracting a precise ROI from 3D CT volumes using the YOLOv8 architecture. By applying YOLOv8 to the cumulative intensity projection (CIP) of 3D volumes, arterial bifurcation points are identified as anatomical landmarks. This targeted localization reduces memory consumption, eliminates irrelevant structures, and improves segmentation precision for subsequent analysis.

Stage 2: Segmentation with Single-Depth Vascular Network

Once ROI is localized, segmentation is performed using a custom-built 3D convolutional network, the Single-depth vascular network (SDVN), which is optimized for PA structures. The network features a simple encoder-decoder structure with a single skip connection and residual convolution blocks. This design preserves high-resolution spatial features and anatomical consistency while remaining computationally efficient. The SDVN enables robust segmentation of vessels with varying diameters, making it suitable for clinical deployment.

1.3 The Proved Thesis

Segmentation of peripheral arteries in 3D CT is challenging due to small vessels and low contrast; the framework addresses this via ROI-guided high resolution segmentation.

- **YOLOv8:** Detects arterial bifurcation points and defines ROIs, focusing computational resources on essential vascular structures.

- **SDVN:** Performs detailed segmentation within ROI, preserving fine structural features and accurately capturing small vessels.

By integrating ROI-guided localization with a robust segmentation network, the method produces anatomically consistent and clinically relevant results. This enables a comprehensive vascular analysis and improved assessment of vessel morphology, demonstrating the effectiveness of the two-stage DL framework.

1.4 Thesis Structure

This thesis consists of two main parts: the foundational background and the author's contributions. The background part addresses the key concepts of PA segmentation. The contribution part presents the author's research on PA segmentation, including the proposed novel segmentation and ROI localization method, along with the evaluation performed.

This thesis is organized in the following manner.

Part 1: Background

- **Chapter 2: Background** chapter discusses the circulatory system and the anatomy of peripheral arteries. It also presents a comprehensive review of current research on arterial segmentation.

Part 2: Contributions

- **Chapter 3: Methodology** contributes by detailing pre-processing procedures, the ROI localization strategy, and image analysis techniques, and by proposing two methods for peripheral artery segmentation, including an isolated learning approach using the SDVN model and a transfer learning approach that leverages coronary and pulmonary arteries.
- **Chapter 4: Results and Discussion** Contributes by presenting experimental results and performance evaluation of the proposed segmentation methods, providing comparative analyzes with existing approaches, and discussing the significance and clinical implications of the findings.

Finally, **Chapter 5: Concluding Remarks and Future Work** summarizes the key findings, highlight their clinical implications, and outline potential directions for future research.

Part I

Background

Chapter 2

Background

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The human circulatory system comprises the heart and a complex network of vessels that transport blood throughout the body. Arteries are blood vessels that carry oxygenated blood from the heart, encompassing large systemic arteries like the aorta as well as smaller PAs that supply blood to the limbs and organs [10]. A foundational understanding of arterial anatomy is essential for interpreting medical images, planning interventions, and developing effective segmentation techniques [11]. Medical imaging

allows clinicians to visualize these arterial structures in detail, allowing an accurate assessment and analysis [12].

Segmenting arteries from medical images is crucial for vascular analysis and aids in accurate diagnosis and treatment planning [13]. Accurate segmentation of arterial structures from medical imaging data allows clinicians to quantify vascular characteristics and plan interventions more effectively [14].

A critical factor in segmentation is the choice of imaging modality, as each provides different levels of spatial resolution, contrast, and clinical utility [15]. Common modalities include X-ray angiography, CT, MRA, ultrasound, and intravascular optical coherence tomography (OCT), each with distinct advantages and limitations [16]. For example, CT provides high-resolution 3D visualization but requires exposure to ionizing radiation and contrast agents, while MRA delivers excellent soft tissue contrast without radiation but is more sensitive to motion artifacts [17]. Ultrasound is portable and non-invasive but highly dependent on the operator, while OCT enables microscopic intravascular imaging but is limited to small segments of the vessel [18].

Segmentation techniques have evolved alongside these imaging modalities [11]. Classical method like thresholding, edge detection, and region growing laid the foundation, while later approaches incorporated vessel enhancement filters, morphological operations, and graph-based models [16]. More recently, machine learning (ML), and especially DL, has expanded the field, enabling automated, robust, and highly accurate extraction of vascular structures even in complex or noisy imaging data [12]. Techniques including convolutional neural networks (CNNs), and 3D volumetric networks have proven highly effective for both research and clinical applications [17].

This chapter discusses the human circulatory system along with the anatomy of the PA, artery imaging modalities, and segmentation techniques, covering traditional approaches, ML methods, DL strategies, as well as transfer learning and prompt-based segmentation frameworks.

2.1 The Human Circulatory System

Arteries are vessels that transport oxygenated blood from the heart to different parts of the body. The heart itself consists of two chambers known as ventricles: the left

ventricle and the right ventricle. The left ventricle pumps blood into the aorta, the body's largest systemic artery [19], while the right ventricle directs blood to the pulmonary arteries, carrying it to the lungs [20]. This arrangement illustrates the dual output of the ventricles, with the left ventricle sustaining systemic circulation and the right ventricle supporting pulmonary circulation, as shown in Figure 2.1 [21].

2.1.1 Pulmonary Circulation

A fundamental component of the cardiovascular system is the pulmonary circulation, responsible for oxygenating blood by transporting it between the heart and lungs. This process starts when the right ventricle of the heart pumps deoxygenated blood through the pulmonary arteries to the lungs [22]. Within the pulmonary capillaries, carbon dioxide is exchanged for oxygen through the thin walls of the alveoli, enabling efficient gas exchange [23]. Oxygen-rich blood flows from the lungs into the left atrium through the pulmonary veins, completing this stage of the circulatory process [22]. The pulmonary circulation functions at relatively low pressure, which serves to protect fragile tissues in the lungs from potential harm [23].

Efficiency and regulation of the pulmonary circulation are vital for maintaining adequate oxygen supply to tissues and overall homeostasis [22].

Pulmonary Artery

The pulmonary artery transports deoxygenated blood from the heart to the lungs. It originates from the pulmonary trunk, which emerges from the right ventricle and withstands the high pressure generated during ventricular contraction [25]. The pulmonary trunk then divides into the right and left pulmonary arteries [26]. The right pulmonary artery passes behind the ascending aorta and the superior vena cava before reaching the right lung, while the left pulmonary artery travels directly to the left lung [26].

Both pulmonary arteries branch extensively along the bronchial tree, distributing blood throughout the pulmonary tissue in the lungs [25]. These branches divide into smaller arterioles and capillaries, where oxygen diffuses into blood and carbon dioxide is released [26]. The branching pattern and structure of the pulmonary arteries ensure efficient blood flow to all areas of the lungs [25].

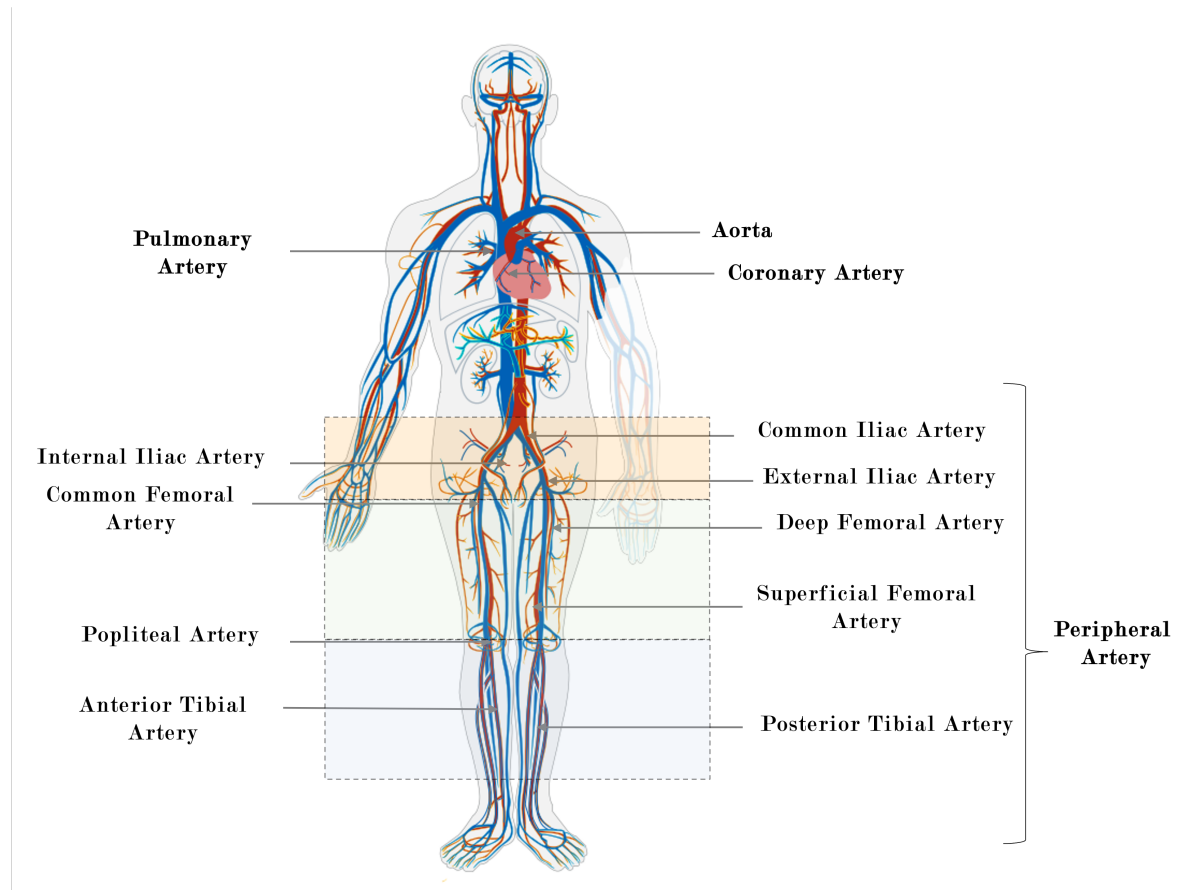


Figure 2.1: Anatomy of the human circulatory system. Inspired by [24] (Creative Commons (CC)).

2.1.2 Systemic Circulation

Systemic circulation is the process by which oxygenated blood is distributed from the left ventricle to the tissues and organs of the body, ensuring the delivery of essential nutrients and the removal of metabolic waste [27]. This pathway begins with the aorta, the principal artery responsible for transporting oxygen-rich blood away from the heart [28]. The aorta is anatomically divided into three segments: the ascending aorta, the aortic arch, and the descending aorta [28].

From these segments, the main arterial branches arise to supply blood to all regions of the body [27]. These branches follow a predictable anatomical pattern corresponding to the thoracic, abdominal, and pelvic regions [28].

The following sections outline the main branches of the aorta, beginning with the coronary arteries and extending to the PAs.

Coronary Artery

The coronary arteries are essential vessels within the systemic circulation. Their primary function is to supply oxygenated blood to the myocardium [29]. The coronary arteries arise from the base of the ascending aorta [30].

There are two primary coronary arteries:

- Left coronary artery (LCA).
- Right coronary artery (RCA).

The left coronary artery is relatively short and bifurcates into two main branches. The first branch is the left anterior descending artery, which descends along the anterior interventricular sulcus [31]. It supplies blood to the anterior walls of both ventricles as well as to the interventricular septum [32].

The second branch is the circumflex artery (LCx), which follows the coronary sulcus around the left side of the heart and extends to the posterior surface [31]. It provides blood primarily to the lateral and posterior walls of the left ventricle [32].

The right coronary artery runs along the right atrioventricular groove. It delivers blood to the right atrium, right ventricle, and portions of the left ventricle [31]. In addition, the RCA supplies the sinoatrial and atrioventricular nodes, which are essential components of the heart's electrical conduction system [32].

The coronary arteries deliver oxygen-rich blood directly to the myocardium. This supply supports continuous and forceful contractions of the heart [31]. The myocardium requires a constant and ample supply of oxygen. Any interruption in coronary blood flow can quickly affect heart function [32].

Blocking of the coronary arteries, often caused by atherosclerosis, reduces blood flow and oxygen delivery [31]. This condition can cause chest pain known as angina pectoris. If blood flow is severely restricted, it can lead to a myocardial infarction, commonly called a heart attack [32]. These conditions are among the leading causes of disease and death worldwide [31].

The health and integrity of the coronary arteries are vital for maintaining effective cardiac function and overall systemic circulation [32].

Peripheral Arteries

In systemic circulation, the heart pumps oxygen-rich blood into the ascending aorta. From the abdominal aorta, blood is distributed to various organs and tissues through branching arteries [33]. The PAs originate at the level of the fourth lumbar vertebra. At this point, the abdominal aorta is split into the right and left common iliac arteries [33].

- **Common Iliac Arteries:** The abdominal aorta bifurcates into the right and left common iliac arteries, which travel to the pelvis and divide into the internal and external iliac arteries [34]. The internal iliac artery supplies the pelvic organs, while the external iliac artery continues into the lower limb [34].
- **External Iliac Artery:** Runs along the pelvic brim and passes under the inguinal ligament, becoming the femoral artery as it enters the thigh [34].
- **Femoral Artery:** The main artery of the thigh, it enters through the femoral triangle and produces the deep femoral artery (profunda femoris), which supplies the thigh muscles [35]. It travels through the adductor canal and passes through the adductor hiatus to become the popliteal artery [35].
- **Popliteal Artery:** Located behind the knee, it gives branches to the knee joint and then divides into the lower leg arteries [36].
- **Anterior Tibial Artery:** Passes through the interosseous membrane to the anterior compartment of the leg and continues as the dorsalis pedis artery in the dorsum of the foot [36].
- **Posterior Tibial Artery:** Travels down the posterior compartment of the leg, passing behind the medial malleolus to supply the plantar aspect of the foot [36].
- **Fibular (Peroneal) Artery:** Branches off the posterior tibial artery, runs along the lateral compartment of the leg, and supplies the lateral leg muscles and parts of the foot [37].

The PAs act as the main conduits in the legs, ensuring that oxygen and nutrients reach distal tissues to support their function and metabolism.

2.2 Peripheral Artery Disease

PAD is caused by narrowing or obstruction of the PA, primarily due to the accumulation of atheromatous plaques along the arterial walls. Restricted blood flow alters oxygen and nutrients delivery to tissues, leading to vascular dysfunction [38].

PAD often reflects widespread systemic atherosclerosis, affecting the coronary and cerebral arteries and increasing the risk of myocardial infarction and stroke. Early diagnosis is essential to prevent disease progression and manage cardiovascular risks [39]. The diagnosis typically involves clinical evaluation, ankle-brachial index (ABI) measurement, and advanced imaging modalities [40]. Management strategies include lifestyle changes, pharmacological treatment targeting risk factors such as hyperlipidemia and hypertension, antiplatelet therapy, and, in advanced cases, revascularization procedures such as angioplasty or surgical bypass [41].

2.2.1 Pathophysiology and Cardiovascular Complications

PAD significantly contributes to systemic cardiovascular dysfunction. The narrowing of arteries leads to increased vascular resistance, thereby elevating cardiac workload and promoting sustained hypertension. Furthermore, persistent endothelial dysfunction, oxidative stress, and chronic vascular inflammation accelerate the progression of atherosclerosis. Consequently, these pathological mechanisms markedly increase the risk of coronary artery disease (CAD), heart failure, stroke, and renal impairment [41, 48, 49].

Key pathophysiological mechanisms include:

- **Endothelial Dysfunction:** Impaired vasodilation, increased vascular permeability, and prothrombotic state resulting from endothelial injury [48].
- **Vascular Inflammation:** Chronic inflammation exacerbates plaque formation and instability, increasing the risk of cardiovascular events [49].
- **Collateral Circulation:** Collateral vessels develop in response to ischemia, but generally do not fully compensate for arterial occlusion [40].
- **Progressive Vascular Deterioration:** A cycle of continued damage despite compensatory mechanisms contributes to long-term morbidity [41].

Table 2.1: Major complications associated with PAD.

Complication	Description and Clinical Significance
Critical Limb Ischemia (CLI)	Persistent rest pain, non-healing ulcers, and tissue necrosis, often resulting in limb loss if untreated [10].
Gangrene	Irreversible tissue death caused by prolonged ischemia, frequently necessitating amputation [42].
Myocardial Infarction	Increased risk due to systemic atherosclerosis affecting the coronary arteries [43].
Stroke	Elevated risk of ischemic stroke due to atherosclerotic plaques in cerebral arteries [44].
Claudication	Intermittent limb pain during exertion indicative of early ischemia [45].
Non-Healing Ulcers	Chronic wounds resulting from inadequate perfusion, often complicated by infection [46].
Sepsis	Life-threatening systemic infection arising from infected ulcers or gangrenous tissue [47].
Amputation	Surgical removal of a limb due to irreversible tissue damage or severe infection [47].
Tissue Necrosis	Localized tissue death requiring surgical debridement or intervention [42].

PAD-related complications, which result from chronic ischemia and impaired tissue perfusion, significantly increase morbidity and mortality. These complications are detailed in Table 2.1.

2.2.2 Global Epidemiology and Risk Factors of Peripheral Artery Disease

PAD is a leading cause of morbidity and functional impairment worldwide, particularly affecting older adults and people with cardiovascular risk factors. In 2025, an estimated 200 to 237 million people are affected globally, with projections that exceed 360 million

cases by 2050 due to aging populations and increasing prevalence of diabetes and hypertension [9].

The prevalence increases rapidly with age, affecting approximately 21.7% of women and 14.8% of men 65 years and older [50]. Gender differences may be influenced by the presentation of symptoms, hormonal factors, and healthcare utilization patterns. Furthermore, more than 50% of the cases occur in low- and middle-income countries (LMIC), where rapid urbanization, lifestyle changes, and limited access to preventive care contribute to the increase in prevalence and diagnostic delays [51].

Addressing these disparities through targeted public health efforts is essential to mitigate the global burden of PAD [52].

2.3 CT-Based Peripheral Artery Segmentation for Management of Peripheral Artery Disease

Accurate segmentation of PAs is a fundamental step in the management of PAD. This process involves isolating arterial structures from surrounding tissues, allowing detailed visualization and precise quantification of the vascular structure. This detailed arterial mapping is essential for assessing arterial health and guiding clinical decisions [53].

CT imaging is a primary modality for PA segmentation due to its ability to generate high-resolution three-dimensional vascular images [42, 54]. These volumetric datasets provide the anatomical detail necessary for advanced segmentation algorithms to accurately delineate the complex branching patterns and variable anatomy of PAs [54].

PA segmentation from CT plays a vital role in the treatment of PAD by providing a clear and detailed visualization of the vascular structures that supply the limbs. This technique enables several key benefits:

- **The creation of precise 3D models** of the arterial network, which are essential for thorough clinical evaluation and effective treatment planning.
- **Enhanced understanding of patient-specific vascular anatomy**, facilitating personalized intervention strategies.
- **Quantitative analysis of vessel geometry**, allowing for comprehensive evaluation of vascular health and pathology.

- **Monitoring disease progression and therapeutic outcomes** by comparing segmented images over time, thus supporting longitudinal patient management.

Recent advances in AI and ML have increasingly automated PA segmentation, streamlined diagnostic workflows, and enabled earlier detection of PAD. These technologies improve precision medicine by producing patient-specific models of the peripheral arterial system, supporting customized treatment strategies and improved clinical outcomes [54]. CT imaging is central to these developments, as its comprehensive high-resolution vascular datasets provide the essential input for AI- and ML-based algorithms. The resulting segmented representations provide detailed anatomical insights into the peripheral arterial network, directly forming diagnosis, treatment planning, and long-term patient management.

2.4 Imaging Modalities for Artery Segmentation

Accurate artery segmentation depends heavily on the quality and characteristics of the imaging data. Different imaging modalities provide varying levels of spatial resolution, contrast, and anatomical coverage, which directly affect the ability to visualize and delineate vascular structures. Commonly used modalities include X-ray angiography, CTA, MRA, ultrasound, and OCT. Each modality has different advantages and limitations, so choosing the appropriate imaging technique is a critical consideration.

This section provides an overview of the key imaging techniques applied to artery segmentation.

X-ray Angiography

X-ray angiography is an invasive technique that uses iodinated contrast agents to visualize the arterial lumens with high contrast [55]. It provides excellent temporal resolution for dynamic studies [56], although repeated use is limited by exposure to ionizing radiation. Segmentation approaches for X-ray angiography are shaped by their imaging characteristics and the inherent challenges of noise and overlapping structures. Segmentation is typically achieved through contrast enhancement, noise suppression, edge detection, region growth, and DL-based models [57].

Magnetic Resonance Angiography

MRA is a radiation-free and non-invasive technique for arterial imaging that is optimal for longitudinal studies [58]. Despite the fact that segmentation is restricted by reduced spatial resolution and extended acquisition times [59], it offers a significant amount of contrast in soft tissue. These considerations drive the development of segmentation techniques aimed at improving vessel visibility. Vessel enhancement filters, multiscale analysis, and ML algorithms have been developed to improve segmentation accuracy, particularly for small or low-contrast vessels [60].

Table 2.2: Comparison of arterial imaging modalities highlighting key features, segmentation challenges, and recent advancements

Modality	Key Features	Challenges	Recent Advancements
X-ray Angiography	High temporal resolution, contrast-enhanced artery visualization	Invasive, radiation exposure, noise and overlapping structures	DL-based segmentation, validated across multicenter datasets [61]
MRA	Radiation-free, strong soft tissue contrast	Lower spatial resolution, long acquisition times	Adaptive Frangi filters, hybrid 2D–3D segmentation pipelines [62]
Ultrasound Imaging	Portable, safe, real-time imaging	Operator dependence, speckle noise, limited depth penetration	DL models, anatomical border analysis, attention mechanisms [63]
OCT	Micrometer-scale resolution, detailed structural imaging	Limited penetration depth, invasive acquisition	FCNs, semantic segmentation for retinal structures [64]
CT Scan	High-resolution 3D reconstructions, rich spatial information	Radiation exposure, contrast agent risks	U-Net, V-Net architectures for segmentation [65]

Ultrasound Imaging

As a non-invasive technique, ultrasound imaging applies high-frequency sound waves to capture real-time visualization of internal vascular anatomy [66]. Doppler-based modalities further enable the assessment of the dynamics of blood flow within the

arteries. Although ultrasound offers high temporal resolution and is widely accessible, its segmentation accuracy is limited by operator dependence, speckle noise, and restricted penetration depth. To address these challenges, automated frameworks that combine image pre-processing, statistical modeling, and neural networks have been introduced to improve boundary delineation and consistency [67].

Optical Coherence Tomography

OCT is an invasive imaging modality that provides micrometer-scale resolution, allowing detailed visualization of arterial microstructures [68]. Despite its shallow penetration depth, OCT delivers high-resolution structural data that support the development of precise segmentation techniques. Methods such as contour extraction, graph-based algorithms, and DL architectures have been used to achieve high-fidelity delineation of arterial walls and related features [69].

Computed Tomography Scan

CT scan is a noninvasive technique that generates high-resolution, three-dimensional images of the vasculature [70]. Although its use is limited by exposure to ionizing radiation and contrast agents, modern low-dose protocols can help mitigate these risks [71]. The rich volumetric information provided by CT scans enables advanced segmentation approaches, including multiscale feature fusion, DL, and hybrid ML methods for vessel extraction and morphological analysis [72].

Each imaging modality exhibits distinct advantages and limitations for arterial segmentation. Table 2.2 summarizes their key characteristics, segmentation challenges, and recent advances.

2.5 Dimensionality in Artery Segmentation

The dimensional structure of medical imaging data affects the accuracy and methodology of arterial segmentation. Although 2D data offer computational efficiency and simpler implementation, 3D data preserve spatial continuity and provide a more comprehensive anatomical representation. The format of the imaging data directly influences the accuracy of segmentation, computational requirements, and clinical applicability [72, 60].

This section reviews the advantages, limitations, and emerging trends in the use of 2D and 3D imaging data to delineate vascular structures.

Slice-by-Slice Approach

The 2D imaging data are acquired as individual slices from CT. Each slice is processed independently, allowing computationally efficient segmentation suitable for real-time applications and resource-constrained settings [73]. Traditional techniques, such as thresholding, edge detection, and region growth, remain widely used because of their simplicity and low computational cost. More recently, CNNs, particularly 2D U-Net architectures, have achieved strong performance in segmenting arterial structures from single-slice data [74]. A key limitation of 2D segmentation is the lack of spatial continuity across slices. This can lead to discontinuities in reconstructed vessels, particularly in cases with bifurcations, or overlapping vascular structures [75].

3D Imaging Data

3D imaging data are acquired through volumetric CT scans [70]. These datasets maintain spatial relationships across slices, allowing anatomically consistent segmentation of complex vascular structures [60]. DL models, particularly 3D CNNs, leverage volumetric context to capture intricate spatial features essential for delineating entire vascular trees [72].

The use of 3D data allows for anatomically consistent artery segmentation, captures complex vessel structures, and improves the accuracy of morphological analysis [71]. However, 3D models require substantial memory and processing power. Furthermore, creating annotated 3D datasets is resource intensive, and the limited availability of large high-quality volumetric datasets restricts clinical applications [58].

A summary comparison of the features, challenges, and recent advances in the 2D and 3D approach to artery segmentation is provided in Table 2.3, highlighting the trade-offs between computational efficiency and anatomical completeness.

Hybrid and Advanced Segmentation Techniques

Hybrid approaches have been developed to integrate 2D and 3D segmentation, leveraging the advantages of each while mitigating their respective limitations. One common strategy

Table 2.3: Comparison of 2D and 3D imaging data for artery segmentation.

Dimensionality	Key Features	Segmentation Challenges	Challenges	Recent Advances
2D Imaging	Slice-by-slice acquisition from CT, computationally efficient	Limited spatial continuity, prone to vessel discontinuities [73]		2D U-Net and CNN models, registration-based integration [76]
3D Imaging	Volumetric data from CT scans, preserves spatial relationships	High memory and processing demands, limited annotated datasets [65]		3D CNNs, transformer-based models, multi-view integration [75]

is the use of 2.5D models, which process multiple adjacent 2D slices simultaneously. This approach incorporates a partial volumetric context to improve vessel continuity and anatomical accuracy while maintaining computational efficiency [77].

Cascade architectures are another widely adopted solution, where a 2D network performs initial segmentation or coarse localization, followed by a 3D refinement stage that enforces volumetric consistency and captures complex spatial relationships [78]. Multistage pipelines such as these reduce computational overhead while enhancing the fidelity of reconstructed vascular structures.

Recent advances in DL further enhance segmentation performance. Attention mechanisms, including spatial and channel modules, allow networks to selectively focus on relevant vascular regions, suppress noise, and accurately delineate small or tortuous vessels [79]. Transformer-based models extend this capability by capturing long-range dependencies and global context across slices or volumetric patches, improving the robustness of vessel extraction in challenging datasets [80].

Moreover, multiview learning integrates axial, sagittal, and coronal perspectives to improve anatomical consistency [81], while self-supervised and semi-supervised frameworks leverage unlabeled or sparsely annotated data to address the scarcity of volumetric annotations [82]. Graph-based neural networks offer another approach by explicitly modeling the topological structure of vascular trees, improving connectivity, and reducing segmentation discontinuities [83].

Collectively, these hybrid and advanced methods aim to achieve high-precision artery segmentation while addressing the computational, anatomical, and annotation challenges inherent in conventional 2D or 3D approaches.

2.6 Classical Approaches

Classical image processing methods have been the foundation for arterial segmentation. These techniques typically rely on engineered features and intrinsic image properties, such as intensity, edges, shape, and topology, to distinguish the arteries from surrounding tissues.

Thresholding and Intensity-Based Segmentation

Traditional segmentation of the arteries begins with thresholding, using the contrast difference between the vessels and surrounding tissue, particularly in contrast-enhanced CT scans. To address intensity inhomogeneity, adaptive and multilevel thresholding methods have been developed [84]. Despite these advances, thresholding alone is sensitive to noise, partial volume effects, and non-uniform contrast distribution, which can limit segmentation accuracy in complex vascular structures.

Region Growing and Region Merging

Region-growing methods start from user-defined or automatically detected seed points and iteratively include neighboring pixels based on similarity criteria such as intensity and gradient. These techniques preserve vessel connectivity and have been improved by incorporating constraints to prevent leakage, including gradient thresholds and shape restrictions [85]. Region merging strategies complement region growth by combining over-segmented areas to refine vessel delineation [86].

Edge-Based Segmentation

Edge-based segmentation methods use gradient operators to detect vessel boundaries. Artery segmentation has been approached using active contour models, also known as snakes [87], and subsequently with level-set methods [88]. These deformable models optimize energy functions that combine edge strength and region homogeneity. Recent

adaptations include the incorporation of vesselness measures in the energy term to improve the adherence of the contour to the boundaries of the vessel [89]. However, these approaches are highly sensitive to both initialization and image noise.

Vessel Enhancement Filtering

Vessel enhancement filtering is based on the second-order local structure of images. Frangi et al. [90] proposed a multiscale vesselness filter that uses the eigenvalues of the Hessian matrix to highlight tubular structures. Later studies introduced improved filters to better suppress non-vessel structures and adapt to different vessel sizes [91]. These enhancement techniques are applied as a preprocessing step, enabling a more accurate segmentation of the arteries.

Morphology for Artery Segmentation

Mathematical morphology techniques, including dilation, erosion, and skeletonization, are used to clean segmented arteries, fill gaps, and extract centerlines [92]. These operations improve the connectivity and smoothness of segmented vessels, which is essential for accurate clinical quantification. Topology-preserving morphological filters have been developed to maintain vessel tree structures during segmentation refinement [93].

Graph-Based Artery Segmentation Method

Graph-based approaches represent vessels as interconnected networks, using algorithms such as shortest path and minimal cost pathfinding to extract arterial centerlines and segmentations. Fast Marching and Dijkstra algorithms have been adapted for the tracing of 3D vessels from seed points [94]. Recent classical approaches combine vesselness maps with graph search to improve robustness against noise and vessel discontinuities [95].

Classical artery segmentation approaches are based on explicit modeling of vessel characteristics and local image features. Advances in vessel enhancement filters, region-based techniques, and graph-based methods have significantly improved segmentation quality. However, imaging artifacts, complex vessel geometries, and the need for manual initialization or parameter tuning continue to limit their effectiveness.

2.7 Machine Learning

ML techniques have improved artery segmentation by allowing models to learn discriminative representations from data, adapting to diverse vessel appearances, noise levels, and imaging conditions. Methods include feature-based supervised learning, graphical models, and clustering-based techniques.

Feature-Based Supervised Learning

Early ML approaches extracted descriptive features from image pixels or regions as inputs to classifiers that distinguish vessel pixels from the background. Features include intensity values, gradient magnitude, texture descriptors such as Gabor filters and Local Binary Patterns, and shape-related measures derived from the Hessian matrix [92]. Multi-scale feature extraction captures vessels of varying calibers and improves robustness to noise and intensity variations.

Classifiers include SVMs, random forests, k-nearest neighbors, and boosting algorithms [96, 97]. For example, multi-scale features combined with an SVM classifier improve vessel segmentation accuracy. Random forests handle high-dimensional feature spaces and provide probabilistic output useful for post-processing. These methods depend on the quality and relevance of the features and often ignore spatial dependencies, which can produce noisy segmentation maps.

Graphical Models and Structured Prediction

Graphical models such as markov random fields and conditional random fields (CRFs) have been used to model spatial dependencies and enforce smoothness in segmentation. They combine the output of the classifier with pairwise terms that encourage the consistency of the label between neighboring pixels [98].

Graph-cut algorithms efficiently minimize the energy functions defined by these models, producing refined and spatially coherent segmentations. Graph-based minimal path techniques combined with ML-based vessel measures trace artery centerlines by solving shortest path problems on weighted graphs [99], using both learned appearance models and vessel connectivity constraints.

Clustering-Based Methods

Clustering algorithms such as k-means, fuzzy c-means, and Gaussian Mixture Models (GMM) partition image pixels into vessel and background groups based on intensity or texture similarity [100]. Incorporating prior knowledge of vessel shape or applying morphological post-processing can enhance vessel continuity and connectivity in segmented results [101].

ML has improved arterial segmentation through statistical learning and pattern recognition [102]. Classical ML methods depend on manually designed features and shallow classifiers, making them sensitive to noise, imaging artifacts, and inter-patient variability [103]. Their generalization across acquisition protocols is limited, requiring extensive feature engineering and parameter tuning [5].

These limitations have led to the shift to DL, where hierarchical feature learning from raw data provides higher accuracy and robustness while reducing reliance on domain expertise and manual intervention.

2.8 Deep Learning for Artery Segmentation

DL has transformed arterial segmentation by enabling models to learn spatially coherent features directly from CT imaging data [104]. This approach eliminates the dependence on manual feature design while capturing both local vessel patterns and global vascular structures, resulting in more accurate segmentation of the arteries.

Convolutional Neural Network

CNNs are applied for artery segmentation due to their ability to extract spatially localized vessel features. Fully convolutional networks (FCNs) provide pixel-wise predictions but often have difficulty preserving fine vessel details.

3D CNNs are used for volumetric artery segmentation in CT scans. Extending convolutions across all three dimensions allows the network to capture vessel continuity and preserve the topology of arterial trees. Duan et al. proposed a context-aware 3D FCN for artery segmentation, integrating spatial priors to suppress vessel-like artifacts and improve anatomical precision [105]. AngioNet, a CNN-based architecture for X-ray angiography, improves segmentation by integrating an Angiographic Processing Network

(APN) that enhances low-contrast vessel regions and reduces oversegmentation [106]. Similarly, Wang et al. introduced a 3D CNN with dense residual and local contextual transformer modules, achieving superior performance on coronary CT scan datasets [65].

U-Net Variants

The U-Net architecture has an encoder-decoder design with skip connections that preserves high-resolution spatial information while integrating contextual features on multiple scales [65]. The U-Net variations have been adapted for artery and vessel segmentation to address challenges such as thin vessel detection and maintaining structural continuity.

Residual U-Net introduces residual connections to improve gradient flow and training stability. Attention U-Net incorporates attention gates to selectively focus on vessel-like regions, improving performance in complex vascular networks. Multiscale U-Net models extract features at multiple resolutions, enabling detection of both small capillaries and larger arteries [107, 108].

V-Net for Volumetric Artery Segmentation

V-Net is a 3D CNN designed for segmentation of medical volumetric images [109]. The encoder-decoder design with residual connections enables the learning of features across all three dimensions, which is useful for artery segmentation in CT scan volumes. V-Net processes volumetric patches to capture vessel continuity and preserve the topology of arterial trees.

Tang et al. extended the V-Net architecture for multi-label segmentation of anatomical structures in cardiac CT scans, optimizing the network using a Dice-based loss across multiple classes and applying post-processing to refine vessel surfaces [110]. Their method achieved fast segmentation of whole CT scan volumes with improved anatomical accuracy.

Patch-based training in V-Net may encounter difficulty in capturing the global context. Overlapping inference patches and hybrid strategies ensure full vessel coverage and maintain spatial coherence [104]. Post-processing techniques such as 3D morphological filtering and CRFs further refine segmentation maps and maintain branching structures.

Transformer-Based Models

Transformer-based architectures are applied to segment the arteries to capture long-range dependencies in images or volumetric data. Vision Transformers (ViTs) and hybrid CNN-Transformer networks use self-attention mechanisms to model both local vessel features and global vascular structures. Swin Transformers, with hierarchical patch-based attention, reduce computational cost while preserving spatial resolution [16].

Zafari-Ghadim et al. reviewed transformer-based models for stroke and vascular segmentation, highlighting their ability to capture complex spatial information [111]. The study emphasized the role of hierarchical attention and multi-scale modeling for accurate vascular structure representation.

Transformer models require large annotated datasets or pretraining to generalize effectively. They are effective in segmenting long vessels, bifurcations, and complex branching patterns, but computational complexity and sensitivity to data quality remain significant challenges.

Recurrent Neural Networks and Sequential Models

Recurrent neural networks (RNNs), including LSTM and GRU layers, capture the sequential nature of arteries along vessel paths. By modeling long-range dependencies, RNNs improve continuity in thin branches. Hybrid CNN-RNN architectures combine CNN-based spatial feature extraction with sequential modeling, enhancing segmentation quality and reducing fragmentation [112, 113].

The features learned from RNN-based models can also be combined with graph-based minimal path methods to extract artery centerlines and preserve vascular connectivity in complex branching networks.

Patch-Based Volumetric Training

Patch-based volumetric training is used to manage GPU memory requirements in 3D artery segmentation. Networks are trained on smaller volumetric patches, allowing efficient memory usage and parallel processing. During inference, overlapping patches ensure complete coverage of arterial structures and reduce boundary artifacts [114].

Post-processing techniques, such as 3D morphological filtering and CRFs, refine segmentation maps, suppress artifacts, and preserve vessel connectivity across the volume [114].

While DL has been successful, segmentation of the arteries still poses challenges [4]. These techniques and their associated challenges are summarized in Table 2.4. Small arteries occupy only a small portion of the image, leading to class imbalance [115]. Volumetric networks require substantial computational resources, and Transformer-based models require large annotated datasets or pretraining [116]. Generalization across scanners and imaging protocols is limited, and preserving continuous tree-shaped artery structures remains difficult [115].

Table 2.4: Recent DL techniques for artery segmentation.

Technique	Key Features	Challenges	Example Applications (with References)
Convolutional Neural Networks	Spatial feature extraction, pixel-wise prediction, 2D/3D segmentation	Limited fine vessel detail, high memory requirements for 3D volumes	Automated coronary segmentation in CT scans [106, 105, 65]
U-Net Variants	Encoder-decoder with skip connections, residual and attention modules	Overfitting on small datasets, high computational cost	Multi-scale artery segmentation in CT scans [107, 108]
V-Net for Volumetric Segmentation	3D convolutions with residual blocks, volumetric patch processing	Memory-intensive, limited capture of global context	3D cerebral artery extraction; pulmonary vessel tree reconstruction [109, 110, 114]
Transformer-Based Models	Self-attention, global context modeling, hierarchical patch attention	Requires large annotated datasets, computationally expensive	Segmentation of long PAs; bifurcation and branching structure delineation [117, 111, 118]
Recurrent and Sequential Models	Sequential modeling with LSTM/GRU integration, long-range dependency capture	Training instability, reduced spatial context	Temporal tracking of vessels in CT scans [112, 113]
Patch-Based Volumetric Training	Memory-efficient localized training with overlapping inference	Reduced global context, potential boundary artifacts	Large-volume whole-body vessel segmentation in CT scans [114, 119, 120]

2.9 Transfer Learning for Artery Segmentation

Transfer learning initializes artery segmentation networks with pre-trained models from large datasets. Fine-tuning of vascular data accelerates training, reduces overfitting, and improves generalization across CT datasets.

Early CNN layers capture transferable edge and texture features, while deeper layers adapt to artery-specific patterns. Pre-trained Vision Transformers improve CT segmentation, especially in low-contrast regions [118].

Retinal vessel models have been adapted to coronary and cerebral artery segmentation through selective layer freezing and domain adaptation. Self-supervised pre-training on unlabeled CT volumes captures vascular continuity, boosting downstream segmentation [121]. A pre-trained cross anatomy framework was fine-tuned for the coronary and brain arteries using a shape-sensitive layer freezing strategy [122]. Multi-target adversarial training aligns feature distributions between scanners and populations and uses multi-teacher distillation to improve performance [123]. Style adaptation transfers target domain characteristics to source features in latent space, improving segmentation consistency in heterogeneous CT datasets [124].

Transfer learning enables accurate segmentation of the arteries with limited annotations. Variations in resolution, contrast, and anatomy can limit transferability, so selecting source tasks, fine-tuning strategies, and augmentation pipelines is critical for optimal performance. These strategies are summarized in Table 2.5.

2.10 Multi-Structure and Prompt-Based Segmentation Frameworks

Recent progress in deep learning has resulted in generalist models capable of segmenting multiple anatomical structures. Among these, Segment Anything Model for Medical Imaging (**SAM-Med**) [126] and **TotalSegmentator** have emerged as prominent tools for automated artery and organ segmentation in CT datasets. A comparison of these models is presented in Table 2.6.

Table 2.5: Summary of transfer learning strategies in artery segmentation.

Approach	Method Summary	Advantages / Constraints
Pre-training on Large Datasets	Initialize models on large-scale datasets before vascular fine-tuning	Reduces training time; improves generalization; may require domain-specific adaptation [118, 121]
Selective Layer Freezing	Freeze early layers and fine-tune deeper layers for artery-specific features	Preserves transferable features; balances adaptation and overfitting [125, 122]
Self-Supervised Pre-training	Learn representations from unlabeled CT volumes	Captures vascular continuity; useful with limited annotations [121]
Cross-Anatomy Transfer	Transfer models between anatomically distinct domains (e.g., liver to coronary)	Requires shape-aware strategies; improves flexibility across tasks [122]
Adversarial Domain Adaptation	Align feature distributions across domains using adversarial objectives	Improves cross-domain performance; requires complex training setup [123]
Style Adaptation in Latent Space	Harmonize style between source and target features in latent space	Enhances consistency in heterogeneous datasets; sensitive to style mismatch [124]

SAM-Med: Segment Anything Model for Medical Imaging

SAM-Med [126] is a medical adaptation of the Meta AI segment anything model (SAM), fine-tuned on large-scale CT datasets to perform prompt-based segmentation.

For artery segmentation, SAM-Med operates as an interactive, prompt-dependent model. Users provide prompts such as bounding boxes, points, or coarse masks to guide the segmentation process. Although flexible, performance depends on the complexity of the vascular anatomy and the precision of user-provided instructions [126].

TotalSegmentator: Comprehensive Anatomical Segmentation

TotalSegmentator is a deep learning-based framework built on the nnU-Net architecture. It is trained to segment over 100 anatomical structures from CT scans, including major arteries such as the aorta, carotid, iliac, and femoral arteries. Unlike task-specific models, TotalSegmentator is designed for full-body segmentation.

For arterial applications, TotalSegmentator provides high-resolution masks suitable for quantitative analysis, surgical planning, and disease monitoring. Its open-source implementation and compatibility with DICOM workflows enhance accessibility for research and clinical practice. The model has demonstrated high Dice scores across multiple vascular structures [127].

Table 2.6: Comparison of SAM Med and TotalSegmentator covering challenges, training data, and applications in artery segmentation

Aspect	SAM-Med	TotalSegmentator
Challenges	Requires high-quality prompts; struggles with fine-grained or ambiguous anatomy	Limited to CT modality; less adaptable to unseen anatomical variations
Training Data Type	Adapted from SAM using multi-modal CT datasets with prompt supervision	Supervised training on manually annotated CT scans
Applications	Interactive segmentation, semi-automated labeling, research prototyping	Full-body anatomical segmentation, clinical workflows, dataset annotation

2.11 Conclusion

This chapter provided a comprehensive overview of the foundational concepts relevant to arteries segmentation. It began with an introduction to the human circulatory system, establishing the anatomical and physiological context necessary to understand vascular imaging. The discussion then focused on PAD, highlighting its clinical significance and the role of imaging in its diagnosis and management.

CT-based segmentation of PA was examined as a critical tool for assessing PAD, followed by a review of various imaging modalities commonly employed in vascular analysis. The chapter also addressed the importance of dimensionality in segmentation tasks, distinguishing between 2D, 2.5D, and 3D approaches.

Classical image processing techniques were discussed alongside machine learning methods, illustrating the evolution of segmentation strategies. The emergence of DL

was explored in detail, emphasizing its transformative impact on medical image analysis. Additionally, the potential of transfer learning, particularly in leveraging pretrained models, was considered, along with recent advancements in multi-structure and prompt-based segmentation frameworks.

In summary, this chapter established the theoretical and technological foundation for the segmentation framework developed in this study.

Part II

Contributions

Chapter 3

Methodology

Contents

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The focus of this section is to locate and segment the PA from 3D CT scans. To achieve this, a dual-strategy approach is adopted, which combines ROI localization with a segmentation methodology.

The ROI localization step is designed to identify and isolate the spatial region containing the PA, thereby reducing background complexity and focusing the subsequent segmentation process on the most relevant anatomical structures.

For the segmentation task, two strategies are employed, namely the Transfer Learning Approach and the Isolated Learning Approach. These approaches are designed to investigate complementary pathways to improve segmentation performance using DL techniques.

The Transfer Learning Approach involves initializing segmentation models with features learned from anatomically related vascular structures, specifically the coronary

artery (CA) and pulmonary arteries (PulA). The pretrained models are subsequently fine-tuned on the PA dataset to adapt them to the target segmentation task.

In parallel, the Isolated Learning Approach trains segmentation models directly on PA data without any external pretraining. This strategy is designed to capture the unique characteristics of the target vascular region through an independent learning process.

Following the segmentation stage, a visualization pipeline is implemented to support the interpretation and analysis of the segmented vascular structure. This pipeline incorporates curved planar reformation (CPR), which produces an anatomically aligned visualization of the artery, allowing a detailed evaluation along its centerline. In addition, a cluster-based visualization technique is employed to emphasize distinct vascular segments and improve structural clarity.

A comprehensive overview of the methodology, including the integration of both strategies and the visualization process within the overall workflow, is presented in Figure 3.1. The sections that follow present a thorough description.

3.1 Dataset

This section presents an overview of the three CT imaging datasets used in this study, each representing a specific arterial region: PA, PulA and CA. These datasets encompass anatomically and clinically diverse vascular domains, providing support for both Isolated Learning and Transfer Learning approaches. Variations in imaging protocols, anatomical coverage, and vessel morphology in the datasets provide diverse information that contributes to the development of PA segmentation. Detailed information about each dataset is provided in the subsequent subsections.

3.1.1 Peripheral Artery Dataset

The PA dataset used comprises CT scans from five distinct sources, each offering varied anatomical coverage and imaging characteristics. This diversity supports the development of segmentation models that are applicable in a variety of clinical scenarios and imaging protocols.

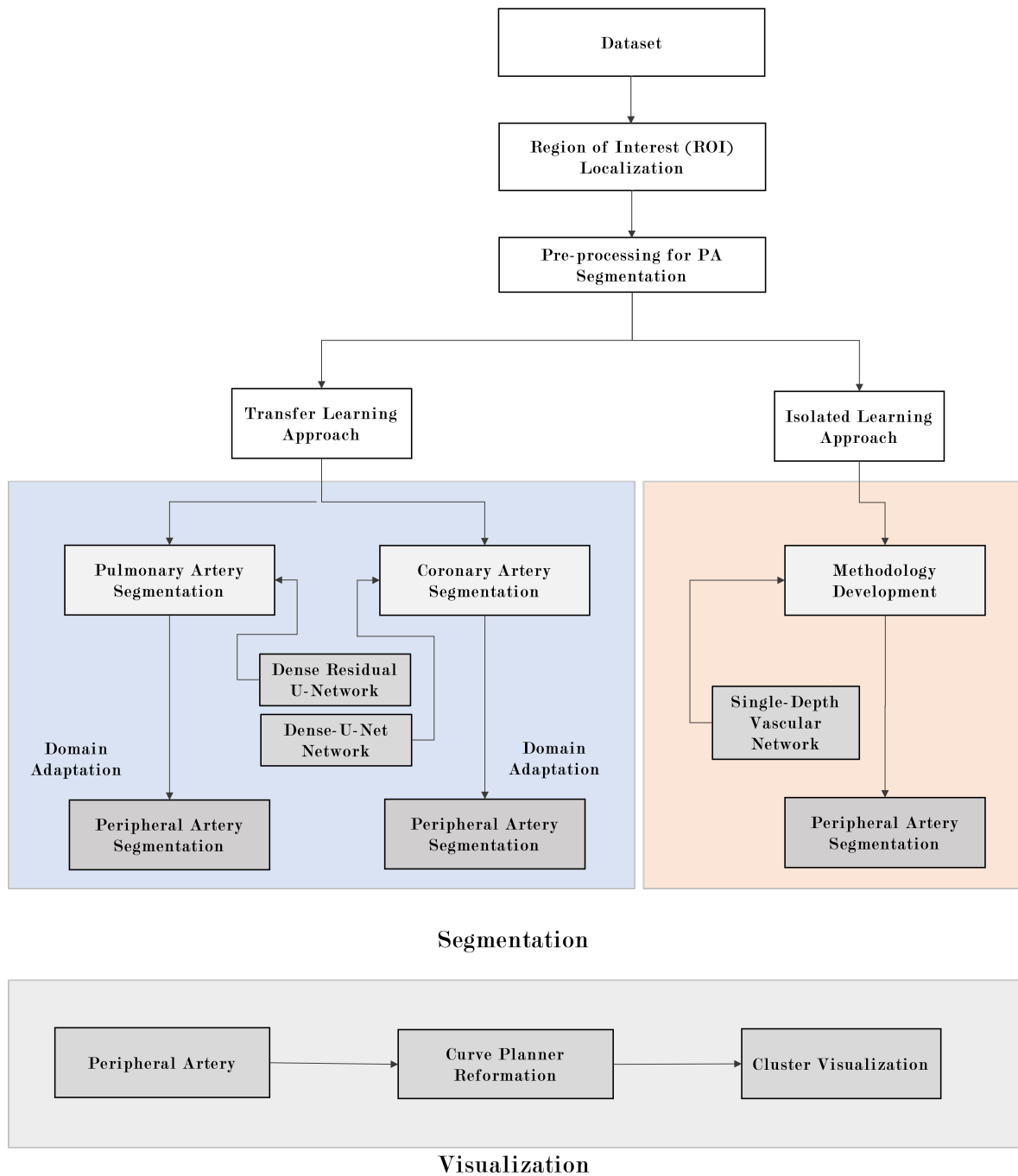


Figure 3.1: Schematic overview of the PA segmentation methodology. The workflow integrates two strategies: the transfer learning approach, leveraging pretrained models from CA and PulA domains, and the isolated learning approach, trained on PA data. Following segmentation, a visualization stage is applied, including CPR and cluster-based visualization.

The KiTS19 Grand Challenge [128], RIDER Lung CT [128], and Dongyang Hospital dataset [128] are publicly available under the CC BY-NC-SA 4.0 license and are governed



Figure 3.2: Differences in field of view, dimensions, and spacing among five CT scans. The figure highlights variations in anatomical coverage across the scans [Z2].

by EULAs. These datasets contain vascular structures and imaging characteristics relevant to PA segmentation. They include a variety of imaging conditions and anatomical regions that contribute to model training. Differences in voxel dimensions, contrast, and anatomical coverage allow the model to adapt to a wide range of imaging scenarios, boosting its adaptability in diverse clinical contexts.

Two additional datasets are obtained from the Gennimatas Hospital in Athens, Greece. The first dataset consists of full-body CT scans of 17 patients (13 men, 4 women) aged 38 to 77 years, with an average age of 59.1 ± 11.6 years. The second dataset focuses on the torso region and includes 19 patients (11 men, 8 women) aged 17 to 91 years, with an average age of 60.2 years (standard deviation 20.3 years).

Ethical clearance for utilizing these datasets was obtained from the relevant committees under protocol numbers 9876/28.3.24 and 11293/9.4.24. CT imaging for all patients was performed using a GE Revolution EVO scanner, and participants were chosen solely on the basis of a confirmed PAD diagnosis, without further selection criteria.

Table 3.1: Summary of imaging characteristics across five CT datasets used in this study, including resolution, axial slice count (minimum, average, maximum), voxel spacing, number of cases, contrast-to-noise ratio, signal-to-noise ratio, number of slices covering PA at 1 mm intervals, and arterial regions represented [Z2]

CT Scan Specification	KiTS	RIDER	Dongyang	Gennimatas_1	Gennimatas_2
Resolution (X, Y)	512, 512	512, 512	512, 666	512, 512	512, 512
Axial Slices(Min/Avg/Max)	94/146/1059	260/1008/1140	122/149/251	91/769/2311	91/292/906
Spacing (x, y)[Min, Max](mm)	[0.44, 0.98]	[0.69, 1.37]	[0.54, 0.75]	[0.84, 0.98]	[0.71, 0.98]
Spacing (z) [Min, Max](mm)	[0.50, 5.00]	[0.62, 2.50]	[2.50, 3.03]	[0.63, 3.75]	[0.60, 5.00]
Number of Cases	20	18	18	17	19
Contrast-to-Noise Ratio	0.99 ± 0.53	0.89 ± 0.38	1.05 ± 0.44	1.93 ± 0.83	2.41 ± 0.74
Signal-to-Noise Ratio	1.61 ± 4.18	3.33 ± 1.88	3.50 ± 0.98	3.52 ± 1.53	3.26 ± 0.85
PAs Number of Slices (1mm interval)(Min/Avg/Max)	180/228/301	180/245/283	180/185/237	253/346/848	346/700/786
PAs Region	Common iliac, Internal iliac, Common iliac, Common iliac, External iliac, Internal iliac, Internal iliac, Common femoral, External iliac, External iliac, Popliteal, Common femoral, Anterior tibial, Popliteal Posterior tibial				

Figure 3.2 illustrates the variation in field of view, scan dimensions, and voxel spacing between the included datasets. Table 3.1 provides a detailed summary of the corresponding scan specifications.

3.1.2 Pulmonary Artery Dataset

The transfer learning approach is developed using the publicly accessible dataset provided by the MICCAI 2022 Pula Segmentation Challenge (PARSE 2022) [129]. The key characteristics, including patient age, pixel spacing, and number of image slices, are summarized in Table 3.2, with values reported as minimum, maximum, and mean.

The scans are collected from three medical institutions: the Chinese PLA General Hospital, the Harbin Medical University Cancer Hospital, and the Hongqi Hospital. The

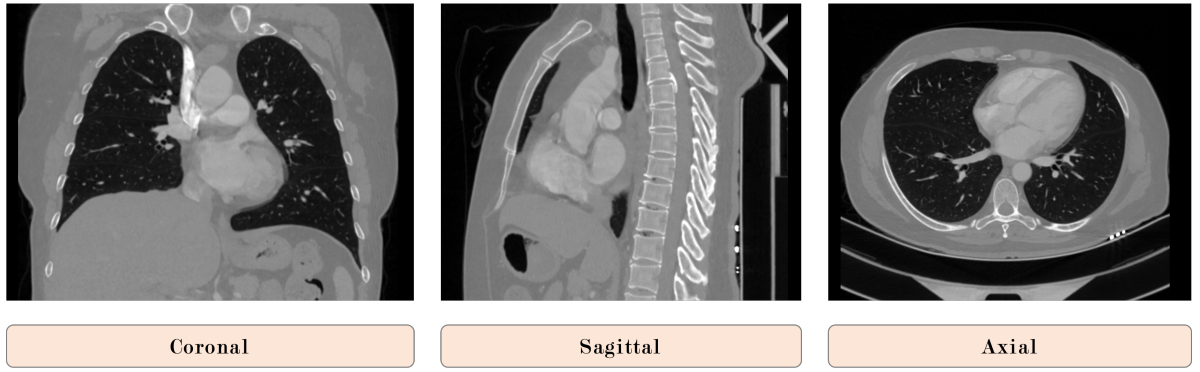


Figure 3.3: Coronal, axial, and sagittal view of a PulA CT scan, illustrating the anatomical structure across multiple planes.

Table 3.2: Summary of PulA dataset including sample count, gender, age, slice count, and pixel spacing

Parameter	Statistics
Total Samples	100
Gender (F/M)	79 / 21
Age Range (years)	29–71 (56.3)
Number of Slices	228–390 (303)
Pixel Spacing (mm)	0.5039–0.9238 (0.6740)

annotation process was performed by a group of ten experienced clinical specialists, each with at least five years in the field. These experts are divided into two groups of five, and each group independently annotated the dataset. CT scans are acquired using Siemens scanners in multiple medical centers. Annotations are created using the MIMICS software, which employs a region-growing algorithm. The procedure began with fine-tuning the window settings to enhance the display of PulA structures. The seed points are placed manually and iteratively refined to generate preliminary masks. Then, these annotations are reviewed and adjusted for accuracy. The final ground truth for each scan is generated by combining five separate annotations using a majority voting strategy. Figure 3.3 shows representative coronal, axial and sagittal views from a PulA CT scan, illustrating its anatomical appearance in different planes.

3.1.3 Coronary Artery Dataset

The ImageCAS [130] dataset consists of 1,000 CT scans collected at Guangdong Provincial People’s Hospital during the period 2012 and 2018. Each scan is annotated for the LCA and RCA. Annotations are independently performed by two experienced radiologists and subsequently reviewed by a third expert to ensure consistency and precision.

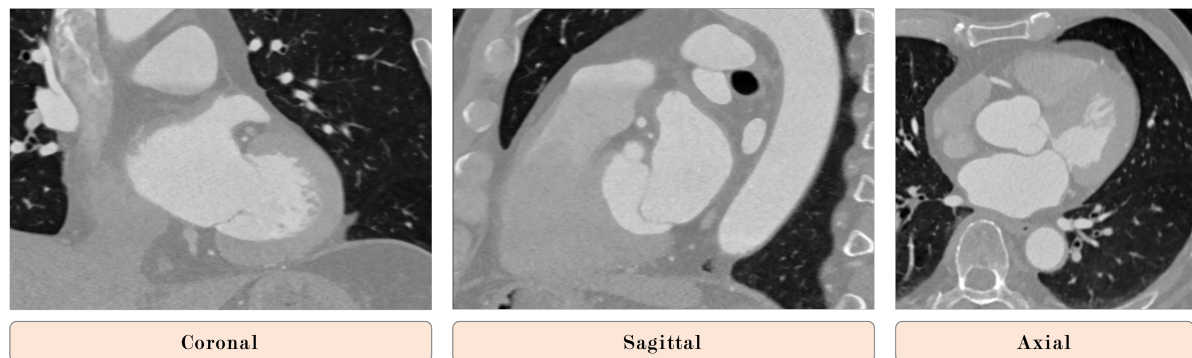


Figure 3.4: Representative CT scan from the ImageCAS dataset shown in axial, sagittal, and coronal planes, illustrating overall image quality.

Table 3.3: Summary of CA dataset including patient count, age distribution, CT volume dimensions, and voxel spacing.

Parameter	Statistics
Number of Patients	1,000 (586M / 414F)
Average Age	57.7 (M), 60.0 (F) years
CT Volume Dimensions	$512 \times 512 \times 206\text{--}275$
Voxel Spacing	0.25–0.45 mm

The dataset includes 586 male and 414 female patients, with average ages of 57.7 and 60.0 years, respectively. Each CT volume has an in-plane resolution of 512×512 pixels, with the number of axial slices per scan varying between 206 and 275. The spacing of the voxels falls within the range of 0.25 to 0.45 mm, reflecting differences in the acquisition protocols and the configuration of the scanner. These differences contribute to dataset diversity and help in training models capable of generalizing across multiple imaging scenarios. The imaging characteristics of the dataset are summarized in Table 3.3. In

addition, a representative CT scan is shown in Figure 3.4 across the axial, coronal, and sagittal planes, highlighting the vessel structures and anatomical detail.

3.2 Region of Interest Localization

CT imaging of the lower extremities often covers a diverse set of anatomical structures, many of which are not related to PAs, as shown in Figure 3.2. These irrelevant regions contribute to class imbalance and decrease the effectiveness of the model in capturing important vascular details. Identifying and extracting the relevant region is therefore an essential first step before the segmentation process.

ROI localization is performed automatically with YOLOv8 [131], a modern deep learning model designed for object detection and keypoint identification. Developed by Ultralytics, YOLOv8 combines real-time object detection with keypoint estimation, making it particularly effective for medical imaging applications that require precise anatomical localization. Its ability to simultaneously predict bounding boxes and keypoints enables an accurate identification of PA bifurcation points, which serve as critical landmarks for downstream segmentation and analysis.

Recent benchmark studies by Jegham et al. [132], have demonstrated the superior performance of YOLOv8 over earlier YOLO versions in terms of both inference speed and detection precision. These advantages position YOLOv8 as an efficient tool for complex medical imaging applications, where timely processing and precise results are critical.

The proposed ROI localization pipeline uses YOLOv8 to locate bifurcation points and delineate their surrounding regions. By focusing on these bifurcation points, the model effectively filters out non-informative anatomical areas, thereby improving the efficiency of subsequent segmentation tasks. Figure 3.5 illustrates the overall pipeline, highlighting the transformation from raw CT volumes to annotated 2D projections used for detection.

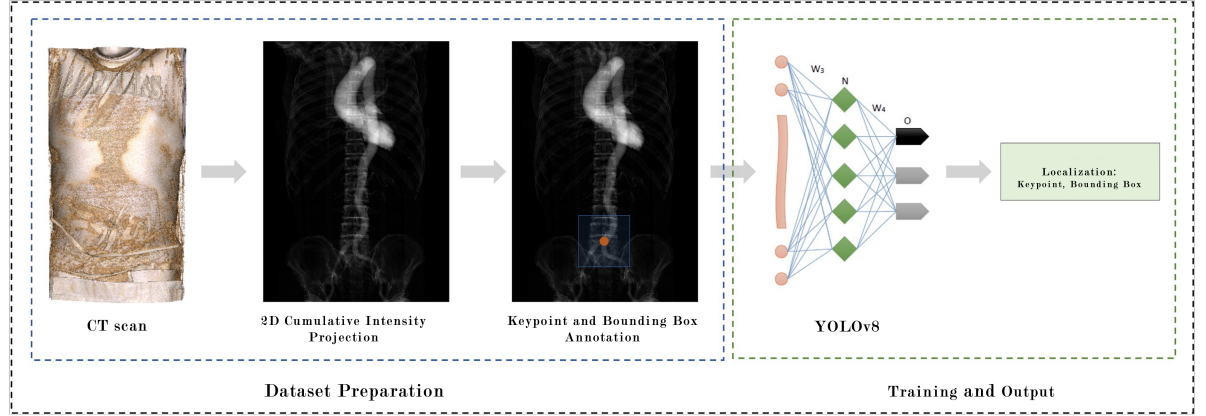


Figure 3.5: Pipeline for ROI localization using YOLOv8. Key arterial bifurcation points are detected along with their bounding boxes from 2D projections of 3D CT volumes [Z2].

3.2.1 Dataset Division for Peripheral Artery

The dataset for PA is partitioned into training (80%), validation (10%), and testing (10%) sets. This split ensures sufficient data for model training while maintaining representative samples for performance evaluation.

3.2.2 Data Preparation for Region of Interest Localization

Accurate localization of ROIs in CT scans requires transforming raw 3D CT data into structured inputs suitable for model training.

The transformation involves four main stages:

- **Intensity clipping**
- **Cumulative intensity projection**
- **Intensity normalization**

Each stage is described in detail below.

Intensity Clipping

The initial preprocessing step involves intensity clipping, applied to 3D CT volumes to reduce noise and eliminate irrelevant intensity variations. Voxel intensities are limited to a predefined range that aligns with the expected attenuation values of vascular tissues.

This targeted clipping improves the contrast between the PA and surrounding anatomical structures, resulting in clearer visualization of vascular features. This enhancement is particularly beneficial for the subsequent CIP step.

Cumulative Intensity Projection

CIP is a volumetric data reduction technique that transforms 3D imaging data into a 2D representation by summing voxel intensities along a specified anatomical axis. This approach is particularly effective in vascular imaging, where accumulated intensities accentuate vessel morphology and spatial distribution.

In this study, CIP is employed as a critical preprocessing step to enhance the visibility of the PA on CT scans. The projection is performed along the axis oriented according to the natural alignment of the imaging data to best preserve vessel continuity and structure. The resulting 2D image retains key morphological information while substantially reducing dimensionality and computational load.

The CIP is defined as follows:

$$\text{CIP}(x, y) = \sum_{z=1}^N I(x, y, z) \quad (3.1)$$

where:

- $I(x, y, z)$ indicates the intensity value of the voxel at coordinates (x, y, z) ,
- z is the index along the projection axis,
- N is the total number of slices along the z -axis.

By aggregating intensity values along the depth axis, CIP enhances regions with high cumulative intensity corresponding to the PA, thus improving their visibility.

Normalization

After generating the CIP images, normalization is applied to ensure consistency across the dataset and improve the stability of model training. This step standardizes the intensity values of each 2D (projection) by rescaling to a standard range between 0 and 1. The transformation is defined as follows.

$$I_{\text{norm}} = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (3.2)$$

where:

- I corresponds to the raw pixel intensity,
- $I_{\min}$ and $I_{\max}$ indicate the lowest and highest intensity values in the image,
- I_{norm} represents the normalized intensity.

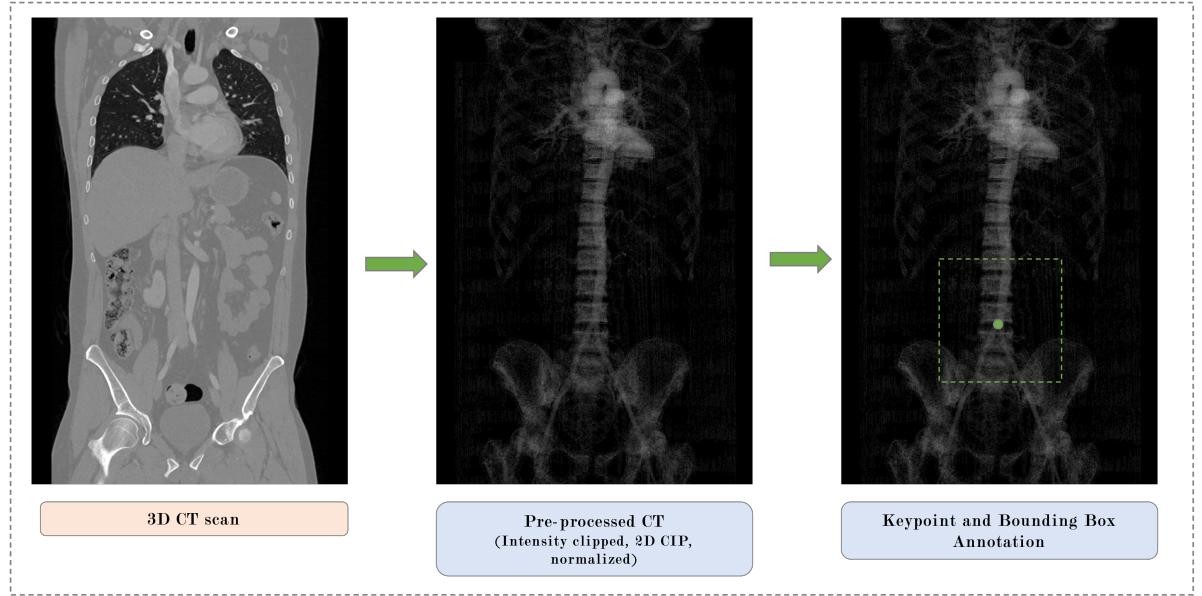


Figure 3.6: CT image pre-processing and annotation. CT scans subjected to intensity clipping, CIP, and normalization, followed by keypoint and bounding box annotations to locate ROI

3.2.3 Annotation of Keypoint and Bounding Box

Accurate annotation of PA bifurcations is crucial for supervised learning. In this study, expert annotators manually identified bifurcation points in each 2D CIP image using the Label Studio tool [133]. Each bifurcation is marked with a keypoint at the anatomical location where a vessel branches, providing a precise spatial reference for the model.

Alongside keypoints, rectangular bounding boxes are drawn around the regions surrounding each bifurcation. This dual annotation approach captures both detailed positional information and the broader spatial context. Keypoints enable the model to learn exact localization, while bounding boxes offer structural cues that improve detection robustness.

The key points and bounding boxes define the ROI and capture both precise anatomical locations and the surrounding spatial context, which is essential for effective model

training. These annotations provide the ground truth labels used to train the YOLO, enabling it to effectively learn both the appearance and spatial context of vascular bifurcations within the CT-derived projections.

The pre-processed CT image, following intensity clipping, CIP, and normalization, with keypoint and bounding box annotations for training, is shown in Figure 3.6.

3.2.4 Architecture of YOLOv8

YOLOv8 represents an object detection model developed by Ultralytics [134], featuring a modular and efficient architecture that improves accuracy, speed, and adaptability. The model architecture consists of three main components: the backbone, the neck, and the head, each optimized for a distinct role within the detection pipeline.

Backbone

The backbone extracts hierarchical features from the input image. Building on the CSPDarknet framework, YOLOv8 replaces the traditional C3 module with the more efficient C2f (Cross-Stage Partial with Feature Fusion) module. This innovation improves gradient propagation and reduces parameter count, thus improving training stability and inference speed. The C2f module achieves these improvements by splitting feature maps and reusing them across layers, incorporating residual connections that help maintain spatial and semantic information. The backbone processes the input through multiple convolutional and downsampling layers, generating multiscale feature maps rich in contextual details [134].

Neck

The neck acts as an intermediary between the backbone and the prediction head, facilitating the fusion of features at different scales. YOLOv8 employs a PANet-inspired neck design, allowing effective multiscale feature aggregation, critical for detecting objects of varying sizes. This component performs both upsampling and downsampling operations to align feature maps from different backbone stages. It also integrates skip connections and concatenation layers to preserve both low-level details and high-level semantic information. These combined operations improve the model's capacity to localize and classify objects accurately, even in complex visual environments [134].

Head

The head introduces a significant architectural advancement with its decoupled, anchor-free design. Instead of relying on predefined anchor boxes, YOLOv8 directly predicts object centers, thereby simplifying the training process and enhancing generalization across diverse datasets.

The head is divided into separate branches for classification and regression. The classification branch identifies object categories, while the regression branch estimates the bounding-box coordinates. Additionally, an objectness score quantifies the likelihood of an object's presence in a given region. This separation allows each branch to specialize, resulting in improved accuracy and robustness [131].

Therefore, The architecture of YOLOv8 is modular, scalable, and efficient, supporting various model sizes, from lightweight versions optimized for edge devices to larger configurations suitable for high-performance computing, achieved by adjusting the depth and width of the network. The integration of the C2f-enhanced backbone, PANet-style neck, and anchor-free decoupled head enables YOLOv8 to deliver state-of-the-art performance on multiple computer vision tasks, including object detection, segmentation, and pose estimation [134].

Training YOLOv8

The processed dataset is used to train YOLOv8. Each image includes annotated keypoints and bounding boxes, providing the necessary information for the model to learn precise object localization and pose estimation.

During training, the images are resized to 640×640 pixels. The training process employs data augmentation techniques to enhance the robustness of the model. These include:

- HSV adjustments: Random changes in hue, saturation, and value to simulate varying lighting conditions.
- Geometric transformations: Random rotations, translations, scaling, and shearing to improve model invariance to spatial variations.
- Flip augmentations: Horizontal and vertical flips to increase dataset diversity.

The network is optimized using the Adam optimizer with a learning rate scheduler to ensure stable convergence. The loss function combines bounding box regression loss, objectness loss, and keypoint localization loss, allowing simultaneous optimization for both detection and pose estimation tasks [134].

3.3 Pre-processing for Peripheral Artery Segmentation

Pre-processing for PA segmentation consists of three main steps: resampling to isotropic resolution, intensity clipping, and normalization, as illustrated in Figure 3.7. These steps standardize the input data and improve the reliability and performance of the downstream segmentation models.

Conversion from Anisotropic to Isotropic Resolution

This process resamples CT scans to achieve uniform voxel dimensions in all spatial directions. Given an original voxel spacing of (d_x, d_y, d_z) , the target isotropic spacing is defined as $(1.0, 1.0, 1.0)$ mm. Resampling is performed according to the method described in [135], using the following scaling factors:

$$S_x = \frac{d_x}{d_{\text{iso}}}, \quad S_y = \frac{d_y}{d_{\text{iso}}}, \quad S_z = \frac{d_z}{d_{\text{iso}}} \quad (3.3)$$

The dimensions of the resampled volume are computed as

$$n'_x = \lfloor n_x \cdot S_x \rfloor, \quad n'_y = \lfloor n_y \cdot S_y \rfloor, \quad n'_z = \lfloor n_z \cdot S_z \rfloor \quad (3.4)$$

where:

- d_x, d_y, d_z : original voxel spacings along the x , y , and z axes, respectively,
- n_x, n_y, n_z : original volume dimensions,
- d_{iso} : desired isotropic voxel spacing,
- S_x, S_y, S_z : scaling factors applied to each axis,
- n'_x, n'_y, n'_z : resampled volume dimensions corresponding to the isotropic spacing.

This standardization facilitates consistent spatial resolution, which is critical for segmentation.

Percentile Intensity Clipping

Following resampling, the voxel intensities are clipped to the $[P_{\text{low}}, P_{\text{high}}]$ percentile range to remove extreme outliers while preserving the most informative part of the distribution. In this study, $P_{\text{low}} = 0.5$ and $P_{\text{high}} = 95$. This operation reduces noise, and improves contrast, and minimizes variability between scans. The clipping is expressed mathematically as follows:

$$I_{\text{clip}} = \begin{cases} P_{\text{low}}, & \text{if } I < P_{\text{low}} \\ I, & \text{if } P_{\text{low}} \leq I \leq P_{\text{high}} \\ P_{\text{high}}, & \text{if } I > P_{\text{high}} \end{cases} \quad (3.5)$$

Intensity Normalization

Normalization is applied to scale the image intensities to a standard range, as described in Eq. (3.2). This ensures consistent input for the model and improves the stability of the training.

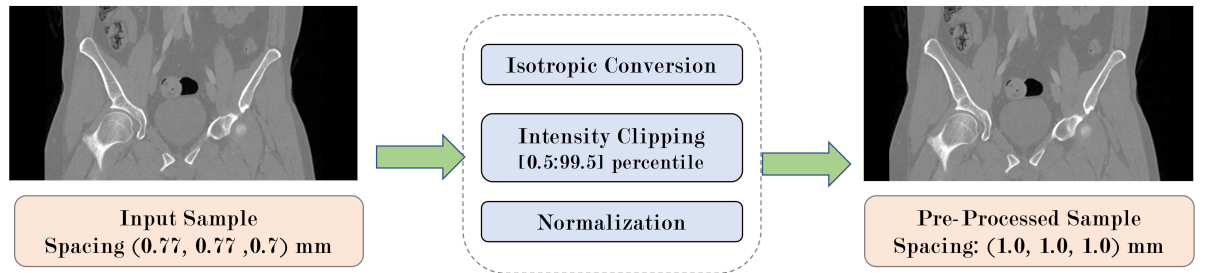


Figure 3.7: Pre-processing workflow for PA segmentation, showing isotropic conversion, intensity clipping, and intensity normalization of CT scan

3.4 Isolated Learning Approach for for Peripheral Artery Segmentation

The isolated learning approach refers to a method in which the network or algorithm performs segmentation using only the task-specific data, without relying on extensive external datasets or pre-trained models. This approach emphasizes self-contained learning, interpretability, and efficiency.

The workflow for the segmentation of the isolated learning approach is illustrated in Figure 3.8. The process begins with extracted ROIs and the pre-processed PA CT scans detailed in the previous section.

A grid-based sampling strategy generates representative patches that serve as input to the SDVN [Z2]. The SDVN produces preliminary segmentation outputs which are then refined through post-processing steps to ensure anatomical consistency. Each stage of this workflow is described in detail in the following subsections.

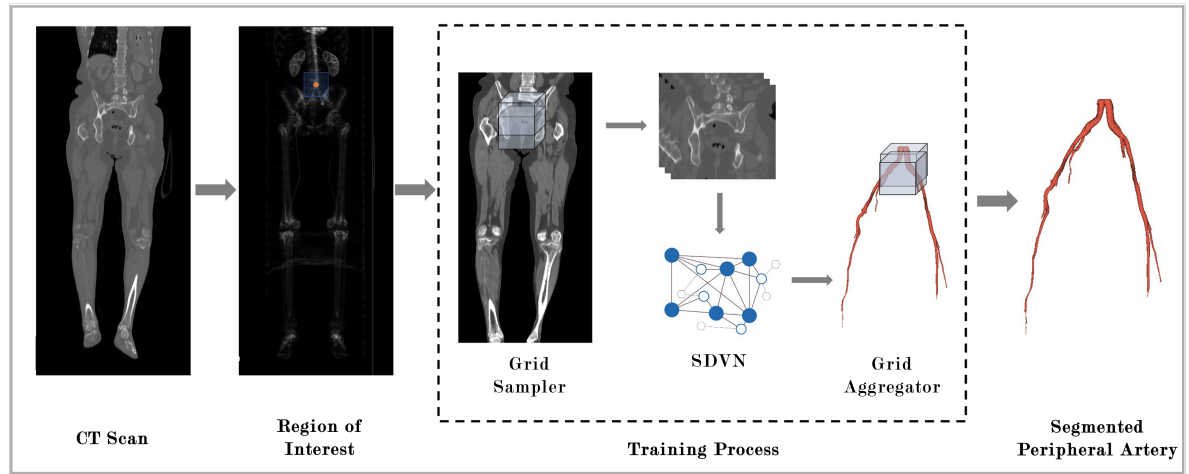


Figure 3.8: Overview of the segmentation pipeline employing the isolated learning approach with SDVN, applied to PA segmentation [Z2].

3.4.1 Grid Samplers

Following ROI localization and CT pre-processing, grid samplers are employed to enable efficient network training. These samplers systematically extract patches from large volumetric datasets, which helps reduce computational costs. Grid sampling also ensures

that spatially representative subsets of the data are selected, allowing the model to train on a diverse and relevant set of features.

3.4.2 Single-Depth Vascular Network

The SDVN is a CNN developed to segment PAs from CT scans. The architecture of SDVN emphasizes preserving high spatial resolution, beginning with an initial convolutional layer that captures essential features from the input.

This step establishes a strong foundation for accurate feature encoding. Figure 3.9 illustrates the network architecture.

The key characteristics of the SDVN include the following:

- A simplified single encoder-decoder structure connected by one skip connection, reducing overall complexity.
- Residual convolutional blocks are applied before the downsampling operation, which preserve vital spatial information and improve the stability of feature representation.
- The simplified network structure minimizes the trainable parameters, accelerating both training and inference.
- The architecture includes a single skip connection that links the encoder to its corresponding decoder, preserving high-resolution features for accurate vessel segmentation.

Through the use of residual blocks and a skip connection positioned to retain critical early features, the SDVN enhances robustness against minor noise and variability in the input. The encoder is built from several $3 \times 3 \times 3$ convolutional layers with stride 2, which capture detailed spatial patterns during downsampling. Each convolutional layer is followed by a Leaky ReLU activation, which introduces controlled nonlinearity and prevents neuron inactivity. As the encoder progresses, it extracts increasingly abstract and deeper features.

Bridge layers serve as intermediaries between the encoder and decoder, ensuring that essential high-dimensional features are effectively transferred and prepared for accurate spatial reconstruction.

The decoder gradually restores spatial resolution through upsampling layers with a stride of 2, aligning the output segmentation map with the original input dimensions. Furthermore, the single skip connection enriches this process by reintroducing high-resolution features, supporting detailed segmentation of the PAs. Group normalization is applied consistently across the network to stabilize and accelerate training.

In general, the SDVN leverages a single encoder-decoder pipeline with residual blocks, a focused skip connection, and group normalization to achieve accurate and detailed segmentation of PAs while maintaining computational efficiency. Its streamlined architecture makes it a practical solution for clinical volumetric image analysis.

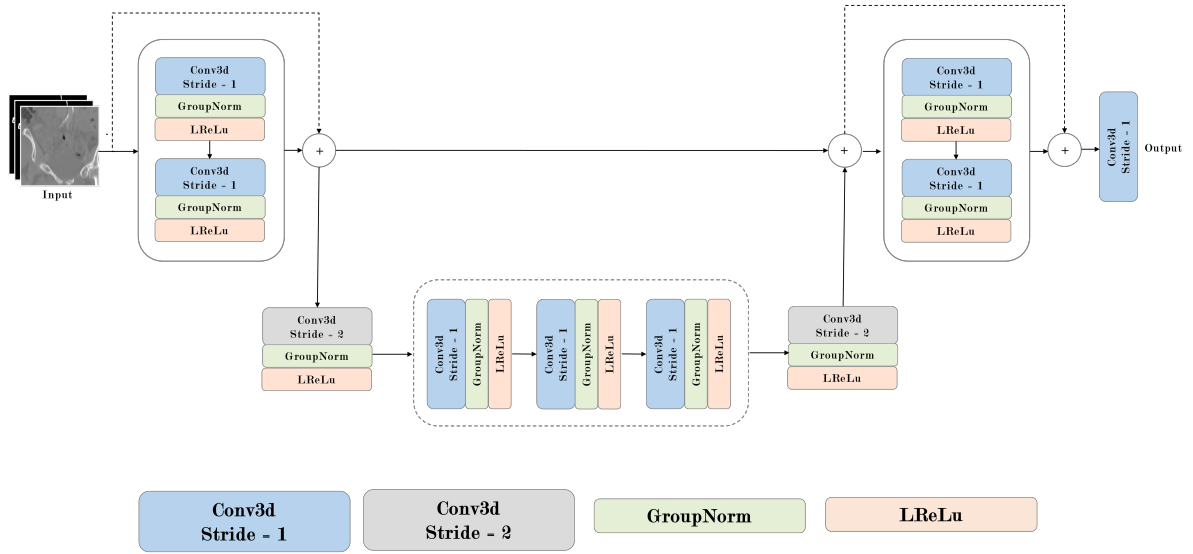


Figure 3.9: The SDVN is a custom-designed CNN optimized for 3D segmentation of PAs in volumetric CT data [Z2]

3.4.3 Loss Function

A composite loss function, called *avg loss*, designed to improve segmentation accuracy by combining three components: soft Dice loss, binary cross-entropy (BCE) loss and soft cDice loss. Each term addresses different aspects of segmentation quality, particularly for tubular structures.

BCE Loss is used to evaluate the error between predicted probabilities and actual labels in pixel-wise binary classification.

$$\text{BCE} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)] \quad (3.6)$$

where y_i denotes the ground truth label, p_i is the predicted probability for the pixel i , and N is the total number of pixels. Although BCE effectively distinguishes classes at the pixel level, it does not explicitly enforce spatial coherence or structural consistency, which are crucial for connected anatomical structures.

Soft Dice Loss improves the overlap between predicted and ground-truth segmentations and is defined as:

$$\text{Dice Loss} = 1 - \frac{2 \sum_{i=1}^N p_i y_i}{\sum_{i=1}^N p_i + \sum_{i=1}^N y_i} \quad (3.7)$$

This loss function focuses on maintaining volumetric consistency, making it especially useful for segmenting vessels in medical images.

Soft clDice Loss incorporates information about the structure's topology by comparing the morphological skeletons of predicted and ground-truth segmentations, focusing on preserving connectivity in tubular structures:

$$\text{clDice Loss} = 1 - \frac{2|S \cap G|}{|S| + |G|} \quad (3.8)$$

Here, S represents the skeletonized pixels of the prediction and G represents the skeletonized pixels of the ground truth. This component ensures that the central paths of the vessels are accurately maintained.

avg loss The *avg loss* is determined by averaging the three constituent terms:

$$\text{avg loss} = \frac{\text{BCE} + \text{Dice Loss} + \text{clDice Loss}}{3} \quad (3.9)$$

By combining pixel-level accuracy, volumetric overlap, and structural connectivity, this approach achieves robust and anatomically consistent segmentation of the PAs.

3.4.4 Grid Aggregator

After network inference, grid aggregators are used to merge segmented patches into a single cohesive volume. This approach merges individual segments while maintaining the

continuity of the vascular network, producing anatomically consistent PA segmentation. Grid aggregators enable the network to effectively manage and combine large-scale volumetric information.

3.4.5 Post-processing

Post-processing involves eliminating false positive areas by preserving connected components, enhancing segmentation reliability.

The volumes are subsequently resampled at their original dimensions to retain alignment with the baseline imaging data.

3.4.6 Training of the Single-Depth Vascular Network

The SDVN model is trained for 250 epochs using a learning rate of 0.001. The experiments are performed on a system featuring an AMD Ryzen Threadripper Pro 3995WX CPU at 2.7 GHz, along with 64 GB of DDR4 RAM (eight 8 GB modules running at 3200 MHz). This configuration provides sufficient computational power and memory bandwidth to handle high-resolution volumetric data, enabling effective network training.

3.5 Transfer Learning Approach for Peripheral Artery Segmentation

In this section, a transfer learning approach is adopted to address the PA segmentation task. Transfer learning involves utilizing models that have been pre-trained on a source domain as an initialization point for training on a related target domain. This technique enables the network to begin with pre-established feature representations, which are subsequently refined to accommodate the specific characteristics of the target dataset.

This framework designates two arterial regions: **PulA** and **CA**. For each source domain, an independent segmentation network is trained to capture region-specific vascular structures. These trained models serve as the foundation for the transfer learning process, providing specialized feature representations that are subsequently adapted to the target domain.

The transfer learning approach is structured into two distinct stages:

- **Stage 1: Pre-training on Arterial Domains** In the initial stage, two separate segmentation networks are trained independently on the PulA and CA datasets. Each network is optimized to learn the specific vascular geometry of its respective arterial region. This specialization facilitates the extraction of domain-specific features.
- **Stage 2: Adaptation for PA Segmentation** In the subsequent stage, the pre-trained models are fine-tuned using PA datasets. This adaptation process involves updating the model parameters to accommodate the unique morphological characteristics and spatial distribution of PA, enabling segmentation in the target domain.

The following subsections provide a detailed description of the segmentation strategies employed for the PulA and CA source domains, followed by the methodology used to adapt the respective networks for PA segmentation.

3.5.1 Coronary Artery Segmentation

The CA segmentation task is utilized as a source domain within the transfer learning framework for PA segmentation. The proposed pipeline for CA segmentation comprises three main components: data preprocessing, segmentation using a 3D Dense-U-Net architecture, and post-processing [Z4]. An overview of the entire pipeline is illustrated in Figure 3.10.

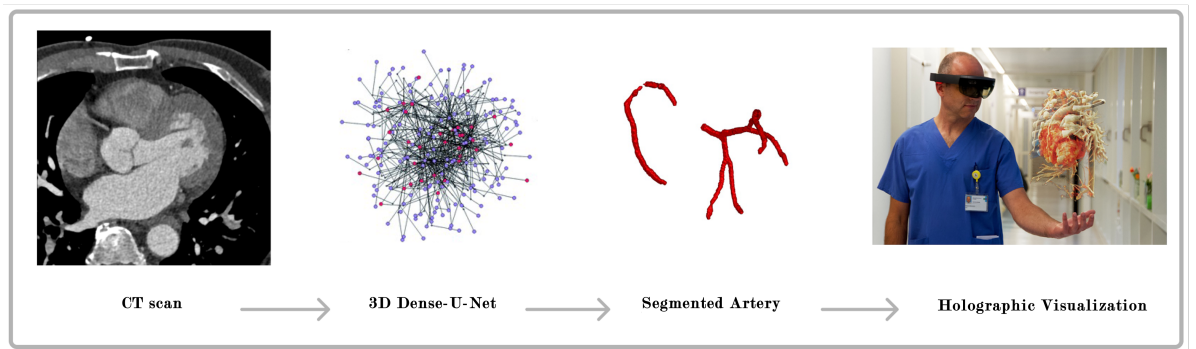


Figure 3.10: Schematic representation of the segmentation pipeline for CA CT scans, followed by MR visualization [Z4].

Preprocessing

The CT datasets undergo a series of pre-processing steps to prepare them for coronary artery segmentation:

1. Intensity values are clipped to the range $[-200, 500]$ HU to suppress noise and exclude irrelevant tissues while preserving CA.
2. The images are normalized to the range $[0, 1]$ to standardize intensity values and support stable model training.
3. Each CT volume is downsampled by a factor of two to reduce computational demand while retaining critical anatomical information.

Figure 3.11 shows an example of an original CT scan and its corresponding pre-processed version.

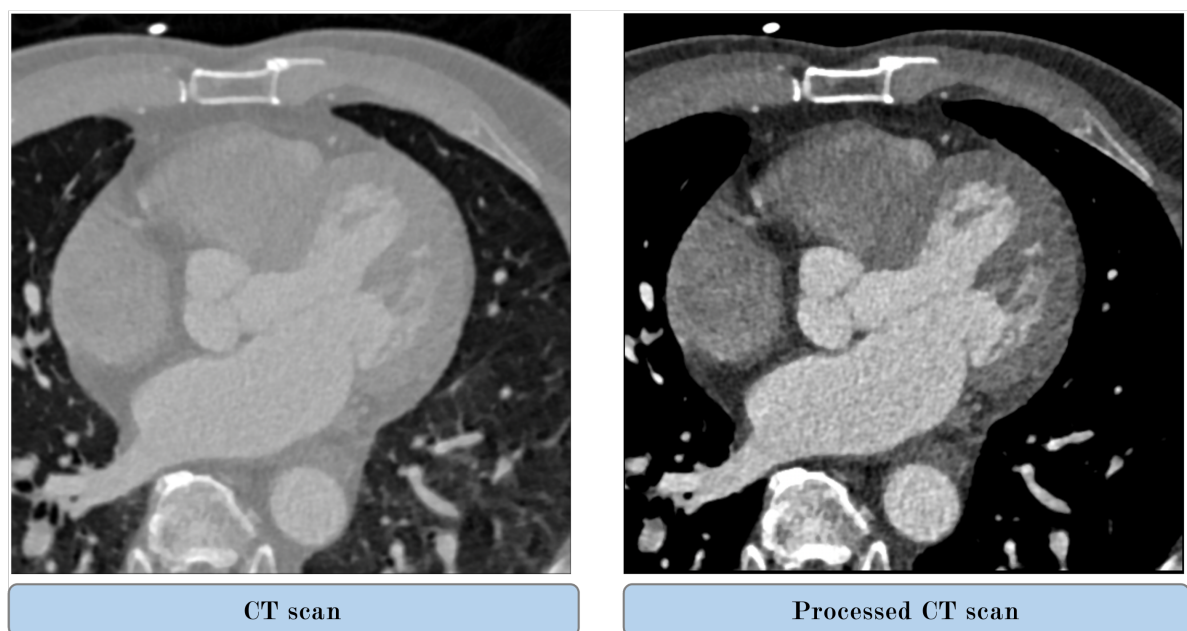


Figure 3.11: Comparison of original CT scan and preprocessed CT scan [Z4]

3D Dense-U-Net Network Architecture

This work utilizes a 3D Dense-U-Net architecture [136], which integrates residual and dense connections within a U-Net design. Residual connections are restricted to individual

down-sampling and up-sampling blocks, whereas dense connections provide pathways for information exchange between these blocks.

Figure 3.12 shows the structure of the network, with residual connections marked in green and dense connections in blue. The model contains four downsampling and four upsampling stages, interconnected to facilitate feature extraction and reconstruction. Each downsampling stage includes convolutional layers followed by a max-pooling operation that reduces spatial resolution while capturing key features. Each upsampling stage consists of convolutional layers paired with a transposed convolution to increase the spatial dimensions of feature maps. To maintain consistent feature map sizes across layers, zero padding is applied after each convolutional layer. This ensures that the outputs retain their original dimensions, allowing the layers to be combined effectively.

The network concludes with a 3D convolutional layer followed by a sigmoid activation function, which produces a probability map classifying each voxel as a background (0) or part of the coronary artery (1).

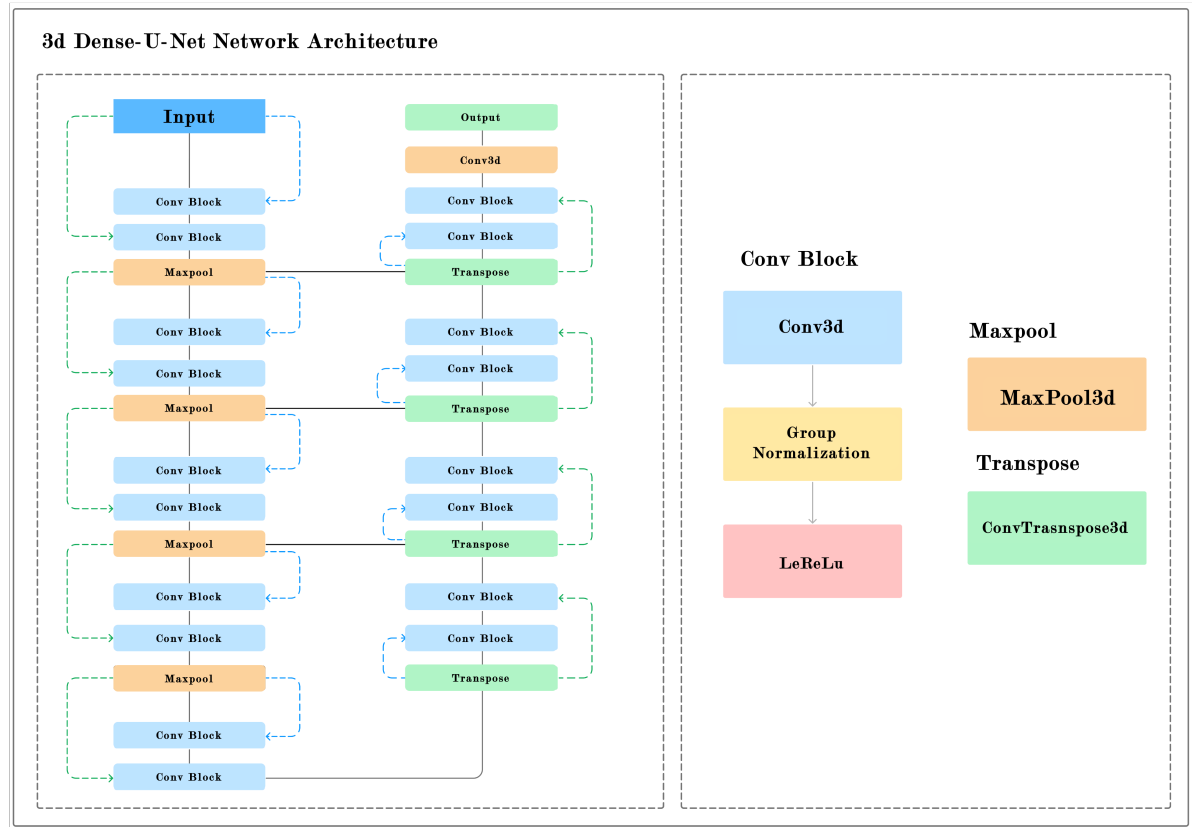


Figure 3.12: 3D Dense-U-Net architecture employed for CA segmentation [Z4]

Post-processing

After segmentation, the predicted volumes are upsampled to their original resolution to ensure consistency with the input CT scans. Morphological operations are then applied to refine the segmentation. These operations remove small isolated regions that often represent noise and improve the continuity of vascular structures.

Training Configuration

The dataset is divided into 70% CT scans for training, 15% for validation, and 15% for testing. The network is trained for 200 epochs using Adam Optimizer [137] with a learning rate of 0.0001.

To address class imbalance and improve segmentation accuracy, the Dice loss function (Eq. 3.7) is employed. This loss promotes greater overlap between the predicted segmentation and the ground truth, which makes it particularly effective for segmenting vascular structures.

3.5.2 Pulmonary Artery Segmentation

Accurate segmentation of the PulA is essential for a detailed vascular analysis and serves as a foundation for transfer learning in this study. The following subsection describes the methodology for PulA segmentation, including data pre-processing, network architecture, loss function, post-processing, and experimental setup [Z1].

Pre-processing

The pre-processing pipeline normalizes intensity values and standardizes CT volume dimensions to facilitate PulA segmentation (Figure 3.13). The original NIfTI volumes are subjected to the following sequence of operations:

1. **Intensity Clipping:** Voxel intensities are clipped to $[-800, 500]$ HU to enhance vessel visibility while suppressing irrelevant tissues and artifacts.
2. **Normalization:** Intensities are linearly scaled to $[0, 1]$, ensuring a consistent range across all volumes.

3. **Patch Extraction:** CT scan is divided into nine overlapping patches of size $256 \times 256 \times \text{number of slices}$, reducing memory requirements and increasing the diversity of training samples.

Processed patches are saved in NIfTI format to maintain compatibility and reproducibility.

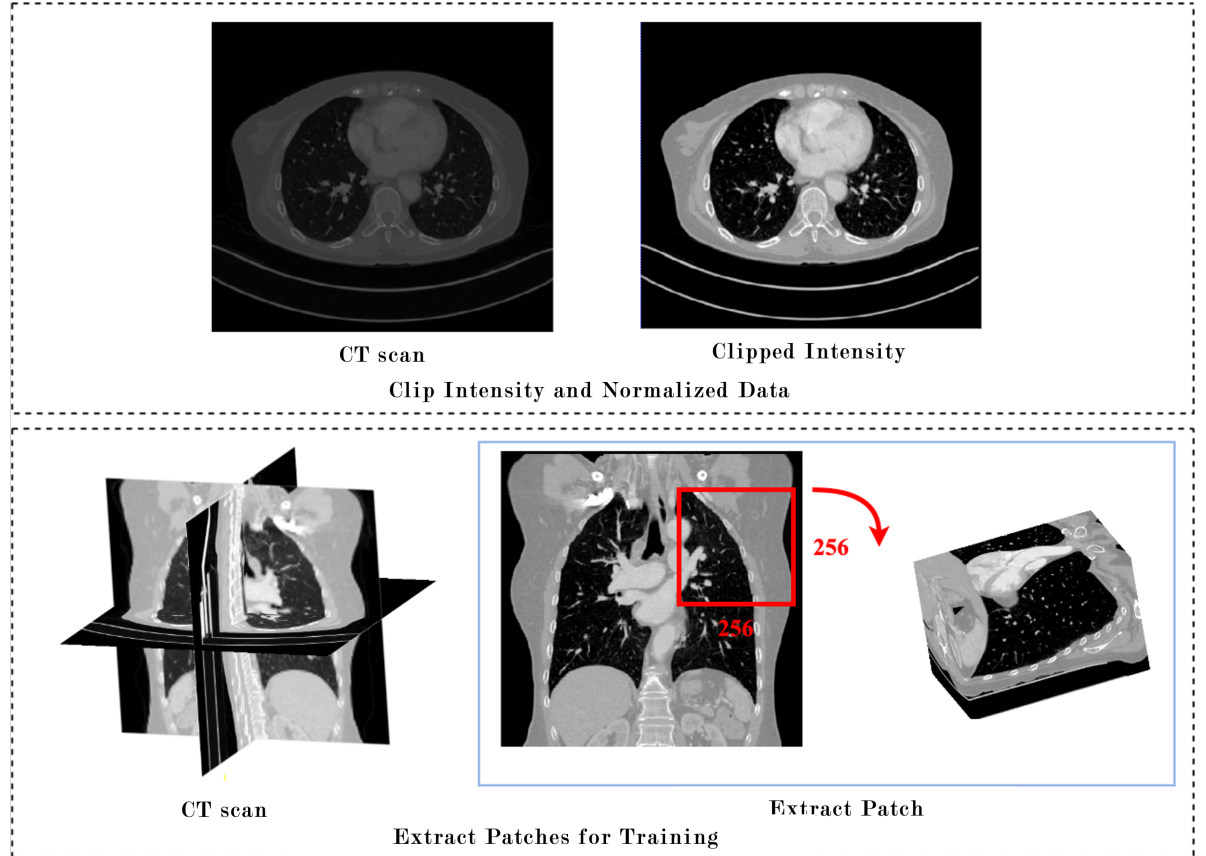


Figure 3.13: Preprocessing workflow for Pula CT scans, incorporating intensity clipping and normalization [Z1]

DRU-Net Architecture for segmentation of Pula

The Pula consists of a main trunk along with fine branching structures, necessitating a segmentation model capable of capturing complex spatial patterns [138].

This study incorporates dense residual blocks within the network, promoting improved gradient flow and accelerating convergence. Each dense residual block consists of four sequential units. Each unit consists of a 3D convolutional layer with kernel size $3 \times 3 \times 3$ and stride 1, followed by group normalization and Leaky ReLU (LReLU) activation.

The output of each unit is passed on as input to the next, encouraging feature reuse and improving the network capacity to capture complex spatial patterns. Group normalization stabilizes training, particularly for small batch sizes [139], while LReLU maintains nonzero gradients for negative inputs, improving the learning of non-linear transformations [140].

Each residual block also includes a parallel $1 \times 1 \times 1$ convolution to adjust the channel dimensions before combining through a residual connection. These connections facilitate gradient propagation and help preserve feature information throughout the network. A schematic of the dense residual block is shown in Figure 3.14.

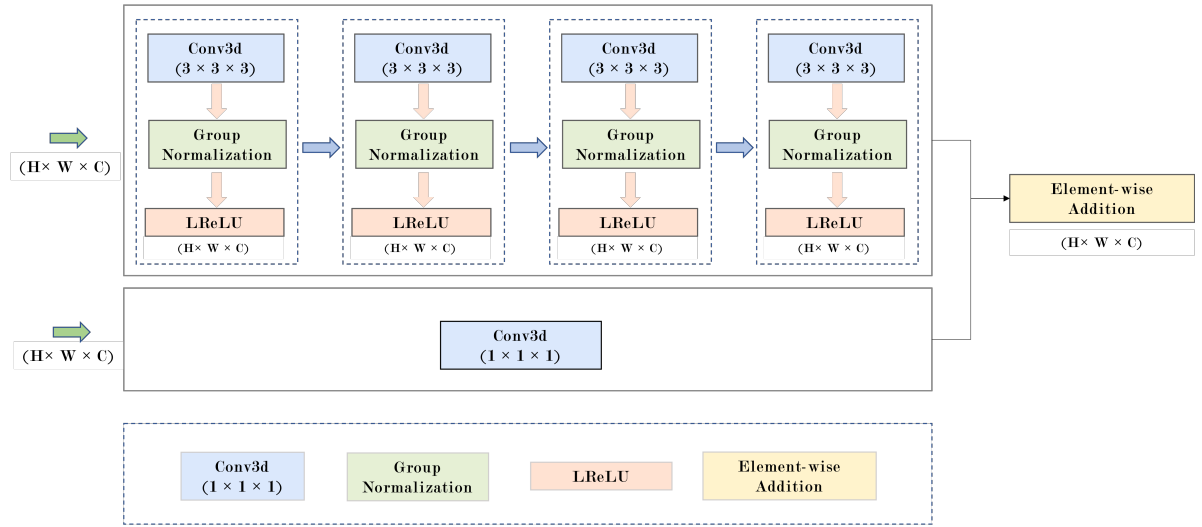


Figure 3.14: Schematic of a Dense Residual Block. Four sequential units each include a 3D convolution ($3 \times 3 \times 3$), group normalization, and Leaky ReLU activation. A parallel $1 \times 1 \times 1$ convolution aligns channel dimensions before residual addition [Z1].

Furthermore, Dense Residual U-Net (DRU-Net) comprises four encoder and four decoder stages. The overall DRU-Net architecture is illustrated in Figure 3.15. Each encoder stage reduces spatial resolution while increasing feature channels through residual blocks followed by transition down blocks, which perform learned downsampling, preserving finer details critical for accurate PA segmentation.

The decoder stages mirror this process by applying transition-up blocks followed by residual blocks to gradually restore the original spatial dimensions. Skip connections link each decoder stage to its corresponding encoder stage, enabling the network to combine high-level contextual information with low-level spatial details for precise segmentation.

Finally, a convolution $1 \times 1 \times 1$ followed by sigmoid activation produces voxelwise probabilities, distinguishing Pula tissue from the background.

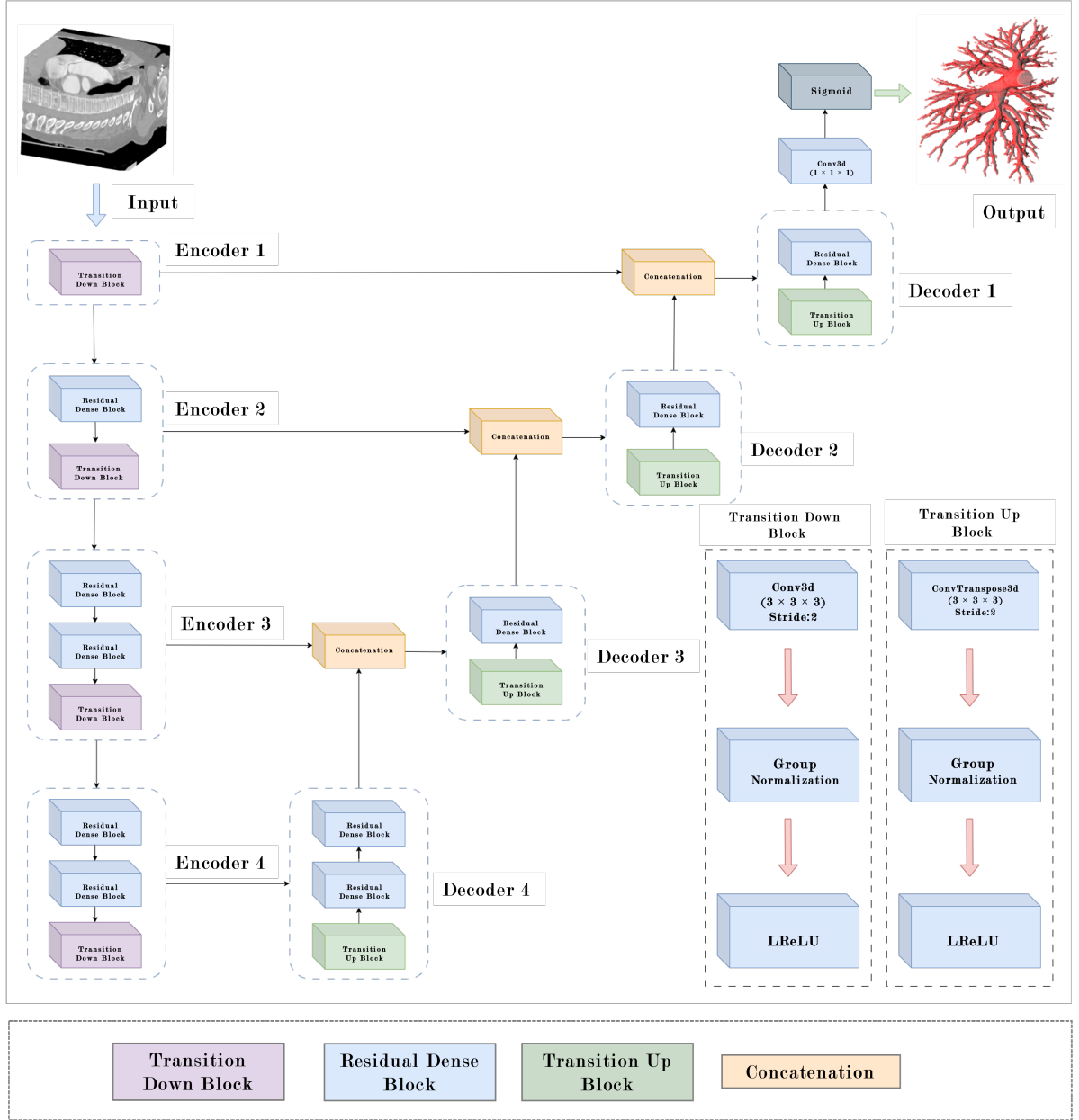


Figure 3.15: DRU-Net architecture for Pula segmentation. Encoder layers extract multiscale features using residual and transition-down blocks, while decoder layers restore resolution via transition-up and residual blocks. Skip connections connect corresponding encoder and decoder stages[Z1].

Post-Processing of Segmentation Outputs

Each CT volume is partitioned into smaller patches during both training and inference, reducing computational complexity while preserving spatial resolution. After segmentation, the patches are reassembled to reconstruct the full 3D volume in its original spatial configuration.

Small false positive regions often appear in areas with low contrast or complex anatomical structures. Morphological techniques are used to address these artifacts. Specifically, the area opening operation removes isolated noise components, while area closing fills small discontinuities within the segmented regions. Together, these steps improve segmentation output by promoting structural continuity and reducing erroneous predictions.

Training Process

The dataset is partitioned into training, validation, and testing subsets, comprising 80%, 10%, and 10% of the data, respectively. Figure 3.16 illustrates the pipeline, covering both the training and inference phases of the PulA segmentation process. Each CT scan is divided into nine randomly sampled patches.

Model optimization uses the Adam optimizer [137] with a learning rate of 0.0001, a batch size of 1, and 200 training epochs.

To address challenges in PulA segmentation, such as class imbalance, low contrast between vessels and surrounding tissues, and the presence of small, thin structures, a hybrid loss function is used that combines Dice loss (Eq. 3.7) and BCE loss (Eq. 3.6). Dice loss promotes overlap between predicted and ground truth regions, effectively handling class imbalance, while BCE loss provides smooth voxel-wise gradients, stabilizing training. The hybrid loss is computed as the average of the two:

$$\text{Loss}_{\text{Hybrid}} = \frac{\text{Loss}_{\text{Dice}} + \text{Loss}_{\text{BCE}}}{2} \quad (3.10)$$

This combination ensures accurate voxel-wise classification and robust structural agreement with ground truth, improving segmentation performance, particularly for small or low-contrast vascular structures.

3.5.3 Domain Adaptation for Peripheral Artery Segmentation

This subsection addresses PA segmentation using a domain adaptation framework that transfers knowledge from two distinct vascular domains. The source domains are modeled using the following architectures:

- **Coronary Arteries:** Modeled using a 3D Dense-U-Net architecture.

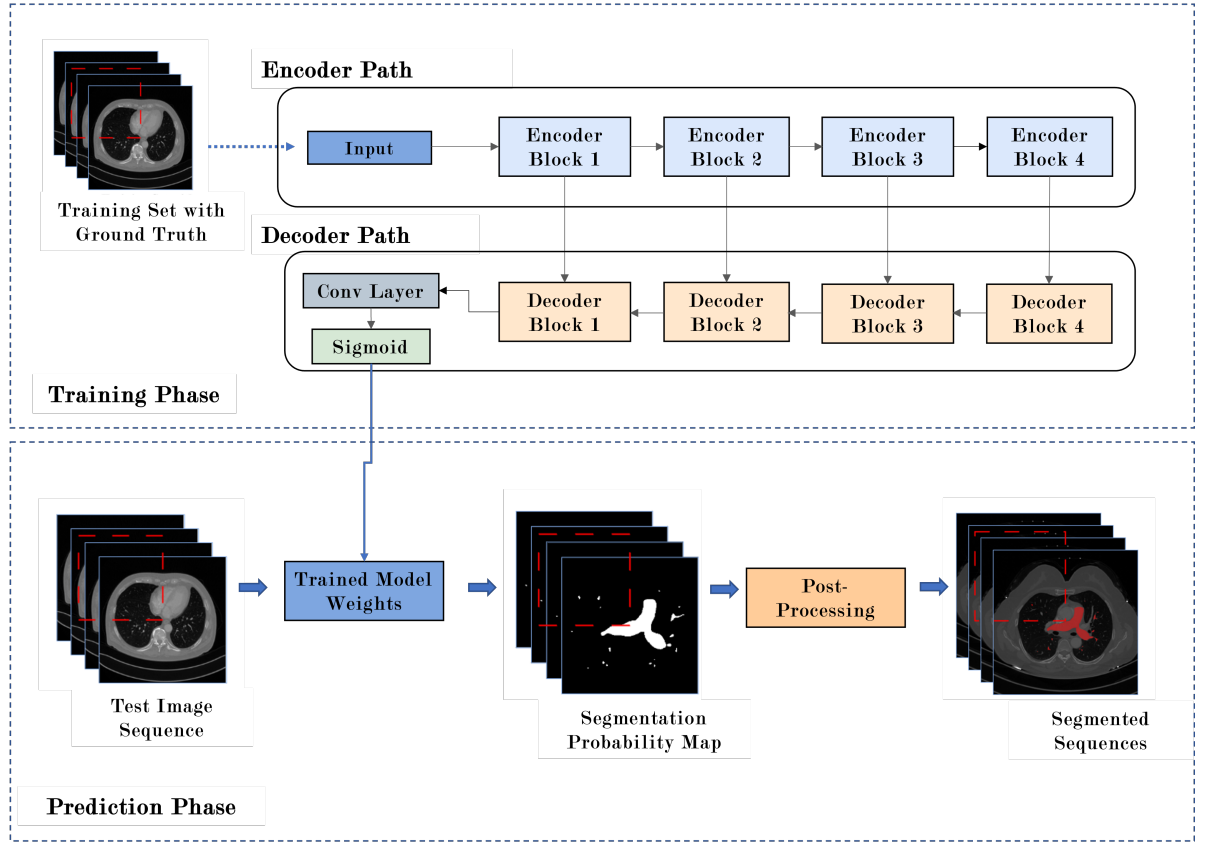


Figure 3.16: Pipeline illustrating both the training and inference phases of the Pula segmentation process [Z1].

- **Pulmonary Arteries:** Modeled using a DRU-Net architecture.

These models are initially pre-trained on their respective datasets and serve as source domains for transfer learning. The goal is to leverage the vascular representations learned by these models to support segmentation performance in the PA dataset, which presents specific challenges due to anatomical variability and reduced contrast.

The PA scans used in this framework are preprocessed according to the pipeline described in Section 3.7, which includes intensity normalization, resampling, and grid-based patch sampling.

Training Strategy

The transfer of vascular knowledge from the source domains to the PA dataset is performed through a combination of frozen encoder representations and task-specific fine-tuning of the decoder layers, while retaining architectural components that preserve

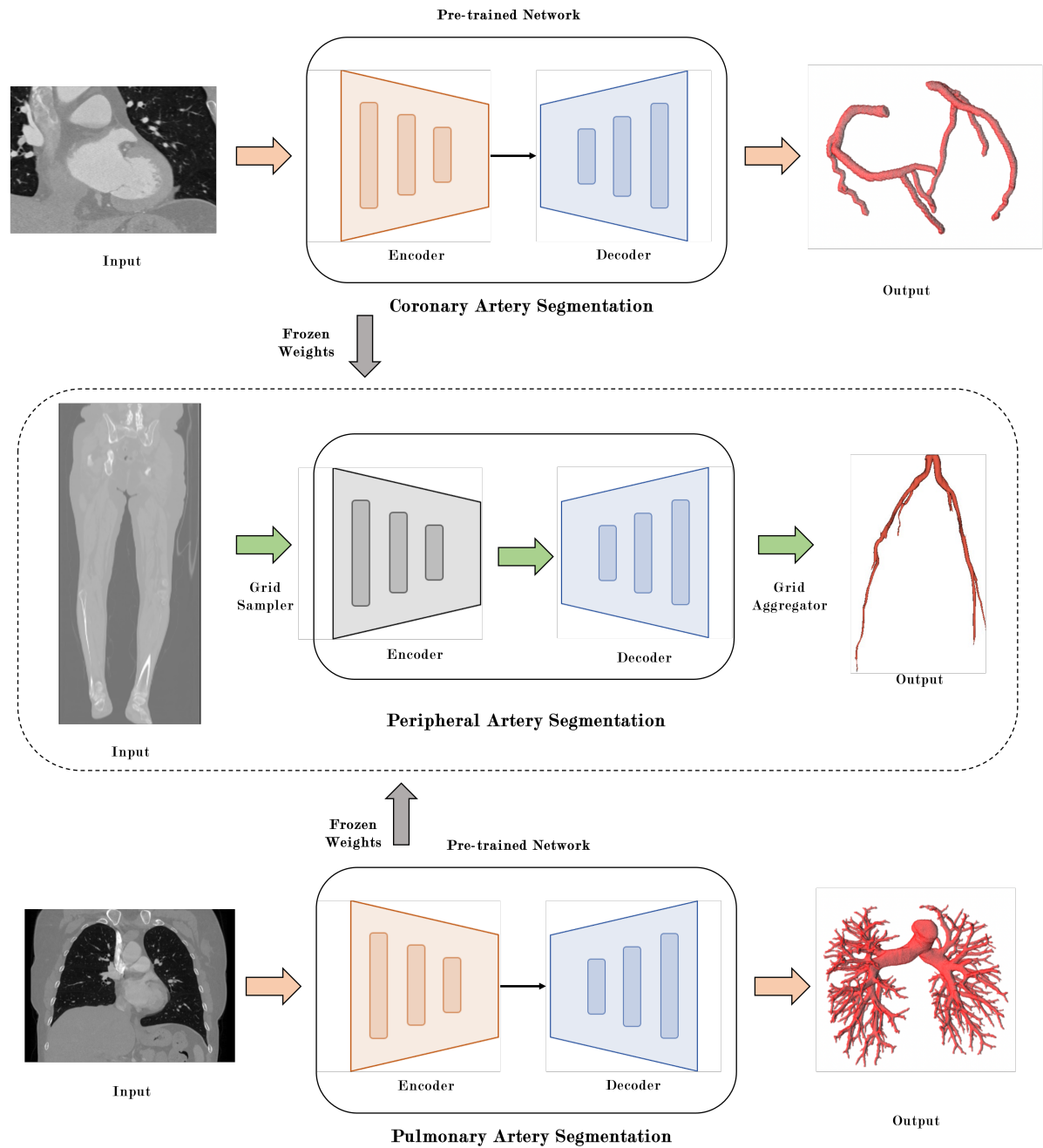


Figure 3.17: Overview of the segmentation pipeline utilizing a transfer learning approach, where source domains CA and PuA are leveraged for PA segmentation. The encoder is frozen to retain general vascular features, while the decoder is fine-tuned to adapt to PA-specific anatomy.

spatial detail and facilitate the propagation of features, as illustrated in Figure 3.17. The main components of this strategy are as follows.

- **Frozen Encoder Layers:** The encoder remains unchanged during training on the PA dataset, preserving vascular characteristics such as vessel orientation, branching patterns, and structural profiles learned from the CA and Pula data.
- **Fine-tuned Decoder Layers:** The decoder is updated to capture PA-specific anatomical details and reconstruct segmentation maps using features extracted by the frozen encoder.
- **Skip Connections:** Dense and residual skip connections are retained to facilitate feature propagation and gradient flow, maintaining spatial resolution and supporting segmentation accuracy.

This combination of frozen encoders, fine-tuned decoders, and retained skip connections enables the framework to utilize pre-learned vascular features while adapting to the unique characteristics of the PA dataset.

3.6 Visualization of Peripheral Artery

Accurate visualization of PA is essential to understand their complex anatomical configurations and subtle variations in tissue. To enable a detailed and consistent analysis, a geometry-standardized visualization pipeline has been established. Furthermore, mixed reality (MR) visualization is utilized for PA analysis to improve spatial coherence and support precise differentiation between vascular structures and surrounding tissues.

3.6.1 Geometry-Standardized Visualization

The complete visualization pipeline comprises CPR, Polar Transformation, together with clustering performed using the Gaussian Mixture Model (GMM) as illustrated in Figure 3.18.

The process initiates with CPR, which aligns the artery along its centerline to generate a linearized representation. This reformation preserves anatomical continuity and allows consistent cross-sectional analysis, thus enhancing the visibility of diagnostically significant features. Subsequently, the artery is mapped into a polar coordinate system. Structuring spatial data in radial and longitudinal dimensions establishes a well-defined analytical domain, simplifying the evaluation of tissue distribution surrounding the

vessel wall. Within this polar domain, voxel-level image features are clustered using a Gaussian Mixture Model. This probabilistic approach effectively captures subtle intensity variations and facilitates the unsupervised classification of different types of tissues [Z5]. To restore anatomical context, the classified data are projected back into the original Cartesian coordinate space.

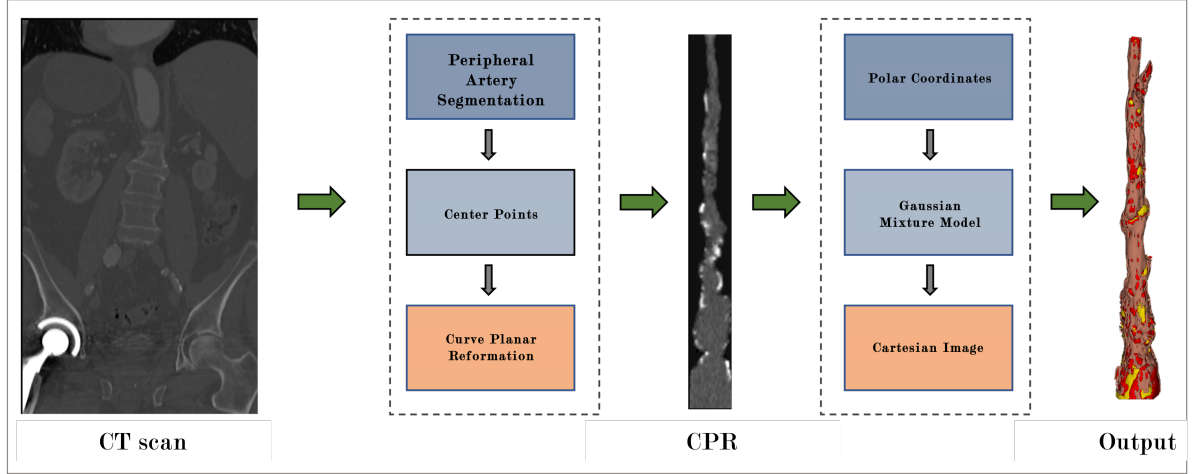


Figure 3.18: Flowchart depicting the visualization framework for PA [Z5]

The following sections present a detailed description of each stage in the visualization pipeline.

Curved Planar Reformation

CPR is employed to linearize the inherent curved geometry of PAs. This transformation facilitates anatomically consistent visualization by aligning the vessel along its extracted centerline, thereby preserving spatial relationships and detailed cross-sectional anatomy [141].

The CPR methodology consists of three stages:

- **3D Dilation.** : A 3D dilation operation is initially applied to the segmented artery to achieve a more comprehensive representation of the vascular morphology. This controlled expansion slightly increases the volume of the vessel by incorporating adjacent tissues while preserving fine anatomical details that are critical to accurate analysis.
- **Cross-Sectional Slice Extraction:** Following dilation, 2D cross-sectional slices are extracted orthogonally along the artery's centerline. Each slice captures the

geometry of the local vessel, covering the lumen and surrounding tissue layers, allowing a detailed morphological analysis [142].

- **3D Reconstruction of the Straightened Artery:** The extracted cross-sectional slices are reoriented and sequentially stacked along a linear axis to reconstruct a 3D volume of the artery in its straightened form. This CPR-based reconstruction mitigates curvature-induced distortions and enhances spatial clarity, thus improving visualization of anatomical structures and vascular characteristics.

Transformation to Polar Coordinates

The CPR-derived artery representation is transformed into polar coordinates to facilitate the radial analysis of circumferential features. This transformation improves the assessment of structural variations around the perimeter of the vessel, allowing better sensitivity to localized changes in arterial wall thickness and surrounding tissue distribution [143]. In the polar coordinate system, each boundary point is characterized by the following.

- **Radial Distance (r):** The Euclidean distance from a reference center point (typically the lumen center) to the boundary point.
- **Angle (θ):** The angular position of the boundary point relative to a predefined horizontal axis.

The conversion from Cartesian coordinates (x, y) to polar coordinates (r, θ) is defined as:

$$r = \sqrt{(x - x_{\text{ref}})^2 + (y - y_{\text{ref}})^2} \quad (3.11)$$

$$\theta = \tan^{-1} \left(\frac{y - y_{\text{ref}}}{x - x_{\text{ref}}} \right) \quad (3.12)$$

Here, $(x_{\text{ref}}, y_{\text{ref}})$ denotes the center of the artery in each 2D cross-sectional slice. This coordinate transformation facilitates analysis of the radial profile and circumferential pattern, which are critical for detailed visualization and quantification of arterial morphology.

Intensity-Based Clustering Using GMM

The tissue composition within the artery is characterized by clustering intensity values from the polar coordinate representation using a GMM. This unsupervised learning

method captures inherent intensity patterns, facilitating the differentiation of distinct arterial regions based on voxel intensity distributions [144].

GMM models the probability distribution of intensity values as a weighted sum of K Gaussian components:

$$p(x) = \sum_{i=1}^K \pi_i \mathcal{N}(x \mid \mu_i, \Sigma_i) \quad (3.13)$$

where:

- π_i denotes the mixing coefficient of the i -th Gaussian component, satisfying $\sum_{i=1}^K \pi_i = 1$,
- μ_i is the mean vector of the i -th component,
- Σ_i represents the covariance matrix of the i -th component,
- $\mathcal{N}(x \mid \mu_i, \Sigma_i)$ is the multivariate Gaussian probability density function.

The Expectation-Maximization (EM) algorithm is used to estimate the model parameters by iteratively maximizing the likelihood of the observed intensity values. The number of Gaussian components, K , is empirically selected based on anatomical knowledge and image complexity to ensure meaningful clustering results. The resulting clusters are visualized within the polar coordinate system, allowing for detailed interpretation of circumferential tissue distribution and localized structural variations (Figure 3.19).

Inverse Mapping from Polar to Cartesian Coordinates

Clusters identified in the polar coordinate system are mapped back to the Cartesian domain using the inverse transformation:

$$x = r \cdot \cos(\theta) + x_{\text{ref}} \quad (3.14)$$

$$y = r \cdot \sin(\theta) + y_{\text{ref}} \quad (3.15)$$

This inverse mapping realigns the clustered data with the original arterial geometry, allowing an accurate overlay with the CT images and improving interpretability for visualization purposes.

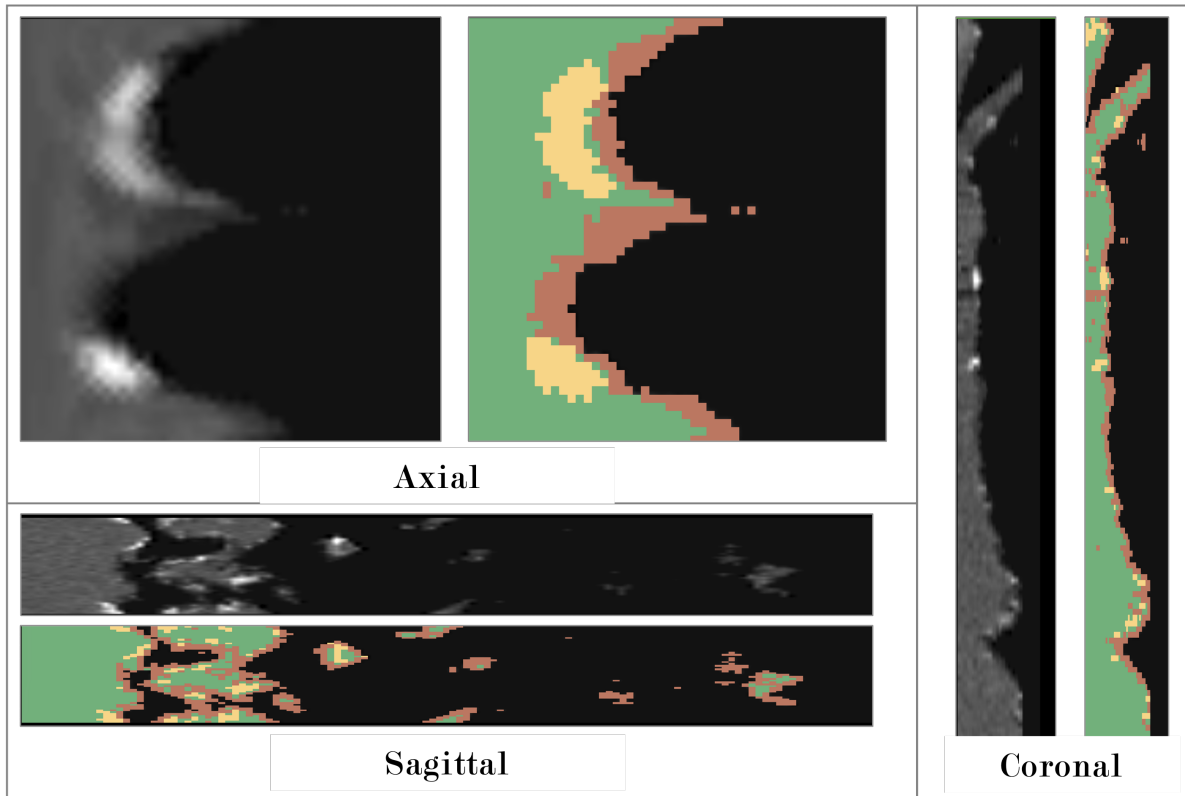


Figure 3.19: Visualization of three distinct clusters identified by GMM within the polar coordinate system, highlighted in green, orange, and yellow [Z5]

3.6.2 Mixed Reality Visualization for Peripheral Artery Analysis

MR enables enhanced visualization and analysis of PA structures by overlaying digital information onto the real world using stereoscopic head-mounted displays. Unlike virtual reality (VR), where users are fully immersed in a synthetic environment, mixed reality allows users to interact with 3D anatomical models via gestures, voice, and virtual interfaces, simulating the experience of handling actual objects.

The approach combines surface rendering for segmented PA structures with volumetric rendering of CT data. Surface rendering highlights vascular anatomy, while volumetric rendering preserves surrounding anatomical context, facilitating a clearer understanding of complex 3D vascular structures that are difficult to interpret on conventional 2D displays. MR also supports intraoperative visualization, allowing for on-the-fly measurements, assessment of vascular morphology, and customization of the display according to surgical requirements.

3.7 Conclusion

This chapter outlined a comprehensive methodological framework for the segmentation of PA. The workflow commenced with the selection and preparation of the dataset, followed by the localization of the ROI to ensure the targeted analysis of the relevant anatomical structures. Subsequent pre-processing steps are employed to enhance image quality and support reliable segmentation outcomes.

To address the segmentation challenge, two complementary strategies are explored: an isolated learning approach utilizing the SDVN model and a transfer learning approach leveraging pre-trained networks originally trained on PulA and CA datasets. These methods are designed to effectively capture vascular morphology while mitigating the challenges associated with image variability and anatomical complexity. Visualization techniques are also incorporated to facilitate a qualitative assessment of the segmentation results.

In summary, the proposed methodology establishes a structured pipeline that integrates data preparation, model development, and result visualization. The subsequent chapter provides an experimental assessment that measures the performance of the proposed techniques in PA segmentation.

Chapter 4

Results and Discussion

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This chapter presents the methodology and experimental evaluation performed for PA segmentation. The discussion begins with the evaluation metrics used to quantitatively assess model performance (Section 4.1), followed by the ROI localization process (Section 4.2), which ensures that segmentation is confined to the relevant anatomical structures.

Section 4.3 introduces the application of the isolated learning approach segmentation using the SDVN model for PA segmentation. Subsequently, Section 4.4 outlines a transfer learning approach which leverages prior knowledge derived from the segmentation of the Pula and CA arteries for the segmentation of PA.

In addition, the visualization of PA, which illustrates the segmented arteries, is presented in Section 4.6. Finally, the chapter concludes with a discussion (Section 4.7) that synthesizes the findings and compares the results with existing methods.

4.1 Evaluation Metrics

The performance of the models is assessed using quantitative metrics. The two metrics considered are:

- ROI Localization Metrics,
- Segmentation Metrics.

4.1.1 Region of Interest Localization Metrics

The accuracy of YOLO-based ROI localization is evaluated using metrics that quantify the performance of a single-object class. The key metrics considered in this study are Average Precision (AP), precision, recall, and F1-score.

Average Precision (AP)

AP quantifies the ability of the detection model to correctly identify and locate objects across varying confidence thresholds. It is calculated as the area under the precision–recall curve [145].

Precision

Precision measures the proportion of true positives (TP) among all predicted positives, calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4.1)$$

where FP denotes false positives. A high precision value indicates a low number of false positives [146].

Recall

Recall quantifies the proportion of actual positives that are correctly detected by the model and is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4.2)$$

where FN denotes false negatives. A high recall value indicates a low number of false negatives [146].

F1-Score

The F1-score combines precision and recall into a single performance metric, defined as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4.3)$$

This metric provides a balanced measure of model performance considering both false positives and false negatives [146].

4.1.2 Segmentation Metrics

Segmentation metrics evaluate the model's ability to accurately define the boundaries of target structures within the ROI. These metrics quantify the correspondence between the predicted segmentation mask and the ground truth. The primary metrics used in this study include the Dice Similarity Coefficient (DSC), Hausdorff Distance (HD), and the 95th percentile Hausdorff Distance (HD95).

Dice Similarity Coefficient

DSC quantifies the overlap between the predicted mask and the ground truth, defined as:

$$DSC = \frac{2|P \cap G|}{|P| + |G|} \quad (4.4)$$

where P denotes the set of pixels in the predicted mask and G denotes the set of pixels in the ground truth. A higher DSC indicates greater overlap and superior segmentation performance [109].

Hausdorff Distance

HD measures the maximum distance between the boundary points of the predicted mask and the ground truth, capturing the largest deviation:

$$HD(P, G) = \max \left\{ \sup_{p \in P} \inf_{g \in G} d(p, g), \sup_{g \in G} \inf_{p \in P} d(g, p) \right\} \quad (4.5)$$

where $d(p, g)$ denotes the Euclidean distance between points p and g . A lower HD indicates a closer correspondence between the predicted and true boundaries [147].

95th Percentile Hausdorff Distance

HD95 provides a robust variant of HD by considering the 95th percentile of boundary distances, thereby reducing the influence of outlier points:

$$HD95(P, G) = 95\text{th percentile}\{d(p, G), d(g, P) \mid p \in P, g \in G\} \quad (4.6)$$

Lower HD95 values indicate better correspondence between the predicted and ground truth boundaries while mitigating the impact of extreme deviations [147].

4.2 Region of Interest Localization

This section presents the results of the proposed ROI localization approach. YOLOv8 detects key anatomical points, specifically arterial bifurcation locations, within the test samples. The detected points enable the precise location of ROI, demonstrating the effectiveness of the method for subsequent processing tasks. Quantitative evaluation shows high detection accuracy and consistent ROI positioning across the multicenter dataset.

Illustrated Results of YOLOv8-Based Arterial Bifurcation Localization

The YOLOv8 model detects arterial bifurcation points in a multicenter dataset that includes a wide range of arterial morphologies and intensity distributions, enhancing

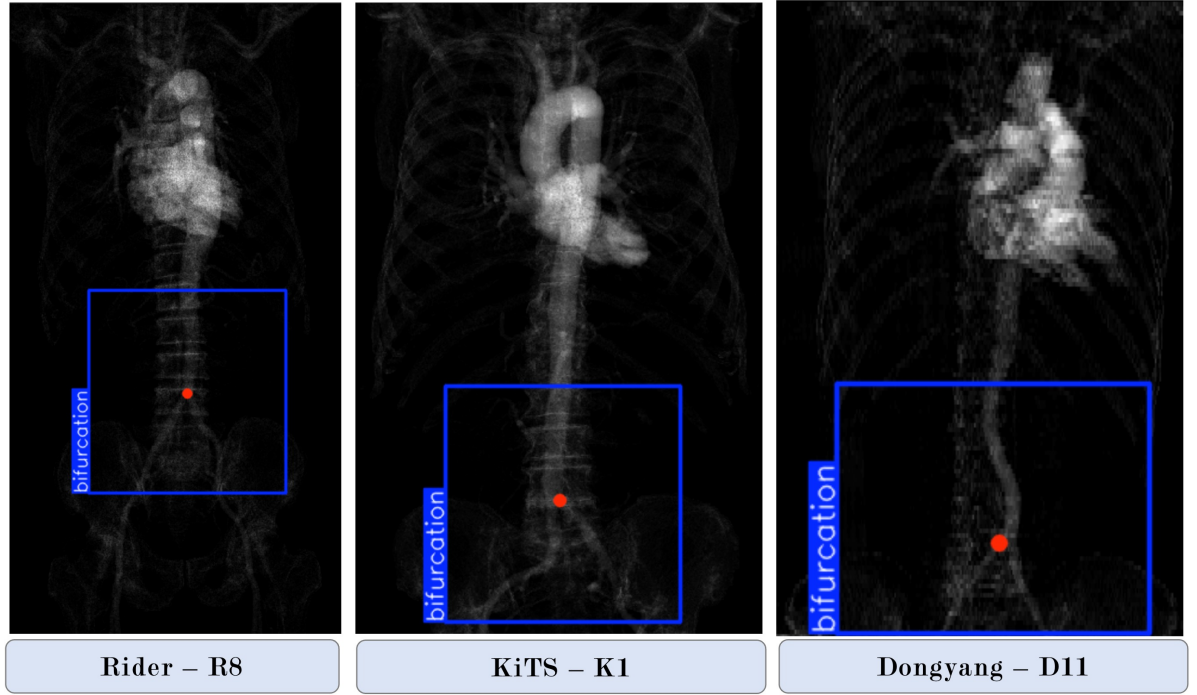


Figure 4.1: Identification of arterial bifurcations using YOLOv8 on 2D CIP images generated from 3D CT scans. The bounding boxes highlight the localized ROIs [Z2].

robustness to anatomical and imaging variations. The model demonstrates high spatial precision, consistently localizing bifurcation points at anatomically expected positions.

Figure 4.1 illustrates the detection results using 2D CIP generated from 3D CT volumes. The bounding boxes represent the regions surrounding each bifurcation point, highlighting the consistent performance of the model in diverse arterial geometries.

Performance Evaluation on Multicenter Dataset

The localization performance of YOLOv8 was evaluated across five CT datasets: Dongyang Hospital, RIDER Lung CT, KiTS19, Gennimatas_1, and Gennimatas_2. The model achieved consistently high scores across standard evaluation metrics, including mean average precision (mAP), precision, recall, and the F1 score, demonstrating robust generalization to varying imaging conditions and anatomical structures. Table 4.1 summarizes the detailed performance results. The results examined in this section have been documented earlier in [Z2].

Table 4.1: YOLOv8 evaluation for bifurcation point detection across five CT datasets, showing strong performance and generalization [Z2]

Metric	Dongyang	RIDER	KiTS	Gennimatas_1	Gennimatas_2
mAP	0.99	0.99	0.99	0.99	0.99
Precision	0.99	0.98	1.00	0.98	0.98
Recall	1.00	1.00	1.00	1.00	0.99
F1-score	0.99	0.99	0.98	0.99	0.99

4.3 Performance Evaluation of Isolated Learning Approach for Peripheral Artery Segmentation

This section presents the performance of the SDVN model in an isolated learning approach to PA segmentation, with an emphasis on its ability to accurately capture vessel morphology and fine distal branches without interference from surrounding structures. Segmentation accuracy is evaluated using DSC, HD, and HD95.

Evaluation of the proposed Method Across Multiple Datasets

The proposed method demonstrates high precision in segmenting the PA tree, including intricate distal branches. Its performance is evaluated across five diverse CT datasets, representing variations in imaging protocols and anatomical complexity. Table 4.2 presents a quantitative comparison of segmentation quality across these datasets.

Table 4.2: Performance of the isolated learning approach using SDVN for PA segmentation across five CT datasets [Z2].

Metric	Dongyang	RIDER	KiTS	Gennimatas_1	Gennimatas_2
DSC	0.90	0.90	0.91	0.90	0.92
HD (mm)	3.03	26.41	11.74	14.28	7.54
HD95 (mm)	1.00	1.40	1.21	1.00	1.00

The proposed method consistently achieves high DSC values, ranging from 0.90 in the Dongyang, RIDER, and Gennimatas_1 datasets to 0.92 in Gennimatas_2, with a peak value of 0.91 observed in the KiTS dataset, as reported in Table 4.2. The boundary accuracy, measured by HD, varies between datasets from 3.03 mm to 26.41 mm, while HD95 remains consistently low, between 1.00 mm and 1.40 mm. These results indicate that SDVN effectively preserves fine vascular structures and minimizes segmentation errors, even in anatomically complex regions.

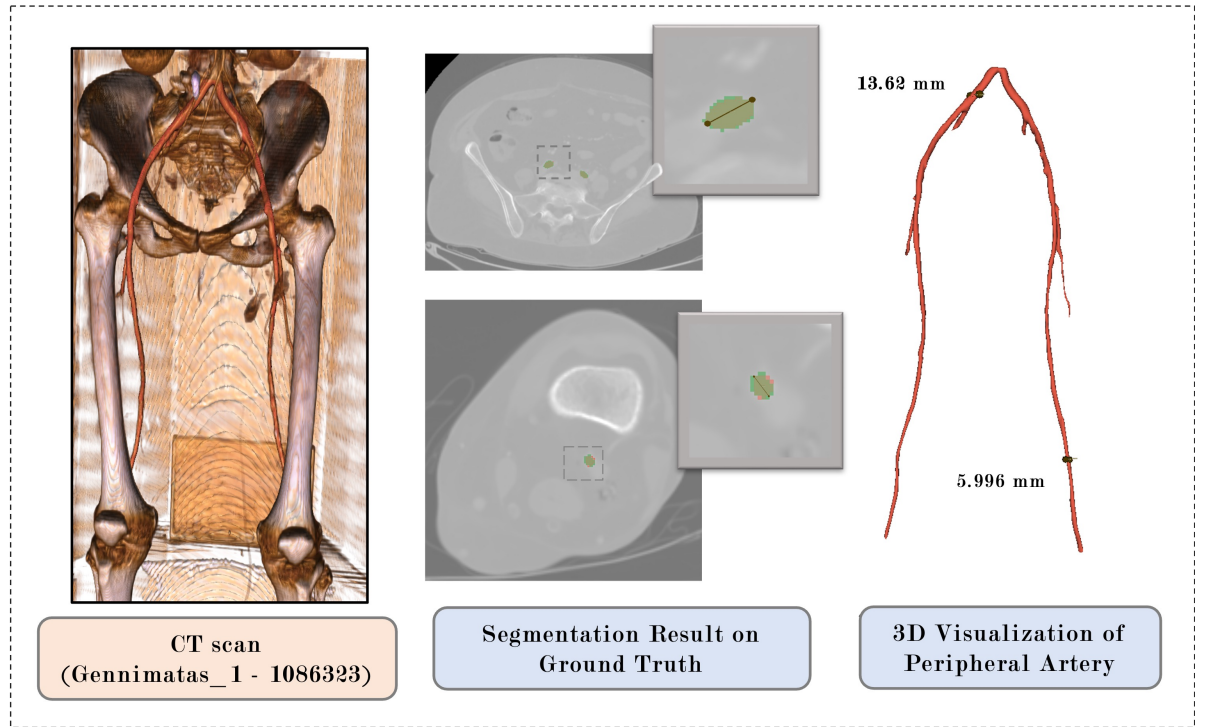


Figure 4.2: Segmentation of the PA obtained with the isolated learning approach using SDVN, including distal branches. The ground truth is represented in green, while the segmentation outputs are displayed in red [Z2].

Furthermore, Figure 4.2 illustrates the results of the segmentation. The proposed method exhibits smooth vessel continuity, precise boundary delineation, and consistent delineation of small distal branches, even in regions with low contrast. These results collectively highlight the suitability of the method for accurate and clinically relevant arterial segmentation.

Table 4.3: Segmentation performance across vessel calibers [Z2].

Metric	3–6 mm	7–9 mm	10–12 mm	13–15 mm	16–18 mm
DSC	0.87	0.91	0.91	0.91	0.95
HD (mm)	9.01	9.47	6.43	4.53	2.14
HD95 (mm)	3.30	1.06	1.10	1.31	0.75

Performance Across Vessel Diameters

Segmentation accuracy is further evaluated across vessel calibers (3-6 mm, 7-9 mm, 10-12 mm, 13-15 mm and 16-18 mm). As shown in Table 4.3, DSC scores increase with vessel diameter, indicating improved overlap for larger arteries. Smaller vessels exhibit slightly higher HD and HD95 due to increased boundary sensitivity. In general, the results demonstrate that the proposed method maintains robust performance in a wide range of arterial diameters, including fine vascular branches.

Table 4.4: Comparison of loss functions for PA segmentation [Z2].

Metric	Dice Loss	BCE Loss	Soft cIDice Loss
DSC	0.86	0.85	0.62
HD (mm)	42.71	38.11	82.50
HD95 (mm)	5.38	6.32	22.95

Effect of Loss Function Design

The influence of various loss functions on segmentation performance is systematically evaluated. Table 4.4 provides a comparative analysis of dice loss, BCE loss, and soft cIDice loss. Dice loss achieved the highest overlap metrics, particularly for larger vessels, indicating superior overall segmentation accuracy. BCE loss demonstrated enhanced sensitivity to detect low-intensity, low-contrast vascular branches. In contrast, soft cIDice_loss resulted in lower DSC and higher HD, reflecting reduced overall overlap

accuracy; however, it more effectively preserved topological continuity at bifurcations, which is crucial for maintaining the structural continuity of the vascular network.

The proposed approach integrates `avg_loss` functions, which are computed as the average of all three functions, thus improving the segmentation accuracy while maintaining vascular topology. Furthermore, the results discussed in this section have been previously documented by the author in [Z2].

4.4 Performance Evaluation of Transfer Learning Approach for Peripheral Artery Segmentation

This study employs two primary arterial datasets, the PULA and the CA, as a basis for transfer learning. Initially, models pre-trained on these datasets are evaluated for their performance in segmenting the corresponding arteries.

Subsequently, the models are applied to PA segmentation and their performance is assessed in this task. The following subsections present the segmentation results for each type of artery, followed by the outcomes of transfer learning in the PA.

4.4.1 Evaluation of Pulmonary Artery Segmentation

The proposed DRU-Net architecture combines dense connections, residual blocks, and the U-Net structure to enhance feature learning and improve segmentation performance. Each layer receives feature maps from all preceding layers, facilitating the flow of information. Residual learning is integrated within both the encoder and decoder pathways, preserving spatial and contextual information critical for accurate segmentation.

The proposed DRU-Net for Pula segmentation is evaluated using the MICCAI PARSE 2022 dataset. Its performance is compared with the 3D U-Net baseline and the top-performing algorithms from the PARSE 2022 Pula Segmentation Challenge. Table 4.5 summarizes the DSC and HD95 for each method. DRU-Net consistently outperforms all competing methods, achieving the highest DSC and the lowest HD95, demonstrating its superior ability to accurately delineate Pula structures.

Table 4.5: Comparison of segmentation performance between top-performing teams from the PARSE 2022 challenge, a 3D U-Net method, and the proposed DRU-Net [Z1].

Metric	Infervision	SenseTime	BIT	3D U-Net	DRU-Net (Proposed)
DSC	0.797	0.797	0.798	0.831	0.878
HD95 (mm)	5.261	4.754	5.361	11.670	4.262

Furthermore, Figure 4.3 provides a representative segmentation output generated by DRU-Net, including the ground truth, predicted segmentation, overlap map, and a 3D visualization of the segmented pulmonary artery.

Visual inspection confirms that DRU-Net effectively segments both the main artery and its thinner branches. These results corroborate the quantitative superiority of DRU-Net, highlighting its ability to preserve fine vascular structures and achieve precise boundary delineation.

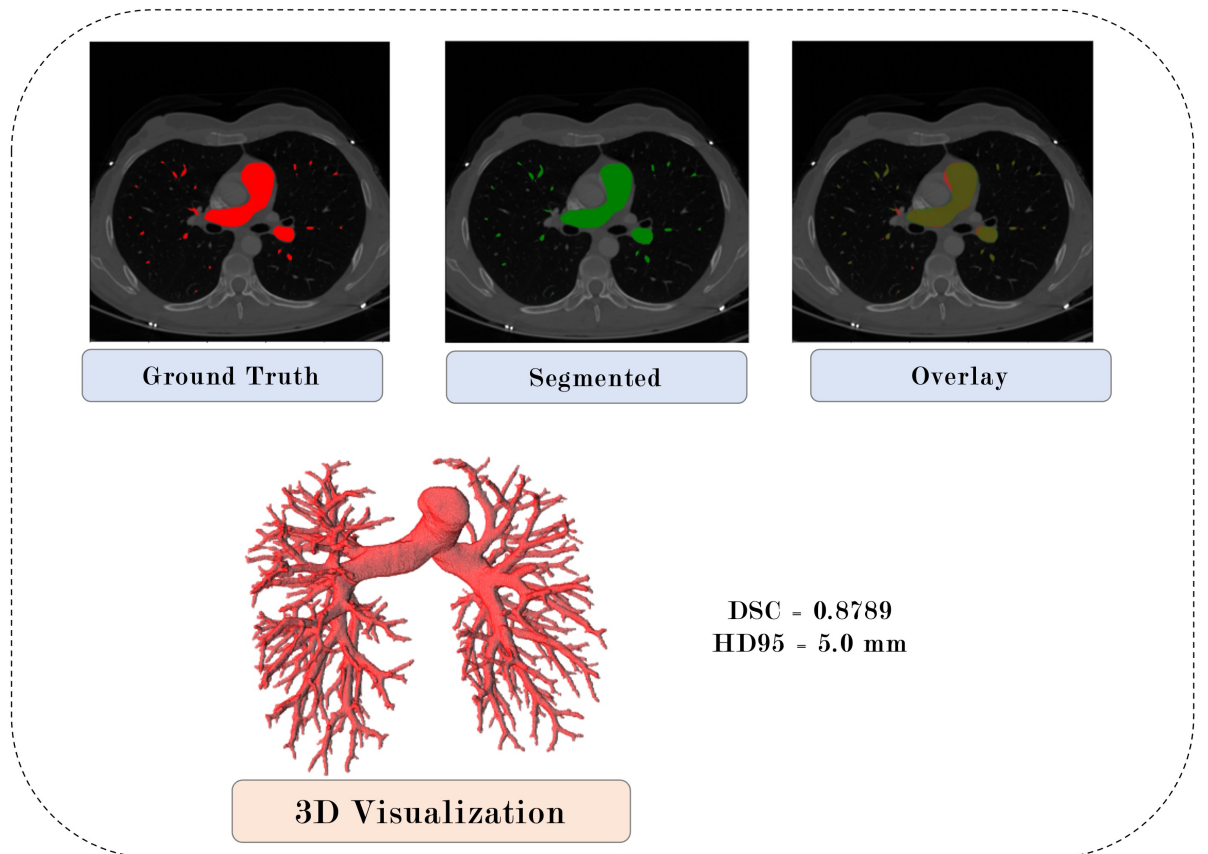


Figure 4.3: Segmentation results using DRU-Net, including ground truth, predicted mask, overlap visualization, and 3D rendering for Pula [Z1].

Accurate Pula artery segmentation is essential for utilizing the network in a transfer learning framework as a pre-trained model. Compared with the top three submissions in the MICCAI PARSE 2022 challenge [148], which achieve mean DSC scores of 0.7969, 0.7968, and 0.7980 with corresponding HD95 values of 5.2607mm, 4.7538mm and 5.3612mm, DRU-Net achieves a higher DSC of 0.8775 and a lower HD95 of 4.2624mm. This indicates improved volumetric overlap and boundary precision, providing a robust pre-trained network that can be effectively leveraged for transfer learning in downstream vascular segmentation tasks.

Effect of Loss Functions

The impact of different loss functions on DRU-Net segmentation performance is also evaluated. The network is trained using BCE, Dice loss, and a hybrid loss function (DBCE). Quantitative and qualitative analyzes are performed to assess overall precision, boundary conformity, and overlap with the ground truth.

Figure 4.4 illustrates representative segmentation results for each loss function. The ground truth is shown in white, the predicted segmentation is shown in red, and the overlapping regions are shown in pink. The hybrid loss demonstrates superior alignment with the ground truth and improved boundary precision compared to BCE or Dice loss individually.

Quantitative evaluation, presented in Table 4.6, confirms that the hybrid loss function attains the highest DSC and the lowest HD95, demonstrating enhanced segmentation accuracy and improved boundary precision. This performance gain is particularly evident in the precise segmentation of the fine vascular branches.

Table 4.6: Pula segmentation performance across different loss functions [Z1].

Metric	Dice Loss	BCE	Hybrid Loss (DBCE)
DSC	0.877	0.877	0.878
HD95 (mm)	4.367	5.560	4.262

Moreover, the results discussed in this section have previously been published by the author in [Z1].

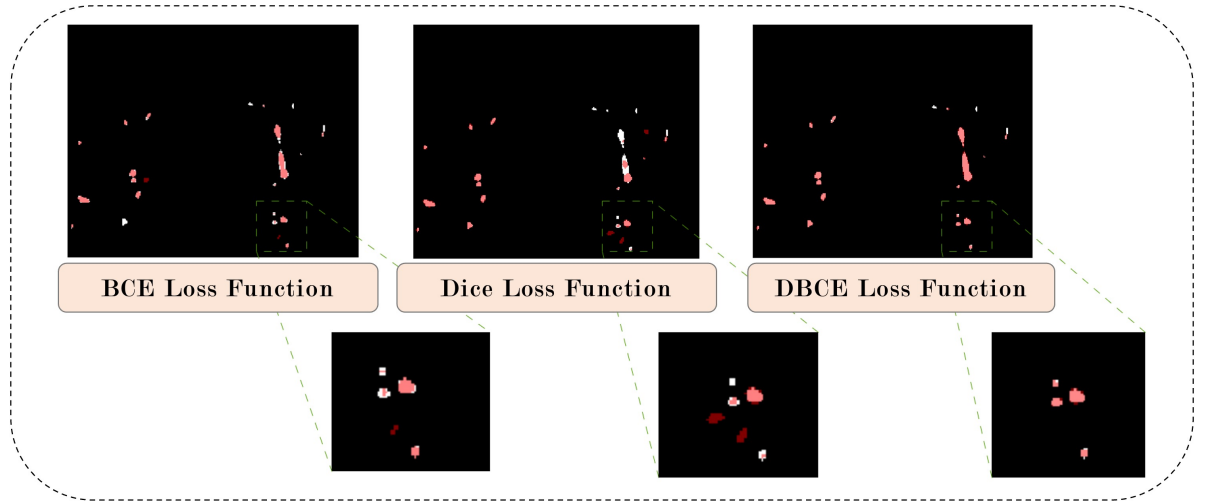


Figure 4.4: Segmentation results using BCE, Dice, and Hybrid Loss Functions. Ground truth is displayed in white, predicted segmentation in red, and areas of overlap in pink [Z1].

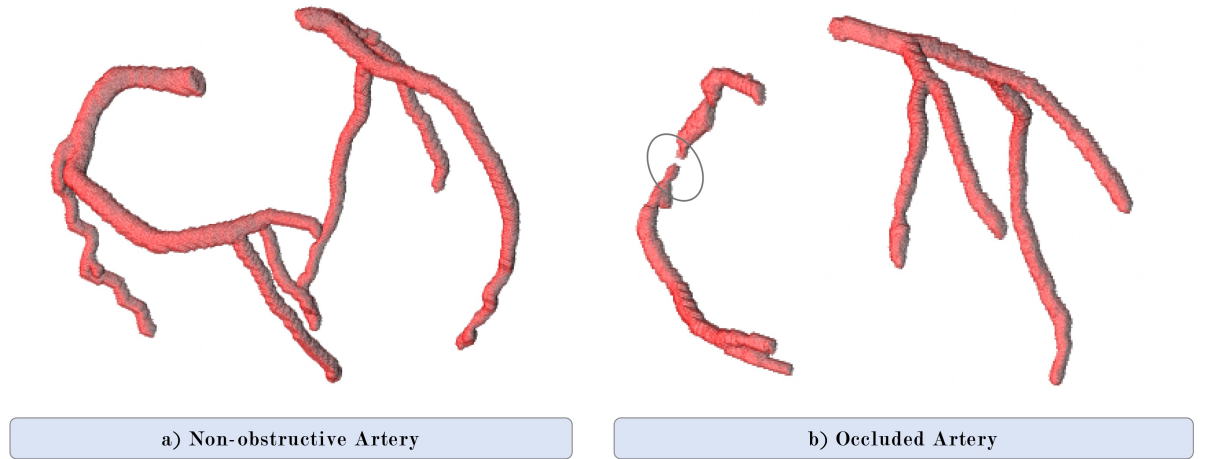


Figure 4.5: Segmentation results for CA, comparing non-obstructive and occluded cases [Z4].

4.4.2 Evaluation of Coronary Artery Segmentation

The segmentation of CA is performed using 3D Dense-U-Net. This network integrates residual connections within down-sampling and up-sampling blocks and dense connections across blocks, which improves feature propagation and alleviates vanishing gradient problems. The architecture consists of four down-sampling and four up-sampling stages, each composed of convolutional layers, max-pooling (for down-sampling) and transposed convolutions (for up-sampling).

For evaluation, the performance of the model is assessed using both quantitative metrics and qualitative visualizations to verify the anatomical precision of the segmented coronary arteries.

Quantitative Evaluation

The segmentation performance of the proposed method is compared with recent state-of-the-art techniques on the ImageCAS dataset [130], as summarized in Table 4.7. The 3D Dense-U-Net achieved a DSC of 0.8206 and a HD of 22.06 mm, demonstrating competitive performance relative to existing methods.

Table 4.7: Comparison of segmentation performance with state-of-the-art methods for CA segmentation. The proposed 3D Dense-U-Net achieves competitive DSC and HD values [Z4]

Method	DSC	HD (mm)
Tree data-based segmentation (3D reeConvGRU) [149]	0.6878	30.33
Graph-based segmentation (GCN) [150]	0.7061	27.87
Patch segmentation (3D U-Net) [151]	0.7201	40.96
Direct segmentation (3D FCN) [152]	0.8058	28.66
Baseline (3D U-Net and UNet++) [130]	0.8296	27.21
Proposed method (3D Dense-U-Net)	0.8206	22.06

It is observed that some cases exhibited lower performance metrics, primarily corresponding to occluded arteries. In these cases, ground-truth masks encompassed the entire artery, whereas the model focused on segmenting the lumen, effectively excluding occluded or diseased regions. This discrepancy underscores the model’s sensitivity to physiologically relevant structures rather than the full vessel.

Subset Analysis

A subset analysis was performed on **42 occluded artery** and **108 non-obstructive artery** CT angiograms. In the non-obstructive artery subset, the model achieved a DSC

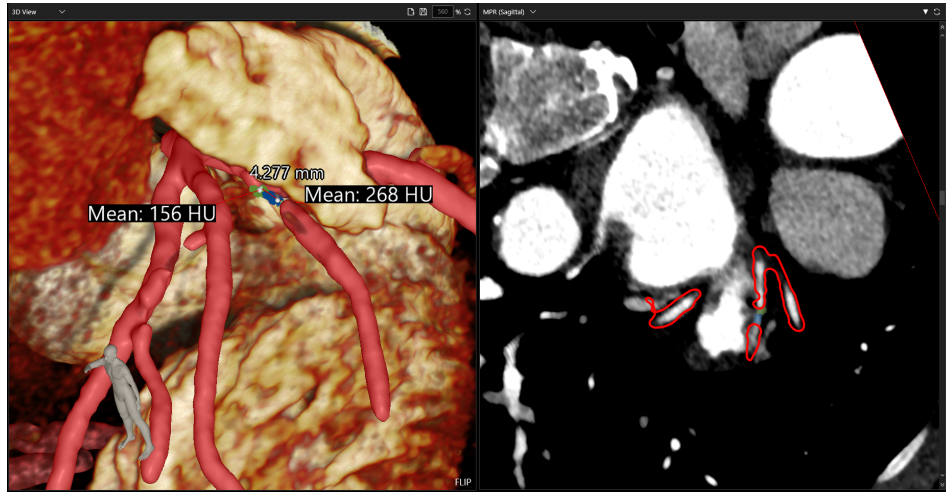


Figure 4.6: 3D volumetric visualization of CT data showing segmentation results and plaque measurements, performed using CarnaLife Holo (MedApp S.A., Poland) [Z4].

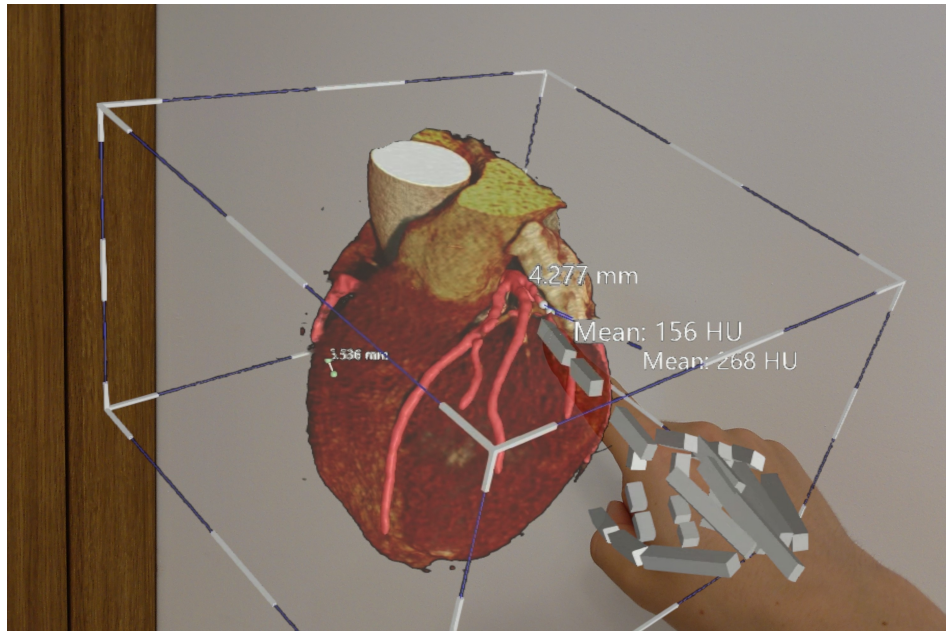


Figure 4.7: Holographic representation of CT scans displaying segmentation outcomes in CarnaLife Holo (MedApp S.A., Poland) [Z4].

of 0.8353 and an HD of 20.23 mm. Figure 4.5 provides representative examples that compare the segmentation results between non-obstructive and occluded arteries.

Qualitative Analysis and Visualization

Qualitative analysis is conducted using mixed reality visualization, integrating two complementary techniques: surface rendering for segmentation results and volumetric

rendering for CT data. This combination provides clinicians with an intuitive understanding of complex three-dimensional vascular structures, which is often difficult to achieve on conventional two-dimensional displays.

In cases of arterial occlusion, mixed reality further enhances clinical interpretation by clearly differentiating segmented arterial regions from areas absent from the model output. To evaluate these regions, Hounsfield Unit (HU) values were analyzed. Segmented vessel regions demonstrated a mean HU value of 268, whereas non-segmented regions had a mean HU value of 150. The close proximity of these values suggests the presence of arterial plaque, providing additional diagnostic context. As shown in Figure 4.7, the holographic representation improves the spatial comprehension of the pathological regions and supports surgical planning.

In addition to pre-operative assessment, mixed reality visualization provides significant intra-operative utility. It enables surgeons to perform on-demand measurements, adapt the visualization to specific procedural requirements, and examine the anatomical context within an immersive environment. A representative volumetric rendering, incorporating segmentation results and plaque measurements, is shown in Figure 4.6.

Overall, the proposed 3D Dense-U-Net effectively segments CA, achieving high accuracy in non-obstructive artery regions while providing clinically relevant visualization of occluded arteries. The combination of quantitative metrics and qualitative 3D visualization demonstrates its utility for both diagnostic assessment and interventional planning. Furthermore, the trained 3D Dense-U-Net is able to serve as a pre-trained network for transfer learning, providing a robust initialization for models targeting peripheral artery segmentation.

In addition, the results presented in this section were previously published by the author in [Z4].

4.4.3 Evaluation of Peripheral Artery Segmentation

The transfer learning approach for PA segmentation is evaluated using models pre-trained on the CA and PulA datasets. These pre-trained models are applied to the PA dataset, enabling adaptation to its distinct anatomical and imaging characteristics.

Evaluation of PA Segmentation via Pula Transfer Learning Approach

The transfer learning approach for PA segmentation was evaluated across five diverse CT datasets. Table 4.8 summarizes the quantitative performance in terms of DSC, HD and HD95.

DSC scores range from 0.57 to 0.80, reflecting moderate overlap with reference annotations. Although the method achieves reasonable performance on some datasets, such as the RIDER dataset with a DSC of 0.80, significant inconsistencies are evident in others. HD and HD95 values are particularly elevated in multiple datasets, highlighting substantial discontinuities in vessel segmentation and frequent omissions of distal branches.

Figure 4.8 illustrates representative segmentation results, showing that although the main vessel paths are partially captured, large gaps and missing distal branches remain. Ground truth vessels are colored green, and predicted segmentations are colored red, highlighting areas where the network fails to maintain continuous vessel structures.

These results indicate that the transfer learning approach provides a partial approximation of PA structures, but struggles to preserve continuity and completeness across heterogeneous datasets.

Table 4.8: PA segmentation performance using Pula-based transfer learning across five CT datasets

Metric	Dongyang	RIDER	KiTS	Gennimatas_1	Gennimatas_2
DSC	0.57	0.80	0.59	0.68	0.66
HD (mm)	62.36	72.13	94.72	27.12	133.42
HD95 (mm)	48.27	2.0	63.3	14.8	118.40

Evaluation of PA Segmentation via CA Transfer Learning

The CA transfer learning approach for PA segmentation is evaluated in five diverse CT datasets. Table 4.9 summarizes the quantitative results, including DSC, HD, and HD95.

DSC scores range from 0.72 to 0.831, indicating moderate overlap with reference annotations. However, analysis of segmentation continuity reveals that the network

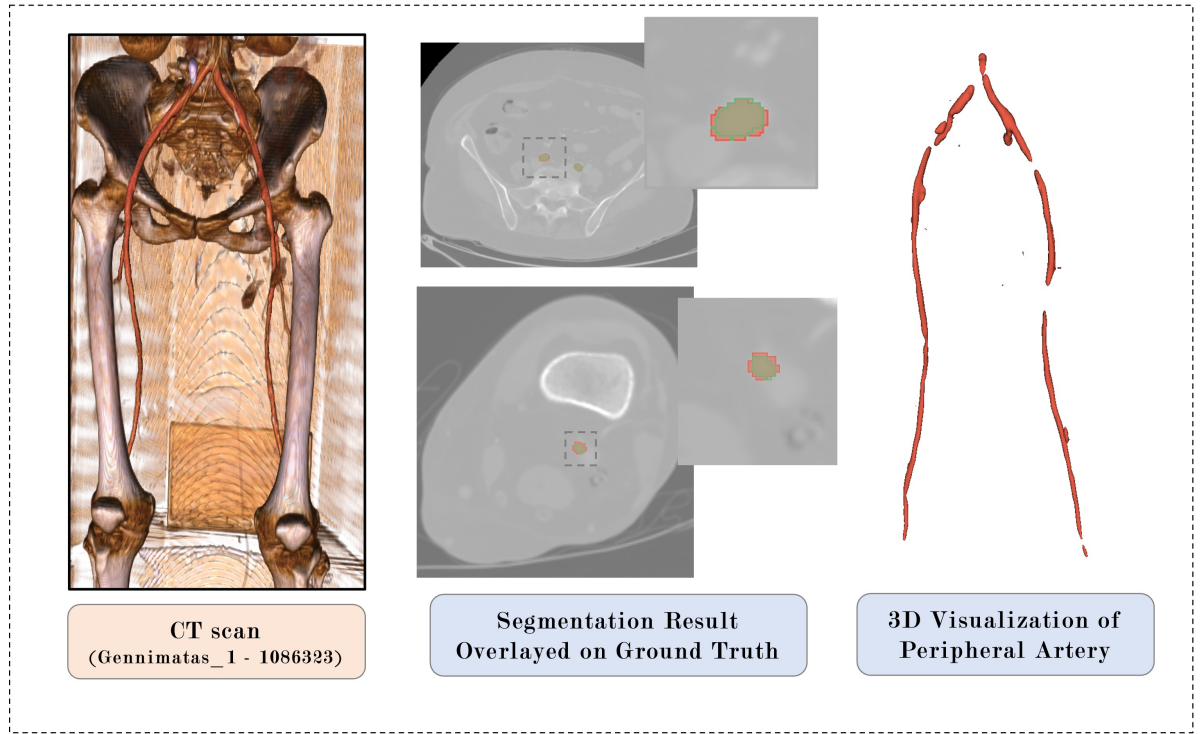


Figure 4.8: PA segmentation using PulaA-based transfer learning approach. The segmentation of the PA system includes distal branches, with ground truth shown in green and predicted results in red.

frequently fails to maintain complete vessel connectivity, with distal branches often missing or partially segmented. HD values, particularly the high measurements observed in some datasets, further reflect inconsistencies in the capture of continuous vessel structures.

Figure 4.9 illustrates representative segmentation results, showing that while the method captures the main route of the vessel, several gaps and missing distal branches remain. Ground truth vessels are colored green, and predicted segmentations are colored red, highlighting the discontinuities in the network output.

These results indicate that, although CA transfer learning provides a reasonable approximation of peripheral vessel structures, its inability to maintain vessel continuity limits its effectiveness.

Table 4.9: PA segmentation performance using CA-based transfer learning across five CT datasets

Metric	Dongyang	RIDER	KiTS	Gennimatas_1	Gennimatas_2
DSC	0.773	0.831	0.80	0.72	0.77
HD (mm)	28.187	72.13	70.84	39.0	31.5
HD95 (mm)	12.47	2.00	5.56	5.35	3.77

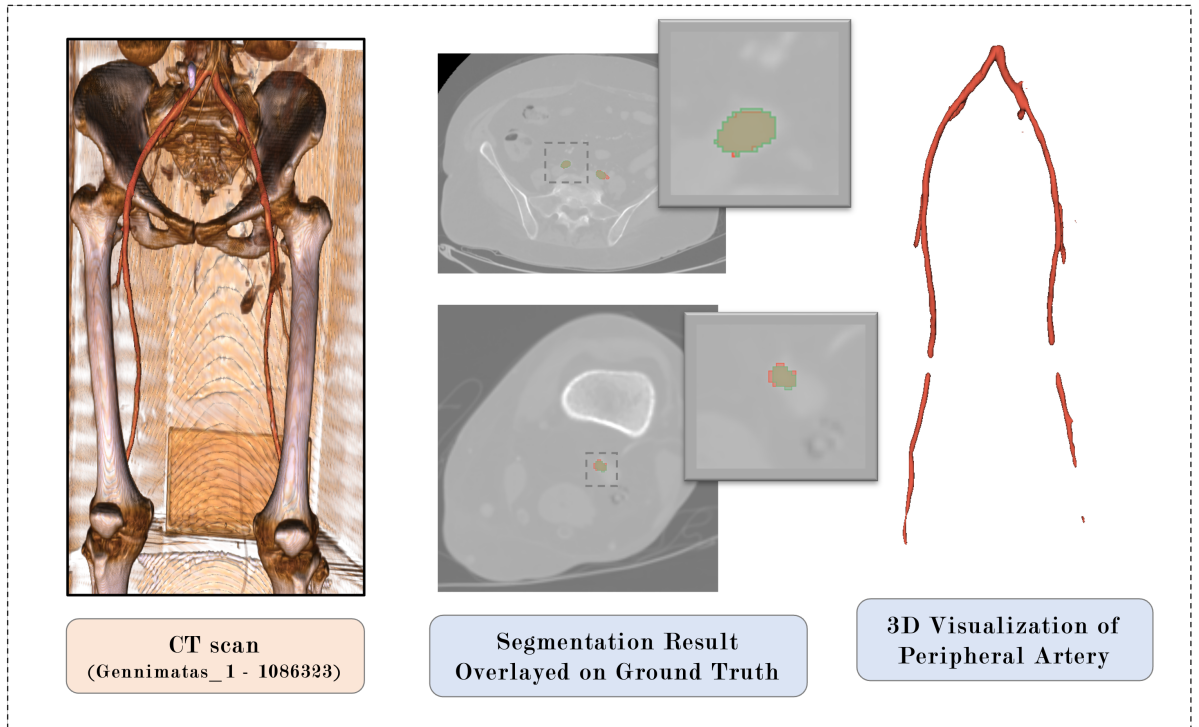


Figure 4.9: PA segmentation using a CA-based transfer learning approach. The segmented PA system includes distal branches, with ground truth shown in green and predicted results in red.

4.5 Visualization of Peripheral Artery

Accurate visualization of the PA is essential to understand the vascular morphology. To achieve this, arterial structure was analyzed that highlights both tissue composition and spatial organization.

The following subsections describe results for cluster-based visualization and mixed-reality representation, providing a comprehensive view of the PA architecture.

4.5.1 Cluster-Based Visualization

The structural characterization of PA was performed using CT, with a GMM applied to differentiate regions within the arterial wall according to intensity distributions. By combining CPR and polar coordinate transformation, the GMM reliably identified anatomically significant clusters corresponding to different tissue types. This approach enabled for the precise segmentation of the arterial regions.

As shown in Figure 4.11, the algorithm classified the artery into three main groups: medium intensity regions (cluster 1), high intensity regions (cluster 2), and low intensity regions (cluster 3).

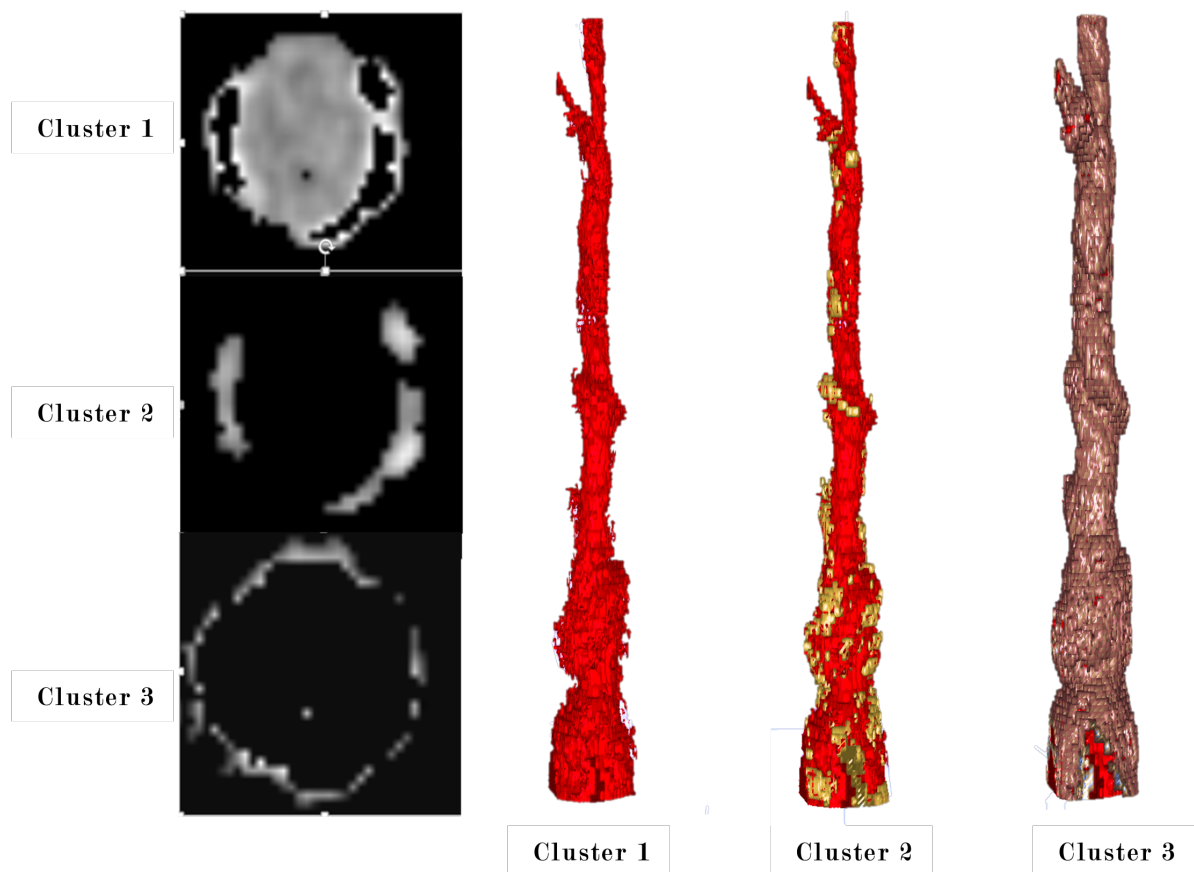


Figure 4.10: 3D visualization of intensity-based clusters within the PA, highlighting structural variations and spatial distribution [Z5].

To further assess the separability of the cluster, a histogram analysis of the HU distributions was performed (Figure 4.10). Cluster 1 (red) exhibits a sharp peak between 200–400 HU, reflecting the dominant tissue component. Cluster 2 (light orange) spans 400–1200 HU with lower frequency, indicating heterogeneous high-density structures.

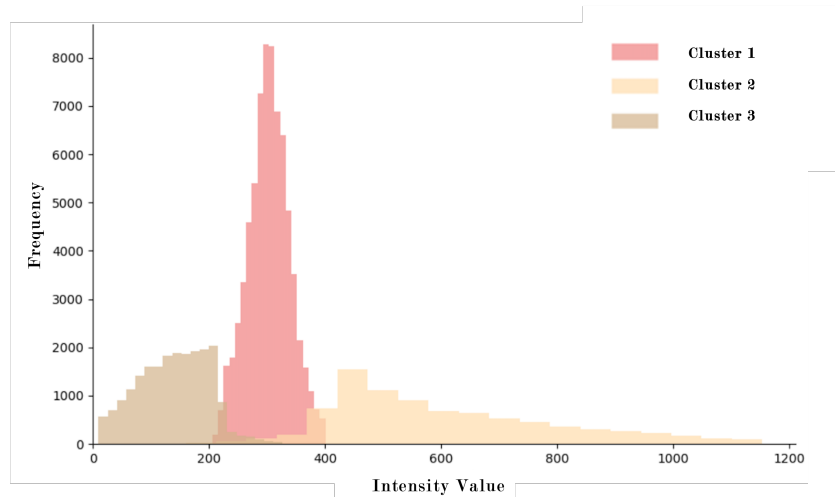


Figure 4.11: GMM-based clustering of PA regions, highlighting intensity-driven spatial groupings within the vascular structure [Z5].

Cluster 3 (beige) peaks at 0–200 HU, representing low-density arterial components and the smallest proportion of pixels.

This clustering framework ensures accurate differentiation of tissue types and improves the interpretability of arterial composition, providing a foundation for quantitative analyzes. These results have previously been published by the author [Z5].

4.5.2 Mixed Reality Visualization

A three-dimensional mixed reality representation of PA is generated to provide a spatially coherent perspective of vascular morphology (Figure 4.12). This immersive visualization allows an intuitive interpretation of the tissue distribution and emphasizes the spatial continuity of segmented regions. By clearly illustrating anatomical location and inter-relationships, the holographic view enhances understanding of the morphology of PA, supporting diagnostic assessment, surgical planning, and advanced vascular research.

4.6 Discussion

In this study, a systematic evaluation is conducted in multicenter datasets to identify the approach that maximizes segmentation precision, preserves vascular topology, and produces results that are both anatomically and clinically reliable.

Two experimental strategies for PA segmentation were analyzed:

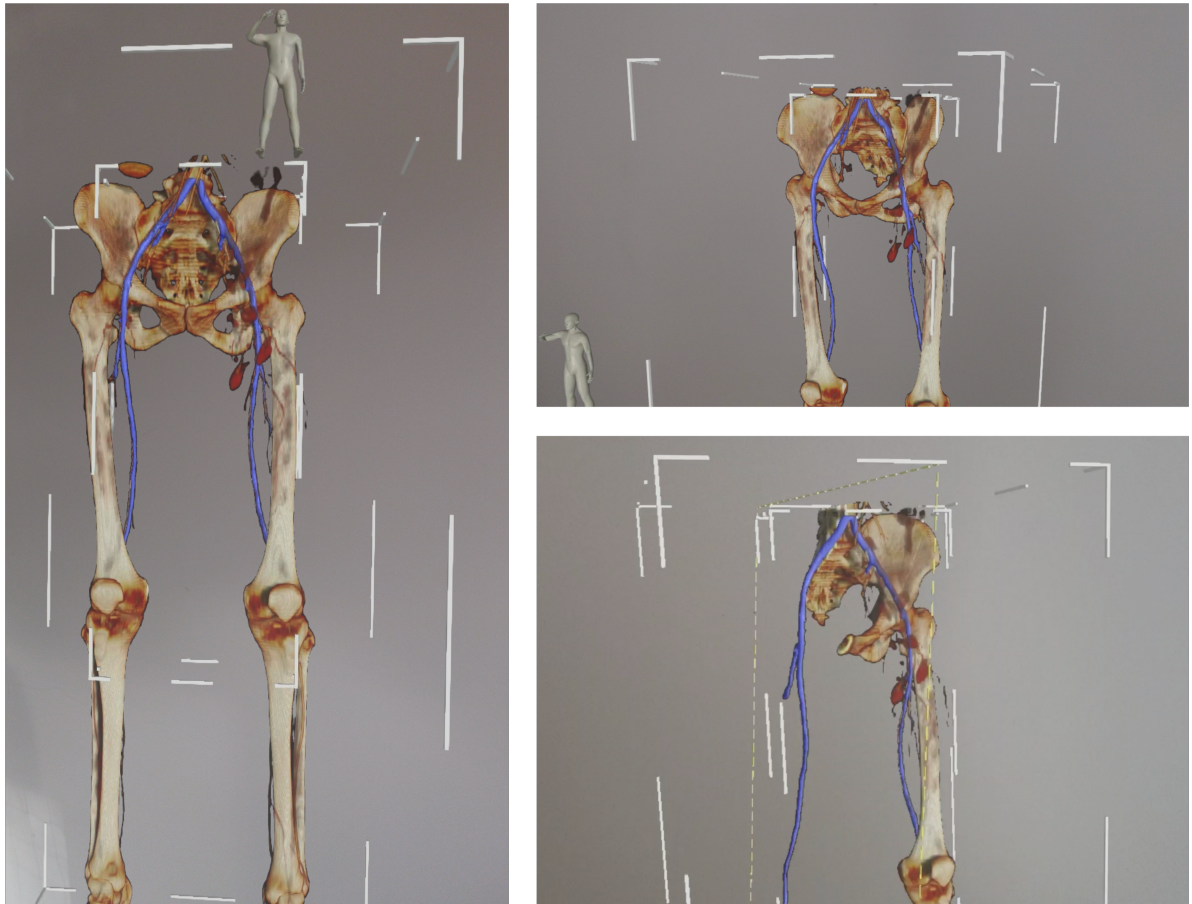


Figure 4.12: Three-dimensional MR visualization of the PA, illustrating anatomical localization and spatial structure.

- Transfer learning via PulA, and CA.
- Isolated training with the SDVN framework.

4.6.1 Comparative Analysis

The quantitative results of five independent CT datasets are summarized in Tables 4.8–4.9 and 4.2, with an integrated comparison provided in Table 4.10.

PulA-based Transfer learning

Transfer learning from the PulA domain exhibits limited segmentation performance, with DSC ranging from 0.57 to 0.80. Considerable variability appears across datasets, and large Hausdorff distances indicate that fine vascular boundaries are not consistently captured. The reduced effectiveness is likely due to structural and morphological

differences between PulA and PA , which limit the utility of the learned characteristics when applied to the segmentation of the peripheral artery. Visual inspection confirms fragmented segmentations, highlighting the challenge of transferring domain knowledge across anatomically dissimilar vascular structures.

CA-based Transfer learning

Transfer learning from CA datasets achieves improved segmentation accuracy, with DSC values between 0.72 and 0.83. Boundary delineation is substantially better than with PulA transfer, and HD95 values remain below 13 mm across datasets. This improvement reflects greater anatomical and morphological similarity between CA and PA, facilitating more effective feature transfer. However, occasional discontinuities in the segmented vessels indicate that, while beneficial, transfer learning does not fully replicate the performance achievable with task-specific training.

Isolated SDVN training

Isolated training using the SDVN framework consistently achieves the highest segmentation performance. The dice coefficients range from 0.90 to 0.92, with HD95 values reduced to near-negligible levels (1.40 mm). Importantly, SDVN preserves vascular connectivity across datasets, a property not reliably maintained by either transfer learning approach. This performance demonstrates the ability of the network to capture elongated branching vascular structures, producing anatomically plausible and clinically reliable segmentations. Visual inspection confirms that SDVN-generated vascular trees are continuous and topologically coherent, in contrast to the fragmented or partially discontinuous output observed with transfer learning.

Cross-Method Analysis

In general, the effectiveness of segmentation follows a clear hierarchy. PulA transfer demonstrates limited precision and inconsistent boundary delineation, CA transfer offers moderate utility when PA annotations are scarce, and isolated SDVN training achieves superior accuracy, precise boundary delineation, and robust preservation of vascular connectivity (Table 4.10). These findings indicate that although transfer

learning leverages pre-existing knowledge, differences in imaging characteristics and anatomical structure between source and target datasets limit its effectiveness. In contrast, dataset-specific training with SDVN captures the unique characteristics and variability of peripheral arteries, leading to improved segmentation outcomes.

Table 4.10: Mean segmentation performance across training strategies including PulA-based transfer learning approach, CA-based transfer learning approach, and isolated learning approach using SDVN.

Method	Mean DSC	Mean HD (mm)	Mean HD95 (mm)
PulA-based Transfer learning $\rightarrow$ PA	0.66	77.95	49.35
CA-based Transfer learning $\rightarrow$ PA	0.78	48.33	5.83
Isolated learning using SDVN $\rightarrow$ PA	0.91	12.60	1.12

These results emphasize the importance of isolated, dataset-specific learning in medical image analysis. Although transfer learning can offer moderate improvements, training directly in the target dataset provides the most effective strategy to achieve high-fidelity, anatomically accurate, and clinically reliable vascular segmentation.

4.6.2 Comparison of Isolated Learning Approach with Existing Methods

The proposed method accurately segments the entire PA region, including distal branches. Its performance was evaluated against widely used segmentation models, including U-Net [153], ResUNet [154], DenseNet [155], SAM-Med3D [156], and TotalSegmentator [127], using HD, HD95, and DSC. A summary of the comparative results is provided in Table 4.11.

The SDVN consistently achieved higher DSC scores and lower HD and HD95 values across all datasets, demonstrating its robustness in capturing PA structures under varying contrast conditions, anatomical variability, and complex branching patterns, as illustrated in Figure 4.13.

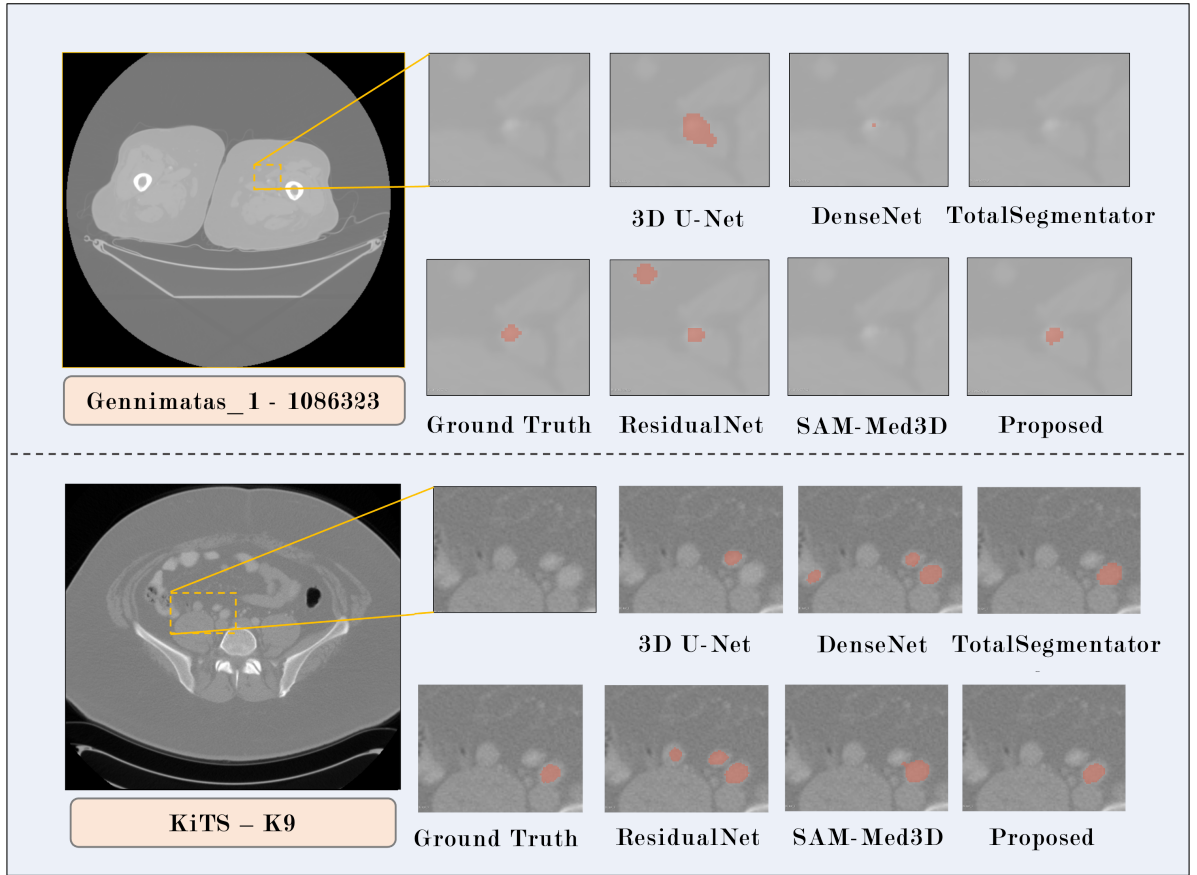


Figure 4.13: Visual comparison of different segmentation methods. The isolated learning approach using SDVN (proposed) demonstrates superior vessel continuity, accurate boundary adherence, and reliable recovery of fine branches [Z2].

Comparison with TotalSegmentator

The complete segmentation of the PA remains a challenge for many existing methods. Figure 4.14 illustrates the extended coverage of the arterial tree achieved by SDVN. Although TotalSegmentator is limited to proximal arteries such as the common iliac, the proposed SDVN method segments the entire peripheral arterial system, including distal branches, which is essential for a comprehensive evaluation of vascular disease.

A direct comparison with the TotalSegmentator for the common iliac artery is presented in Table 4.12. SDVN consistently outperforms TotalSegmentator in Dice score, HD, and HD95 across all datasets.

In summary, the SDVN framework consistently demonstrated strong performance across all evaluated CT datasets. Quantitative comparisons indicate that SDVN provides accurate and robust PA segmentation, often outperforming existing methods. These

Table 4.11: Comparison of the performance of 3D U-Net, ResUNet, DenseNet, SAM-Med3D, TotalSegmentator, and SDVN [Z2].

Dataset	Metric	3D U-Net	ResUNet	DenseNet	SAM-Med3D	TotalSegmentator	SDVN (Proposed)
Dongyang	Dice	0.70	0.77	0.85	0.79	0.78	0.90
	HD (mm)	32.4	36.27	13.95	12.75	14.57	3.03
	HD95 (mm)	13.8	20.73	1.20	2.28	3.83	1.00
RIDER	Dice	0.60	0.78	0.83	0.68	0.69	0.90
	HD (mm)	65.74	31.14	99.34	105.76	106.74	26.41
	HD95 (mm)	12.20	2.44	12.44	21.54	65.50	1.40
KiTS	Dice	0.72	0.82	0.82	0.76	0.75	0.91
	HD (mm)	47.84	43.18	59.04	24.01	43.53	11.74
	HD95 (mm)	13.86	11.28	17.95	3.46	15.02	1.21
Gennimatas_1	Dice	0.67	0.72	0.83	0.67	0.58	0.90
	HD (mm)	45.44	53.44	32.66	53.48	100.00	14.28
	HD95 (mm)	12.40	29.80	1.50	3.00	79.91	1.00
Gennimatas_2	Dice	0.85	0.88	0.88	0.81	0.76	0.92
	HD (mm)	27.23	37.41	39.60	48.25	54.27	7.54
	HD95 (mm)	1.50	5.59	3.39	4.09	30.51	1.00

Table 4.12: Comparison between SDVN and TotalSegmentator for common iliac artery segmentation across datasets [Z2].

Center	SDVN: DSC	TotalSegmentator: DSC	SDVN: HD (mm)	TotalSegmentator: HD (mm)	SDVN: HD95 (mm)	TotalSegmentator: HD95 (mm)
Dongyang	0.91	0.80	2.45	5.42	1.00	1.71
RIDER	0.93	0.82	7.34	16.54	1.00	2.24
KiTS	0.92	0.83	5.80	8.91	1.21	2.29
Gennimatas_1	0.93	0.86	3.23	6.52	1.00	1.00
Gennimatas_2	0.93	0.87	5.03	7.74	1.21	1.00

results highlight the effectiveness and generalizability of the proposed approach in a variety of imaging scenarios.

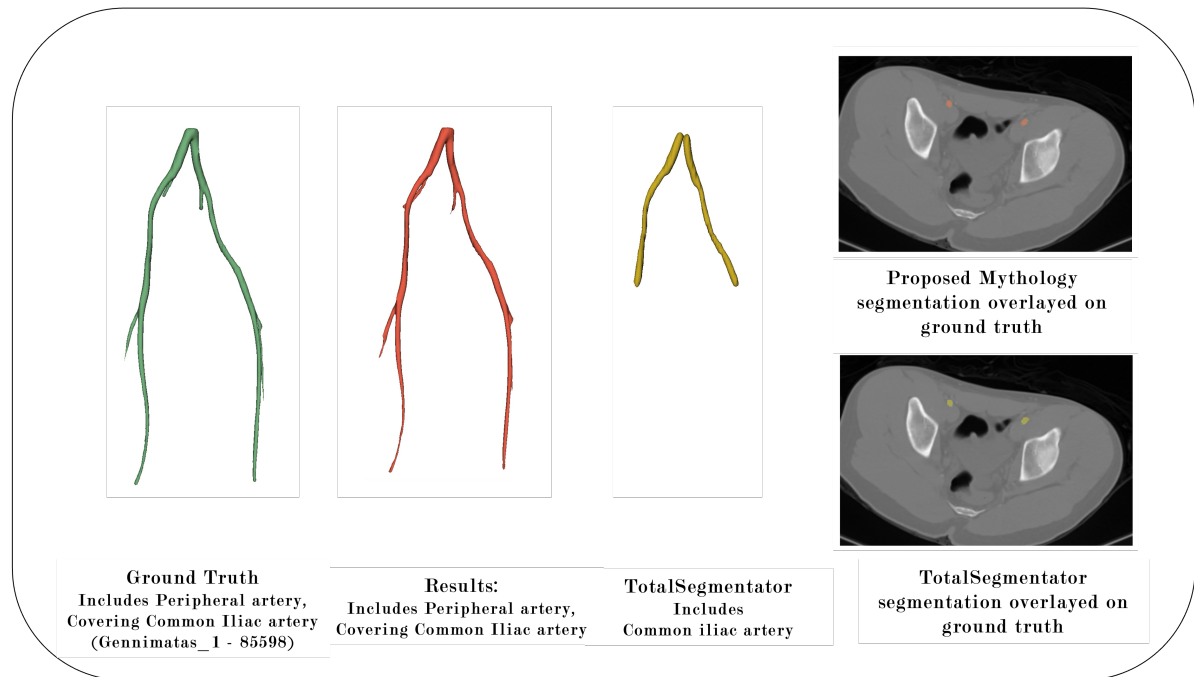


Figure 4.14: Comparison with TotalSegmentator. The isolated learning approach using SDVN captures PA, including distal branches, whereas TotalSegmentator is limited to proximal arteries such as the common iliac [Z2].

4.7 Conclusion

This chapter presents the results of the proposed segmentation framework and examines their implications. Quantitative evaluation metrics provided a robust basis for assessing model performance, while experiments on ROI localization confirmed the reliability and consistency of the pre-processing pipeline.

Among the two segmentation strategies, the isolated learning approach employing the SDVN demonstrated superior performance in accurately segmenting the structures of PA. In contrast, the transfer learning approach, based on pre-trained models trained on Pula and CA datasets, exhibited comparatively lower precision, highlighting the domain-specific challenges in adapting models in different vascular regions.

Visualization of the segmented arteries further validated the effectiveness of the proposed methods, offering intuitive and clinically interpretable representations. The discussion emphasized the strengths and limitations of each approach and underscored them.

In summary, the results affirm the feasibility and potential of the methods developed, with isolated learning being particularly effective for this application. The subsequent chapter synthesizes these findings into overarching conclusions and outlines directions for future research.

Chapter 5

Concluding Remarks and Future Work

The primary objective of this thesis is to develop and evaluate deep learning-based methods for the segmentation of the Peripheral Artery from 3D CT scans. Accurate segmentation of PA is essential for the diagnosis, treatment planning, and surgical guidance of peripheral vascular diseases.

To address this challenge, two distinct strategies were investigated: knowledge transfer and task-specific modeling. These strategies were independently evaluated to determine their relative effectiveness for PA segmentation.

The knowledge transfer strategy involves initializing segmentation models with features learned from anatomically related vascular structures, specifically the Coronary Arteries and Pulmonary Artery branches. These source domains share key morphological and imaging characteristics with the peripheral arteries, such as branching topology, tubular geometry, and contrast-enhanced appearance on CT scans. The pretrained models are then fine-tuned on the PA dataset to adapt the learned representations to the target segmentation task.

The task-specific modeling strategy, on the other hand, trains segmentation models directly on the PA dataset from scratch, without any external pretraining. This approach is intended to capture the unique anatomical and imaging characteristics of the peripheral arteries more effectively through dedicated learning.

Experiments were conducted to compare the performance of these two strategies. The results demonstrated that task-specific modeling consistently outperformed knowledge

transfer, highlighting the importance of directly learning from target domain data for PA segmentation. These findings provide valuable information on the choice of modeling strategies for deep learning-based vascular segmentation tasks.

5.1 Contributions

The main contributions of this study are summarized as follows:

- **Region of Interest (ROI) Localization with YOLOv8:** A YOLOv8-based detection module was integrated to automatically identify and extract peripheral artery regions from whole body CT scans. This step significantly reduced computational cost and processing time while maintaining segmentation accuracy, enabling efficient handling of large-scale 3D medical images.
- **Single-Depth Vascular Network for Segmentation:** A novel 3D SDVN was developed to segment fine and complex structures of peripheral arteries. The network architecture was specifically designed to capture intricate branching patterns and tubular geometries, outperforming conventional 3D CNNs, especially for small and tortuous vessels.
- **Transfer Learning from Coronary and Pulmonary Arteries:** Pre-trained models on coronary arteries and pulmonary arteries were fine-tuned on PA datasets, enabling knowledge transfer from related vascular structures. This approach improved segmentation accuracy, reduced training time, and improved performance where PA data alone were limited.
- **Comprehensive Evaluation:** Extensive experiments evaluated the contributions of each component (ROI extraction, SDVN, and transfer learning). Quantitative metrics demonstrated improved segmentation performance and computational efficiency, validating the effectiveness of the proposed methodology for automated PA analysis.
- **Integration into DECODE Platform:** The proposed algorithm has been integrated into [Z3], an open source cloud-based platform for the non-invasive treatment of peripheral artery disease. This integration enables scalable deployment, facilitating real-world clinical use, and collaborative research.

- **Clinical Relevance:** The framework provides a reliable tool for the early diagnosis, monitoring, and management of peripheral artery disease. By automating segmentation and reducing manual workload, it has significant potential for clinical adoption and improved patient outcomes.
- **Dissemination through Publications:** The outcomes of this research have been distributed through peer-reviewed journals and conference publications [Z1–Z5], contributing novel methods and practical tools to the scientific community in the fields of medical image analysis and cardiovascular health.

5.2 Future Work

The following directions are proposed for future research.

- **Enhanced ROI Detection:** Future work could explore a multistage framework for better ROI detection throughout the body. The initial stages could identify coarse anatomical locations, followed by finer stages focusing on specific arteries and vascular structures. This would allow for the precise analysis of various vascular areas and enhance precision in large-scale or whole-body imaging studies.
- **Advancements in SDVN Architecture:** Research could investigate multiscale, attention-based, or hybrid network architectures to better capture fine vascular structures. Such designs could improve segmentation accuracy for small or intricate vessels, improving the reliability of automated vascular analysis.
- **Multimodal Imaging Integration:** Combining CT with complementary modalities such as MRA or ultrasound could provide richer anatomical and functional information. The use of multimodal data sets may improve segmentation robustness and facilitate detection of clinically relevant features that are not easily visible in a single modality.
- **Explainable AI and Clinical Interpretability:** Incorporating interpretability techniques such as attention visualization, saliency mapping, or region importance analysis could make model outputs more transparent. This would build trust among clinicians and support clinical adoption by clearly highlighting the reasoning behind the predictions of the model.

Appendix A

Author's Research Record

Journal Articles

- [Z1] **M. Zulfiqar**, M. Stanuch, M. Wodzinski, and A. Skalski, “Dru-net: Pulmonary artery segmentation via dense residual u-network with hybrid loss function,” *Sensors*, vol. 23, no. 12, p. 5427, 2023.
- [Z2] **M. Zulfiqar**, M. Stanuch, S. Vagena, F. Sigala, and A. Skalski, “Automated segmentation of peripheral arteries in 3D CT data based on a single-depth vascular network,” *Biomedical Signal Processing and Control*, vol. 112, p. 108410, 2026.
- [Z3] M. A. AboArab, M. Anić, V. T. Potsika, H. Saeed, **M. Zulfiqar**, A. Skalski, E. Stretti, V. Kostopoulos, S. Psarras, G. Pennati et al., “Decode: An open-source cloud-based platform for the noninvasive management of peripheral artery disease,” *Computer Methods and Programs in Biomedicine*, p. 109037, 2025.

Conference Articles

- [Z4] **M. Zulfiqar**, M. Stanuch, and A. Skalski, “Preoperative planning for coronary artery disease using 3D segmentation and Mixed Reality,” in *2023 IEEE International Conference on Imaging Systems and Techniques (IST)*, IEEE, 2023, pp. 1–6.
- [Z5] **M. Zulfiqar**, M. Stanuch, and A. Skalski, “Profiling peripheral artery structures using CT scan data with Curve Planar Reformation and Gaussian Mixture Model in polar coordinates,” in *2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, IEEE, 2024, pp. 7185–7187.

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- [8] Z. Deng, S. Xu, J. Zhang, J. Zhang, D. J. Wang, L. Yan, and Y. Shi, “Shape-aware 3d small vessel segmentation with local contrast guided attention,” in *Medical Image Computing and Computer Assisted Intervention – MICCAI 2023*. Springer, 2023, pp. 354–363.
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