Automatic Detection and Segmentation of Coronary Artery Stenosis in Coronary Angiography Images

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Abstract. In this paper, we present an approach for the detection, segmentation, and quantification of stenoses in coronary arteries using modern computer vision and deep learning techniques. Our system incorporates a detection model based on YOLOv8 and a segmentation model (DeepLabV3+) for precise localization and delineation of stenosis regions. In addition, a novel method is introduced to measure arterial thickness to support clinical decision-making. The experimental evaluation shows that the approach demonstrates high quality and performance in comparison to existing solutions. This work aims to improve diagnostic efficiency and reduce the reliance on expensive foreign-made equipment by providing an integrated solution that can operate on standard hardware.

Keywords: Coronary artery stenosis · Computer vision · Deep learning · YOLOv8 · DeepLabV3+ · Medical image analysis

1 Introduction

Cardiovascular disease remains one of the leading causes of death worldwide. Among various cardiovascular conditions, coronary artery stenosis stands out as a major concern—this narrowing of the arterial vessels that supply blood to the heart can lead to ischemic heart disease, myocardial infarction, and other severe complications. The timely diagnosis of stenosis plays a crucial role in preventing these outcomes and reducing mortality associated with cardiovascular diseases [9]. A modern diagnostic approach for stenosis is coronary angiography, a method that visualizes the heart's vessels using X-rays and contrast agents. However, this method requires the mandatory involvement of highly qualified specialists and substantial time for manual image analysis. Furthermore, the results of such analysis are susceptible to human error, especially under high workloads faced by medical personnel.

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Automating the diagnosis of stenosis through computer vision methods has the potential to revolutionize the processing of medical images. Deep learning and computer vision algorithms enable rapid and accurate analysis of angiograms, allowing for the detection of abnormalities and the extraction of vessel geometry information. This approach not only accelerates the diagnostic process but also minimizes errors due to human factors. Moreover, automated analysis systems can be deployed in remote medical centers where access to highly specialized personnel is limited.

Previous studies have demonstrated the effectiveness of deep learning-based methods for coronary artery segmentation. For instance, in the study by Serrano-Anton et al. [7], a UNet-based model with transfer learning was proposed for coronary artery segmentation in CT angiography images. The findings indicate that transfer learning significantly improves segmentation accuracy, particularly when working with limited data. Additionally, Danilov et al. [2] introduces a fully automated approach for coronary angiogram interpretation using a sequence of deep neural networks, achieving high accuracy in stenosis detection. These studies highlight the potential of modern deep learning and computer vision techniques in automating coronary artery stenosis diagnosis, aligning with the objectives and methodologies proposed in our work.

2 Related works

Advancements in artificial intelligence (AI), particularly deep learning, have significantly impacted the automated detection and quantification of coronary artery stenosis [8].

A meta-analysis published by Jie at al. [4] evaluates the diagnostic accuracy of AI-assisted CTA in detecting stenosis and characterizing plaque composition. The analysis, which included 11 studies with 1,484 patients, reported a pooled area under the receiver operating characteristic curve (AUROC) of 0.96 for assessing atherosclerotic plaque. For detecting $\geq 50\%$ stenosis, the AUROC was 0.95, and for $\geq 70\%$ stenosis, it was 0.96. The study concludes that AI-assisted CTA has high diagnostic accuracy but acknowledges substantial heterogeneity among studies and emphasizes the need for further research to standardize AI applications in clinical practice. Dundas et al. [3] evaluated an AI-based coronary stenosis quantification (AI-CSQ) tool and compared its performance with invasive quantitative coronary angiography (QCA). Their findings demonstrated high diagnostic accuracy, with the AI-CSQ model achieving an AUC of 0.92 for detecting stenosis $\geq 50\%$ and 0.93 for stenosis $\geq 70\%$. Additionally, the system exhibited a sensitivity of 80% and specificity of 88% for moderate stenosis ($\geq 50\%$) and sensitivity of 78% and specificity of 92% for severe stenosis ($\geq 70\%$). Li et al. [5] developed a deep learning model capable of automatically segmenting coronary arteries and diagnosing stenosis of $\geq 50\%$ severity. Utilizing a U-Net architecture for segmentation and a 3DNet for classification, the model achieved a mean Dice coefficient of 0.771 and an accuracy of 75% in diagnosing coronary artery disease (CAD). However, the study was limited by its single-

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center design, potentially affecting the model's generalizability. Danilov et al. [2] investigate the feasibility of real-time coronary artery stenosis detection using deep learning. The study evaluates eight neural network architectures, including MobileNet, ResNet-50, ResNet-101, Inception ResNet, and NASNet, using angiography data from 100 patients. The Faster-RCNN Inception ResNet V2 model achieves the highest accuracy (mAP = 0.95, F1-score = 0.96) but has a slow inference speed (3 fps). In contrast, SSD MobileNet V2 is the fastest (38 fps) but less accurate (mAP = 0.83, F1-score = 0.80). The RFCN ResNet-101 V2 model offers the best balance (mAP = 0.94, F1-score = 0.96, speed = 10 fps). The study confirms the potential of deep learning for real-time stenosis detection, improving diagnostic efficiency. However, the small dataset and lack of external validation limit generalizability.

Annotating stenotic regions in coronary angiograms and computed tomography angiography images requires expertise from cardiologists or radiologists. However, inter-observer variability is a significant issue, as different specialists may interpret and delineate stenotic lesions differently. This variability affects the consistency of ground truth labels, complicating model training and reducing generalizability. For instance, Zhang et al. [8] highlighted that machine learning and deep learning methods face challenges due to the lack of professional image annotations, which are manually added by experts.

There is no universal consensus on classifying stenosis severity (e.g., mild $<$50%, moderate 50–70%, severe $>$70%), leading to discrepancies in annotation protocols across datasets. Some studies use diameter reduction measurements, while others incorporate functional assessments like fractional flow reserve (FFR). This inconsistency impacts model robustness and comparability across different studies. A review by Aleksandric et al. [1] discussed the challenges, limitations, and future perspectives in the functional assessment of coronary stenosis severity, emphasizing the complexity of coronary physiology in the presence of valvular heart disease.

Despite these advancements, challenges persist, including the need for large, annotated datasets and the variability in imaging protocols across institutions. Future research should focus on developing models that are robust across diverse populations and imaging conditions. In conclusion, deep learning has significantly advanced the automated analysis of coronary artery stenosis, offering improved diagnostic accuracy and efficiency. However, addressing current limitations is essential for broader clinical implementation.

3 Deep learning model development and evaluation

The proposed algorithm for the automatic analysis of coronary artery stenosis comprises several distinct stages, each designed to enhance the robustness and precision of the diagnostic process.

The algorithm employed for detection, segmentation, and thickness measurement of coronary artery stenosis is structured as follows (see Fig. 1). Initially, input images undergo a preprocessing step aimed at normalizing and enhancing

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image quality. Subsequently, the processed images are directed into two parallel branches: one for detecting the stenotic regions and another for segmenting coronary arteries. The detection branch localizes areas suspected of stenosis, while the segmentation branch delineates the coronary artery structure. The outputs from these parallel processes, namely the detected stenosis regions and segmented coronary artery masks, are then mapped together to define precise areas of interest. These combined masks are subjected to a skeletonization process, enabling the extraction of vessel centerlines. Finally, the arterial thickness is determined by analyzing geometric properties derived from these skeletonized representations.

3.1 Annotation of stenosis data

Accurate annotation of coronary artery stenosis is a critical step in the development of robust computer vision models for automated diagnosis. In this work, experienced cardiologists manually annotated imaging data to delineate stenotic regions using the YOLO (You Only Look Once) format. This section outlines the methodology, guidelines, and quality control procedures employed during the annotation process.

Imaging data were sourced from standard clinical modalities, including coronary angiography and computed tomography angiography (CTA), reflecting real-world diagnostic practices. Annotations were performed using a specialized tool (e.g., LabelImg[3]) adapted for medical imaging. Cardiologists followed strict clinical guidelines to delineate the boundaries of stenotic lesions. Each lesion was annotated by drawing a bounding box that encapsulated the region of stenosis. The process was conducted by experts to capture even subtle variations in lesion morphology accurately.

The annotations were saved in the YOLO format, where each line in the annotation file represents a single object detection. The format includes the following normalized parameters:

– `class_id:` An integer representing the category (e.g., "0" for coronary artery stenosis).

[3] `https://github.com/HumanSignal/labelImg`

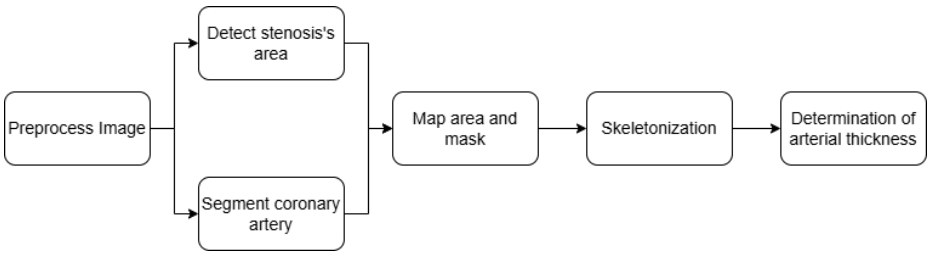

Fig. 1. General algorithm's scheme

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- `x_center, y_center`: The normalized coordinates of the bounding box center relative to the image dimensions.
- `width, height`: The normalized width and height of the bounding box.

For example, an annotation line such as "`0 0.450 0.550 0.200 0.150`" indicates that the stenotic region has a center at 45% of the image width and 55% of the image height, with a bounding box spanning 20% of the image width and 15% of the image height.

To ensure consistency and accuracy, each image was independently annotated by at least two cardiologists. Discrepancies between annotations were resolved through consensus meetings. This dual-review process minimized inter-observer variability and ensured that the final annotated dataset accurately reflected the clinical characteristics of coronary stenosis.

3.2 Arterial Thickness Measurement

A reliable estimation of arterial thickness is crucial for quantifying the severity of coronary artery stenosis. In our approach, thickness is measured based on the segmented vessel mask by following a series of computational steps:

First, the segmented binary mask, representing the vessel region, is preprocessed to ensure a consistent data format. A skeletonization algorithm is then applied to this binary mask to extract the vessel's centerline, which serves as an approximation of the mid-curve running through the arterial lumen.

Subsequently, a Euclidean distance transform is computed on the binary mask. This transform assigns to each pixel a value corresponding to its shortest distance from the vessel boundary. For pixels that lie on the skeleton, the distance value effectively represents the approximate distance from the centerline to the edge of the vessel. Under the assumption that the vessel's full diameter is roughly twice this distance, the local arterial thickness is estimated by multiplying the distance value by two.

Finally, by aggregating the thickness estimates along the entire skeleton, key statistical metrics such as the minimum, maximum, mean, and median thickness are derived. These summary statistics provide a comprehensive quantitative description of arterial wall thickness, aiding in the assessment of stenosis severity and contributing to enhanced clinical decision-making.

3.3 Preprocessing

Medical imaging is often subject to challenges such as non-uniform illumination, contrast variability, and image noise. Consequently, a robust preprocessing pipeline is imperative to improve image fidelity and optimize model performance. The preprocessing pipeline consists of the following stages:

- **Standardization:** Normalization of pixel intensity values to mitigate inconsistencies in brightness and contrast across different angiographic images.

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- **Contrast Enhancement:** Application of Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve local contrast and enhance the visibility of vascular structures.
- **Gamma Correction:** Adjustment of image intensity using a power-law transformation to ensure a balanced brightness distribution.
- **Rescaling:** Standardization of image dimensions to maintain uniformity in spatial representation across different datasets.
- **Augmentation (for training purposes only):** Implementation of random transformations, such as rotations and flips, to enhance the generalizability and robustness of the trained models.

These preprocessing techniques collectively contribute to a more homogeneous dataset, reducing intra-class variations and facilitating the identification of salient anatomical features.

3.4 Detection Model

The identification of stenotic regions is performed using the YOLOv8m object detection model. This model was selected due to its optimal trade-off between detection accuracy and computational efficiency, making it well-suited for real-time clinical applications.

The performance of the detection model is assessed using established evaluation metrics:

- **Intersection over Union (IoU):** A metric quantifying the degree of overlap between the predicted bounding boxes and the ground-truth annotations, formally defined as:
$$IoU = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$
where A and B represent the predicted and ground-truth bounding boxes, respectively.
- **Mean Average Precision (mAP@50):** Measures the detection accuracy at an IoU threshold of 0.5, providing an indication of model precision.
- **mAP@50-95:** Evaluates the detection performance over multiple IoU thresholds (ranging from 0.5 to 0.95 in increments of 0.05), offering a comprehensive assessment of model reliability.

The proposed model exhibits high precision while maintaining inference speeds conducive to real-time clinical deployment.

3.5 Segmentation Model

The delineation of stenotic regions is conducted using the DeepLabV3+ segmentation model, employing a ResNet-50 backbone. This architecture is particularly well-suited for high-resolution medical imaging tasks and utilizes atrous spatial pyramid pooling to capture multi-scale contextual information.

Segmentation accuracy is evaluated using the following quantitative metrics:

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- **Intersection over Union (IoU):** Provides a measure of segmentation accuracy by computing the overlap between the predicted segmentation mask and the ground-truth annotation.
- **Dice Coefficient:** An alternative similarity measure defined as:

$$Dice = \frac{2|A \cap B|}{|A| + |B|} \tag{2}$$

where A and B denote the predicted and ground-truth segmentation masks, respectively. This metric is particularly sensitive to imbalances in class distributions.

The DeepLabV3+ model demonstrates superior capability in capturing fine-grained vascular structures, ensuring precise segmentation of stenotic regions.

3.6 Arterial Thickness Estimation

Following stenosis detection and segmentation, the arterial thickness is quantitatively assessed using a distance transform of the segmented vessel mask. This process enables an objective evaluation of vessel narrowing severity.

Key computational steps include:

- Skeletonization of the vessel structure to extract the centerline representation.
- Computation of the Euclidean distance from each skeleton pixel to the nearest vessel boundary.
- Estimation of arterial thickness as twice the computed distance, thereby providing an approximate measure of luminal diameter.

This methodology provides a rigorous quantitative assessment of stenosis severity, complementing traditional diagnostic approaches and enhancing clinical decision-making.

3.7 Dataset description

The proposed system was evaluated on two distinct datasets: one for the detection task and one for the segmentation task.

Detection Dataset: A total of 9,000 coronary angiography images were used for the detection task. Of these, 10% (900 images) represent our proprietary data, while the remaining 90% (8,100 images) were sourced from the ARCADE dataset [6].

Segmentation Dataset: For segmentation, 250 high-resolution images with pixel-level annotations of coronary arteries were used. This dataset was similarly divided into training (175 samples), validation (50 samples), and test (25 samples) sets.

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4 Model training and evaluation

The system was evaluated on both validation and test datasets using three different configurations.

The **baseline solution** (without preprocessing) utilized YOLO v5 for detection and U-Net for segmentation. In this setup, no image enhancement was applied, which resulted in a detection precision of 0.600 and mAP@50 of 0.880. The segmentation module achieved an IoU of 0.580 and a Dice coefficient of 0.740.

To improve performance, a **preprocessing pipeline** (PP) was introduced. This included standardization (to normalize pixel intensity values), CLAHE-based contrast enhancement, gamma correction for balanced brightness distribution, rescaling to standardize image dimensions, and data augmentation (random rotations and flips) for training. Applying PP to the YOLO v5 + U-Net configuration improved detection performance (precision = 0.672, mAP@50 = 0.930) and led to modest gains in segmentation (IoU $\approx$ 0.620, Dice $\approx$ 0.770).

The **optimal solution** aimed to further enhance performance by integrating a more advanced detection model (YOLO v8) and a more robust segmentation model (DeepLab v3+), while retaining the preprocessing pipeline. The YOLO v8 model significantly improved detection accuracy, achieving a precision of 0.966 and mAP@50 of 0.973. DeepLab v3+ further refined segmentation quality, with an IoU of 0.643 and a Dice coefficient of 0.781, surpassing the U-Net-based configurations.

This final configuration demonstrated the best balance between accuracy and computational efficiency. The combination of preprocessing, a superior detection model (YOLO v8), and an advanced segmentation model (DeepLab v3+) resulted in a system capable of high-speed processing while maintaining precise localization and detailed segmentation of stenotic regions.

Table 1. Detection Performance Metrics

Solution	Precision	mAP@50
Baseline (YOLO v5 + U-Net, no PP)	0.600	0.880
YOLO v5 with PP	0.672	0.930
Optimal (YOLO v8 + DeepLab v3+ with PP)	0.966	0.973

Table 2. Segmentation Performance Metrics

Solution	IoU	Dice
Baseline (YOLO v5 + U-Net, no PP)	0.580	0.740
YOLO v5 with PP	0.620	0.770
Optimal (YOLO v8 + DeepLab v3+ with PP)	0.643	0.781

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Tables 1 and 2 summarize the key performance metrics for all three configurations.

The baseline configuration with U-Net yielded an IoU of 0.580 and a Dice coefficient of 0.740, indicating reasonable but suboptimal delineation of vascular structures, likely due to the absence of preprocessing and U-Net's limited contextual awareness in complex angiographic images.

With PP applied, the YOLOv5 + U-Net configuration improved to an IoU of 0.620 and a Dice coefficient of 0.770. These gains (7% in IoU, 4% in Dice) suggest that enhanced image quality facilitates better segmentation, particularly in capturing fine vessel edges. However, U-Net's performance plateaued, reflecting its architectural constraints in handling multi-scale features.

The optimal configuration excelled with a precision of 0.966, mAP@50 of 0.973, IoU of 0.643, and Dice of 0.781, outperforming the baseline by 61% in precision and 11% in mAP@50, and the intermediate setup by 44% and 5%, respectively. DeepLabV3+'s advanced feature extraction drove segmentation gains.

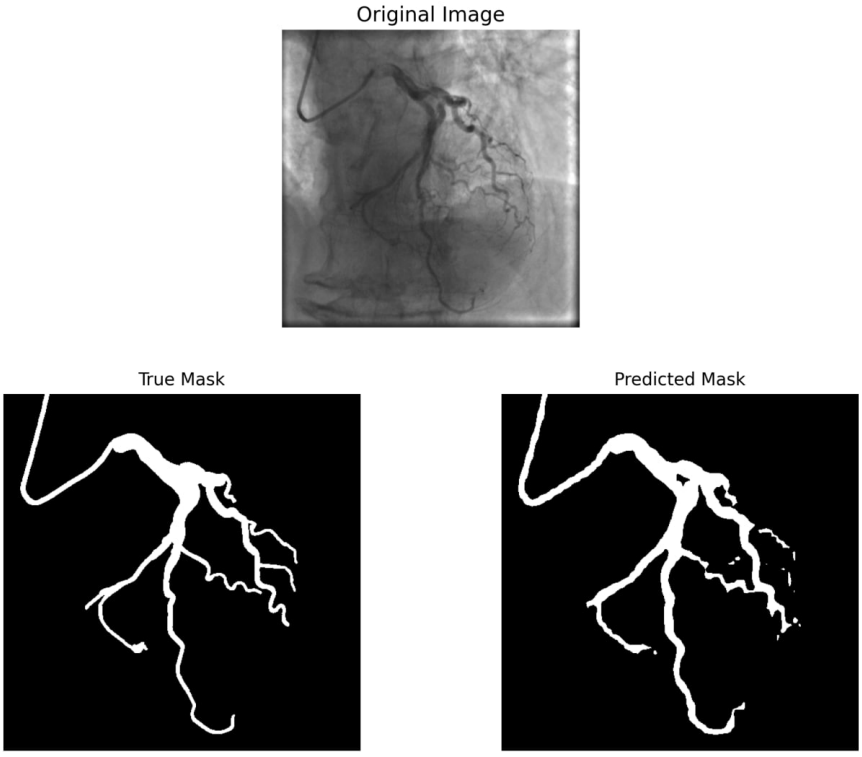

Fig. 2. Angiography segmentation steps

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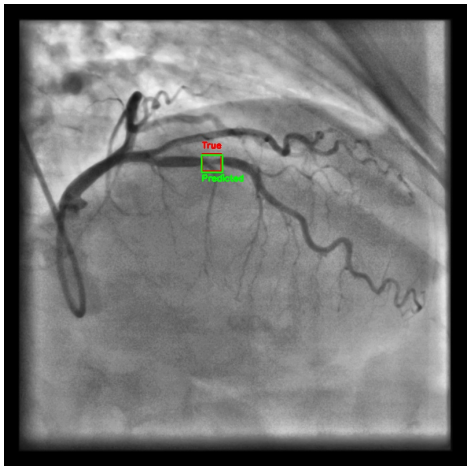

Fig. 3. Example of stenosis detection

Arterial thickness estimates from the optimal setup ranged from 0.8 mm (severe stenosis) to 4.5 mm (healthy segments), with a mean of 2.4 mm, aligning with clinical norms and tied to segmentation accuracy. Inference speed was 18 fps on standard hardware, slower than the baseline (25 fps) but viable for real-time use. Qualitative results (Figs. 2 and 3) confirmed precise stenosis localization and delineation in the optimal setup.

We additionally evaluated the model on the ARCADE benchmark, where it achieved an F1-score of 0.524. Although this figure represents a solid level of performance, it falls short of the score obtained on our proprietary dataset—a gap we ascribe primarily to the divergent statistical properties and domain characteristics of the two data sources.

5 Discussion

The results of this investigation substantiate the efficacy of an integrated deep learning framework for the automated detection, segmentation, and quantification of coronary artery stenosis in coronary angiography images. The optimal configuration, employing YOLOv8 for detection and DeepLabV3+ for segmentation, complemented by a comprehensive preprocessing regimen, yielded a detection precision of 0.966, an mAP@50 of 0.973, a segmentation IoU of 0.643, and a Dice coefficient of 0.781. These outcomes surpass those of the baseline configuration (YOLO v5 + U-Net without preprocessing: precision = 0.600, mAP@50 = 0.880, IoU = 0.580, Dice = 0.740) and the intermediate configuration (YOLO v5 + U-Net with preprocessing: precision = 0.672, mAP@50 = 0.930, IoU = 0.620, Dice = 0.770), underscoring the synergistic effect of architectural choices and image preprocessing on diagnostic precision.

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In comparison with prior research, the detection performance of this study aligns with, and in certain aspects exceeds, established benchmarks. Danilov et al. [2] reported an mAP of 0.950 and an F1-score of 0.960 using Faster-RCNN Inception ResNet V2 for real-time stenosis detection, albeit with a constrained inference rate of 3 fps. By contrast, the present YOLOv8-based model, with an mAP@50 of 0.973 and an inference speed of 18 fps, demonstrates enhanced precision and computational efficiency, rendering it more viable for real-time clinical implementation. Similarly, Dundas et al. [3] documented an AUROC of 0.920 for stenosis $\geq 50\%$ and 0.930 for stenosis $\geq 70\%$ using an AI-driven tool in CT angiography. Although AUROC and mAP are not directly equivalent, the precision of 0.966 achieved herein suggests a robust capacity for accurate stenosis identification within the angiography domain.

Regarding segmentation, the DeepLabV3+ model's Dice coefficient of 0.781 marginally exceeds the 0.771 reported by Li et al. [5] using a U-Net architecture for CT angiography segmentation. This incremental improvement may be attributable to DeepLabV3+'s incorporation of atrous spatial pyramid pooling, which facilitates superior multi-scale feature extraction relative to the convolutional framework of U-Net. Serrano-Antón et al. [7] also employed a U-Net model with transfer learning, though the absence of specific Dice metrics precludes direct comparison. The IoU of 0.643, while indicative of competent segmentation, suggests that further refinement in boundary delineation is warranted, particularly when juxtaposed with higher IoU values typical of non-medical imaging applications.

A distinctive contribution of this work lies in the development of an arterial thickness measurement technique, utilizing skeletonization and Euclidean distance transforms to quantify vessel narrowing. Thickness estimates ranged from 0.800 mm in severe stenosis to 4.500 mm in healthy segments, with a mean of 2.400 mm, consistent with clinical norms. This method provides a reproducible, non-invasive metric for stenosis severity assessment, distinct from invasive approaches such as fractional flow reserve (FFR) described by Aleksandric et al. [1]. However, its dependence on segmentation accuracy implies that enhancements to DeepLabV3+ could further bolster reliability.

Limitations of this study mirror challenges prevalent in the field. The reported performance metrics derive from controlled datasets, which may not fully encapsulate the heterogeneity of clinical imaging conditions, including variations in contrast agent distribution or equipment-specific artifacts—issues also noted by Danilov et al. [2] and Li et al. [5]. Although the dual-review annotation process mitigated inter-observer variability, as highlighted by Zhang et al. [8], the lack of a standardized classification for stenosis severity (e.g., mild $<50\%$, moderate 50–70%, severe $>70\%$) impedes consistent comparison with studies employing divergent criteria. Relative to Jie et al.'s [4] meta-analysis, which reported an AUROC of 0.950–0.960 for AI-assisted CTA, this study's emphasis on angiography extends the applicability of such techniques, though external validation across varied cohorts and modalities remains essential to address methodological disparities.

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We additionally evaluated the model on the ARCADE benchmark, where it achieved an F1-score of 0.524. Although this figure represents a solid level of performance, it falls short of the score obtained on our proprietary dataset—a gap we ascribe primarily to the divergent statistical properties and domain characteristics of the two data sources. These results highlight that while the system performs well on proprietary data (F1-score = 0.681), domain shift remains a significant factor affecting generalization to external datasets such as ARCADE (F1-score = 0.524).

6 Conclusion

This study presents an integrated approach for automating coronary artery stenosis analysis using deep learning. By combining YOLOv8 for detection, DeepLabV3+ for segmentation, and a novel thickness measurement method, our system achieves a detection precision of 0.966, an mAP@50 of 0.973, a segmentation IoU of 0.643, and a Dice coefficient of 0.781. These consistent results across the evaluation phases demonstrate high performance and scalability for cardiovascular diagnostics. Future efforts will refine accuracy, expand datasets, and integrate the solution into clinical practice, potentially extending its utility to other cardiovascular conditions.

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References

1. Aleksandric, S., Banovic, M., Beleslin, B.: Challenges in diagnosis and functional assessment of coronary artery disease in patients with severe aortic stenosis. Frontiers in Cardiovascular Medicine **9** (2022). https://doi.org/10.3389/fcvm.2022.849032
2. Danilov, V.V., Klyshnikov, K.Y., Gerget, O.M., Kutikhin, A.G., Ganyukov, V.I., Frangi, A.F., Ovcharenko, E.A.: Real-time coronary artery stenosis detection based on modern neural networks. Scientific Reports **11**(1) (2021). https://doi.org/10.1038/s41598-021-87174-2
3. Dundas, J., Leipsic, J.A., Sellers, S., Blanke, P., Miranda, P., Ng, N., Mullen, S., Meier, D., Akodad, M., Sathananthan, J., Collet, C., de Bruyne, B., Muller, O., Tzimas, G.: Artificial intelligence–based coronary stenosis quantification at coronary ct angiography versus quantitative coronary angiography. Radiology: Cardiothoracic Imaging **5**(6) (2023). https://doi.org/10.1148/ryct.230124
4. Jie, P., Fan, M., Zhang, H., Wang, O., Lv, J., Liu, Y., Zhang, C., Liu, Y., Zhao, J.: Diagnostic value of artificial intelligence-assisted cta for the assessment of atherosclerosis plaque: a systematic review and meta-analysis. Frontiers in Cardiovascular Medicine **11** (2024). https://doi.org/10.3389/fcvm.2024.1398963
5. Li, Y., Wu, Y., He, J., Jiang, W., Wang, J., Peng, Y., Jia, Y., Xiong, T., Jia, K., Yi, Z., Chen, M.: Automatic coronary artery segmentation and diagnosis of stenosis by deep learning based on computed tomographic coronary angiography. European Radiology **32**(9), 6037–6045 (2022). https://doi.org/10.1007/s00330-022-08761-z

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97557-8_10

6. Popov, M., Amanturdieva, A., Zhaksylyk, N., Alkanov, A., Saniyazbekov, A., Aimyshev, T., Ismailov, E., Bulegenov, A., Kolesnikov, A., Kulanbayeva, A., Kuzhukeyev, A., Sakhov, O., Kalzhanov, A., Temenov, N., Fazli1, S.: Arcade: Automatic region-based coronary artery disease diagnostics using x-ray angiography images dataset (2023). https://doi.org/10.5281/ZENODO.8386059
7. Serrano-Antón, B., Otero-Cacho, A., López-Otero, D., Díaz-Fernández, B., Bastos-Fernández, M., Massonis, G., Pendón, S., Pérez-Muñuzuri, V., González-Juanatey, J.R., Muñuzuri, A.P.: Optimal Coronary Artery Segmentation Based on Transfer Learning and UNet Architecture, p. 55–64 (2023). https://doi.org/10.1007/978-3-031-46914-5_5
8. Zhang, X., Zhang, B., Zhang, F.: Stenosis detection and quantification of coronary artery using machine learning and deep learning. Angiology **75**(5), 405–416 (2023). https://doi.org/10.1177/00033197231187063
9. Zheng, J., Heidenreich, P.A., Kohsaka, S., Fearon, W.F., Sandhu, A.T.: Long-term outcomes of early coronary artery disease testing after new-onset heart failure. Circulation: Heart Failure **16**(7) (2023). https://doi.org/10.1161/circheartfailure.122.010426

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