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Article

Real-Time Detection and Classification of Stenosis in Coronary Arteries: An AI-Driven Approach

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Abstract

Coronary artery disease (CAD) is one among world's major causes of morbidity and mortality, so early and precise detection becomes imperative to improve patient outcome. The current work puts forward real-time stenosis recognition and classification from angiographic images with the help of a YOLOv8 object detector architecture. The five variants, including the YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, were compared with important performance metrics. In them, YOLOv8s demonstrated speed-accuracy tradeoff, achieving 78.13 FPS speed, 0.967 precision, and 0.981 Map 50. The system was verified with angiographic images and proved to dynamically process each frame, with stenotic regions properly identified and classified real time. Comparative study with existing detecting models guaranteed proposed approach achieved higher speed and diagnostic capability. The findings justify CAD real-time diagnostic feasibility with YOLOv8s, with a promising tool to refine precision, reduce human error, and permit timely action within a procedure of coronary angiography. While this study's application of YOLOv8 for detecting and classifying coronary artery stenosis has demonstrated promising results.

Keywords: Coronary artery disease (CAD), Stenosis detection, YOLOv8, Real-time diagnosis, Deep learning, Object detection.

1. Introduction

CAD represents a life-threatening and extremely prevalent cardiovascular disease recognized to be a leading cause of death in both industrial and underdeveloped nations [1]. CAD represents inflammatory and atherosclerotic features and leads to a multitude of presentations such as myocardial infarction (MI), unstable angina, abrupt cardiac death and stable angina [2]. Genetic determinants responsible for CAD have been researched extremely vigorously by genome-wide association studies (GWASs) to establish a series of genetic variants responsible for CAD vulnerability very strongly [3]. The evidence indicates environmental factor and genetic vulnerability interaction during CAD development, indicating a future imperative to understand CAD holistically and utilize advanced diagnostic techniques to counter CAD, a multifactorial disease [2, 4].

Also, CAD pathogenesis includes complex molecular and cellular processes, including venous cell reprogramming during development of the coronary artery, and microRNA and genetic partners across diverse ancestor populations [5–7]. Furthermore, identification of CAD and MI risk loci, such as ADAMTS7 and ABO blood group system, has been helpful to explore genetic etiology of these diseases [8, 9]. The importance of coronary artery development and congenital abnormalities, along involves the functions of tissue inhibitors and matrix metalloproteinases in CAD, further establishes CAD's multifactorial etiology [10, 11].

Additionally, CAD's financial influence is significant, the healthcare industry and society as a whole are greatly impacted by direct as well as indirect costs [12]. Asymptomatic CAD's incidence among diabetes mellitus subjects further indicates clinicians' challenge to recognize and treat early CAD among such a high-risk population [12]. Moreover, breast arterial calcification's novel CAD risk predictor role and discovering novel susceptibility loci present CAD's shifting research paradigm and diagnostic models [13, 14].

An estimated 71 million persons in the United States suffer from at least one cardiovascular illness, which is responsible for 5 million cases of heart failure and 12 million cases of coronary artery disease [15]. Additionally, as a prior study showed, the most common diagnosis in emergency rooms was CAD [16]. In the United States, CAD is estimated to cost $3000 per patient annually, both directly and indirectly [17].

In 2021, coronary heart disease—the most prevalent kind of heart disease—killed 375,476 people. About 5% of persons over the age of 20 have CAD, or 1 in 20 [18]. About two out of ten CAD deaths in 2021 happened to people under the age of 65 [19]. Additionally, CAD has been identified as the leading cause of cardiovascular death globally [20]. In most countries across the world, CAD is the leading cause of fatalities, it poses a severe threat to communities [21]. According to the 2010 Global Burden of Disease Study, CAD is a modern epidemic, accounting for 13% of deaths [22].

Improved patient outcomes from CAD, a major cause of death globally, depend heavily on an accurate and fast diagnosis [23]. Cardiovascular imaging techniques nowadays are mostly based on simple quantitative measurements of ventricular anatomy and function and qualitative visual assessment. To augment the diagnostic potential of heart imaging, there are significant needs for advanced methods of image analysis to allow more extensive quantitation of imaging phenotypes. [24]. Employing such novel methods, further understandings can be gained into CAD pathophysiology and diagnostic decision-making be improved to attain better patient management and therapeutic outcome, as shown in Fig. 1.

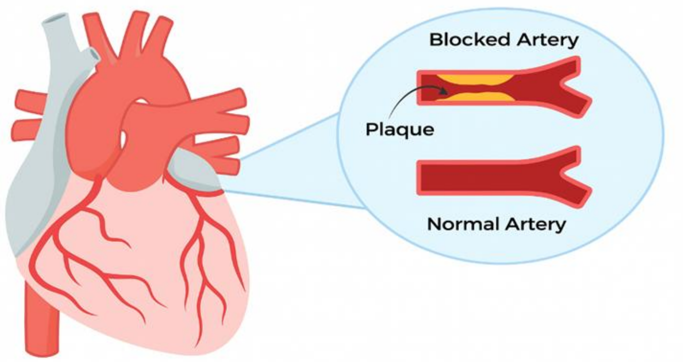

Figure 1. Illustration of coronary arteries and arterial blockage [25].

One of the main tasks in computer vision is object detection (OD), which involves locating and classifying particular things in photos, videos, or live feeds [26]. In many industrial applications, YOLO (You Only Look Once) has been a preferred solution to OD. It enables real-time object recognition with a process that divides incoming photos into a grid and outputs bounding boxes and class probabilities for each cell in the grid [27]. Because a single network pass is sufficient, this enables quick and efficient object detection [28]. Certain OD algorithms have been applied to tasks like vessel segmentation in X-ray coronary angiography and CAD identification using computer tomography pictures in applications where cardiovascular illnesses are a consideration [29]. The YOLO algorithm, especially, has been used toward creating CAD detection methods with a deep learning-based solution, outlining its potential and usability within applications where medical images are a factor [30, 31].

Although object detection (OD) methods have been widely applied to applications of cardiovascular imaging, so far, very little exists in literature on their application to finding coronary artery stenosis. Recent literature, however, has taken initial strides to benefit from the potential of advanced OD technologies to achieve very high levels of diagnostic precision and overcome traditional methods.

These findings further emphasized the need to develop real-time operable intelligent diagnostic systems. In clinical practice, besides being precise, speed becomes equally important, where time plays a crucial role, including early recognition to predetermine treatment outcome. There, therefore, exists a significant necessity to further develop research into algorithm integration to merge complex, high-performance algorithms with accuracy and rapid processing to achieve real-time medical imaging and decision-making.

The aim here is to develop and evaluate a real-time system to detect and categorize stenosis from the coronary artery by utilizing the structure of object detector YOLOv8, with a target to simultaneously attain optimization between accuracy and inference speed with a view to help with decisions during a procedure involving coronary angiography.

2. Literature Review

In the last few years, techniques based on artificial intelligence (AI) have introduced radical advances to the diagnosis of cardiovascular disorders using images. A thorough analysis of current AI applications for coronary heart disease diagnosis, prediction, and classification was conducted by Ferdowsi et al. (2025), with an emphasis on how deep learning methods improve diagnostic precision and risk assessment across all imaging platforms (angiography, CT, echocardiography) [32].

In the same way, Khera et al. in 2024 [33] emphasized that artificial intelligence (AI) can push cardiovascular practice and research across all disciplines. In their comprehensive review, they claimed that the accelerated progress taking place within AI-based technology is unlocking new avenues in cardiovascular care, including advancements in new technology-assisted forms of clinical detection and diagnosis, digitization of native biomarkers, and high-performance platforms to assess the quality of care and predict clinical outcomes. These developments will particularly enhance the capacity for cardiovascular screening and monitoring, redirected towards those who did not have prior access to specific forms of care. Furthermore, Khera et al. in 2024 [33] note that AI is driving clinical and biological evolution, offering more personalised, precise, and efficient cardiac care. Their view is that point-of-care applications involving multi-modal cardiovascular AI platforms will come on line soon and will transform therapeutic and diagnostic approaches. They also developed an important roadmap that supports fair, managed advancement to adaptation that promotes safety, equity, positive collaboration, and ultimately better societal cardiovascular health outcomes.

In addition, the AI-based system for stenosis diagnosis from real-time coronary angiographic images developed by Akgül et al. in 2024 [34] had very strong results with significant high scores in both F1-score and mAP 50 metrics and indicates the fantastic capability of their method. This work clearly demonstrates the incredible ability of an object detection-based AI model to accurately automate the quantification of the severity of stenosis in a clinical setting [34]. The most recent reviews and applications indicate that artificial intelligence (AI) has become a larger and more important tool in cardiovascular imaging, which should provide a sound rationale for innovative contributions from this work in this regard. Coronary artery segmentation utilizing deep learning approaches, which is necessary for accurate stenoisis identification, has received considerable attention in some studies. For instance, Zhang et al. [35] integrated modules specifically for distraction, boundary perception, and context in order to suggest a progressive perception learning (PPL) framework that achieved excellent segmentation results beyond many state-of-the-art methods with Dice scores greater than 95% on a cohort of 1,086 subjects. Similarly, Fazlali et al. [36] presented a segmentation methodology that did not use annotated training data by utilizing vesselness probability metrics and superpixels. Compared to traditional graph-cut approaches, their model preserved computational efficiency, reduced false positive generation, and increased segmentation accuracy. Another use case of deep learning-based classification and object detection methods is for stenosis detection. Du et al. [37] trained a deep learning pipeline to identify segments and further classify lesions using a dataset comprised of 20,612 angiograms. Their ability to classify lesions using the model achieved F1 scores of between 0.802 and 0.854 and showed a high recognition accuracy of 98.4%. While these results are promising, one of the main limitations of the related work is the lack of publicly available training datasets in the public domain, limiting reproducibility and future progress in the research area.

Leasion detection and anatomical structure segmentation are important medical imaging analysis tasks that have frequently relied on existing object detection architectures such as YOLO [38], DINO-DETR [39], and Grounding DINO [40]. YOLO relies on a convolutional neural network (CNN)-based model that allows for real-time inference, while DINO-DETR and Grounding DINO are transformer-based models that rely on self-attention mechanisms to improve object location and feature representation. The recent advancements in YOLO, DINO-DETR, and Grounding DINO architectures through the use of query-based object location techniques with knowledge distillation has shown more powerful performance in difficult detection challenges. More illustrations or model architecture figures would be beneficial for a comprehensive explanation of the YOLO, DINO-DETR, and Grounding DINO architectures. MMDetection [41] is an open-source object detection toolbox with explicit implementations of many of today's state-of-the-art models, including versions based on YOLO and DINO architectures. The modular pipeline allows integration with different training and evaluation paradigms, making MMDetection a popular choice for medical image analysis as it allows other researchers to repeat their investigations under systematic comparison of each object detection model. Researchers have successfully applied MMDetection-based pipelines to disease classification and anatomical structure detection. Integration into the CAD diagnosis work flow improves the accuracy and efficiency of automated stenosis detection. It accordingly provides controlled and reproducible experiments with ease of hyperparameter efficiency.

The objective of this study is to develop a diagnostic tool for precisely identifying stenotic lesions that is both highly accurate and efficient. Furthermore, by curating and preprocessing a high-quality annotated dataset, it addresses present issues with the lack of training data and allows for reliable evaluation in a variety of clinical scenarios. Supporting early diagnosis, enhancing clinical judgement, and advancing unique cardiovascular care are the main objectives, particularly in underprivileged areas with little access to specific medical infrastructure.

3. Materials and Methods

3.1 Source Data

The dataset used in the present study comprised a collection of angiographic images from one hundred patients who underwent coronary angiography. These procedures were performed using Coroscop (Siemens) and Innova (GE Healthcare) image-guided surgery systems at the Research Institute for Complex Problems of Cardiovascular Diseases (Kemerovo, Russia).All patients had angiographically and/or functionally confirmed one-vessel coronary artery disease, characterized by either ≥70% diameter stenosis via quantitative coronary analysis or 50–69% stenosis with a fractional flow reserve (FFR) ≤ 0.80 or evidence of regional ischemia from stress echocardiography. Significant coronary stenosis was defined in accordance with the 2017 U.S. Appropriate Use Criteria for coronary revascularization in patients with stable ischemic heart disease. The study protocol was approved by the Local Ethics Committee of the Research Institute (approval letter No. 112, dated May 11, 2018), and written informed consent was obtained from all participants. A single operator performed coronary angiography in line with the 2018 ESC/EACTS Guidelines on myocardial revascularization and also confirmed the presence or absence of stenosis based on angiographic imaging. From each patient's imaging series, radiopaque coronary artery images with visible stenotic segments were selected and converted into individual grayscale images. Non-informative images were excluded by an interventional cardiologist, ensuring only images with clear contrast passage through stenotic vessels were retained. In total, the dataset comprises 8,325 grey scale pictures with pixel sizes varying from 512 × 512 to 1000 × 1000. Image annotation was performed using the free version of LabelBox (SaaS). For each image, the stenotic region was localized with a bounding box, and its area was calculated. Based on the bounding box area, objects were classified into three categories following the dataset known as Common Objects in Context (COCO) standard: small (area < 322), medium (322 ≤ area ≤ 962), and large (area > 962). This resulted in 2,509 small objects (30%), 5,704 medium objects (69%), and 113 large objects (1%), as shown in Figs 2 and 3.

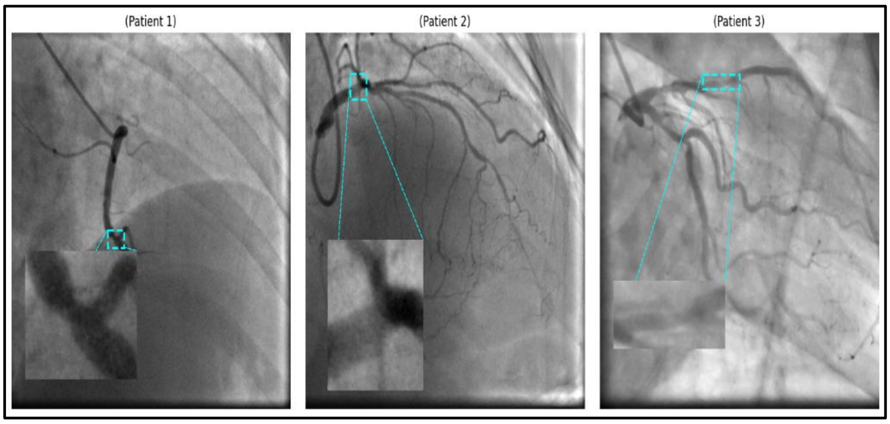

Figure 2. Data tagging of the source pictures using the stenotic lesions' callouts that were found.

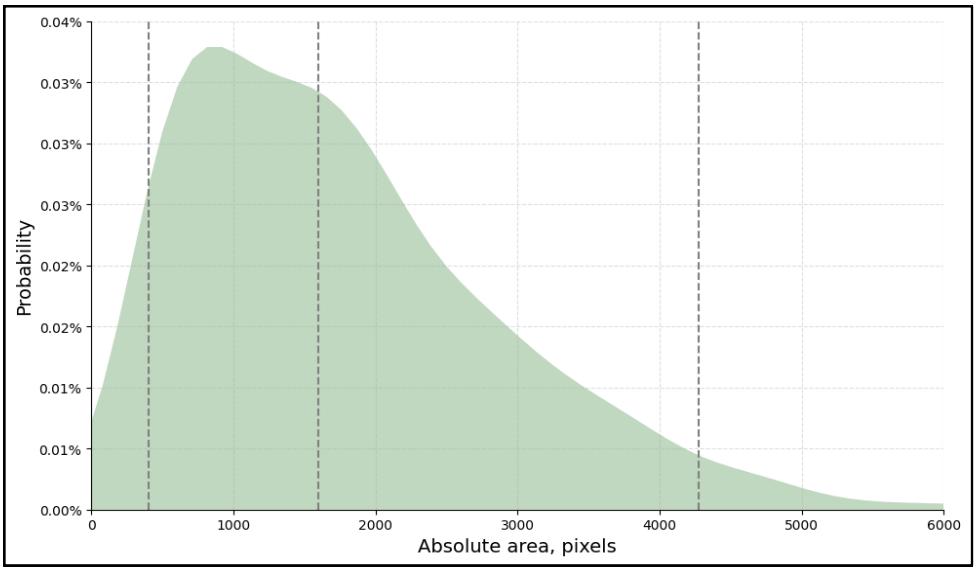

Figure 3. Distribution of the input dataset's absolute stenotic area.

3.2 Data Preprocessing

In medical image analysis, particularly in coronary artery disease (CAD) detection using X-ray angiography, preprocessing is a vital step that directly influences the performance of deep learning models. Raw angiographic images often suffer from low contrast, noise, and unclear vessel boundaries, which can hinder accurate segmentation and classification of lesions. Preprocessing techniques are therefore essential to enhance image quality and highlight significant anatomical features, as shown in Figs 4.

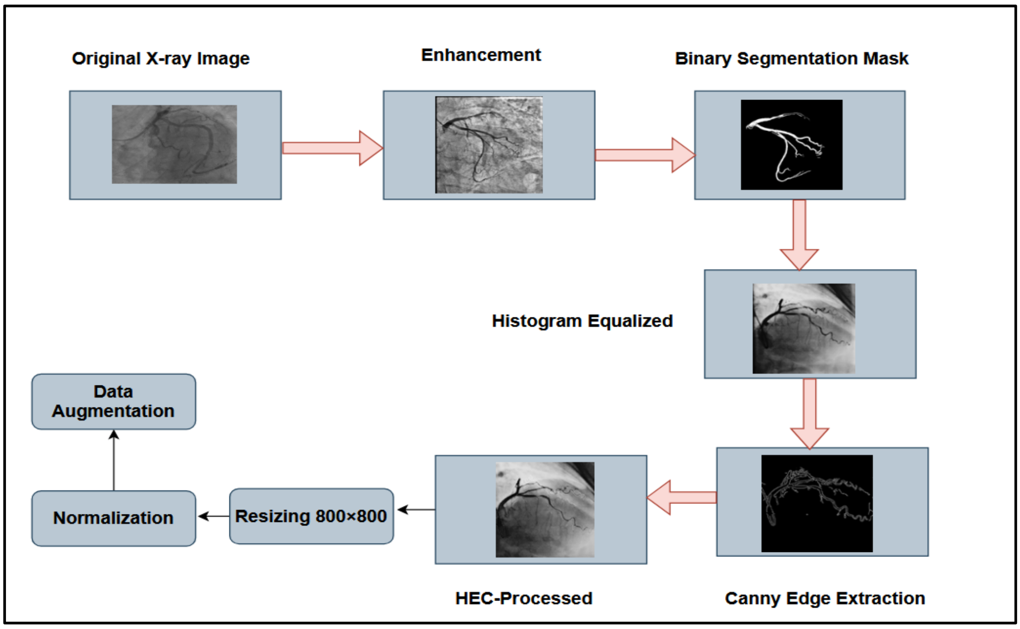

Figure 4. Data Pre-processing.

The preprocessing step is extremely important for improving image quality and ensuring proper model training for accurate detection and classification. Several enhancement and augmentation methods were applied to enhance the visibility of lesions and segmentation performance of the original x-ray angiographic images. To ensure accurate evaluation of the model, the splitting of data for the three datasets was done with the same approach. The 8,325 angiographic images that were used for the stenosis detection were created from the following proportions: 70% for training (5,830 images), 20% for validation (1,661 images) and 10% for testing (834 images). This method was applied consistently through the training, tuning and performance evaluation processes, as shown in Figs 5.

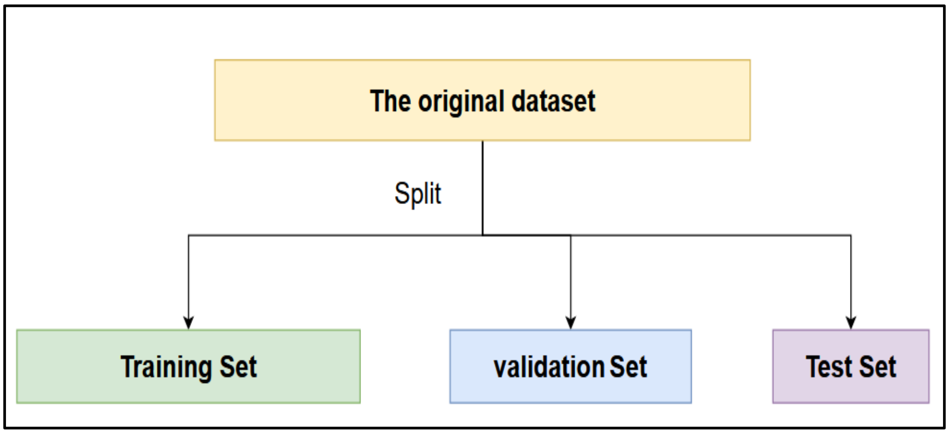

Figure 5. The splitting of the data.

3.3 Architecture

The experiments of this study utilized Python version 3.8, in the Google Colab environment, with CUDA support activated for optimal performance. The following libraries were necessary for the implementation: OpenCV for image processing, PyTorch for constructing and training a deep learning model, and Ultralytics to implement cutting-edge object detection algorithms. We decided to use the YOLOv8 object detection architecture in five different model sizes in this study: The varieties are YOLO8 versions (nano), (small), (medium), (large), and YOLOv8x (extra-large). By using the range of model sizes, we could examine performance across a range of computational demand and complexity, while also having the ability to balance accuracy and efficiency as shown in Table 1 and Fig. 6.

Table1. Hyperparameter values.

Hyperparameter	Range
Batch Size	16
Number Epochs	150
Image Size	640
Hyperparameter	Range
Batch Size	16

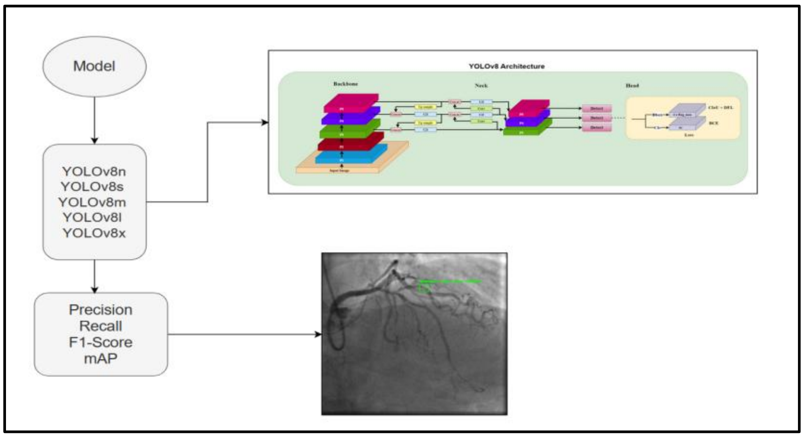

Figure 6. YOLOv8 model architecture for object detection and classification.

4. Result

In this study, we evaluated YOLOv8 architecture has five variations: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. for the task of detecting and classifying coronary artery stenosis. Out of the examined models, YOLOv8s was one of the most suited for real-time clinical-use case (especially inside live coronary angiograms) due to its best combination of detection performance and inference speed. The system operates in real time by integrating the selected model with a continuous video feed from angiographic imaging systems, enabling dynamic, frame-by-frame analysis for timely stenosis detection and classification. This enables the identification of stenotic regions and real-time classification of their severity levels (e.g., *Moderate*, *Severe*). The outputs—including the class label (*Stenosis*), severity classification, and area of the detected region—are superimposed on the live image using bounding boxes and textual annotations. The system achieves a total frame processing time of approximately **20.9 milliseconds**, distributed as follows:

- **Preprocessing:** 3.1 ms
- **Inference:** 16.2 ms
- **Postprocessing:** 1.6 ms

Using the formula:

$$FPS = \frac{1000}{Inference\ Time\ (ms)} \tag{1}$$

This results in an effective processing speed of approximately 47.85 frames per second (FPS). Such performance can be sustained through deployment on high-performance GPUs or low-latency edge computing devices, enabling near-instant feedback during procedures. This capability enhances clinical decision-making by offering immediate visual insights, thereby improving diagnostic accuracy, reducing human error, and enabling timely intervention. Overall, the YOLOv8s-based system demonstrates both clinical significance and technical viability for real-time diagnostic support in cardiovascular care. It's crucial to remember that real-time performance should be evaluated using the whole amount of processing time, which includes postprocessing, inference, and preprocessing—not just the inference time alone. Table 2 presents a comparative analysis of the inference speeds (FPS) of the YOLOv8 variants. The results highlight a clear trade-off between model complexity and real-time performance. While YOLOv8n and YOLOv8s offer high-speed inference suitable for real-time scenarios, YOLOv8m, YOLOv8l, and YOLOv8x deliver enhanced detection accuracy at the cost of increased latency. This evaluation helps guide model selection based on application-specific priorities of speed versus accuracy in medical image analysis, as shown in Table 2 and Figs 7.

Table 2. Inference speed (FPS) of YOLOv8 model variants for stenosis detection.

Model	Frames Per Second (FPS)
YOLOv8n	63.30
YOLOv8s	78.13
YOLOv8m	32.15
YOLOv8l	21.10
YOLOv8x	14.90

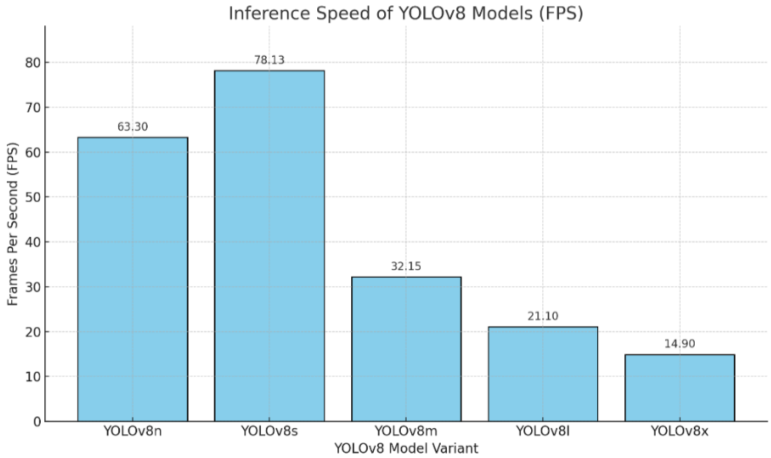

Figure 7. YOLOv8 model inference speed comparison (FPS).

We evaluated model based on the following performance metrics as Table3 and Figs. 8 and 9.

Table 3. YOLOv8 model performance metrics.

Model	Precision	Recall	F1 Score	mAP50
YOLOv8s	0.967	0.962	0.965	0.981
YOLOv8n	0.960	0.935	0.947	0.968
YOLOv8m	0.970	0.965	0.967	0.984
YOLOv8l	0.978	0.964	0.971	0.983
YOLOv8x	0.970	0.952	0.961	0.976

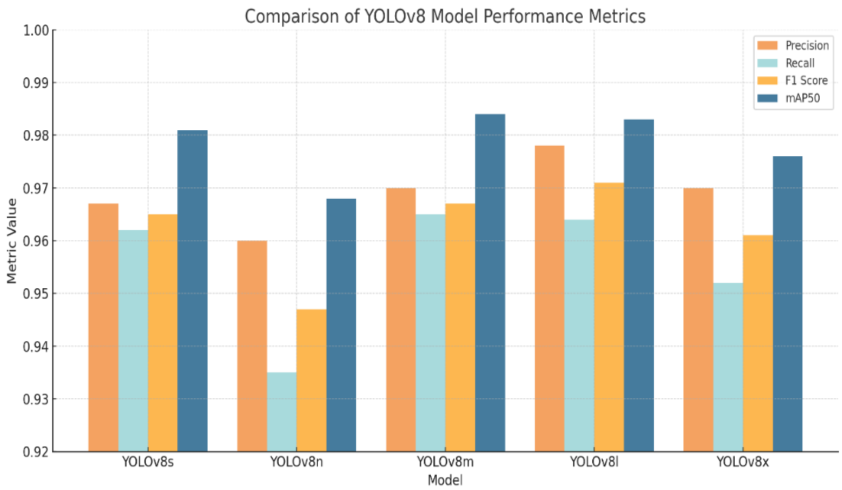

Figure 8. YOLOv8_performance_comparison.

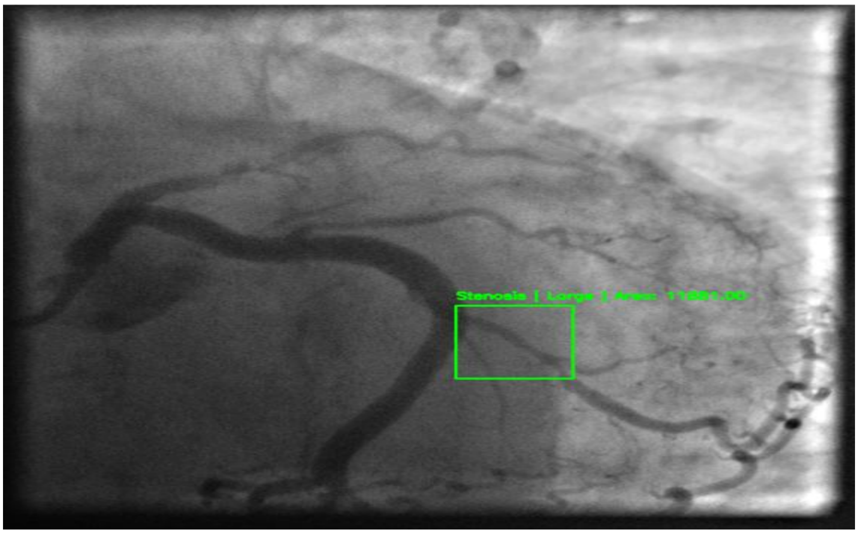

Figure 9. YOLOv8s detection large stenosis region and classification.

Numerous detection models have been applied to the task of coronary artery stenosis detection. **One-stage detectors**, such as **YOLOv8s**, provide **fast and efficient real-time detection** with competitive accuracy, making them particularly well-suited for **clinical applications** where speed and responsiveness are critical. In contrast, two-stage detectors such as Faster R-CNN are recognized for their high detection accuracy; however, they involve greater computational complexity and slower inference times. Their application in clinical settings with time constraints may be hampered by these limitations. This, balancing speed and precision becomes a critical factor when choosing an appropriate model for real-time medical diagnostics, as shown in Table 4.

Table 4. Performance comparison of detection models.

Method	Prec (%)	Rec (%)	F1 score	mAP (%)	Inference Time
M. Popov et al. [42]	0.36%	0.45%	0.4%	--	--
H. Duan et al. [43]	96.62%	95.06%	95.83%	97.6%	--
V.Danilov et al. [44]	--	-	0.96%	0.94%	10 fps
Ours	0.97%	0.964%	0.966%	0.982	78.13 fps

5. Conclusion

The global burden of disease and death from coronary artery disease (CAD) is ever-growing, reinforcing the need for precise and prompt diagnostic technologies that can improve care. In this study, we developed and evaluated a real-time stenosis detection and classification system using the YOLOv8 object detection architecture. We tested five variants: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. Our findings indicated that the YOLOv8s variant was the best choice for a real-time clinical system, especially during coronary angiography procedures, because it provided a good compromise between accuracy of detection and inference speed. The system's processing speed was 78.13 FPS, with distinct time partitions: preprocessing (3.1 ms), inference (16.2 ms), and postprocessing (1.6 ms). Additional performance metrics confirmed the effectiveness of the YOLOv8s model, obtaining precision 0.967, recall 0.962, F1 score 0.965, and mAP@50 0.981. The YOLOv8l variant did record the highest accuracy of all the models, but the slower inference speed highlighted the accuracy-computational efficiency trade-off. With regard to other studies, our YOLOv8s-based system had a higher accuracy, greater processing speed, and greater F1 score and mAP while maintaining real-time inference as compared to other systems. While two-stage detectors like the highly accurate but slower processing Faster R-CNN model can be a hindrance in a clinical setting, the YOLOv8s model makes a great addition to time-sensitive clinical environments as it outperforms super fast and accurate. All in all, the clinical potential of the YOLOv8s-based system supports real-time diagnostics in cardiovascular care, showcasing its unmistakable technical prowess. The system will be of utmost use when it comes to accurately and efficiently detecting coronary artery stenosis, therefore, enhancing intra-procedural decision making, reducing diagnostic delays, and improving the general care of patients suffering from coronary heart disease. The focus of future studies should be to seamlessly incorporate the system into the hospital-grade angiography suites and perform thorough validation with larger and more diverse data sets to increase its clinical reliability and applicability.

6. Future Work

While this study's application of YOLOv8 for detecting and classifying coronary artery stenosis has demonstrated promising results, there are still several significant gaps that require further investigation and improvement. One of the biggest gaps is broadening the scope of the data by adding angiographic imaging modalities, different imaging conditions, and the variability of patients to improve model robustness and generalizability. The design of a clinical workflow with YOLOv8 to connect to PACS, a hospital imaging platform, and accommodate clinician workflows in an easy-to-navigate way will require some effort. We will also need to establish protective measures for patient information, such as HIPAA and GDPR compliant frameworks, to be regulatory compliant. In addition, the deployment of YOLOv8 on the edge could be refined for situations with limited resources where real-time usage is important. Although the device is functioning, YOLOv8's edge performance is only 78.13 FPS and would need optimized settings. Techniques like model quantization or pruning can assist in increasing a system's performance and deployment scalability. The ability to classify severity of stenosis is available but enabling it to detect total occlusions in the future by adding assessments of plaque morphology and calcification could increase the interpretation of the total clinical picture. These enhancements would refine clinical decision-making and enable more personalized treatment planning. Improved clinical decision-making and treatment planning would also be aided by further advancements in system explainability, trust, acceptance, and integration through the use of clinical XAI methods like Grad-CAM, saliency maps, and attention-based visualizations. Finally, large-scope validation and in-field deployment studies are crucial alongside diagnostic accuracy and manual comparison error rate workflows. These benchmarks are necessary for attaining regulatory approval and ensuring the system can be safely adopted in routine cardiovascular care.

Conflicts of Interest

The authors declare no conflict of interest.

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