JAPSC
Journal of Asian Pacific Society of Cardiology

REVIEW
Imaging

Computational Methods for Analysing X-ray-guided Coronary Angiography: From Key Frame Selection to Vessel Segmentation, Stenosis Detection and Classification

Tiana Chen [1], Yu Ren [2,3], Wei Liu [2], Jonathan Yap [4,5], Khung Keong Yeo [4,5], Tat-Jen Cham [3] and Hwee Kuan Lee [1,2,6,7,8]

1. School of Computing, National University of Singapore, Singapore; 2. Bioinformatics Institute, Agency for Science, Technology and Research, Singapore; 3. College of Computing and Data Science, Nanyang Technological University, Singapore; 4. Singapore Health Services, Singapore; 5. National Heart Centre Singapore, Singapore; 6. School of Biological Sciences, Nanyang Technological University, Singapore; 7. International Research Laboratory on Artificial Intelligence, Singapore; 8. A Centre for Frontier AI Research, Singapore*

Abstract

Coronary artery disease (CAD) is a leading cause of mortality globally, highlighting the need for accurate diagnostic tools. X-ray-guided coronary angiography is the foundation for assessing CAD, involving three key tasks: key frame selection, vessel segmentation and stenosis detection. This review summarises conventional and advanced artificial intelligence (AI) methods applied to these tasks. AI's integration is vital for enhancing efficiency and reproducibility, allowing real-time analysis and reducing manual labour. However, challenges remain, including the need for large, annotated datasets and difficulties in implementing AI systems in clinical trials. We discuss these challenges and the limitations of current AI approaches, exploring future directions for AI-driven solutions. Ultimately, we provide insights into AI's potential to improve the precision and efficiency of coronary angiography analysis and CAD diagnosis, contributing to better clinical outcomes and advancing cardiovascular medicine.

Keywords

Artificial intelligence, computer vision, coronary artery disease, X-ray coronary angiogram, image segmentation, stenosis detection

Received: 25 October 2024 **Accepted:** 2 February 2025

Citation: *Journal of Asian Pacific Society of Cardiology* 2025;4:e22. **DOI:** https://doi.org/10.15420/japsc.2024.46

Disclosure: JY has received speaker honoraria from Abbott, Biosensors, Biotronik, Boston Scientific, Edwards, GE Healthcare, J&J, Kaneka, Medtronic and Terumo, and is the secretary of the Singapore Cardiac Society. KKY has received research funding from Amgen, Astra Zeneca, Abbott Vascular, Bayer, Boston Scientific, Shockwave Medical and Novartis (via institution); consulting fees from Abbott Vascular, Medtronic, Novartis and Peijia Medical; speaker fees from Shockwave Medical, Abbott Vascular, Boston Scientific, Medtronic, Alvimedica, Biotronik, Orbus Neich, Amgen, Novartis, Astra Zeneca, Microport, Terumo and Omnicare; is a cofounder of and owns equity in Trisail, for which Orbus Neich is an investor; and is vice-chair of the Chapter of Cardiologists, Academy of Medicine Singapore, deputy editor of *AsiaIntervention*, on the editorial board of the *Korean Circulation Journal*, editor of *JMA Journal*, and commissioner for the Lancet Commission on Tackling Cardiovascular Disease in the Asia-Pacific Region. JY is an associate editor and KKY is editor-in-chief of the *Journal of the Asian Pacific Society of Cardiology*; this did not influence peer review. All other authors have no conflicts of interest to declare.

Correspondence: Hwee Kuan Lee, Bioinformatics Institute, Agency for Science, Technology and Research, 30 Biopolis St, #07-01 Matrix, Singapore 138671, Singapore. E: leehk@bii.a-star.edu.sg

Copyright: © The Author(s) 2025. This work is open access and is licensed under CC BY-NC 4.0. Users may copy, redistribute and make derivative works for non-commercial purposes, provided the original work is cited correctly.

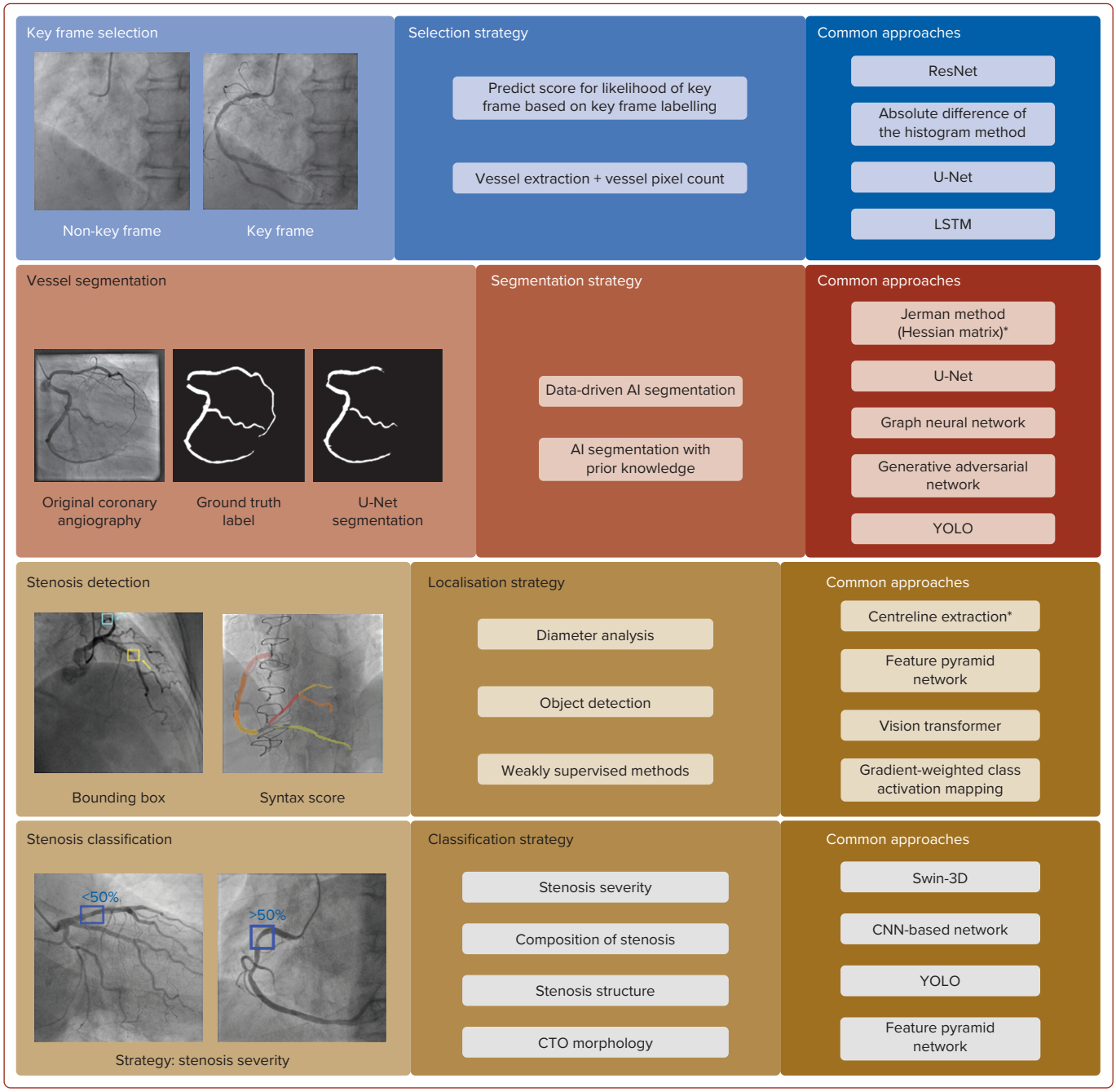
Coronary artery disease (CAD) is a leading cause of heart-related morbidity and mortality, driven by the build-up of atherosclerotic plaques in the coronary arteries. X-ray coronary angiography remains the foundation of invasive assessment for diagnosing and evaluating CAD, whereas adjunct tools such as intravascular imaging and physiological assessments are often used for borderline lesions. Although non-invasive methods, such as CT coronary angiography, can aid in CAD detection, coronary angiography is indispensable for planning interventions in confirmed cases.

The procedure of coronary angiography requires multiple image projections to visualise the 3D coronary structure and is subject to diagnostic variability among cardiologists. The diagnostic variability could be caused by several factors, including challenges posed by lesion length, calcification and imaging quality.[1] In addition, cardiologists may incorporate patient-specific clinical contexts into their assessments, leading to differences in interpretation. The lack of standardised visual assessment methods further contributes to the diagnostic variability. Artificial intelligence (AI)-assisted analysis could be a potential supplement to the diagnostic process and provide more consistent assessments, although it has yet to be fully integrated into clinical practice.

Scope of Review

The integration of AI in angiogram analysis is an emerging and rapidly advancing field. Since the last published review, there have been new studies, many of which used multiple recent AI paradigms, such as graph neural networks (GNNs), vision transformer and a self-supervised training regime.[2–5] In this review, we sought to bring out both the clinical and

Figure 1: Summary of Typical Tasks of Coronary Angiography Analysis and Corresponding Strategies and Methods



**Conventional methods discussed in Angiography Analysis Tasks and Conventional Methods. AI = artificial intelligence; CNN = convolutional neural network; CTO = chronic total occlusion; LSTM = long short-term memory; YOLO = You Only Look Once. Source: Popov et al. 2024.*[50] *Reproduced under a Creative Commons CC0 license.*

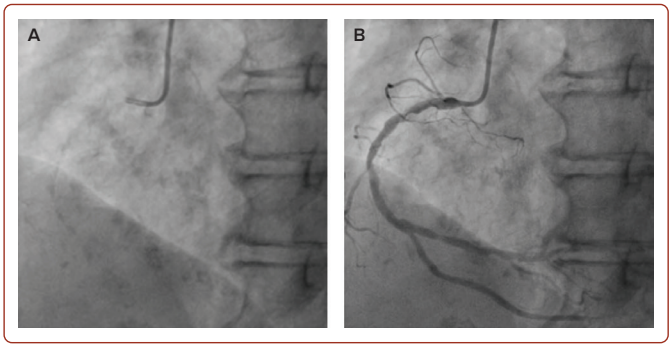
computational aspects that are important considerations for developing a usable angiographic analysis tool.

This review is for clinicians who want to learn about the latest advances in AI research, and how these popular methods have been translated for use in coronary angiography analysis and AI researchers working with coronary angiography data who want to understand the clinical aspects of their AI models and how they could bring about practical benefits.

In the section below, we describe the three main coronary angiography analysis tasks, namely key frame selection, vessel segmentation and stenosis detection, and briefly mention some conventional methods covering automatic image processing methods. The next section describes studies that have integrated AI within their coronary angiography analysis pipeline according to the three analysis tasks.

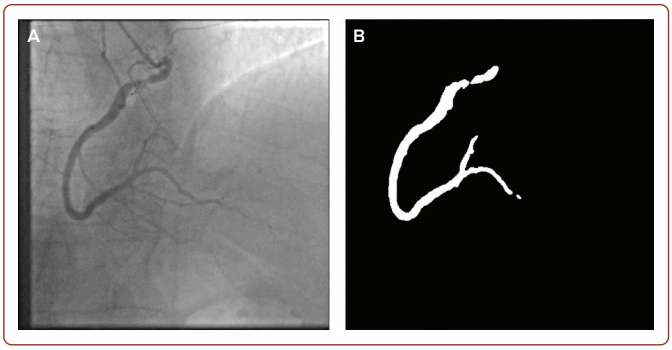
In the discussion, we highlight key patterns observed and offer our insights regarding the current directions for AI-guided coronary angiography analysis, including vessel structure, temporal features and multiple views of angiography. We also discuss the challenges of the lack of open data, data annotation and angiography sequence data. In the application section, we discuss the potential applications of the AI-automated coronary angiography analysis pipeline, as well as the gap between the development of AI models and real-world deployment. In *Figure 1*, the mainstream methods mentioned in the first two sections are listed with regard to the three analysis tasks.

Figure 2: Two Frames, Key and Non-key, Selected from a Single Coronary Angiography Video



A: Non-key frame. B: Key frame.

Figure 3: Original Coronary Angiography and Vessel Extraction Using the U-Net Method



A: Original coronary angiography. B: Vessel extracted by the U-Net model. Source: Popov et al. 2024.[50] Reproduced under a Creative Commons CC0 license.

Angiography Analysis Tasks and Conventional Methods

Angiography data are unique and distinct from natural images. As such, extracting meaningful results commonly requires several steps that can be tackled separately. These steps can be broken down into three main tasks: key frame selection; vessel segmentation; and stenosis detection, localisation and quantification. However, in some cases, key frame selection and vessel segmentation are not performed before stenosis detection.[4,6–19]

Key Frame Selection

Key frame selection involves selecting usable frames from the video sequence. Because angiography videos are taken in real time as the contrast dye is injected into the vessels, the full outline of the vessels is only visible in the middle segment of the video, with no vessels seen in the beginning and end frames. Frames where the contrast dye traces the full vessels are termed key frames. *Figure 2A* is taken before the contrast dye is injected, whereas *Figure 2B* can be defined as a key frame, with the contrast dye having been fully injected, and a clearer structure of the vessels is seen compared with *Figure 2A*.

The straightforward manual method of identifying key frames uses a rule-based system. The three selection criteria for key frames are that the contrast agent is fully injected in the vessel, the heart motion of adjacent frames is minimal and the full coronary vessel is clearly visible in the frame.[20] Another strategy for key frame selection is to extract the vessel in the angiography frames that align with the task of vessel segmentation described below. Image processing is used to enhance vessel features in the angiogram and then key frames are selected.[21,22]

Vessel Segmentation

After the selection of key frames, the next step is commonly vessel segmentation, which is the process of isolating arteries from the background of the frame. Because the background of the frame is often noisy, vessel segmentation can facilitate the detection and quantification of stenosis by removing false-positive artefacts, thereby allowing stenosis detection to only focus on areas containing vessels in the image. The early work of vessel segmentation mainly uses image processing methods to enhance contrast and reduce noise in the angiogram frames. Another strategy is to search for vessel edges or centre lines, or for the boundary between the vessel and the background of the frame.[23,24]

Stenosis Detection, Localisation and Quantification

Ultimately, the goal of coronary angiography is to identify and characterise stenosis. After selecting usable key frames and segmenting the main vessels, the final stage of image analysis involves isolating potential regions where there is a narrowing of the arteries and measuring the degree of narrowing. This yields a diagnosis that may inform cardiologists of any downstream clinical interventions that may be needed.

Conventionally, automated identification and quantification of stenosis mainly involves vessel skeletonisation/segmentation and diameter calculation.[22,25–28] Diameter analysis detects stenosis by evaluating the diameter of the coronary arteries for abnormal narrowing. In addition, during the detection and localisation of vessel stenosis, the severity of stenosis (percentage of artery blockage) is determined based on the estimated diameter at the site of the stenosis and of the normal artery (i.e. stenosis quantification).[25–27]

AI Methods in Coronary Angiography Analysis

In this section, various AI methods are examined in relation to the three primary tasks of coronary angiography analysis. We describe the AI methods proposed in different studies. It is important to note that, because different studies use different coronary angiography datasets, we do not directly compare the evaluation results of the methods presented in the studies. Other tasks within coronary angiography analysis where AI approaches can be used are briefly discussed.

Key Frame Selection

AI methods for key frame selection include variations of convolutional neural network (CNN) and long short-term memory (LSTM) models.[27,29–34] Working on single image, CNN focuses on the local features of the input image while preserving the spatial information. In coronary angiography analysis, CNNs work like automated pattern detectors, scanning each angiogram frame to highlight important features, such as clear contrasts between arteries and surrounding areas. LSTM models, which extract temporal information from sequential data, help track changes in the angiography video over time, identifying patterns in artery movement and dye flow.

Instead of having a good or bad strategy, key frame selection strategies depend on how coronary angiography videos are labelled. One common approach involves directly labelling frames as 'key' or 'non-key' based on the criteria listed in the previous Key Frame Selection section, framing the task as supervised binary classification, where AI models are trained to distinguish key and non-key frames with given annotated labels. LSTM models also analyse temporal relationships between consecutive frames to improve the selection.[27]

Table 1: Summary of Artificial Intelligence Segmentation Methods in Coronary Angiography Analysis

Category	AI model	Reference	Detail	Data	Performance (F1 score)
AI segmentation	MLP	Cervantes-Sanchez et al. 2019[36]	–	130 images (public)	0.686
	Vanilla CNN	Nasr-Esfahani et al. 2016[37]	Angiography patch segmentation	44 images	0.932
	U-Net	Yang et al. 2019[39]	–	3,302 images (private)	0.917
		Xian et al. 2020[40]	–	3,200 images (private)	0.900
		Shen et al. 2023[41]	–	50 images (private)	0.879
		Kaba et al. 2023[42]	–	170 images (private)	0.847
		Meng et al. 2023[43]	–	616 images	0.894
	DeepLab	Iyer et al. 2021[44]	–	462 images (private)	0.864
	PSPNet	Zhu et al. 2021[45]	–	130 patients	Accuracy: 0.957 Sensitivity: 0.947 Specificity: 0.951
	cGAN	Du et al. 2021[19]	20 classes of coronary artery segments	13,373 images	0.804
	GNN	Shin et al. 2019[3]	–	3,137 images	Accuracy: 0.952 Sensitivity: 0.970 Specificity: 0.951
	DARL	Kim et al. 2023[5]	Pseudo segmentation masks generation (self-supervised learning)	1,621 images (public)	0.636
Methods with vessel structure	Style transfer network	Mulay et al. 2021[62]	Style transfer model pretrained on boundary sketch images	164 images (public)	0.710
	U-Net	Park et al. 2023[71]	Considering edge and centreline	7,982 images (private)	0.931
		Han et al. 2021,[72] Han et al. 2022[73]	Considering vessel direction and centreline	300 images	0.850, 0.856
		Xiong et al. 2023[49]	Considering vessel connectivity with pixel level	314 images	0.889
Object detection methods	YOLOv8	Popov et al. 2024[50]	–	1,500 images (public: ARCADE)	0.490
		Liu et al. 2023[74]	–	1,500 images (public: ARCADE)	0.411
Transfer learning	–	Bilal et al. 2023[15]	–	1,500 images (public: ARCADE)	0.377
	–	Mulay et al. 2021[62]	Style transfer model pretrained on boundary sketch images	164 images (public)	0.710

AI = artificial intelligence; ARCADE = Automatic Region-based Coronary Artery Disease Diagnostics using X-ray angiography images; CNN = convolutional neural network; GNN = graph neural network; MLP = multilayer perceptron.

Another approach uses vessel mask annotations. A segmentation model (see Vessel Segmentation, below) uses ground truth vessel masks (manually annotated) as correct answers to supervise training, and key frames are identified based on the predicted vessel masks from the model. Frames with masks (*Figure 3B*) containing the most white pixels, which represent vessels, are selected as key frames.[30,31,35] Although this method aligns with clinical practice, more effort is required to generate pixel-level vessel masks compared with simpler image-level labels of key/non-key frames.

A subtask related to key frame selection, specifically end-systolic and end-diastolic frame detection, is discussed in the *Supplementary Material*.

Vessel Segmentation

Accurate vessel extraction from coronary angiography frames and videos supports key tasks such as stenosis localisation and vessel diameter measurement. The process involves inputting angiography frames (*Figure 3A*) and generating corresponding vessel masks (*Figure 3B*). This section covers two main segmentation strategies: data-driven AI methods and AI methods integrating prior knowledge, which is vessel structure in angiography analysis. *Table 1* summarises the methods discussed and their performance.

Early segmentation models used simpler neural networks, such as multilayer perceptrons or basic CNNs, focusing on small image regions or key features.[36,37] Preprocessing techniques, such as cropping and applying image-processing filters, were used to highlight important areas. These methods are now outdated, as modern deep learning models automatically detect which features to focus on.

U-Net, a CNN architecture for segmentation, has been widely applied to coronary angiography and has shown reliable performance comparable to other segmentation methods in medical imaging.[38–43] Advanced models, including DeepLabv3+ and Pyramid Scene Parsing Network, improve segmentation by focusing on angiography images at different scales.[44–47] You Only Look Once (YOLO) models allow real-time vessel

Table 2: Summary of Artificial Intelligence Stenosis Detection Methods in Coronary Angiography Analysis

Category	AI model	Reference	Detail	Data	Performance (F1 score)
Object detection methods	U-Net	Lin et al. 2023[51]	Stenosis segmentation	1,500 images (public: ARCADE)	0.535
	RetinaNet	Avram et al. 2023[52], Labrecque Langlais et al. 2023[54]	Output stenosis severity	2,338 images[52] (private)	Bounding box IoU: 13%[52]
	DSSD network	Wu et al. 2020[30]	Check predictions of stenosis among consecutive frames	148 videos	0.604
	YOLOv8	Osama et al. 2023[12]	–	236 images (public)	0.682
		Wu et al. 2023[16]	One-stage stenosis detection	2,453 (cranial view), 3,338 (LAO view) (private)	0.659 (cranial view), 0.704 (LAO view)
		Popov et al. 2024[50]	Segmentation of the stenosis	1,500 images (public: ARCADE)	0.400
	FPN	Du et al. 2021[19]	–	7,239 images	0.829, 0.810 (CTO), 0.802 (calcification), 0.823 (thrombosis), 0.854 (dissection)
		Liu et al. 2019[11]	Chronic total occlusion detection	2,059 images	0.885
		Chen et al. 2020[8]	Image-level classification of different lesion types	2,801 images	0.919 (thrombus), 0.946 (CTO), 0.973 (calcification)
		Cong et al. 2023[33]	Image-level classification of stenosis with CAM for stenosis localisation	13,744 images (private)	0.700 (LCA), 0.770 (RCA)
	Attention mechanism	Pang et al. 2021[18]	Pairwise comparison of predictions among different frames	1,494 images	0.881
		Han et al. 2023[10]	Compare predictions of consecutive frames	2,097 images	0.909
		Moon et al. 2021[21]	Image-level stenosis classification	452 videos (private)	Accuracy: 0.934
		Jungiewicz et al. 2023[4]	Image-level stenosis classification	2,400 images (private)	0.945
Transfer learning	ViT	Jungiewicz et al. 2023[4]	Image-level stenosis classification	2,400 images (private)	0.945
	RCNN	Pokhrel et al. 2023[9]	–	1,200 images (public: ARCADE)	0.535
		Di Cosmo et al. 2023[6]	Federated learning for sharing model parameters among institutions	1,219 images (Dataset 1) 7,492 images (Dataset 2) (private)	0.701 (Dataset 1), 0.877 (Dataset 2)
	Inception model	Cong et al. 2019[32]	Image-level classification of stenosis with CAM for stenosis localisation	194 patients (private)	0.720 (LCA), 0.830 (RCA)
		Moon et al. 2021[21]	Image-level stenosis classification	452 videos (private)	Accuracy: 0.934
Weakly supervised methods	Grad-CAM	Cong et al. 2019[32]	Image-level classification of stenosis with CAM for stenosis localisation	194 patients (private)	0.720 (LCA), 0.830 (RCA)
		Moon et al. 2021[21]	Image-level classification of stenosis with CAM for stenosis localisation	194 patients (private)	0.720 (LCA), 0.830 (RCA)

AI = artificial intelligence; ARCADE = Automatic Region-based Coronary Artery Disease Diagnostics using X-ray angiography images; CAM = class activation mapping; CTO = chronic total occlusion; FPN = feature pyramid network; Grad-CAM = gradient-weighted class activation mapping; IoU = intersection over union; LAO = left anterior oblique; LCA = left coronary artery; RCA = right coronary artery; RCNN = region-based convolutional neural network; GNN = graph neural network; MLP = multilayer perceptron; ViT = vision transformer.

classification and segmentation (*Supplementary Figure 1*). However, detecting smaller vessels requires high-quality labelled data (*Supplementary Figures 2 and 3*). When real data with labels are limited, diffusion modules generate synthetic angiograms to expand training datasets.[5]

Another approach models coronary vessel structures using GNNs.[3] The GNN approach involves dividing the angiogram into sections, identifying likely vessel points and linking them if they are sufficiently close (*Supplementary Figure 4*). Further improvements involve the use of vessel edges and centrelines in basic segmentation methods. One approach tracks an artery by detecting these features, whereas another predicts vessel shapes by analysing how each pixel connects to its neighbours.[48,49]

Intuitively speaking, vessel segmentation strategies that integrate the vessel structure are expected to perform better, because they can help exclude artefacts such as the spine and catheter in coronary angiography. However, comparing segmentation methods remains challenging due to the use of different datasets across studies.

Among the studies based on the public Automatic Region-based Coronary Artery Disease Diagnostics using X-ray angiography images (ARCADE) dataset (see Challenges of X-Ray Coronary Angiography Data), the YOLOv8 object detection architecture achieves the best performance, even without the use of unique vessel structure information in the coronary angiography images.[50] Temporal information of angiography sequences would further improve segmentation performance.

Stenosis Detection

In clinical practice, AI algorithms for CAD diagnosis must detect the presence of stenosis, determine its location and assess its severity. We categorise stenosis analysis into two main tasks: detection and

classification (see Stenosis Classification). Stenosis detection identifies stenosis within a coronary angiography frame and locates its position, usually treated as a unified task. Different detection strategies based on labelling methods are discussed in this section, with a summary provided in *Table 2*.

When angiography images are fully labelled for stenosis, the task becomes object detection. Advanced deep learning models, including CNN-based approaches, have been used to locate stenosis and apply regression techniques to estimate its severity.[51,52] Transformer models, such as Swin3D, also offer state-of-the-art performance to estimate the severity of the stenosis.[53,54] In addition, a modified YOLOv8 model detects stenosis and classifies it into four types based on provided labels.[12,16,50] A feature pyramid network (FPN), which finds features in different resolutions, has been developed to detect chronic total occlusion.[55] Global context captures the overall structure of coronary arteries, whereas local context focuses on fine details, identifying specific lesions or blockages.[8,11]

With the increasing use of transformer models for the analysis of sequences of data, similar approaches have been applied to analyse sequential frames in coronary angiography videos.[56] Transformers, compared with CNN, also focus on distant features spatially or temporally.[10,18] For example, an attention-based model compares selected areas in angiography images from multiple frames to find differences and similarities.[18]

When the labels indicating stenosis are not very detailed (e.g. when only the presence of stenosis is marked for the whole image), weakly supervised learning methods can help locate stenosis. One approach treats the task as a simple yes-or-no classification (determining whether stenosis is present in the frame) and uses these labels to guide training.[32] Afterwards, a technique called gradient-weighted class activation mapping (Grad-CAM) is used to highlight which areas of the image the trained model found most important for identifying stenosis.[57] These highlighted areas likely show where the stenosis is located. An example of this technique is shown in *Supplementary Figure 5*.

Similar to key frame selection, AI-based strategies for stenosis detection mainly depend on how stenosis is annotated. Different annotation types, such as image-level labels, bounding boxes and artery segmentation, lead to different stenosis detection approaches, including image-level classification with weakly supervised learning, object detection and segmentation methods. Comparing these strategies is challenging because studies often use different datasets. In studies using the ARCADE dataset with stenosis segmentation annotations, the U-Net model architecture shows the best performance, followed by the region-based CNN model, which identifies potential regions of stenosis in angiography images before analysing and classifying them, and the YOLOv8 model.[50,51]

Stenosis Classification

After detecting the location of the stenosis in the coronary artery, it is beneficial to classify the stenosis based on various criteria. The most direct classification approach involves assessing the severity of the stenosis. Different methods use different thresholds to categorise the degree of blockage. For example, stenosis can be classified as less than 25%, greater than 25%, or as chronic total occlusion.[32] However, it is clinically irrelevant to differentiate between stenosis levels below 25%. Alternatively, classification can be based on thresholds such as <50% or ≥50%.[21]

Stenosis can be classified into three main types based on its composition: cholesterol deposit plaque; calcification; and thrombus, which is caused by blood clots.[8,19] These classifications are important because they influence treatment planning. Stenosis can also be classified by its structure into three types: local stenosis (less than 20 mm in length); diffuse stenosis (greater than 20 mm; also called long lesions); and bifurcation stenosis, which occurs near the origin of a side branch.[16] These structural differences influence the choice of stents and techniques used during interventions. In cases of chronic total occlusion, lesions can be further classified by the shape of their proximal stump as either tapered or blunt.[11] A tapered stump has a funnel-shaped narrowing, whereas a blunt stump has a flat, abrupt end. This distinction helps interventional cardiologists select appropriate strategies for treatment.

Other Tasks

Beyond detecting, locating and classifying stenosis, studies have explored the use of AI for preparing angiography images before segmentation. Selective feature mapping highlights key areas in images to focus AI processing on relevant details.[58] Other studies involve tasks of classifying coronary projections and distinguishing arteries, such as the left and right coronary arteries.[32,52,54] These classification tasks are important for reducing differences in angiography images and improving the performance of AI models. In addition, researchers have investigated related tasks, such as predicting fractional flow reserve, which, however, requires data from invasive fractional flow reserve measurement.[59,60]

Discussion

Leveraging Coronary Angiography Data Properties for Analysis

Coronary angiography images have unique features that set them apart from regular images. Unlike natural images, coronary angiograms are usually shown in greyscale and contain high-contrast areas that highlight the contrast dye in the coronary arteries. In addition, these images consist of sequential frames and specific patterns of blood vessel structures. Researchers have taken advantage of these characteristics to create specialised methods for detecting coronary vessels in X-ray angiography images.

The sequential nature of coronary angiography makes it important to choose key frames from the sequence. As mentioned in the Key Frame Selection section describing angiography analysis tasks, key frames are a selected subset of frames within the sequence. However, if the quality of these angiographic sequences is inconsistent (especially regarding how completely the contrast dye has been injected), the quality of the chosen key frames may also vary. This inconsistency can negatively impact subsequent tasks, such as vessel segmentation and stenosis detection, potentially resulting in a lower performance of the AI models.

Conversely, the sequential nature of angiography frames can be used to improve analysis. Several studies have taken advantage of the information from video sequences to gather additional details that are important for their tasks. Relying on just one frame can lead to inaccuracies due to the movement and bending of blood vessels, as well as due to the uneven distribution of the contrast dye, which can create false indications of stenosis. Therefore, choosing the 'right' frame is crucial for subsequent tasks. Using multiple consecutive frames can enhance vessel segmentation and stenosis detection by providing a more complete view. Different methods use the information from these frames to either set constraints or compare them to extract meaningful details.[10,18,30,34,61]

Furthermore, inspired by the branch-like structure of the coronary tree, new methods have been developed that consider how vessels are organised in coronary angiography images. The greyscale images and clear boundaries in angiography are similar to the sketch drawings used in style transfer learning.[62] This technique uses a model trained on sketch drawings to improve the analysis of angiography images, making it easier to identify and understand the structures in greyscale images. Such approaches show promise for enhancing coronary angiography analysis, especially when limited data are available.

Another approach to enhance analysis is to use 3D spatial information by incorporating frames from multiple angles of projection, in addition to using information from sequential frames. Previous studies have combined features from different projection angles.[10] However, there may be better ways to represent the 3D structure of the heart by connecting these frames more effectively. One promising method involves physically modelling blood flow using X-ray coronary angiography sequences. Because the contrast dye highlights blood flow in these images, integrating knowledge about blood flow (e.g. how fluids move) could improve AI models. This would provide valuable insights into blood flow patterns, vessel positions and potential sites of stenosis.

Challenges of X-Ray Coronary Angiography Data

There are several reasons why clinical data are often less accessible than other types of data. One significant reason is the requirement to anonymise data by removing patient identifiers to protect privacy. Furthermore, research involving clinical data is typically subject to stringent regulatory oversight, which can restrict the availability of such data for public use. In addition, X-ray coronary angiography is an invasive procedure and less frequently performed than other imaging techniques, resulting in a smaller pool of available data. These factors collectively contribute to the current scarcity of publicly accessible repositories for clinical X-ray coronary angiography data.

Popov et al. recently established a publicly accessible angiogram dataset, ARCADE, which comprises 1,500 meticulously annotated coronary angiography images for both vessel segmentation and stenosis detection.[50] The vessel segmentation annotations in the ARCADE dataset are illustrated in *Supplementary Figures 2 and 6*, whereas the annotations for stenosis detection highlight the segments of artery masks where stenosis is present (*Supplementary Figure 3*). This dataset serves as a valuable benchmark for evaluating the performance of AI methods. However, the vessel segmentation and stenosis detection data in ARCADE are organised into separate datasets with non-overlapping individual frames, thereby disconnecting the two tasks in terms of training data. In addition, the dataset consists solely of angiography frames rather than continuous video sequences.

In contrast, Antczak and Liberadzki provide another publicly accessible angiogram dataset comprising 1,394 frames with stenosis and 125 frames from a control group.[63] This dataset also includes over 5,000 frames of synthetic images. However, the dataset features only fragments of initial coronary angiography frames (*Supplementary Figure 7*). Both the ARCADE and Antczak datasets exclusively include selected key frames rather than complete sequences of coronary angiography frames, thereby omitting the temporal correlation between frames. More recently, Jiménez-Partinen et al. published a dataset containing coronary angiography videos, which includes 382 videos with selected key frames obtained from 42 patients.[64]

Due to the limited availability of coronary angiography datasets, researchers have turned to a technique called transfer learning as a useful solution.[4,6,15,62] Transfer learning involves taking a model that was trained on other datasets and adjusting it for the specific task of analysing coronary angiography images.

A more advanced strategy based on transfer learning is called federated learning, which addresses data privacy concerns.[6] In this approach, two coronary angiography datasets from different institutions are used, sharing only the model's settings (weights) between them. Federated learning provides a promising way to overcome the challenges of limited data and restrictions on data sharing. However, there is still a concern that the model may not perform well on new datasets if it is too closely tailored to the small datasets on which it was trained.

Another major challenge in training and evaluating AI models for analysing medical images is the lack of high-quality labelled data. Creating these labels often requires specialised knowledge and is usually done by cardiologists or qualified analysts. There can also be differences in how different annotators label the same images, which is a concern. When experts are not available, one option is for clinicians to guide AI researchers in labelling the data by pointing out important features, such as arteries and areas of stenosis in coronary angiography images. Although this can help create larger datasets, it may reduce the quality of the labels. Therefore, it is essential to establish a strong process for labelling data.

To reduce the need for manual labelling of images, self-supervised and weakly supervised learning methods provide promising alternatives. For example, self-supervised learning can create vessel segmentation masks by using frames with fully injected dye and synthetic frames made from background images without dye.[5] Adversarial learning techniques can then train models to tell the difference between real and synthetic vessel images and masks. Similarly, weakly supervised methods like Grad-CAM can help locate stenosis in images without needing detailed annotations, such as bounding boxes.[21,32,33] These approaches can greatly lessen the dependency on large datasets that require extensive manual labelling.

The lack of labelled data also limits the types of analysis that AI researchers can conduct. Some studies have tried to focus on specific clinical features, like end-diastolic frames, minor vessels and different types of stenosis (see Stenosis Classification).[8,11,19,31,65] Creating supervised AI systems that can accurately identify these clinical features depends greatly on having detailed labels. As a result, there is not much research available on these specific areas beyond the studies mentioned. However, these detailed analyses are essential for helping clinicians make informed decisions about patient treatment plans.

Application

When developing an AI-based tool for analysing coronary angiography, it is important to think about how it will be used in real clinical settings. These tools are meant to support clinicians in diagnosing and assessing patients, not to take the place of trained cardiologists.

To ensure smooth integration, we suggest several potential uses for an AI coronary angiography analysis system in clinical, research and industry environments. We also discuss the gap between creating AI methods and using them in practice, highlighting the challenges and factors that need to be considered for successful implementation in the real world.

Clinical Application

From a clinical standpoint, the main goal of analysing a coronary angiogram is to find patients with stenosis, to determine how severe the stenosis is and to use this information to guide treatment decisions. This process can be time-consuming, even for experienced cardiologists, and often does not provide a great return on their time investment. An AI-based tool for analysing coronary angiograms could greatly improve this process by helping cardiologists interpret the images. Such a tool could speed up the diagnostic workflow by automatically identifying patients with normal or mild stenosis, allowing clinicians to focus on patients with more serious stenosis. Existing models have shown they can tell the difference between stenosis severities of <50% and ≥50%.[21] There is hope that these models could be useful for safety screening, especially in busy hospitals and clinical trials.[21] For example, CathWorks FFRangio software has been deployed for the clinical quantitative and qualitative analysis of previously acquired angiography DICOM data for patients with coronary artery disease.[66]

Another significant limitation of the diagnostic process is the variation in interpretations by the same cardiologist. Although it is theoretically possible to get a second opinion from another cardiologist, this is often impractical because of limited resources. This situation presents a valuable opportunity for AI tools that analyse coronary angiography images to support the diagnostic process and assist cardiologists in improving consistency and efficiency in the diagnosis and treatment of patients.

AI tools could also play an important role as a recommendation system for next steps. For example, if significant blockage is found, a cardiologist may choose to schedule a percutaneous coronary intervention (PCI). In some situations, a cardiologist may decide to perform an ad hoc PCI immediately after a diagnostic coronary angiogram. This decision often depends on the severity and complexity of CAD and can vary widely among cardiologists. An AI system could assist in providing evaluations on stenosis severity for the cardiologist to make decisions whether an ad hoc PCI is suitable by offering additional insights, which could help address the 4.3% and 8.9% rates of inappropriate PCI use in urgent and non-urgent situations, respectively.[67] Furthermore, the AI system could suggest obtaining additional coronary angiography images from different angles based on the current view.

Validation Checks

A well-trained AI tool has the potential to improve the coronary angiography analysis task by improving quality checks during procedures and helping train medical students. AI systems can quickly analyse images, allowing doctors to adjust in real time, which can improve accuracy and save time. For example, AI-based tools like quantitative coronary angiography can measure the narrowing of arteries more precisely, helping doctors plan treatments more effectively.[68] AI can also be used in education, giving medical students hands-on practice with analysing angiograms. These applications are yet to be developed and open up exciting possibilities for further research and development.

Another use for AI in coronary angiography analysis is auditing insurance claims. Accurate diagnoses are important for approving medical procedures, but sometimes clinicians may overdiagnose coronary artery disease. For example, a study in the US found that 17% of coronary bypass surgeries and 10% of stenting procedures were unnecessary.[69] In Switzerland, there is a link between private insurance coverage and the number of coronary procedures performed, raising concerns about the accuracy of CAD diagnoses.[70] However, insurance claim audits are often done by people without much experience in interpreting coronary angiograms. An AI tool could serve as a supplementary aid to assist auditors by providing additional insights to support the evaluation of these claims, helping to improve consistency and reduce errors without replacing expert judgement.

From Development to Deployment

Clinicians and AI scientists often have different goals when developing AI tools for coronary angiography analysis. However, the most successful AI tools will be those that can transition smoothly from development to real-world use. Practising cardiologists may focus on certain key factors when evaluating a new AI algorithm, such as how fast it can provide results (inference speed) and whether it has been tested and validated in real clinical trials.

When deploying AI tools for coronary angiography analysis, the speed at which the model can give results is important, especially in situations like during an ad hoc PCI (see Clinical Application). Although many studies have focused on prediction accuracy, the speed of the model is also critical. In one study, researchers compared different models to find a balance between speed and accuracy.[17] The authors of that study concluded that AI systems with an inference time of <66 ms would be suitable for coronary angiography diagnosis. Another approach, the style transfer network, reported real-time performance, analysing a 300 × 300 angiography image in 0.05 s and a 512 × 512 image in 0.1 s, achieving a speed of 10 frames per second.[62]

Another important factor to consider is whether the proposed AI system has been tested on an external dataset. In most studies, AI research teams work with a public health institution and use their coronary angiography data to train and evaluate their models. However, this means that both the training and evaluation data come from the same source, which can introduce similar biases. For example, another hospital may have X-ray angiographies with different lighting, contrast or projection angles. External validation is crucial to ensure that the AI model works well with different data and is not overly dependent on one specific dataset.

So far, only four studies have used external validation. Moon et al. included 380 images from 76 videos from three hospitals, whereas Yang et al. used an external dataset of 181 images.[21,39] Kim et al. used public coronary angiography datasets for validation, and Avram et al. and Labrecque Langlais et al. validated their stenosis percentage prediction on 464 coronary angiography videos.[5,52,54] Most papers we reviewed only show good performance on the original dataset, but external validation proves that the model can handle data from other sources.

To take the model from development to deployment, the next step could involve clinical trials. In medicine, clinical trials help determine whether a new diagnostic tool makes a meaningful difference for real patients. However, none of the studies we reviewed have reached the clinical trial stage yet, which highlights a gap between developing AI tools and implementing them in real-world practice.

Conclusion

Coronary angiography analysis is essential for diagnosing CADs and creating treatment plans. However, a major challenge in applying deep learning to automate this analysis is the limited availability of well-

annotated public datasets. This challenge limits the comparison of the three tasks between different strategies because different datasets have been used and the annotation of the different datasets tends to be in different forms (e.g. the stenosis can be annotated as an image label, bounding box or small segments of the artery). Despite this, the present review highlights several advanced AI techniques that show strong performance.

Future progress could focus on taking advantage of the unique features of coronary angiography data, integrating multiple types of data and using self-supervised or weakly supervised methods. With continuous improvements in AI models and techniques, along with more clinical trials, automatic coronary angiography analysis tools could soon be integrated into routine clinical practice, offering great potential for improving patient care. ❑

Clinical Perspective

- Research into the use of artificial intelligence (AI) to analyse coronary angiograms is increasing, but although some AI methods have demonstrated accurate results internally, most have not been well validated externally.
- AI methods for coronary angiography analysis mainly focus on key frame selection, vessel segmentation and stenosis detection. In key frame selection, AI algorithms automatically identify frames where the contrast agent fully outlines the coronary arteries; for vessel segmentation, it isolates coronary arteries from the background; and in stenosis detection it identifies narrowed artery regions and assesses severity.
- One of the main challenges for advancing the use of AI in coronary angiography analysis is the lack of large, publicly available datasets, which are essential for developing and validating robust AI models. Addressing this gap presents an opportunity for improvement.
- There remains a gap between algorithm development and the application of AI as a clinical assistant in real-world clinical practice.
- Key opportunities include applying AI to provide analytical support for PCI procedures, train medical students effectively and assist in auditing insurance claims.

1. Shah R, Yow E, Jones WS, et al. Comparison of visual assessment of coronary stenosis with independent quantitative coronary angiography: findings from the Prospective Multicenter Imaging Study for Evaluation of Chest Pain (PROMISE) trial. *Am Heart J* 2017;184:1–9. https://doi.org/10.1016/j.ahj.2016.10.014; PMID: 27892881.
2. Popov M, Aimyshev T, Ismailov E, et al. A review of modern approaches for coronary angiography imaging analysis. *arXiv* 28 September 2022. https://doi.org/10.48550/arXiv.2209.13997; preprint.
3. Shin SY, Lee S, Yun ID, Lee KM. Deep vessel segmentation by learning graphical connectivity. *Med Image Anal* 2019;58:101556. https://doi.org/10.1016/j.media.2019.101556; PMID: 31536906.
4. Jungiewicz M, Jastrzebski P, Wawryka P, et al. Vision transformer in stenosis detection of coronary arteries. *Expert Syst Appl* 2023;228:120234. https://doi.org/10.1016/j.eswa.2023.120234.
5. Kim B, Oh Y, Ye JC. Diffusion adversarial representation learning for self-supervised vessel segmentation. *arXiv* 15 February 2023. https://doi.org/10.48550/arXiv.2209.14566; preprint.
6. Di Cosmo M, Migliorelli G, Francioni M, et al. A federated learning framework for stenosis detection. Presented at: International Conference on Image Analysis and Processing, Udine, Italy, 11 September 2023. https://doi.org/10.1007/978-3-031-51026-7_19.
7. Kobat MA, Barua PD, Tuncer T, et al. Automated stenosis classification on invasive coronary angiography using modified dual cross pattern with iterative feature selection. *Multimed Tools Appl* 2023;83:35957–77. https://doi.org/10.1007/s11042-023-16697-9.
8. Chen S, Tang Y, Shi X, et al. Convolution pyramid network: a classification network on coronary artery angiogram images. *Annu Int Conf IEEE Eng Med Biol Soc* 2020;2020:1186–9. https://doi.org/10.1109/EMBC44109.2020.9176545; PMID: 33018199.
9. Pokhrel S, Bhandari S, Vazquez E, et al. ConvNeXtv2 fusion with mask R-CNN for automatic region based coronary artery stenosis detection for disease diagnosis. *arXiv* 7 October 2023. https://doi.org/10.48550/arXiv.2310.04749; preprint.
10. Han T, Ai D, Li X, et al. Coronary artery stenosis detection via proposal-shifted spatial–temporal transformer in X-ray angiography. *Comput Biol Med* 2023;153:106546. https://doi.org/10.1016/j.compbiomed.2023.106546; PMID: 36641935.
11. Liu X, Du T, Zhang H, Sun C. Detection and classification of chronic total occlusion lesions using deep learning. *Annu Int Conf IEEE Eng Med Biol Soc* 2019;2019:828–31. https://doi.org/10.1109/EMBC.2019.8856696; PMID: 31946023.
12. Osama M, Kumar R, Shahid M. Empowering cardiologists with deep learning YOLOv8 model for accurate coronary artery stenosis detection in angiography images. Presented at: International Conference on IoT, Communication and Automation Technology (ICICAT 2023), Gorakhpur, India, 23–24 June 2023. https://doi.org/10.1109/ICICAT57735.2023.10263760.
13. Ovalle-Magallanes E, Avina-Cervantes JG, Cruz-Aceves I, Ruiz-Pinales J. Transfer learning for stenosis detection in X-ray coronary angiography. *Mathematics* 2020;8:1510. https://doi.org/10.3390/math8091510.
14. Ovalle-Magallanes E, Avina-Cervantes JG, Cruz-Aceves I, Ruiz-Pinales J. Hybrid classical–quantum convolutional neural network for stenosis detection in X-ray coronary angiography. *Expert Syst Appl* 2022;189:116112. https://doi.org/10.1016/j.eswa.2021.116112.
15. Bilal M, Martinho D, Sim R, et al. Multivessel coronary artery segmentation and stenosis localisation using ensemble learning. *arXiv* 27 October 2023; https://doi.org/10.48550/arXiv.2310.17954; preprint.
16. Wu H, Zhao J, Li J, et al. One-stage detection without segmentation for multi-type coronary lesions in angiography images using deep learning. *Diagnostics (Basel)* 2023;13:3011. https://doi.org/10.3390/diagnostics13183011; PMID: 37761378.
17. Danilov VV, Klyshnikov KY, Gerget OM, et al. Real-time coronary artery stenosis detection based on modern neural networks. *Sci Rep* 2021;11:7582. https://doi.org/10.1038/s41598-021-87174-2; PMID: 33828165.
18. Pang K, Ai D, Fang H, et al. Stenosis-DetNet: sequence consistency-based stenosis detection for X-ray coronary angiography. *Comput Med Imaging Graph* 2021;89:(101900). https://doi.org/10.1016/j.compmedimag.2021.101900; PMID: 33744790.
19. Du T, Xie L, Zhang H, et al. Training and validation of a deep learning architecture for the automatic analysis of coronary angiography. *EuroIntervention* 2021;17:32–40. https://doi.org/10.4244/EIJ-D-20-00570; PMID: 32830647.
20. Gao Z, Wang L, Soroushmehr R, et al. Vessel segmentation for X-ray coronary angiography using ensemble methods with deep learning and filter-based features. *BMC Med Imaging* 2022;22:10. https://doi.org/10.1186/s12880-022-00734-4; PMID: 35045816.
21. Moon JH, Lee DY, Cha WC, et al. Automatic stenosis recognition from coronary angiography using convolutional neural networks. *Comput Methods Programs Biomed* 2021;198:105819. https://doi.org/10.1016/j.cmpb.2020.105819; PMID: 33213972.
22. Kavipriya K, Hiremath M. Identification of coronary artery stenosis based on hybrid segmentation and feature fusion. *Automatika* 2023;64:622–33. https://doi.org/10.1080/00051144.2023.2205727.
23. M'hiri F, Duong L, Desrosiers C, Cheriet M. Vessel walker: coronary arteries segmentation using random walks and hessian-based vesselness filter. Presented at: 2013 IEEE 10th International Symposium on Biomedical Imaging (ISBI 2013), San Francisco, CA, US, 7–11 April 2013. https://doi.org/10.1109/ISBI.2013.6556625.
24. Jiang H, He B, Fang D, et al. A region growing vessel segmentation algorithm based on spectrum information. *Comp Math Methods Med* 2013;2013:743870. https://doi.org/10.1155/2013/743870; PMID: 24324524.
25. Wan T, Feng H, Tong C, et al. Automated identification and grading of coronary artery stenoses with X-ray angiography. *Comput Methods Programs Biomed* 2018;167:13–22. https://doi.org/10.1016/j.cmpb.2018.10.013; PMID: 30501856.
26. Zhao C, Vij A, Malhotra S, et al. Automatic extraction and stenosis evaluation of coronary arteries in invasive coronary angiograms. *Comput Biol Med* 2021;136:104667. https://doi.org/10.1016/j.compbiomed.2021.104667; PMID: 34315031.
27. Zhou C, Dinh TV, Kong H, et al. Automated deep learning analysis of angiography video sequences for coronary artery disease. *arXiv* 29 January 2021. https://doi.org/10.48550/arXiv.2101.12505; preprint.
28. Liu X, Wang X, Chen D, Zhang H. Automatic quantitative coronary analysis based on deep learning. *Appl Sci* 2023;13:2975. https://doi.org/10.3390/app13052975.
29. O'Shea K, Nash R. An introduction to convolutional neural networks. *arXiv* 2 December 2015. https://doi.org/10.48550/arXiv.1511.08458; preprint.
30. Wu W, Zhang J, Xie H, et al. Automatic detection of coronary artery stenosis by convolutional neural network with temporal constraint. *Comput Biol Med* 2020;118:103657. https://doi.org/10.1016/j.compbiomed.2020.103657; PMID: 32174325.
31. Ciusdel C, Turcea A, Puiu A, et al. Deep neural networks for ECG-free cardiac phase and end-diastolic frame detection on coronary angiographies. *Comput Med Imaging Graph* 2020;84:101749. https://doi.org/10.1016/j.compmedimag.2020.101749; PMID: 32623295.
32. Cong C, Kato Y, Vasconcellos HD, et al. Automated stenosis detection and classification in x-ray angiography using deep neural network. Presented at: 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), San Diego, CA, US, 18–21 November 2019. https://doi.org/10.1109/BIBM47256.2019.8983033.
33. Cong C, Kato Y, Vasconcellos HDD, et al. Deep learning-based end-to-end automated stenosis classification and localization on catheter coronary angiography. *Front Cardiovasc Med* 2023;10:944135. https://doi.org/10.3389/fcvm.2023.944135; PMID: 36824452.
34. Zhang R, Qin B, Zhao J, et al. Locating X-ray coronary angiogram keyframes via long short-term spatiotemporal attention with image-to-patch contrastive learning. *IEEE Trans Med Imaging* 2024;43:51–63. https://doi.org/10.1109/TMI.2023.3286859; PMID: 37327091.
35. Moalla H, Ghrab A, Bahloul A, et al. Deep AngioKey: a novel approach for objective keyframe extraction in coronary angiography analysis. *Research Square* 30 October 2023. https://doi.org/10.21203/rs.3.rs-3498564/v1; preprint.
36. Cervantes-Sanchez F, Cruz-Aceves I, Hernandez-Aguirre A, et al. Automatic segmentation of coronary arteries in X-ray angiograms using multiscale analysis and artificial neural networks. *Appl Sci* 2019;9:5507. https://doi.org/10.3390/app9245507.
37. Nasr-Esfahani E, Samavi S, Karimi N, et al. Vessel extraction in X-ray angiograms using deep learning. *Annu Int Conf IEEE Eng Med Biol Soc* 2016:2016:643–6. https://doi.org/10.1109/EMBC.2016.7590784; PMID: 28268410.

38. Ronneberger O, Fischer P, Brox T. U-net: convolutional networks for biomedical image segmentation. Presented at: 18th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI 2015), Munich, Germany, 8 October 2015. https://doi.org/10.1007/978-3-319-24574-4_28.
39. Yang S, Kweon J, Roh J-H, et al. Deep learning segmentation of major vessels in X-ray coronary angiography. *Sci Rep* 2019;9:16897. https://doi.org/10.1038/s41598-019-53254-7; PMID: 31729445.
40. Xian Z, Wang X, Yan S, et al. Main coronary vessel segmentation using deep learning in smart medical. *Math Probl Eng* 2020;2020:1–9. https://doi.org/10.1155/2020/8858344.
41. Shen Y, Chen Z, Tong J, et al. DBCU-Net: deep learning approach for segmentation of coronary angiography images. *Int J Cardiovasc Imaging* 2023;39:1571–9. https://doi.org/10.1007/s10554-023-02849-3; PMID: 37017823.
42. Kaba Ş, Haci H, Isin A, et al. The application of deep learning for the segmentation and classification of coronary arteries. *Diagnostics (Basel)* 2023;13:2274. https://doi.org/10.3390/diagnostics13132274; PMID: 37443668.
43. Meng Y, Du Z, Zhao C, et al. Automatic extraction of coronary arteries using deep learning in invasive coronary angiograms. *Technol Health Care* 2023;31:2303–17. https://doi.org/10.3233/THC-230278; PMID: 37545276.
44. Iyer K, Najarian CP, Fattah AA, et al. AngioNet: a convolutional neural network for vessel segmentation in X-ray angiography. *Sci Rep* 2021;11:18066. https://doi.org/10.1038/s41598-021-97355-8; PMID: 34508124.
45. Zhu X, Cheng Z, Wang S, et al. Coronary angiography image segmentation based on PSPNet. *Comput Methods Programs Biomed* 2021;200:105897. https://doi.org/10.1016/j.cmpb.2020.105897; PMID: 33317873.
46. Chen LC, Zhu Y, Papandreou G, et al. Encoder–decoder with atrous separable convolution for semantic image segmentation. Presented at: ECCV 2018 European Conference on Computer Vision, Munich, Germany, 11 September 2018. https://doi.org/10.1007/978-3-030-01234-2_49.
47. Zhao H, Shi J, Qi X, et al. Pyramid scene parsing network. Presented at: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, US, 21–26 July 2017. https://doi.org/10.1109/CVPR.2017.660.
48. Lalinia M, Sahafi A. Coronary vessel segmentation in X-ray angiography images using edge-based tracking method. *Sens Imaging* 2024;25:32. https://doi.org/10.1007/s11220-024-00481-6.
49. Xiong J, Lyu P, Fang W, et al. CAS_NeXt: towards accurate and topology-preserving coronary artery segmentation in digital substraction angiography. Presented at: 2023 4th International Conference on Control, Robotics and Intelligent System (CCRIS 2023), Guangzhou, China, 25–27 August 2023. https://doi.org/10.1145/3622896.3622913.
50. Popov M, Amanturdieva A, Zhaksylyk N, et al. Dataset for automatic region-based coronary artery disease diagnostics using X-ray angiography images. *Sci Data* 2024;11:20. https://doi.org/10.1038/s41597-023-02871-z; PMID: 38172163.
51. Lin H, Liu T, Katsaggelos A, Kline A. StenUNet: automatic stenosis detection from X-ray coronary angiography. *arXiv* 23 October 2023. https://doi.org/10.48550/arXiv.2310.14961; preprint.
52. Avram R, Olgin JE, Ahmed Z, et al. CathAI: fully automated coronary angiography interpretation and stenosis estimation. *NPJ Digit Med* 2023;6:142. https://doi.org/10.1038/s41746-023-00880-1; PMID: 37568050.
53. Yang YQ, Guo YX, Xiong J-Y, et al. Swin3D: a pretrained transformer backbone for 3D indoor scene understanding. *Comput Vis Media* 2025;11:83–101. https://doi.org/10.26599/CVM.2025.9450383.
54. Labrecque Langlais E, Corbin D, Tastet O, et al. Evaluation of stenoses using AI video models applied to coronary angiographies. *NPJ Digit Med* 2024;7:138. https://doi.org/10.1038/s41746-024-01134-4; PMID: 38783037.
55. Lin TY, Dollár P, Girshick R, et al. Feature pyramid networks for object detection. Presented at: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, US, 21–26 July 2017. https://doi.org/10.1109/CVPR.2017.106.
56. Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need. Presented at: 31st Annual Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, US, 6 December 2017.
57. Selvaraju RR, Cogswell M, Das A, et al. Grad-CAM: visual explanations from deep networks via gradient-based localization. Presented at: 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 22–29 October 2017. https://doi.org/10.1109/ICCV.2017.74.
58. Jo K, Kweon J, Kim Y-H, Choi J. Segmentation of the main vessel of the left anterior descending artery using selective feature mapping in coronary angiography. *IEEE Access* 2019;7:919–30. https://doi.org/10.1109/ACCESS.2018.2886009.
59. Roguin A, Dogosh AA, Feld Y, et al. Early feasibility of automated artificial intelligence angiography based fractional flow reserve estimation. *Am J Cardiol* 2021;139:8–14. https://doi.org/10.1016/j.amjcard.2020.10.022; PMID: 33058806.
60. Omori H, Kawase Y, Mizukami T, et al. Diagnostic accuracy of artificial intelligence-based angiography-derived fractional flow reserve using pressure wire-based fractional flow reserve as a reference. *Circ J* 2023;87:783–90. https://doi.org/10.1253/circj.CJ-22-0771; PMID: 36990778.
61. Hao D, Ding S, Qiu L, et al. Sequential vessel segmentation via deep channel attention network. *Neural Netw* 2020;128:172–87. https://doi.org/10.1016/j.neunet.2020.05.005; PMID: 32447262.
62. Mulay S, Ram K, Murugesan B, Sivaprakasam M. Style transfer based coronary artery segmentation in X-ray angiogram. Presented at: 2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW), Montreal, Canada, 11–17 October 2021. https://doi.org/10.1109/ICCVW54120.2021.00378.
63. Antczak K, Liberadzki Ł. Stenosis detection with deep convolutional neural networks. Presented at: 22nd International Conference on Circuits, Systems, Communications and Computers (CSCC 2018) Majorca, Spain, 14–17 July 2018. https://doi.org/10.1051/matecconf/201821004001.
64. Jiménez-Partinen A, Molina-Cabello MA, Thurnhofer-Hemsi K, et al. CADICA: a new dataset for coronary artery disease detection by using invasive coronary angiography. *Expert Systems* 2024;41:e13708. https://doi.org/10.1111/exsy.13708.
65. Meng Y, Dong M, Dai X, et al. Automatic identification of end-diastolic and end-systolic cardiac frames from invasive coronary angiography videos. *Technol Health Care* 2022;30:1107–16. https://doi.org/10.3233/THC-213693; PMID: 35599518.
66. Witberg G, De Bruyne B, Fearon WF, et al. Diagnostic performance of angiogram-derived fractional flow reserve: a pooled analysis of 5 prospective cohort studies. *JACC Cardiovasc Interv* 2020;13:488–97. https://doi.org/10.1016/j.jcin.2019.10.045; PMID: 32007461.
67. Liu Y, Chen Y, Chang Z, et al. Appropriateness of percutaneous coronary interventions: a systematic review and meta-analysis. *J Cardiovasc Dev Dis* 2023;10:93. https://doi.org/10.3390/jcdd10030093; PMID: 36975857.
68. Yongcheol K, Yoon H-J, Suh J, et al. Artificial intelligence-based fully automated quantitative coronary angiography vs optical coherence tomography-guided PCI: the FLASH trial. *JACC Cardiovasc Interv* 2025;18:187–97. https://doi.org/10.1016/j.jcin.2024.10.025, PMID: 39614852.
69. Leape LL, Park RE, Bashore TM, et al. Effect of variability in the interpretation of coronary angiograms on the appropriateness of use of coronary revascularization procedures. *Am Heart J* 2000;139:106–13. https://doi.org/10.1016/S0002-8703(00)90316-8, PMID: 10618570.
70. Struja T, Suter F, Rohrmann S, et al. Comparison of cardiovascular procedure rates in patients with supplementary vs basic insurance in Switzerland. *JAMA Netw Open* 2023;6:e2251965. https://doi.org/10.1001/jamanetworkopen.2022.51965; PMID: 36662521.
71. Park J, Kweon J, Kim YI, et al. Selective ensemble methods for deep learning segmentation of major vessels in invasive coronary angiography. *Med Phys* 2023;50:7822–39. https://doi.org/10.1002/mp.16554; PMID: 37310802.
72. Han T, Bian Y, An R, et al. Direction- and centerline-aware joint learning network (JLNet) for vessel segmentation in X-ray angiography images. Presented at: ICDSP 2021: 2021 5th International Conference on Digital Signal Processing, Chengdu, China (online), 26–28 February 2021. https://doi.org/10.1145/3458380.3458383.
73. Han T, Ai D, Wang Y, et al. Recursive centerline- and direction-aware joint learning network with ensemble strategy for vessel segmentation in X-ray angiography images. *Comput Methods Programs Biomed* 2022;220:106787. https://doi.org/10.1016/j.cmpb.2022.106787; PMID: 35436660.
74. Liu T, Lin H, Katsaggelos AK, Kline A. YOLO-Angio: an algorithm for coronary anatomy segmentation. *arXiv* 24 October 2023. https://doi.org/10.48550/arXiv.2310.15898; preprint.