Journal of Associated Medical Sciences 2025; 58(3): 111-121

JAMS
Journal of Associated Medical Sciences

Scopus Indexed & Thai-Journal Citation Index Centre (TCI)

Journal of Associated Medical Sciences

Journal homepage: https://www.tci-thaijo.org/index.php/bulletinAMS/index

Edge-based AI approach for blood vessel segmentation in coronary X-ray angiography

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ARTICLE INFO

Article history:
Received 3 March 2025
Accepted as revised 26 May 2025
Available online 6 June 2025

Keywords:
Computer-aided diagnosis (CAD), machine learning for medical imaging, feature selection, cardiovascular disease, Sorbel edge detection, Prewitt edge detection, Robert's edge detection, Canny edge detection.

ABSTRACT

Background: An organizational report indicates that heart attacks lead to seventy percent of human fatalities. Heart-related diseases strike people in India who range between the ages of 30-60 years. X-ray coronary angiography functions as the key procedure for detecting these conditions. The manual process of heart vessel segmentation by cardiologists becomes slow and needs significant effort because different professional skill levels affect the consistency of their output results.

Objective: A study proposes automatic coronary angiography segmentation through artificial intelligence analysis of edge features to accurately detect the main cardiovascular artery system edges.

Materials and methods: The Mendeley public database contained 100 patient images for training purposes and 34 images for validation purposes. The VGG Image Annotator tool served to create binary masks for annotation purposes. The analysis incorporated traditional edge detection methods that included Sobel, Prewitt, and Roberts along with Canny.

Results: The tested model obtained 99% accuracy alongside a positive predictive value (PPV) of 96% and Sensitivity of 94% and Dice Coefficient of 95%. The upcoming research will focus on developing soft computing approaches for detecting stenosis in segmented images.

Conclusion: The method demonstrates better performance metrics that show superior capability to previous techniques implemented in this field. New studies are needed to analyze soft computing techniques to identify vascular structures in coronary angiographic images.

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doi: 10.12982/JAMS.2025.079
E-ISSN: 2539-6056

Introduction

Cardiovascular Disease (CVD) is a situation in which arteries that supply blood to the heart muscles become narrowed or blocked due to fatty deposits of plaque. Cholesterol and fat-like substances may be responsible for forming plaques. Plaques reduce blood flow or cause complete blockage of arteries. When the heart does not receive enough blood that contains oxygen due to narrowed or blocked arteries, it may result in chest pain or serious complications such as heart attacks. Cardiovascular disease (CVD) is to be more responsible for a significant amount of mortality globally and is considered the cause of fatalities.[1] Invasive coronary angiography (ICA) remains the gold standard for diagnosing coronary vessel disease.

However, its effectiveness can be influenced by patient-specific anatomical variations and image quality dependency. Despite its widespread use, previous studies have struggled to achieve optimal performance and accuracy in predictive analysis. Accurate assessment of the degree of vessel stenosis plays a crucial role in guiding treatment management and improving patient outcomes. The formation of coronary artery plaque leads to the development of the condition. Plaque is a substance composed the cholesterol, calcium, fatty deposits, and other materials present in the human blood. Over time, these fatty deposits lead to the narrowing (stenosis) and hardening (sclerosis) of the artery walls, a condition known as atherosclerosis.

This process reduces the elasticity of the arteries and restricts blood flow, which can limit the supply of oxygen and nutrients to the heart muscle. If the plaque ruptures, it can trigger the formation of blood clots, further obstruct the blood flow and potentially lead to serious conditions such as heart attack, or other types of coronary disease (CAD).[2] The plaques are detected by some physical observation of heart abnormalities by medical practice. Abnormalities of the coronary arteries can lead to severe consequences, including myocardial infarction, heart failure, or sudden cardiac arrest. In recent years, substantial efforts have been directed towards enhancing diagnostic methods in cardiology to facilitate early detection and treatment, ultimately improving patient survival rates and quality of life.[3] The medical term stenosis defines a lumen constriction that reduces coronary artery blood flow to the heart tissue. The accumulation of plaque leads to arterial narrowing that produces an irritated condition known as myocardial infarction or heart attack. The spread of arterial plaque causes inflammation in the proximal side wall which raises the heart attack danger.

Figure 1A shows the first image describes the catheter injected from the leg and guided to aorta, that means catheter is typically inserted into a blood vessel through a small incision, most commonly in the femoral artery located in the leg. This minimally invasive procedure is known as catheterization. The catheter is a thin, flexible tube that is carefully guided through the vascular system using real-time imaging techniques, such as fluoroscopy (X-ray guidance). Figure 1B shows catheter tip stopped at artery Positioning the catheter at this location is critical for identifying any blockages, narrowing (stenosis), or other abnormalities that may impair blood flow to the heart muscle and for planning potential interventions like angioplasty or stenting. Figure 1C shows the die injected into the arteries for stenosis in left coronary artery. During the procedure, a contrast dye is often injected through the catheter to enhance the visibility of blood vessels on imaging using coronary angiography, helping physicians assess the extent of disease or abnormalities and guide the intervention precisely. There are some popular approaches for imaging tests such as X-ray angiography, CT scan, and MRI scan systems. The manual observation and detection of blood vessels in coronary angiography images leads to subjectivity, time consumption, and variability depending on the observer's expertise and experience. Therefore, automatic detection of coronary vessels is needed for accurate, fast, and objective detection and diagnosis.

Nowadays, people rely more on machines than on human beings. Therefore, artificial intelligence plays a vital role in medical diagnosis. There are various AI techniques that integrate medical image analysis using digital image processing and computer vision. At this stage, X-ray angiography imaging is taken of a segmented part of the arteries. Segmentation techniques performed by experienced human professionals often yield better results than machines. Research institutions utilize artificial intelligence approaches with computer-aided systems and digital image processing to boost blood vessel identification in coronary angiography picture segmentation practices. The two main approaches for segmentation methods are divided into supervised methods and unsupervised procedures. The image structure serves as the sole foundation for segmentation methods because the analysis depends on intensity and gradient information. The methods edge detection, thresholding, deformation and graph cuts become tools to recognize image boundaries for object definition.[5,6] Multiple machine-learning models exist for both segmenting and reconstructing the structure of coronary arteries. The techniques used for this purpose include edge

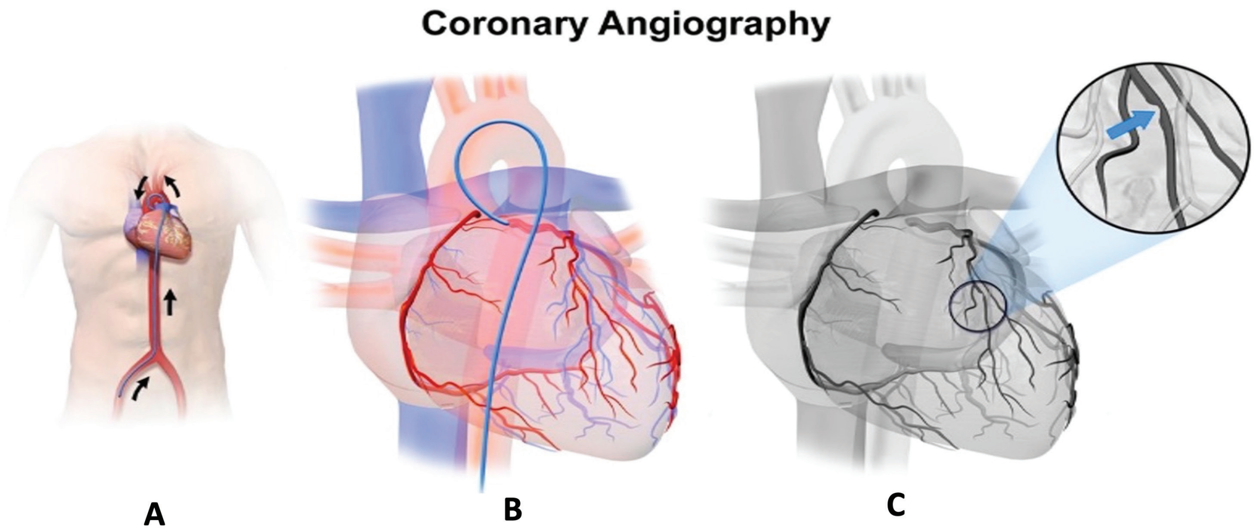

***Figure 1**. Coronary angiography depicting blood vessels.*[4]

detection, region-based analysis, tracking techniques, feature extraction and learning-based methods as well as others.[7,8] In this study, we concentrate on feature-based machine learning techniques to detect blood vessels in coronary angiography images. The methods use self-learning abilities to extract information from historical data to enhance the precision of segmentation results.[9,10]

The algorithms enhance the segmentation process while shortening the computation time required. Especially in X-ray heart angiography image segmentation, vessel boundary detection is obscured by the low contrast of images and noisiness, besides the overlap of structures.[11] The main challenges are the necessity of many annotated images and variability in imaging conditions that impede generalization ability. Most previous methods failed to handle the information on a fine level with handcrafted features and were prone to overfitting.[12] The various contributions to this manuscript are as follows:

1. **Problem identification:** Outlined the problems of manual segmentation of coronary angiography images, which is affected by the variation in expertise of different cardiologists and time-consuming processes.
2. **Integration of traditional edge detection algorithms:** Traditional edge detection algorithms like as Sobel edge detector, Prewitt edge detector, Robert's edge detector, and Canny edge detector have been employed in extracting dominating edges of a cardiovascular artery system from angiography images.
3. **Artificial intelligence application**: It incorporated a Random Forest algorithm in selecting and refining the strong edges detected by the traditional edge detection methods, increasing the accuracy of segmentation.

The hypothesis of coronary angiography images segmentation using automatic techniques of edge-based feature analysis using Random Forest, would offer a means to achieve such an effective result as more prominence and consistent results, while at the same time fewer man-hours spent on manual segmentations.[13] These methods are expected to provide higher consistency and overcome the variability and time burden of cardiologists performing the segmentation.

The article focuses on study of coronary angiography and section I is an introduction to coronary angiography. In section II we review published research on segmentation of cardiovascular images, specifically, feature based machine learning approaches. In section III we describe our system and spend a great deal of time discussing our machine learning model. In section IV there is detail of the edge detection technique which is used to recognize edges. section V presents experimental results and performance evaluation of the model. In the final section both research and findings of the study are summarized.

Literature review

The study proposes Early diagnosis becomes vital for preventing significant health risks associated with cardiovascular diseases at a global level because of their broad prevalence. The ECG tool functions as a main diagnostic instrument, yet existing diagnosis processes miss accurate interpretations. The combination of BiAE technology that unites BiLSTM cells with autoencoders makes ECG signal features easier to extract. The new algorithm uses its abilities to detect important elements that guide accurate classification. Among the ten machine learning models, SVM obtained 96% accuracy for classifying ECG signal types while categorizing them into five groups. Using AI for ECG diagnosis helps medical staff diagnose patients more accurately while also speeding up the process through improved efficiency and decreased operator mistakes. New advancements make it possible to discover CVDs at an earlier stage and identify them better. The application of artificial intelligence in ECG signal analysis will transform patient diagnosis as well as cardiac medical care procedures.[14]

Diagnosis of atherosclerosis and stroke risk heavily relies on accurate carotid plaque segmentation together with classification methods in ultrasound imaging context. Current techniques maintain either complex procedures or neglect task correlations which results in diminished performance levels. RCCM-Net represents a new multi-task learning framework which unites RCM for region confidence analysis with CCM for sample category confidence management to boost segmentation together with classification results. RCM provides probabilistic assessment of plaques for classification purposes followed by CCM which creates categorical sample weights to improve segmentation. The performance of RCCM-Net surpassed both standalone and multi-task approaches when analyzing 1270 ultrasound images because it reached 85.82% accuracy in classification plus 84.92% Dice-similarity coefficient. An ablation study demonstrated that RCM together with CCM achieved their target purpose. The results demonstrate that RCCM-Net shows promise for medical examination of carotid artery plaques. Through this method doctors would achieve better early identification of atherosclerosis and stroke prevention treatment opportunities.[15]

Medical staff must perform manual corrections to traditional edge detection algorithms in quantitative coronary angiography, resulting in reduced accuracy. AngioPy improves segmentation precision through added features that let users mark ground-truth points which minimizes the requirement for manual input. AngioPy demonstrated excellent performance with an F1 score of 0.927 after its evaluation of 2455 images from FAME 2 before validating its results on 580 images. Measurements of vessel dimensions between AngioPys and Medis QFR® revealed outstanding agreement when r was 0.96 at p<0.001 level. Minimum luminal diameter analysis through the model produced an excellent correlation score of r=0.93. The reliability of AngioPy as a coronary segmentation system is supported by these research results. Manual corrections are not required because this system improves the efficiency of QCA. The technology demonstrates the capability to transform diagnostic and clinical operational models related to coronary disease diagnosis.[16]

Cardiovascular diseases act as the main death-causing factors which require prompt diagnosis together with precise identification. The process of feature engineering required by traditional machine learning hinders effectiveness when dealing with complex datasets. DL models feature automatic feature abstraction while delivering better efficiency along with accuracy levels. The research describes the creation of EnsCVDD-Net and BlCVDD-Net as DL models for CVD classification through the combination of LeNet with GRU and MLP structures. The selection of optimal data balancing methods together with feature selection algorithms helps improve model operational efficiency. The EnsCVDD-Net model reached a performance mark of 88% accuracy; however, BlCVDD-Net exceeded the competitive models with a remarkable 91% accuracy. SHAP Additive exPlanations provides interpretation through its capability to assess feature contribution levels. The proposed frameworks represent a beneficial technique for enhancing cardiovascular disease screening accuracy.[17]

Personalized medical interventions become necessary because cardiovascular diseases exist with multiple complex characteristics. Predictive analysis is improved through AI and ML techniques to enhance diagnosis and treatment methods. The researchers applied statistical approaches together with AI/ML techniques to discover vital transcriptomic markers for CVD predictive purposes. Genes were evaluated using three statistical methods that ended in feature prioritization procedures before employing ML methodology. Soft voting ensemble was used as the ML model framework to achieve 96% accuracy performance. The research identified eighteen important biomarkers which were verified through clinical record comparisons. Biomarkers function as initial warning signals for detecting CVD. The AI-based prediction system provides healthcare professionals with a dependable methodology for patient-specific care.[18]

Progressive diagnostic tools are crucial for medical care because cardiovascular disease remains a primary global health challenge. The necessity of automated cardiac MRI analysis involves supervised learning approaches that require significant labeled data. The research describes a partially supervised Strong-Teacher Consistency Network which segments multi-class cardiac MRI structures by utilizing unlabeled data. The model employs a multi-teacher framework, hybrid loss functions, and virtual adversarial training for robust learning. The model achieves advanced accuracy in its performance evaluation using the MM-WHS and ACDC datasets relative to other existing models. The system obtains a 90.14% success rate on MM-WHS tasks and 78.45% accuracy on ACDC while using limited labeled data. The methodology provides better performance than both fully supervised and single-teacher systems. The innovation increases automated cardiovascular diagnostic accuracy when working with small, labeled datasets.[19]

The authors proposed solving the traditional boundaries encountered when performing vascular hemodynamic evaluations manually in clinical settings. The research team created a deep learning method to process CT images through automatic segmentation followed by vessel reconstruction and prediction of computational fluid dynamics (CFD). A CNN design update performed segmentation, and the MC algorithm did 3D reconstruction tasks. The Res2-CD-UNet model demonstrated superiority over previous methods because it achieved a 92.76% accuracy rate on aortic-artery data while attaining 94.57% accuracy on lower-limb artery data sets. The model achieved better relative geometric errors and computed results at a much faster pace. The software used OpenFOAM to conduct CFD simulations that delivered improved efficiency. The method enables physicians to view accurate arterial hemodynamics while maintaining fast speeds and operability. The application of this approach demonstrates high promise to enhance medical diagnostic systems for blood vessels.[20]

The left ventricular wall identification process in myocardial perfusion scintigraphy images gets improved thanks to U-Net convolutional neural networks for detecting coronary artery diseases. An analysis of 83 clinical exams with 4,150 images showed that the AI segmentation yielded an 87% dice coefficient (DC) together with an intersection over Union of 0.8 compared to conventional methods. Communication science validated the model both internally and externally to meet clinical practice requirements. The integration of artificial intelligence results in improved accuracy and efficiency when performing diagnoses in myocardial imaging procedures. This development will help researchers conduct future studies with the focus on artifact correction.[21]

The research introduces SCS-SLSP as a semi-supervised cardiac image segmentation framework which combines SPG modules with SL theoretical principles. The soft labeling mechanism of SL identifies in-distribution pixels as well as uncertain areas and SPG enhances the extraction of vital features through its modules. The Hard Uncertain Pixel Mining (HM) module achieves higher accuracy through two methods which include trustworthy pseudo-label allocation and hard case processing using contrastive learning. The SCS-SLSP system demonstrated superior performance than current methods when working with restricted amounts of labeled data through tests on three open-source datasets. The dice score increased by 0.41% for the ACDC dataset which used 10% labeled data while reducing segmentation errors substantially. By using this approach, both hospital operations can get improved segmentation results with better accuracy and efficiency.[22]

This work presents CapNet which represents a light deep-learning system designed for cardiac MRI segmentation to reduce the excessive operational costs of transformer-based models. The model uses both convolutional structures and mixing mechanics to perform efficient training operations using fewer computational parameters. The adoption of attention mechanisms allows the model to adapt to different cardiac shape variations.

Tversky Shape Power Distance loss serves as a new loss function which boosts segmental accuracy in the process. Open-source assessments conducted on three public datasets reveal that CapNet achieves exceptional dice similarity scores better than present-day standard models. A statistical review verifies its successful performance even with decreased computing demands.[23]

The research presents an AI-based system for cardiac ultrasound image segmentation which lowers requirements for large, annotated dataset dependency. The system makes use of artificial intelligence generative capabilities to generate multi-class RGB masks which directly segment heart structures. The novel implementation of conditional generative adversarial networks (CGAN) produces better accuracy because it includes conditional inputs and paired RGB masks. The methodology achieves superior performance than state-of-the-art models during evaluations on three separate datasets. This technique allows superior segmentation while being less sensitive to noise. The method helps automate cardiac imaging operations while minimizing expenses alongside dependence on human experts.[24]

Materials and methods

1. **Dataset**: Our research utilized a dataset comprising images of heart blood vessels along with their corresponding annotated vessel masks. This publicly available dataset was sourced from Mendeley and included a dataset consisting of 134 angiography images out of which 100 angiography images were used for training and 34 images for validation purpose.[25] The binary masks were annotated using the VGG Image Annotator tool. All images underwent a preprocessing step, including cleaning, before being used for segmentation.
2. **Methods**: In the field of medical imaging, identifying and analyzing targets can be highly challenging, particularly when dealing with low-quality images of blood vessels in coronary angiography, which often suffer from poor pixel resolution and inadequate color schemes. The proposed technique involves several steps, including data preprocessing and feature-based segmentation. Segmentation is performed by selecting features through machine learning techniques. In this study, we propose a segmentation model that applies machine learning algorithms to segment blood vessels in X-ray coronary angiography images.

This model begins by processing the data using Random Forest methodology while performing feature selection activities. The results undergo machine learning model analysis to conduct the assessment. This methodology provides a more efficient solution for diagnosing coronary artery blockages, reducing the time required by cardiologists or physicians. The segmentation of heart blood vessels involves several steps using different types of filters. As shown in Figure 2, the process starts by taking coronary angiography images of blood vessels as input. These images undergo preprocessing using a Gabor filter, which smooths the images while minimizing noise interference. The following image demonstrates different edge detection techniques (Canny, Sobel, Prewitt and Roberts) used after preprocessing. After appropriate segmentation of coronary angiography blood vessels, the Random Forest algorithm selects essential heart image features. The system performs training subsequently and its output results are assessed alongside visualization processing. Edge detection techniques serve as fundamental tools for accurate heart vessel segmentation processes.

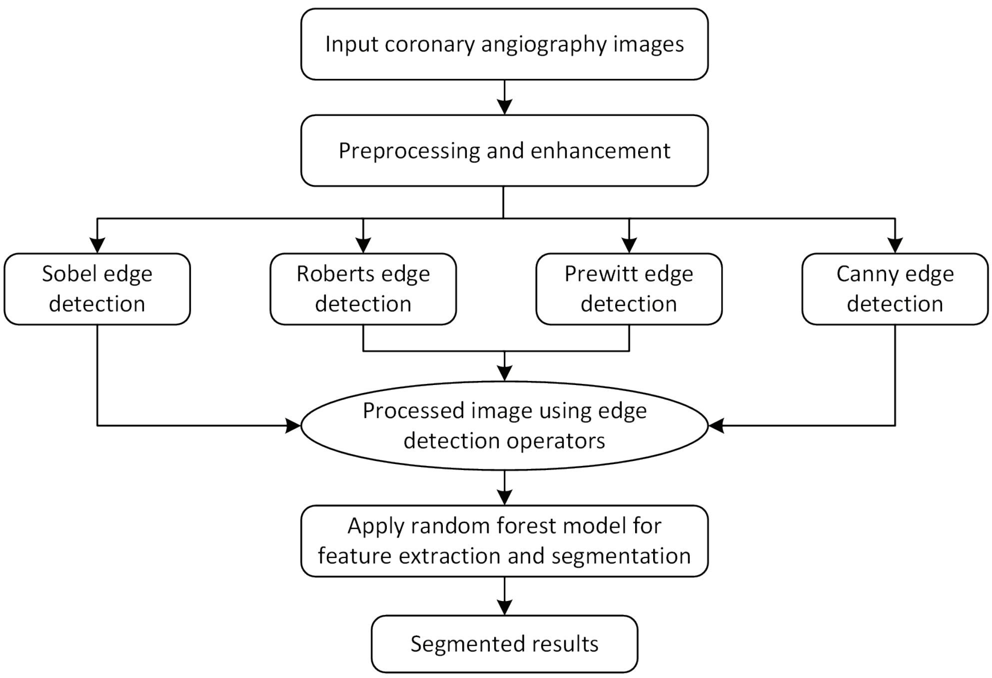

Figure 2. *Proposed model for vessel segmentation.*

Canny edge detection algorithm

The Canny edge detection technique is a technique in the literature for detecting edges in an image, and it is applied to different tasks such as image segmentation. This technique balances two major performance criteria. First is effective edge detection and the second is precise edge localization, which means that the edge points are as close as possible to the true edges, and each edge has only one response. The algorithm processes edges through gradient analysis which examines intensity changes and directions of gradient alterations.[26] There is various process in the algorithm will be as follows as smoothing of image that reduces noise in the image for better accuracy in detecting edges. Computation of gradient based on calculation of the magnitude and direction of change in intensity. Lastly, double thresholding which classifies the edges into strong and weak concerning the level of intensity. Strong edges are of utmost importance in creating a continuous chain of edges, which is the main factor in segmenting regions of interest in an image. The algorithm connects the pixels along the strong edges to help in the separation and segmentation of meaningful areas in the image.

Sobel edge detection

The detection of edges in images, commonly known as Sobel edge detection, is one of the techniques designed for such purposes. The procedure basically works by convolving an image with what is called a Sobel kernel-special matrices that enhance the difference in intensity between neighboring pixels. It yields a map of gradient magnitudes that then show the edges of an image.[27] This output is generally used as the base for further image segmentation processes in which the edges outline the borders that demarcate regions within the image.

Roberts edge detection

The Roberts edge detection algorithm is the simplest method for detecting edges in an image. This is like the 2-D gradient operator on grayscale images. The algorithm processes edges through gradient analysis which examines intensity changes and directions of gradient alterations.

$$[G] = [G_x] + [G_y] \tag{1}$$

[Gx] and $[G_y]$ describe the gradients in the x and y directions, respectively. These outcomes after magnitude map, highlighting edges of an image. This information about the gradient can easily be used for segmentation using the detected edges to delineate different regions within the image.[28] However, care must be taken that in comparison with other operators such as Sobel or Canny, the Roberts edge-detection algorithm is less reliable. Due to its smaller kernel size, which has a limited detailed information of image.

Prewitt's edge detection

The basic yet effective edge detection method called Prewitt's enhances image edge detection for analysis purposes. The Prewitt Kernel works as a 3×3 matrix component of this algorithm to detect intensity changes between adjacent image pixels. The edge detection process determines partial derivative values through gradient values that extend in horizontal (Gx) as well as vertical (Gy) directions. Equations allow the determination of these gradient values.

$$G_x = [A_2+cA_3+A_4] - [A_0+cA_7+A_6] \tag{2}$$

$$G_y = [A_6+cA_5+A_4] - [A_0+cA_1+A_2] \tag{3}$$

Here, c is a constant that assigns greater importance to pixels nearer to the center of the mask. The operation produces a gradient magnitude, which helps in identifying edges within the image. Further, it can be used in edge information on image segmentation for which the edges define regions between different portions within the image.[29] Owing to its larger kernel size and better capability in capturing edge details of an image, the Prewitt method usually would be more reliable compared to the Roberts method. However, it still will not be considered as robust as other advanced algorithms in edge detection techniques, whereas Sobel and Canny methods, use advanced techniques for the same operation in images.

Random Forest classifier (RF)

The Random Forest classifier serves the dual purpose of feature selection and classification. For blood vessel segmentation, it selects important features such as color, texture, etc., from the input data, which are then used by a segmentation algorithm to do the actual segmentation.[30] Following is a sequence of actions when a classifier is applied:

Feature selection: Running Random Forest algorithm on the training data with extracted features; assessing the importance of features depending on how decision trees have been split.

Segmentation: The selected features become the input for a segmentation algorithm that performs the segmentation, either by traditional image processing methods or by machine learning techniques.

Evaluation: Measure the outcomes of the segmentation algorithm in terms of performance metrics such as confusion matrices.

The classification performance will improve when Random Forest classifier feature selection methods work together with appropriate segmentation methods.

Performance metrics

The performance assessment of the classification model includes accuracy measurements taken during training and testing operations. A confusion matrix provides an evaluation of the predicted data against real dataset labels. The classification outcomes consist of four cases where correct classifications receive labels true positive and true negative but incorrect ones become false positive or false negative. The assessment of the classification model performance relies mainly on the positive predictive value (PPV) together with Sensitivity as the commonly utilized metrics in these experiments.

Positive Prediction Value (PPV): the model, in essence, quantifying how sure it is that such a prediction of positive is actually positive - that is, the number of true positives compared against the total sum of actual true and false positives.[31] PPV can be calculated in Equation (4).

$$\text{Positive Prediction Value} = \frac{TP}{TP+FP} \quad (4)$$

Sensitivity: Sensitivity determines whether the model detects genuine positive situations accurately. The ratio between authentic positive outcomes and all actual positive results yields sensitivity measurement. This calculation excludes only true positive (TP) and false negative (FN) from the count.[32] Equation (5) states the mathematical formula for sensitivity calculation.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

Dice Coefficient (DC): The dice coefficient functions as an evaluation measure for binary classification models. This measure tracks how well the model identifies positive cases without excessive numbers of incorrect positive or negative classifications. The model's performance effectiveness receives a balanced assessment through a harmonic mean calculation involving accuracy and sensitivity results.[33] The performance evaluation of the DC occurs through Equation (6).

$$\text{Dice Coefficient} = 2 \times \frac{(\text{Positive Prediction Value} * \text{Sensitivity})}{(\text{Positive Prediction Value} + \text{Sensitivity})} \quad (6)$$

Accuracy: A model achieves accuracy when it predicts correctly for every output it generates. Equation (7) provides a method to calculate accuracy.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Confusion metrics used to check the performance of the generated model through machine learning on various levels of confidence.

Results

This section showcases the model's experimental results. In this study, the predicted masks were assessed by comparing them with the annotated masks for evaluation. The model is based on a segmentation approach that utilizes feature extraction from coronary angiography blood vessel images. Different edge detection methods, involving Sobel, Roberts, Prewitt, and Canny, play an important role in enhancing the features of an image. Each operator may be used in different ways to extract edges or boundaries in coronary angiography images to ensure that all details concerning the feature under study are captured. These processed images highlight blood vessels and other critical structures for highly informative features toward which the subsequent machine learning model shall be working. The use of multiple operators in the system enhances diversity among the extracted edge information, promoting the robustness of segmentation. The edges of vessels in coronary angiography were identified using Sobel, Roberts, Prewitt, and Canny edge detection methods. Then, an AI-driven Random Forest model was applied to identify and select the most optimal edges from the results of these algorithms. In this process, an image is analyzed using a Random Forest model-based method of feature extraction concerning segmentation. In this feature selection, only the most relevant information of the image content, like vessel or other boundary edges, is kept while noise is reduced and segmentation accuracy improved. Such features make the Random Forest model highly effective for non-linear relationships and handling high-dimensional data. The model then segments the image into meaningful regions once it extracts the relevant features, hence isolating main elements like blood vessels while discarding less important background regions.

An AI-based technique demonstrates its ability to segment coronary angiography blood vessels in heart patients as presented in Figure 2. The segmented blood vessels demonstrate high correspondence to their corresponding annotated ground truth images. The performance evaluation of this proposed method utilizes accuracy alongside DC, PPV, and sensitivity which stem from confusion matrix calculations.

Figure 3 indicates the segmented image using an angiography image and the ground truth images. Performance of blood vessel segmentation from coronary angiography images using the Random Forest-based model. The three columns represent, respectively, the original grayscale images, the annotated ground truth masks by experts, and the predicted segmentation by the model. The accuracy is 99% with a dice coefficient of 95%, indicating a large overlap between the vessel areas predicted by the model and the ground truth images. In fact, a PPV of 96% depicts that most of the vessels predicted by the network are correctly classified with only a tiny number of false positives, while a sensitivity of 94% underlines how strong the model is in terms of detecting most vessel areas. As illustrated in the figure, though there are slight mistakes, in general the predicted results match the annotated masks very well, A confusion matrix developed with segmentation results enables researchers to determine the total counts of true positive, false positive, true negative and false negative outcomes. The collected information aids both verification and accuracy enhancement for segmentation procedures.

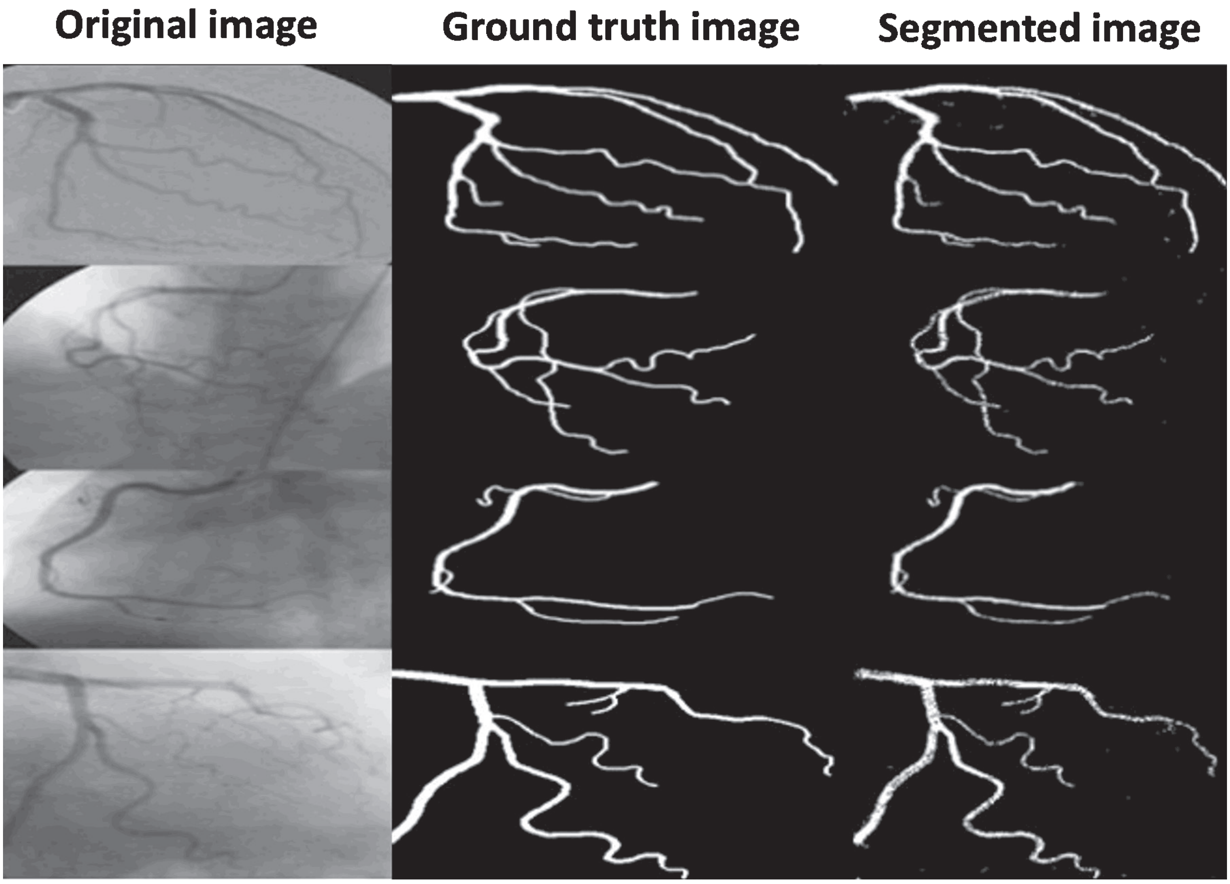

Figure 3. *Outcome of segmented blood vessels in coronary angiography.*

Table 1 clearly demonstrates that various performance metrics of the Artificial Intelligence based model, such as accuracy, PPV, DC, and sensitivity, have been analyzed in the context of the current work involving edge-based feature selection and the AI model. Several evaluation metrics have been computed and compared against other existing models with datasets.

Table 1 highlights the use of edge detection techniques such as Sobel, Roberts, Prewitt, and Canny algorithms for vessel segmentation. The experimental results demonstrate the performance of the proposed model in terms of PPV, sensitivity, DC, and accuracy, comparing favorably to other existing models. From Table 1, it is evident that the predicted results for blood vessel segmentation in coronary angiography images deliver promising outcomes. In the proposed model, a total of 134 images were utilized for training and testing. The research designated 80% of images for training purposes and reserved 20% for validation. Specialized AI features were integrated into the Random Forest model by the research team to obtain precise target region localization.

Table 1. Comparison table of predicted results.

Methods	Authors	Material	PPV	Sensitivity	DC	Accuracy
Deep learning (MTNet)	Ruochen Liu, Song Gao *et.al*.[35]	Retinal blood vessels	80%	98%	88%	96%
Machine learning (supervised method)	Hyungjoo Cho,June-Goo Lee, *et al*.[36]	Angiography images	84%	80%	82%	82%
DL (PSPNet)	Xiliang Zhu, Zhaoyun Cheng, *et. al*.[37]	Coronary angiography image segmentation	86%	94%	89%	95%
Deep learning (U-Net)	Dongxue Lian *et.al*.[38]	Coronary angiography images	84%	87%	83%	98%
Edged based feature using AI	Our's	Coronary angiography Images	96%	94%	95%	99%

Note*: PPV: positive predictive value, DC: dice coefficient.*

The following table compares various approaches applied to image-based datasets in medical imaging with respect to metrics such as PPV, sensitivity, DC, and accuracy. A performance study of each technique adopted using different datasets is conducted—retinal blood vessels, angiography images, and coronary angiography images. The proposed methodology, marked as "Our's," is the edge-based feature extraction approach which has been empowered by a Random Forest model on coronary angiography images. Conclusively, the proposed approach outperforms other methods on most metrics. Having identified the image of retinal blood vessels with a deep learning model, the first approach of MTNet reached 80% PPV, with 98% sensitivity, 88% DC, and accuracy at 96%. MTNet, while performing exceptionally in sensitivity to identify true positive cases, performed lower in PPV, probably due to increased false positives[34]. This trend underlines the need for a model characterized by better balance in terms of all metrics. In the case of angiography images, regarding the overall performance of machine learning supervised techniques, the PPV is 84%, sensitivity is 80%, DC is 82%, and accuracy is 82%. This approach has given a moderately good performance; however, the sensitivity resulting from this approach is relatively low, which means failing to detect some positive cases.[35] Moreover, the DC illustrating the overlap between the predicted and ground truth segmentations is low, which suggests possible drawbacks in the accuracy of segmentation. The deep learning-based image segmentation approach in coronary angiography, PSPNet, gives a PPV of 86%, sensitivity of 94%, DC of 89%, and accuracy of 95%. Compared to all the earlier-described techniques, this technique gives much better sensitivity and overall segmentation accuracy.[36] Hence, it signifies higher capacity for detection and classification of features in medical images. However, a slightly lower PPV against "Our's" indicates that there is still room for improvement in this technique to get better precision. using U-Net as the architectural framework for examining images from coronary angiography. The accuracy, precision, recall and specificity of their approach were 84%, 87%, 83% and 98%, respectively.[37] Edge-based feature extraction using AI shows much better performance than their methods.

The method in the last row, "Our's," represents an edge-based feature extraction technique by employing a Random Forest model on coronary angiography images. It outperformed well with a PPV of 96%, sensitivity of 94%, DC of 95%, and accuracy of 99%. Compared to all other techniques, the "Our's" method was superior for most metrics with the highest PPV, DC, and accuracy. With the high PPV, the method seems to minimize false positives effectively, making it more accurate. Its sensitivity is also compared with PSPNet at 94%, hence showing very good capability for the detection of true positives. Moreover, the DC has indicated excellent overlap between predicted and ground truth segmentations at 95%, hence highly reliable for correct analysis of images. Thus, at the highest accuracy of 99%, it is also quite robust and has the potential for clinical medical use.

Data availability statement

The dataset used in this experiment is publicly available on the Mendeley website.

Conclusion

Based on the results and analysis, the experimental findings prove that the developed protocol executes segmentation tasks in coronary angiography images with superior effectiveness. The proposed method produced segmentation results with accuracy reaching 99% and dice coefficient at 95% and positive predictive value at 96% and Sensitivity at 94%. The method's superior scores confirm that it ranks above former techniques known to work in this domain. Research in this field should investigate potential soft computing methods for classifying coronary angiography vascular structures.

Ethical approval

There was no human or animal ethics violated in this experiment.

Funding

None

Conflict of interest

There is no conflict of interest for this manuscript.

Credit authorship contribution statement

The first two authors designed and implement the core idea, while the third author provide expert insights on the experimental results and analysis.

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