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Blockage in Coronary Artery Detection and Quantification in Coronary Angiography

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Abstract—The segmentation of the coronary angiography is extremely crucial in computer-aided diagnosis of arterial motion evaluation. It is difficult to create an automated vessel segmentation method using vascular structures because of the wide range of intensities and noise. The suggested method is an unsupervised method that uses coronary angiogram of the heart as a source and in order to get vascular centerlines, segment vessels, and identify heart vein blockages. First, a preprocessing procedure is utilised to enhance and get rid of the image's low frequency noise using morphological filters and a contrast constrained adaptive histogram equalisation. The extraction of the vascular structure is done using a morphological hessian-based method. The wide and narrow vessels are removed using two distinct scales. After that, the vessel's axis of rotation is extracted. In order to find the bifurcation, it employs a branch detection algorithm. Obstructions are located by considering the diameter across the vessel's cross section. The efficiency of the suggested method has been evaluated, as evidenced by testing results on a variety of images, achieving an accuracy of 97.08%.

Keywords-Coronary artery, vascular segmentation, Blockage detection, morphological operation,

I. INTRODUCTION *(HEADING 1)*

Coronary artery disease (CAD), which is mostly caused by the buildup of plaque, is brought on by blockages in the arteries that supply the heart. The condition is the most lethal in developed nations, with a mortality rate of between 30 and 50 percent among those between the ages of 35 and 64. Only 20% of coronary artery disorders are detected before heart attacks, despite the availability of early effective diagnostic tools. Vascular structures differ in image brightness, noise, and cross sections, hence it is extremely difficult to create a fully automated and precise vascular segmentation system. Since contrast varies throughout the arteries and intensity discrepancies might result in leakages, coronary angiography image vessel extraction using intensity information is inadequate. Utilising shapes before vascular segmentation is difficult because plagued vessels have unusual and unique forms.

The automated segmentation of vascular structures has been suggested using a number of different techniques. A boundary model is used in one such classification approach to determine the borders of the segmented image based on gradient or intensity data. The boundary model is built using the training data available [1-2]. A parametric curve evolution-based vessel extraction approach is reviewed in [3]. The extraction of the centerline is pioneered in [4]. It is required to submit user inputs in [5] at the vessel branch. This article provides a tubular vessel model by modelling the vessel construction as an envelope made up of a group of spheres. The intensity histogram is used to estimate the background and vessel intensity distributions after raising the level set to record the vessel margins. The minimum route approach is the foundation for segmentation. The initialised vessel obtained from the registration of a pre-segmented reference image, is deformed using a level set approach based on histogram information [6]. The unique variational strategy for segmentation is explained in [7], which is based on the level set approach under intensity in homogeneity. Without requiring the vessel's end points, [8] uses a model of each vessel as a tubular structure to detect the vessel and its branches. [9] discusses yet another technique for coronary artery excision. The preprocessing of the angiographic picture in this approach uses an adaptive and multi-hierarchy strategy. The final image is created by merging subimages that are collected at various stages. Using a matched filter-based method[10], dual-sided thresholding and the first order derivative of a Gaussian picture are employed to enhance and segment the retinal vessels. Improved vessels are achieved using morphological filters[11]. Both the supervised and unsupervised techniques are employed for segmenting vessels are covered in [12, 13]. Multiscale medialness function is suggested as yet another approach to extract the heart vascular anatomy [14]. The vascular system's 3D structure is recreated using the volume rendering technique after the blood vessels have been taken out.

The proposed method is utilised to identify blockages and segment the vascular anatomy in cardiac angiography pictures. In this format, the chapter is structured: The proposed method for identifying and quantifying plaques in coronary arteries in angiographic visuals is explained in Section 2. The preprocessing of the image is followed by the extraction of the centerline and the bifurcation is discovered using the vessel branching method. Finally, the vessel blockages are identified. Section 3 compares the performance of the proposed strategy

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with current approaches. Finally, Section 4 provides a conclusion to the suggested strategy.

II. SYSTEM ARCHITECTURE

The segmentation of coronary angiograms is a challenge that can be resolved by the integrated structure of the suggested approach. The vessel bifurcations are then recovered from the picture by navigating through the intensity gaps along the vessel direction after the image has initially been improved. Figure 1 depicts the proposed system architecture.

A. Preprocessing

Preprocessing is the initial phase, which is used to improve the original image and make illumination adjustments.

A) Adaptive histogram equalisation with contrast constraints

To enhance the visuals, contrast constrained adaptive histogram equalisation is used. By broadening the low-contrast image's grey level qualities, the histogram is equalised [17]. This technique does local histogram equalisation after dividing the picture into parts [18]. The user can specify the clip value. The noise level specification may be slowed down and the contrast level can be raised thanks to the clipping restriction. The clipping limit in this research is set at between 0 and 0.01.

B) Morphological filtering

Morphological filters are used to improve the vascular architecture. Vascular structures seem to stand out more from the background. The top hat transform is the foundation of the morphological filter. The largest vessel selected as a standard for breadth. The vessel width in the suggested method ranges from 1 to 8 pixels. Noise has an impact on top hat metamorphosis. As a result, the loaded picture's pixel values are altered to be smaller than or equal to those in the input image. Variations in intensity result from this. The issue is addressed by a modified top hat transform [19] that executes a closure operation followed by an opening operation without the need for a comparator or minimum operator.

B. Broad and narrow vessel extraction

The Broad and narrow vessels are retrieved from the morphologically improved image using the hessian matrix and the Eigen value technique, and the Canny edge operator is used for taking out arterial structures. The vessels with changing width are represented by the second order derivative at various scales. Non-vascular structure is suppressed and contrast is improved by using the difference in the eigen values of the hessian matrix. In this work, is chosen as 1 and 2.5.

C. Detection of Vessel Bifurcation

The vascular system expands before creating new branches. Identifying the vessel branches is a hurdle. While the algorithm advances through the vessel tree, the vessel branches are monitored.

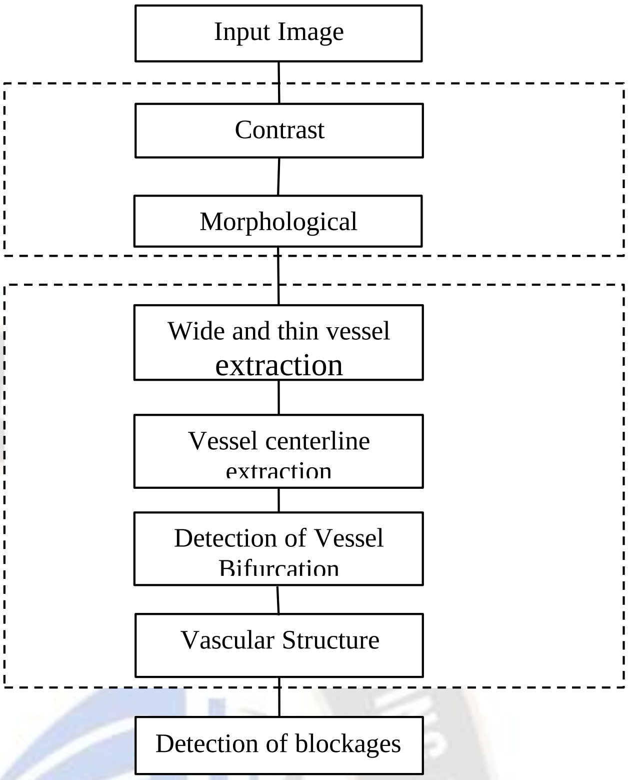

Fig. 1: Flowchart of proposed system

Algorithm:

1. Create a sphere S2 with R as radius.
2. Take Samples of N in di directions.
3. Build tubular structures with a R of 1 and a length as radius in each of the N directions.
4. Determine the average intensity for individual tube, say $I_{mean(di)}$.
5. Using the parent intensity as a reference, apply the threshold to the predicted intensity. I_{thres}.
6. Deploy the subclass of direction where the average intensities are greater than threshold.
7. Perform k-means algorithm [21] on the direction detected. That That is and with three clusters [22].
8. If there are fewer than three clusters, then
   No branches
9. Else

i) Determine the direction's centroid for each cluster. There are 3 branch directions as a consequence.

ii) The direction with the highest volume overlap with the root branch is deleted.

iii) Do the product of root branch's tangent and the remaining directions at terminating point.

iv) The root branch is prolonged in the direction of the candidate that is most closely associated with tangent at termination point.

v) A fresh branch is formed with the tree structure's last candidate direction.

D. Detection of Blockages

The disease known as plaque causes the coronary arteries to constrict and have less blood flow. Plaques that are obstructions are taken into account when a region of interest is being detected, and a canny edge operator is used. Blood vessel obstruction is identified and quantified at each point i based on

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the area of cross section, where i can have values ranging from 1-n, where n is the count of places along the midline.
Determine the diameter of D. The following is how blockages are found.

i) Let Di-1 be the diameter at position Pi-1
ii) Di,n-1=Di-1
iii) If (Di,n>Di,n-1) then
   a. It computes the sites where Di, if diameter centered at Pi,n-1 is greater than n.
   b. Estimated places greater are identified as obstructions.

E. Quantification of plaques

The elliptical curve fitting method [23] is used to determine the cross-sectional area of coronary arteries in both healthy and sick arteries. The area under the fitted ellipse curve is used to estimate the severity of the blockages. The following equation is used to compute the area.
where r_1 denotes the ellipse's major axis and r_2 its minor axis. To calculate risk factor, the blockages are measured based on the percentage of blockages. Using the following equation, the percentage of blockages is computed.
where $Area_N$ represent the area of the normal artery and $Area_{AN}$ represents the area of the abnormal artery containing blockages.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, 15 real-time image datasets of patients aged 35 to 78 were used in the experiment. The patients whose images were utilized for the trial had no prior history of coronary stent insertion, pacemaker implantation, bypass surgery, or iodinated contrast material allergy. On genuine images with obstructions, the proposed approach is put to the test. The proposed method is put into practice using Matlab 12 and an i3 processor. The suggested approach has the following qualities: i) It is powerful when it is first recognized. ii) It may operate without human input by following the vessel tree. iii) It can automatically identify blockages by accounting for blood artery constriction based on the diameter and cross-sectional area. Preprocessing requires relatively little calculation and takes just about 3 seconds, while tracking the vessels and the centerline takes approximately 8 seconds and detecting obstructions takes around 12 seconds. Even if the coronary artery is automatically divided, there is still opportunity for blockage detection. Long obstructions continue to be underreported and blockages are discovered based on the diameter profile. According to the proposed strategy, lengthy obstructions are taken into account depending on the artery's minimum diameter. Figures 3 and 4 illustrate the real-time input image and the preprocessed image with contrast enhancement, respectively. The vessel centerline and borders are shown on several color maps. The color maps offer an effective technique to identify the vessel's cross-sectional area. Figure 2 displays the results of the proposed system. The proposed approach dealt with the fewest false positives possible. 12 datasets had an average of 18 false positives. The proposed method is contrasted with two cutting-edge methods, the vascular structural pattern detector (SPD) [14] and probabilistic tracking operator (PTO) [13] and the results are shown in figure 3 and 4.

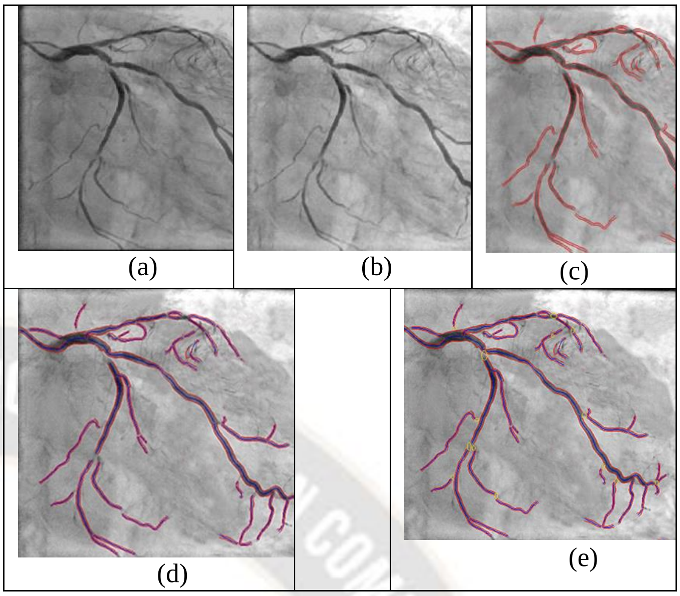


Figure 2: Proposed Method (a) Input image (b) Contrast enhanced image (c) Extracted vessel edges (d) Centerline extraction shown in blue color (e) Blockage detected are marked by fitting ellipse in yellow color

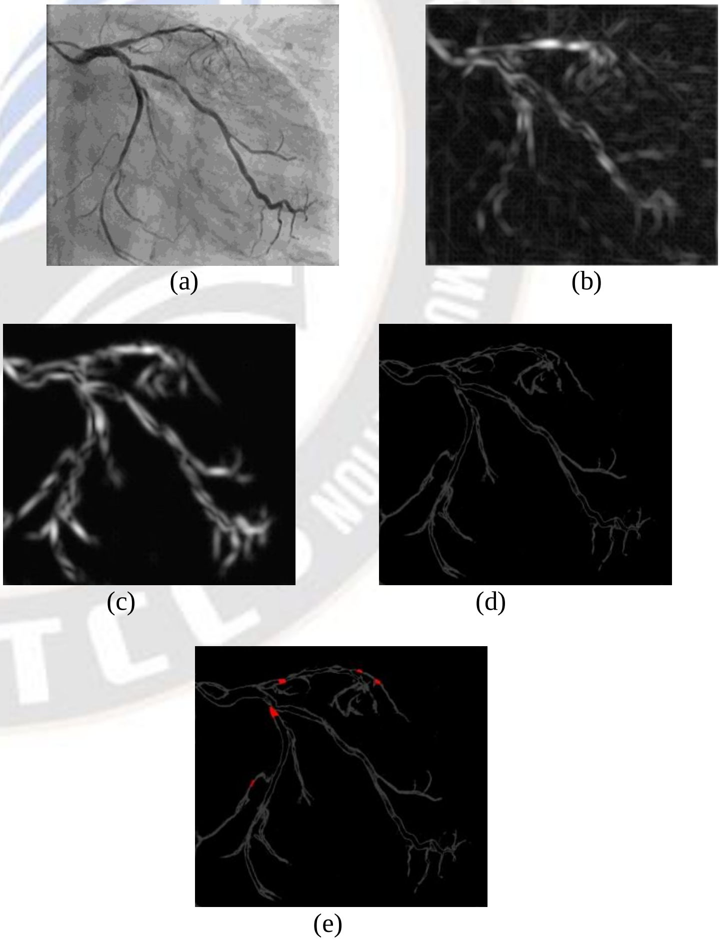
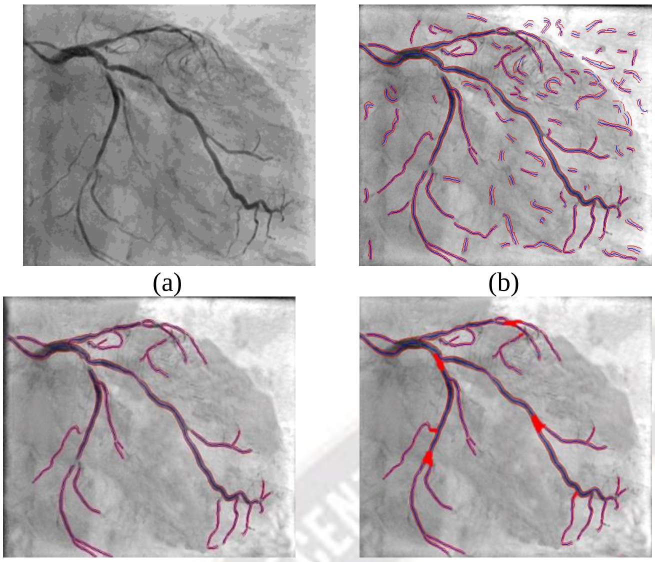


Figure 3: Results of SPD (a) Input Image (b) Gabor Filter (c) Hessian vessel extraction (d) Extracted Vessel (e) Plaque detection



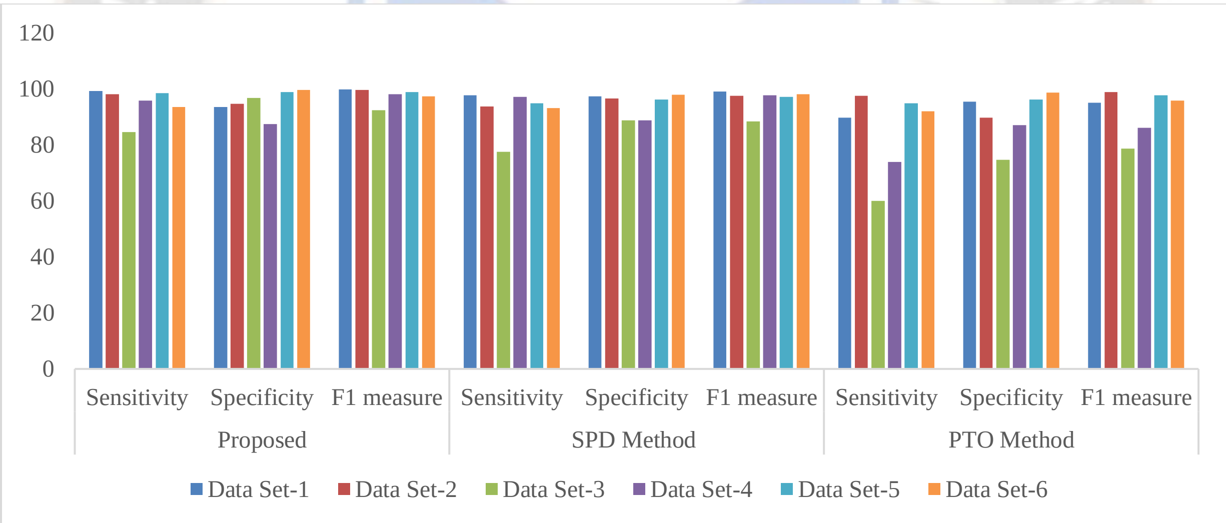
(a) (b) (c) (d)

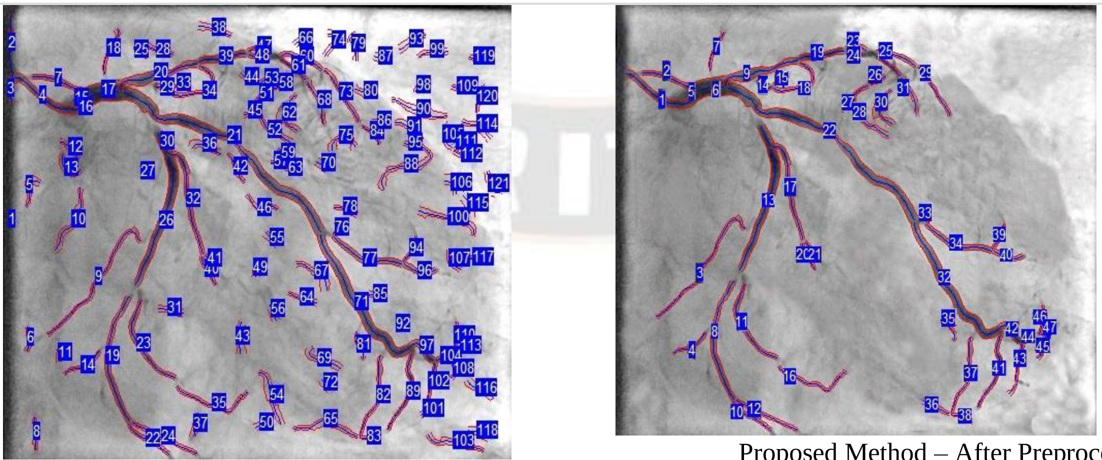
Figure 4: Results of PTO (a) Input Image (b) Centerline extraction (c) Lumen Segmentation (d) Plaque Detection

The performance of the suggested strategy is assessed using a number of performance measures. Clinicians can greatly benefit from the segmentation of coronary arteries and the identification of blockages when establishing a diagnosis of coronary artery disorders. By separating the veins from other unimportant anatomical features and visualizing the coronary tree from proximal to distal ends, coronary disorders may be accurately diagnosed. On 12 patient datasets, the suggested method was evaluated. Table 1 displays the outcomes of performance evaluation on six datasets.

The proposed strategy was created with the goal of achieving the best results in vascular structure extraction, with an average sensitivity of 96.08%. The outcomes of the vessel extraction before and after preprocessing are shown in Figure 5. The tiny vascular structures seen on the cardiac muscles are treated prior to preprocessing. These vessels are veiled after preprocessing due to consistent intensity fluctuation. The results demonstrate that precise and exact vessels are created following preprocessing. The outcomes of vessels collected both before and after preprocessing are shown in Table 2.

TABLE 1. COMPARISON OF PERFORMANCE METRICS BASED ON VESSEL EXTRACTION





Before Preprocessing

Proposed Method – After Preprocessing

Figure 5 Results of vessel extracted before and after preprocessing

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TABLE 2 COMPARISON ON NUMBER OF VESSELS EXTRACTED

Dataset	Before Preprocessing	After Preprocessing	
		Proposed	SPD
1	134	44	48
2	121	47	45
3	96	23	30
4	115	47	43
5	93	28	30
6	128	45	47

The proposed work's comparative performance metrics are shown in Figure 6. Given that the disparity might not be directly tied to any section of the vessels, additional modifications would not always be needed based on the locations of disparities. The sensitivity of the proposed method tends to decline as segmentation gets closer to the distal end of the tube.

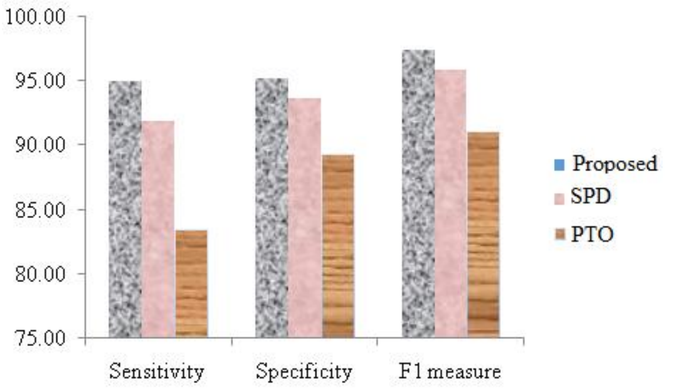

Figure 6 Performance analysis based on sensitivity, specificity and F1 measure

The comparative study of the proposed work using the SPD and PTO Methods is shown in Figure 7 in terms of Accuracy(ACC), Area overlap (AO) and false discovery rate (FDR). The results show that the proposed approach provides improved vessel segmentation outcomes.

TABLE 3 PERFORMANCE ASSESSMENT OF PROPOSED APPROACH

#Dataset	ACC	AO	FDR
1	94.45	94.38	5.68
2	93.49	93.43	6.75
3	96.05	96.57	3.55
4	88.13	87.65	12.35
5	99.83	99.72	0.39
6	99.97	99.85	0.29

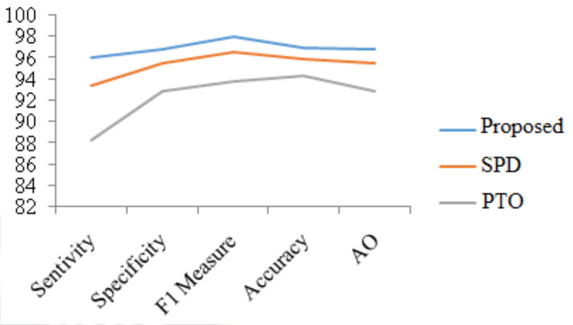

Figure 7 Comparative Analysis

The outcomes also show that, when performance measurements are averaged, the proposed approach performs better than the preceding work. The percentage of identified artery segment (DAS) is determined to assess the vascular segment detection. The suggested technique obtained 97%, whereas the DAS% produced by PTO is 92.36% and the detected artery segment on 12 datasets provided by SPD reached 95.46%.

TABLE 4. PERFORMANCE EVALUATION

Techniques	Accuracy	AO	FDR
Proposed Work	97.08	97.055	3.233
Work [15]	96.099	95.39	4.37
Work [16]	95.02	93.005	6.995

80% of the patient dataset, or 12 patients, were employed on a patient-by-patient basis for the identification of blockages. Three patients, or the remaining 20%, were removed because the images were of low quality and had motion artefacts. The shortcoming of the work is that the extraction phase of centerline necessitates initializing the coronary artery's start point. The user must interpret the starting point for each data collection. After startup, the centerlines in the vessels and across vessel branches can be obtained automatically. The centerlines can be used to find obstructions. Based on an examination of obstructions, the performance is displayed in table 5

TABLE 5. PERFORMANCE ANALYSIS BASED ON THE NUMBER OF BLOCKS

Dataset	**Sensitivity**	**Specificity**	**Accuracy**
1	99.57	82.02	97.59
2	99.68	77.45	96.54
3	99.09	85.42	97.35
4	98.63	77.45	95.78

5	98.29	78.23	95.05
6	98.44	77.57	95.44

The results of coronary angiographic image blockage identification on six datasets are displayed in Table 6. Ten images from each dataset are processed. 60 images in total have been processed.

The two third portion of the image along the height and width is chosen and the vessels in those areas are considered as major vessels and the rest of the vessels are chosen as minor vessels.The large vessels are those that make up the second-third of the image's height and breadth, while the minor vessels are those that make up the remaining third. The severity of a heart attack is seen in Table 7

TABLE 6 DETECTION OF BLOCKAGES IN CORONARY ANGIOGRAPHIC IMAGES

Parameters	Number : #6 datasets	Blockages	
	No of images	Present	Absent
Significant CAD	60	51	9
One vessel Blockage	28	21	7
Two vessel Blockage	15	14	1
More than Three vessel Blockage	17	16	1

TABLE 7 SEVERITY OF HEART ATTACK

Data set	Percentage of block	Severity
#1	98	Severe
#2	20	Minimal
#3	77	Severe
#4	65	Moderate
#5	30	Mild
#6	26	Minimal

The outcomes demonstrate that during CT angiography, the healthy vascular lumen is roughly uniform. Contrast agent is used during CT angiography. The contrast agent does not penetrate the areas of the vessels where the plaques are located. As a result, such vessel lumen do not have the same intensity, and the extraction of the lumen does not apply to these areas. These areas are utilized to measure the blocks and determine how severe a heart attack is. Two kinds of analysis were used: one to assess the vessel segmentation and the other based on plaque detection.

IV. CONCLUSION

The proposed work enables the separation of arteries and the diagnosis of coronary artery blockages. The results of the experiments demonstrate that the proposed approach delivered findings with a level of precision comparable to that of experts. According to the findings, the average sensitivity over the entire sample of 12 data points is 97.08%, with a deviation of 2.85. By combining morphological and intensity information, the study will be expanded in the future to include the identification of blockages, which might increase the ability to detect coronary artery diseases.

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