RESEARCH PAPER

Blood Vessels Disease Detection of Coronary Angiography Images using Deep learning Model

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Abstract:

Presently Coronary artery disease, often caused by the narrowing of the coronary artery lumen due to atherosclerosis, is a leading cause of death. Coronary angiography also known as cardiac catheterization or X-ray angiography, is a medical procedure that uses X-ray imaging to visualize the coronary arteries, which supply blood to the heart muscle. X-ray angiography is procedure to assess the blood flow through these arteries and to identify any blockages or abnormalities. The accuracy of X-ray angiography depends on the quality of the imaging equipment as well as experience and expertise of the radiologist. Poor image quality could affect the accurate diagnosis of coronary arteries. Manual interpretation of angiography images are subjective and time consuming. In some cases, small or diffuse blockages may not be easily visible, and additional imaging techniques may be required. Therefore, early automated detection of blockage of heart vessels became necessary for detection and diagnosis. The artificial intelligence algorithms could play a vital role in this area. In this paper, a deep-learning based algorithm has been used for recognition of blockage in coronary angiographic visuals. Here, we proposed deep learning (YOLOv8) models for the detection of blockage into blood vessels coronary angiography images. In this experiment about 2000 labelled X-ray angiography images has been used from Mendeley. For Experimentation purpose, images are preprocessed and augmented. Total 80% images have been used for training and 20% images has been used for testing. The experimental results show that the measuring metrices of proposed model for detection of blood vessels blockage area in rectangular box. The performance of model represented by predicted value of Precision, recall, mean average precision (mAP) and F1 score are, 99.4%, 100%, 99.5% and 99.7% respectively.

Keywords: CAD, Heart Angiography, Yolov8, Deep learning, blockage detection;

How to cite this article: Osama M, Kumar R, Shahid M, Singh CK. Blood Vessels Disease Detection of Coronary Angiography Images using Deep Learning Model. Int J Drug Deliv Technol. 2026;16(14s): 487-497.

DOI: 10.25258/ijddt.16.14s.50

Introduction:

Coronary artery disease (CAD), also known as coronary heart disease (CHD) or simply heart disease, is a common and serious cardiovascular condition that primarily affects the coronary arteries [1]. These arteries supply oxygen-rich blood to the heart muscle, allowing the heart to function properly. CAD occurs when these arteries become narrowed or blocked due to the buildup of plaque, a substance made up of cholesterol, fat, calcium, and other substances [2]. There are the many reasons to develops the coronary arteries disease on human body.

Atherosclerosis: The primary cause of CAD is atherosclerosis, a gradual process in which plaque accumulates on the inner walls of the coronary arteries over time [3]. Plaque buildup narrows the arteries, reducing blood flow to the heart.

Reduced Blood Flow: As the coronary arteries narrow, they can limit the amount of oxygen and nutrients that reach the heart muscle [4]. This reduced blood flow can lead to various symptoms, such as chest pain or discomfort known as angina.

Heart Attack (Myocardial Infarction): If a plaque in one of the coronary arteries ruptures or if a blood clot forms over a plaque, it can suddenly block blood flow to a portion of the heart muscle [5]. This can result in a heart attack, which can cause permanent damage to the heart muscle.

Risk Factors: Several risk factors contribute to the development of CAD, including high blood pressure, high cholesterol levels, smoking, diabetes, obesity, a sedentary lifestyle, a family history of heart disease, and advanced age [6]. Managing these risk factors can help prevent or slow the progression of CAD.

Symptoms: CAD may be asymptomatic (no symptoms) in its early stages. However, as the disease progresses [7]. common symptoms can include chest pain or discomfort (angina), shortness of breath, fatigue, and in severe cases, heart attack symptoms like chest pain, shortness of breath, and pain radiating to the arm, neck, or jaw.

Diagnosis: CAD is typically diagnosed through various tests, including electrocardiograms (ECGs or EKGs), stress tests, coronary angiography (as described in a previous response), and imaging studies like CT angiography or MRI [8].

CAD management involves lifestyle changes (e.g., diet, exercise, smoking cessation), medications (e.g., statins, antiplatelet drugs), and medical procedures (e.g., angioplasty, stent placement, coronary artery bypass grafting) to alleviate symptoms, improve blood flow, and reduce the risk of complications. Prevention and early intervention are crucial in managing coronary artery disease. Lifestyle modifications and appropriate medical treatment can help individuals reduce their risk factors and maintain heart health. Regular medical check-ups and discussions with a healthcare provider are essential for those at risk or with a history of CAD[9]. Using some regular strategies to prevent from the coronary arteries disease-

Healthy Diet used to adopt a diet rich in fruits, vegetables, whole grains, lean proteins (such as fish, poultry, and legumes), and low-fat dairy products[10]. Limit saturated and trans fats, cholesterol, and sodium intake. Regular Physical Activity preforms to make Aim for at least 150 minutes of moderate-intensity aerobic exercise or 75 minutes of vigorous-intensity exercise per week. As well as we have also Achieve and maintain a healthy body weight by balancing caloric intake with physical activity[11]. Consult with a healthcare provider or registered dietitian for personalized guidance on weight management.

Smoking is a major risk factor for CAD. Seek assistance and support to quit smoking[12]. Avoid exposure to second hand smoke. If you drink alcohol, do so in moderation[13]. This generally means up to one drink per day for women and up to two drinks per day for men. And we have also manage the stress using a healthy ways, such as relaxation techniques, meditation, yoga, or engaging in hobbies[14]. Prioritize work-life balance and take time for self-care.

Coronary angiography is a medical procedure that uses X-ray imaging to visualize the coronary arteries, which supply blood to the heart muscle[15]. The process of obtaining coronary angiography images involves several steps:

1. Patient Preparation: Before the procedure, the patient is prepared for angiography. This typically includes reviewing the patient's medical history, conducting a physical examination, and checking for any allergies, particularly to iodine-based contrast dye.
2. Local Anaesthesia: Local anaesthesia is applied to numb the area (usually the groin or wrist) where the catheter will be inserted. In some cases, conscious sedation may be administered to help the patient relax during the procedure.
3. Catheter Insertion: A thin, flexible tube called a catheter is inserted into a blood vessel (usually the femoral artery in the groin or the radial artery in the wrist) using a needle and guide wire. The catheter is carefully threaded through the blood vessel and advanced to the coronary arteries.
4. Contrast Injection: Once the catheter is in the desired position within the coronary arteries, a contrast dye (iodine-based) is injected through the catheter directly into the coronary arteries. This dye makes the coronary arteries visible on X-ray images.
5. X-ray Imaging: X-ray equipment is used to capture real-time images of the coronary arteries as the contrast dye flows through them. Multiple X-ray images are taken from various angles to provide a comprehensive view of the coronary arteries.
6. Image Interpretation: The angiography images are closely monitored and interpreted by a specialized healthcare team, usually consisting of interventional cardiologists and radiologic technologists. They assess the size, shape, and any abnormalities or blockages in the coronary arteries.
7. Treatment Intervention (if necessary): In some cases, if a significant blockage is identified during the angiography, a treatment procedure may be performed immediately. This could include angioplasty (a procedure to widen the narrowed artery) or stent placement (inserting a small metal mesh tube to keep the artery open).
8. Catheter Removal and Haemostasis: After the procedure, the catheter is carefully removed, and pressure is applied to the insertion site to

prevent bleeding. A bandage or pressure device may be used to aid in haemostasis.

9. Recovery and Monitoring: The patient is typically observed in a recovery area for a period to ensure stability. Vital signs are monitored, and the patient is assessed for any potential complications.

We are likely describing the visualization of coronary artery blockages or stenosis (narrowing) through this imaging technique. Currently automatically detect the blockage of artery of heart using various artificial intelligent technique. At present time deep learning technique, such as convolutional neural network (CNN) model has to predict the image recognition task and also included image analysis. CNNs is a model of deep neural network that can learn to extract features from images and classify them into different categories[16]. A series of CNN-based object recognition algorithms titled You Only Look Once (YOLO) are able to quickly locate and identify multiple objects in an image. Our research is a continuation of earlier work on deep learning-based medical image analysis, which has demonstrated promising outcomes for detecting a number of diseases, which include breast cancer, lung cancer, and diabetic retinopathy. But to our knowledge, no prior research has evaluated how effectively YOLO algorithms work in recognizing stenosis in coronary arteries in radiographic images[17]. We want to figure out how well the cutting-edge YOLOv8 algorithm performs for accurately detecting coronary artery stenosis in angiography pictures. Our objective was to establish a fast and precise tool for cardiologists for recognizing CVD, which would eventually lead to better patient outcomes.

To accomplish this, we collected a dataset of angiography images from patients diagnosed with CAD, and annotated the images to indicate the presence or absence of coronary artery stenosis. We then trained the YOLOv8 algorithm on this dataset using transfer learning, which involves fine-tuning a pre-trained model on a new dataset [18].

In recent years, deep learning has emerged as a promising tool for medical image analysis, offering several advantages over traditional image analysis methods. For example, deep learning algorithms can learn to extract complex features from images without requiring handcrafted features or prior knowledge about the underlying anatomy or pathology. Deep learning also offers high scalability, enabling the analysis of large datasets with millions of images [19]. Our aims to contribute to the growing body of literature on deep learning-based medical image analysis by evaluating the performance of the YOLOv8 algorithm for detecting coronary artery stenosis in angiography images. Our findings have the potential to impact clinical practice by providing cardiologists with a fast and reliable tool for diagnosing CVD. Ultimately, this could lead to improved patient outcomes and reduced healthcare costs.

Literature Review:

In this paper author discuss about the recognition the stenosis of heart angiography images using cnn model of deep learning. The proposed method can be:

In this paper author reported as pipeline based on deep learning for automated analysis to rapidly and objectively find the coronary angiograms. As well as highlighted to coronary arteries of interest and quantitively potential stenosis. The author proposed the three stages to consisting of key frame extraction, vessel segmentation and stenosis measurement for automated analysis method. Where also combined with powerful deep learning method such as ResNet and U-Net architecture with traditional image processing and geometrical analysis. Using above model to improved the key frame extraction precision is 98.4%, as well as vessel segmentation of F1-Score is 0.891 and stenosis quality measurement is 20.7% that show the Type I Error rate.[20]

In this paper, author addressed the segmentation of vessels and diagnosis of disease in coronary angiogram arteries images and proposed an Encoder and Decoder architecture of deep learning, where Encoder method is based on ResNet architecture, and the deep features are exacted automatically and Decoder also produces the results of segmented vessels by balanced cross-entropy cost function. The experiment results show that the algorithm has exacted the feature and edge information effectively. Such as the segmentation result of precision for three typical vessels are 0.8365, 0.8924 and 0.6297 as well as the F-measure score are 0.8514, 0.8786 and 0.7298, respectively.[21]

The author introduced about the Automatic segmentation of coronary artery and diagnosis of stenosis using deep learning approaches based on computed tomographic coronary angiography images. In segmentation process, which have extracted the region of interest (ROI) from computed tomographic coronary angiography images with U-Net architecture. The second task is an identification process, that are implemented using 3DNet model. The computed tomographic coronary angiography images and clinical parameters were input into 3DNet, and the coronary arteries diagnosis output. The predicted result of segmentation model had evaluated the mean Dice Cofficient value of 0.771±0.021. Based on this deep learning model, its is built an automated diagnosis model such as classification model for coronary arteries disease. The average accuracy and the receiver operating characteristic curve (AUC) had 0.750 ± 0.056 and 0.737, respectively.[22]

This paper was described about the segmentation of coronary angiography images using DBCU-Net model of deep learning approach. which is an extension of various deep learning approaches like as U-Net, DenseNet and bi-directional ConvLSTM(BConvLSTM). The main contribution of this model was the feature extraction of U-Net instead of convolution network, where the dense connectivity and the bi-directional ConvLSTM to highlight salient features. The result achieved average Accuracy, Precision, Recall and F1-score for coronary artery segmentation of 0.985, 0.913, 0.847 and 0.879 respectively.[23]

The author was proposing a real-time system for fetal cardiac substructure detection using yolo model (You Only Look Once) framework on US video. In YOLO model could be used end-to-end neural network to predictions the cardiac substructure of objects, boxes, and corresponding to classes with probabilities simultaneously. To evaluate the reliable performance and 40 fetal echocardiography videos for trained with the new YOLOv7 architecture and fine-tuned to work optimally and run efficiently. This proposed model conducted with nine cardiac substructure objects such as the left atrium, right atrium, left ventricle, right ventricle, tricuspid valve, pulmonary valve, mitral valve, aortic valve, and aorta. And corresponding achieved results of the highest mean average precision of 82.10% respectively. [24]

In this paper, author proposed the two-step deep-learning model to partially detection of stenosis from X-ray coronary angiography images. In these two steps, it is used two distinct convolutional neural network architectures in deep learning, first is shows that automatically identify and classify the various view angle, and second is shows that to determine the bounding boxes of these regions of interest in coronary angiography where stenosis is detected. Some deep leaning processes like as Transfer learning and data augmentation techniques (increase the data) were used to improve the performance of the system corresponding these two tasks. The author can achieved the results of this model having a 97% accuracy for the task of classifying the Left/Right Coronary Artery (LCA/RCA) with angle view and also predict the recall value is 0.68/0.73 for determination of the regions of interest, for LCA and RCA, respectively.[25]

The author had presented the Automatic Region-based CAD image diagnostics using X-ray angiography images which takes more challenge to held at MICCAI 2023. Author can used three-stage approach for combines preprocessing and feature selection for artery segmentation by classical computer vision to improve the vessel contrast, followed by YOLOv8 model to propose possible vessel by generating a vessel map. Since the final segmentation process is based on a logic-based approach to reconstruct the coronary arteries in a visual based sorting method. There are using confusion metric to evaluate the results of F1 score is 42.2% and 42.89% on the validation and hold-out sets respectively.[26]

In this paper, the author identify calcification in coronary OCT images using a rectangle bounding box and prediction bias was also be reduced in automated prediction models. The author can be used the approach of a deep learning model based object detection to instantly draw the bounding box of blockage region in coronary OCT images. Which was predict of uncertainty measurement based on the expected calibration errors. Thus assessing the certainty level of detection results of coronary OCT images can be achieved. So the predicted results of calibrated confidence in a confidence error is ~0.13. Finaly the confidence calibration on calcification detection could be provide a more trustful result.[27]

In this paper, the author discussed about the automatically detection of Coronary Metallic Stent Based on various deep learning model like as YOLOv3 and R-FCN. Author used two trained model for image training. First task is the "You Only Look Once" version 3 (YOLOv3) and the second task is Region-based Fully Convolutional Network (R-FCN), to detect metal support struts in IVOCT (intravascular optical coherence tomography). Using theses two model the results was achieved in between the YOLOv3 and R-FCN that having the precision, recall, and AP all above 95% in 0.4 IoU threshold.[28]

This paper was focused on the uses of deep learning approaches-based KD detection from cardiac ultrasound images. The proposed study of a framework of deep learning architecture Scaled by YOLO version HarD-Net. Which was also added the recent YOLO version but using with the CS Dark-Net backbone replaced by the CSP HarD-Net framework. From above proposed model, the experimental result calculated that the mean average precision (mAP) of Scaled YOLOv, and HarDNet was 72.63 %, which is higher than Scaled YOLOv. YOLOv are 70.05 % and 67.79 % respectively.[29]

In this paper the author proposed about a coronary artery fibrous plaque detection method based on deep learning with Convolutional Neural Networks (CNN) automatically. The author present a novel techniques for identifying a path to capture the context and a symmetric expanding path that representation of precise localization. This model can utilizes the feature based contracting path and the expanding path, where the features can present the context and as well as accurate localization, both model was used the multi-scale feature for plaque detection. In this Experimental process the results predict using proposed method to find a coincidence is 91.04%, accuracy is 94.12%, and recall is 94.12% respectively.[30]

In this literature, the author discussed about the automatics detection of vulnerable plaque for intravascular optical coherence tomography (IVOCT) images based on deep learning convolutional neural network (DCNN). The model was composed mainly four modules such as firstly applied pre-processing, deed convolutional neural networks (DCNNs), post-processing, and lastly ensemble them. Using this model the Experimental results should be achieve that a precision rate is 88.84%, recall rate is 95.02%, and the overlap rate is 85.09% as well as the related detection quality score is 88.46% respectively.[31]

Material and Method:

Datasets: The data is used in this study that collected from the Mendeley. In this dataset, it was present a set of angiographic imaging series who underwent coronary angiography using Coroscopy (Siemens) and Innova (GE Healthcare) image-guided surgery systems at the Research Institute for Complex Problems of Cardiovascular Diseases (Kemerovo, Russia). All patients had angiographically and/or functionally confirmed one-vessel coronary artery disease (≥70% diameter stenosis by quantitative coronary analysis or 50 - 69% with FFR (fractional flow reserve) ≤ 0.80 or stress echocardiography evidence of regional ischemia). Angiographic images of the radiopaque overlaid coronary arteries with stenotic segments were selected and then converted into separate images. An interventional cardiologist rejected non-informative images and selected only those containing contrast passages through a stenotic vessel. A total of 8325 grayscale images (100 patients) of 512×512 to 1000×1000 pixels were included in the dataset [32]. All collected image are annotated from the imglab tool. This tool is very useful for labelling the image for the yolov8 model. After the labelling the dataset, it is splited into three part such as training, testing and validation according to yoloV8 model.

Preprocessing: The angiography images of heart vessels were preprocesses the images using the set of various image processing techniques. The preprocessing steps for coronary angiography images play a important role in preparing the dataset for analysis and diagnosis of blockage of vessels. Augmentation helps in creating a diverse dataset by applying various transformations to the existing images. In the context of coronary angiography, augmentation techniques may include rotation, scaling, flipping, and translation. And also handle the variations in patient positioning and image acquisition. Contrast enhancement improves visibility of structures within the image by adjusting the intensity levels. In coronary angiography, enhancing the contrast is crucial for highlighting blood vessels and identifying potential blockages or abnormalities. Techniques such as histogram equalization, contrast stretching, and adaptive histogram equalization can be applied to enhance the visibility of fine details in angiography images. Noise reduction ensures image quality by suppressing unwanted noise while preserving essential details. Filters such as Gaussian filters, median filters, and wavelet denoising are commonly employed to reduce noise in coronary angiography images. And last part is Normalization involves scaling the pixel values of images to a standard range, making them consistent across different images. This step is essential for ensuring that the input data has a uniform distribution, which is particularly important for machine learning algorithms. Normalization can help in improving the convergence of training algorithms and ensures that the models are not biased towards specific intensity ranges present in the original images. These proposed model work on the deep learning YOLOv8 architecture. Firstly, we are applying the data preprocessing, data augmentation of the dataset and then using the deep learning models to evaluate the detection of blockage of heart vessels. Which provides time preserving environment for diagnosis of the cardiovascular diseases to the cardiologist/physician. The steps for the blockage detection of heart vessels have been given in Figure 1.

YoloV8 Model:

The proposed framework for coronary vessels blockage detection is based on the YOLOv8 architecture. The YOLOv8 model is an improved version of the YOLOv5 model. This model uses a large number of backbone network and used feature fusion techniques for improvement to achieve better accuracy in term of object detection tasks. The model of YOLOv8 can be described using this image as follows:

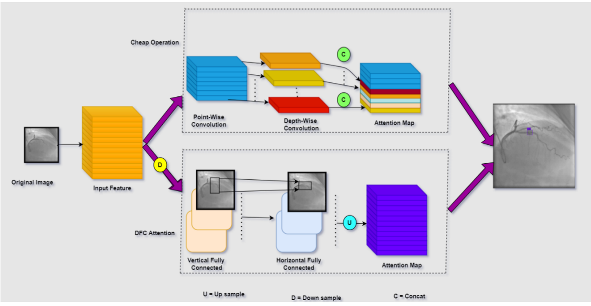

Figure 1: YOLOv8 Architecture for Coronary arteries detection

From figure1, YOLOv8 mostly uses images will be fixed size during training and inference. Commonly required sizes of images include 416x416, 608x608, and 1024x1024 pixels respectively. The Smaller sizes resultant images in faster inference but may sacrifice detection accuracy, while larger sizes of resultant images improved detection accuracy. YOLOv8 architecture is utilize multi-scale feature fusion techniques to integrate features from different layers of the backbone network, allowing the model to capture objects of various sizes and scales more effectively. In above model, both point wise and depth wise convolutional layers are playing important task for extracting the feature the input images and provide the facility to detect the object. Point-wise convolutions are worked in YOLOv8 architecture after feature maps with higher spatial resolution. It helps to decrease the computational cost by reducing the number of channels. After the complete the processes of Point wise convolutions, it followed to depth wise convolutions or other convolutional operations to further process the feature. Depth wise convolutions are primarily used in YOLOv8 model for efficient feature extraction to achieve the accurate blockage detection of heart vessels.

Evaluation: In this paper, we have to evaluated the confusion metrics for evaluate the performance of deep learning (YOLOv8 architecture) model. The performance of the proposed deep learning model for coronary artery blockage detection was evaluated using several performance metrics, including precision, recall, and mAP (Mean Average Precision) score form Equation 1,2 and 3 which is described in below. The results of the evaluation were compared to those of other deep learning models reported in the literature.

Precision: It is a measure of a model's predictions with respect to positive instances. It quantifies the proportion of true positive predictions out of the total predicted positive and false positive instances. Precision is commonly used as an evaluation metric in binary classification tasks[33]. A larger precision value identifies some false positives, which means the model is predicting some incorrect positive predictions. Thus, it is more accurate in identifying true positive instances. Where the goal is to accurately predict true positive instances from a given set of data. Precision can be calculated in Eq. (1).

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \quad \textbf{(1)}$$

Recall: Recall is defining the ability of a model of correctly identify the all-positive predication over the total actual positive prediction. It is also called the sensitivity. Which quantifies the proportion of true positive instance out of the total actual positive predication[34]. A highest sensitivity value indicates some false negatives, that means the model is making some incorrect negative predictions, so it is more effective in capturing all the positive predication. Recall is commonly used for an evaluation metric in binary classification approaches, where the main goal is accurately identifying all positive instances from a given datasets of heart vessels, such as detecting diseases, anomalies, or rare events. So, Recall can be calculated in Eq. (2)

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad \textbf{(2)}$$

Mean Average Precision: mAP is the mean average precision values on different recall levels, that provides the overall measurement of all predicated model. All these predicted models is performing in accuracy of object detection. mAP is basically used for evaluation metric in object detection tasks to assess the better performance of a model in object detecting with interest of high precision across different recall values[35]. mAP can be calculated in Eq. (3)

$$\boldsymbol{mAP(mean\ average\ precision)} = \left(\frac{\boldsymbol{1}}{\boldsymbol{N}}\right) \sum (\boldsymbol{Precision\ at\ each\ recall\ value}) \quad \textbf{(3)}$$

F1 Score: This is often a compliment relationship between precision and recall. There could be cases depending on the domain where we would want either precision or recall to be an important metric values[36]. However, generally, we would be create a model that can perform better results on both. Where the F1 score of metric comes in equation 4. F1 score combines precision and recall into a single metric.

$$F1\ Score = \frac{2*P*R}{P+R} \quad (4)$$

Experimental Results:

The proposed YOLOv8 architecture of deep learning framework for accurate detection of coronary artery blockage using angiography images. The experiment result evaluated using formula of confusion matrix having the equation 1, 2, 3 and 4 to achieved a precision of 99.4%, a recall of 100%, a mean average precision (mAP) of 99.5% during the evaluation process. Then corresponding 99.7% of F1 Score is predicted with the help of precision and recall. Precision represents the proportion of true positive instance among all the positive instance made by the model, while recall represents the proportion of true positive predictions among all the actual positive cases in the dataset. mAP is a commonly used metric to evaluate object detection tasks, and it measures the average precision across different levels of confidence thresholds.

Table 1: Performance of Confusion Metrics Parameter Values

Performance Metrics	Predicted Values
Precision	99.4
Recall	100
mAP	99.5
F1 Score	99.7

From above table 1, give the detail information of performance of confidence matric of YOLOv8 model of detection of blockage of coronary artery using angiography images with analysis of precision, recall and mean average precision for evaluation parameters respectively. From figure2 show that these predicted value of confusion metrics is represented as in the form of graphical representation.

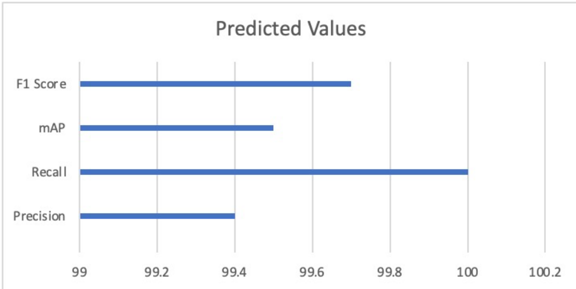

Figure 2: Graphical representation of Confusion Metrices

All these evaluated performances also be present in graphical view with relative confusion metrics parameters in below.

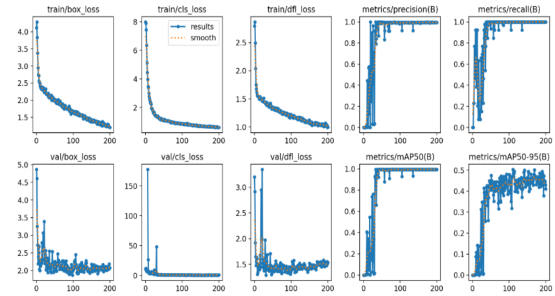

Figure 3: Evaluation of all metrices loss in graphical representation

From above figure3. It is clear that all training and validation losses is reduces with increasing the number of iterations of training images. All reduces parameter is classification loss and box losses with respect to training and validation. The achieved precision of 99.4% indicates a relatively high level of accuracy in identifying the blockage of coronary artery cases as positive by the model. Similarly, the recall 100% indicates that the model is able to detect a significant proportion of coronary artery stenosis cases in the angiography images. As well as the evaluated results of mean average precision (mAP) of 99.5% indicates an overall good performance in detecting and localizing coronary artery blockages in the images. Using these evaluation parameters, we have to detect the blockage of coronary arteries with original images and applied labelled images, which is mention in blow.

Original Images	Predicted Results with Accuracy

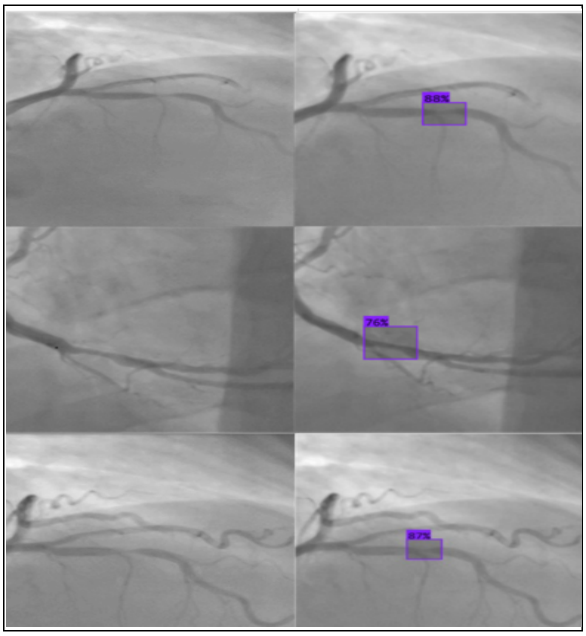

Figure 4: Predicted Results of arteries blockage detection

So, from above figure indicate that evaluation parameter with confidence detection archived the better results. Heart angiography is a medical imaging approaches that provide the visualization of blockage vessels in the heart. There is a very prominence diagnostic tool useds in cardiology images that helps to identify blockages or narrowing in the blood vessels that supply the heart with the help of YOLOv8 Models. When it comes to interpreting medical images, confidence detection is a crucial parameter that indicates the level of model in its predictions. Where, a high level of confidence values provides the detection of blockages or narrowing in the blood vessels is essential for accurate diagnosis and treatment. The tested result of image having 88%, 76% and 87% confidence detection in heart angiography images means that the model is fairly confident in its detections.

Discussion:

The discussion of this result proposed YOLOv8 framework for blockage detection of coronary artery using angiography images are promising and as well as the recall value of 100% may indicate some room for improvement. The precision value of 99.4% indicates the model that able to accurately provide the positive cases of blockage of coronary artery, which is important in decreasing the false positives instance and avoiding unnecessary interventions instances. However, the predicted recall value of 100% may be suggest that some false negatives, which indicate the cases of blockage of coronary artery.

Table 2: Comparison Table of various YOLO models

Authors (Year)	**Model**	**Dataset**	**Precision**	**Recall**	**mAP**	**F1 Score**
Aldughayfiq, B. et al (2023)	YOLO-v5 Based Deep Learning	Pressure Ulcer datasets	65.9 %	69.2%	76.9%	67.5%
Montalbo, F. J. P. (2020)	YOLOv4-Tiny with Transfer Learning	Brain Tumours datasets	90.3 %	88.6%	93.1%	89.5%
Çakır, M. et al (2023)	YOLOv5-x	Aortic Valve datasets	99.9 %	97.5%	99.5%	98.7%
Mammeri, S. et al (2023)	YOLOv7 with transfer learning	lung cancer image datasets	82.7 %	74.7%	81.3%	78.5%
Our's	**YOLOv8 Model**	**Coronary Angiography Images**	**99.4 %**	**100.0 %**	**99.5 %**	**99.7 %**

From above table 2, it is shows the performance of all comparative YOLO model with predicting results of precision, recall, mAP and f1 score respectively.

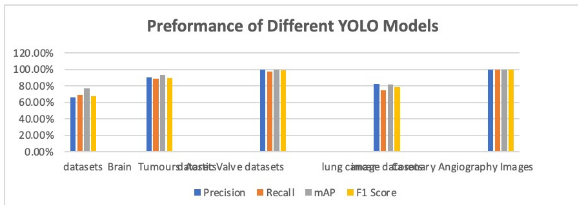

Figure 5: Representation of various YOLO model performance

From figure 5, the representation of various YOLO model preforms the comparisons of different datasets. Where the achieved results are in line with the findings of other studies that have utilized deep learning for cardiovascular imaging tasks. For example, a study Çakır, Mervenur, et al. (2023) used Deep Learning-Based Automatic Detection of Aortic Valve on Echocardiographic Images and this model achieved a precision of 99.9%, a recall of 97.5%, f1 score predicted by 98.7% and corresponding mAP score is 99.5% respectively. Another study by Montalbo, F. J. P. (2020) achieved a precision of 90.3% and a recall of 88.6% using a Computer-Aided Diagnosis of Brain Tumors Using a Fine-Tuned YOLO-based Model with Transfer Learning techniques. The achieved precision and recall values in this study are comparable to these studies, indicating the effectiveness of the proposed deep learning framework for coronary vessels blockage detection in angiography images. There are several potential reasons for the relatively lower recall value in this study. One possible reason is the complexity and variability of coronary artery stenosis patterns in angiography images. The shape, size, and location of the stenosis lesions may vary among patients and even among different angiography images of the same patient, making it challenging for the model to accurately detect all cases. Another reason may be the limitations of the dataset used in this study. The dataset may not fully represent the diversity of coronary artery stenosis cases in different populations and clinical settings, which could affect the generalizability of the model's performance. Despite the limitations, the proposed deep learning framework has the potential to empower cardiologists with accurate coronary artery stenosis detection in angiography images. The achieved precision value of 99.4% indicates a high level of accuracy in identifying positive cases, which can aid in early detection and timely intervention for patients with coronary artery stenosis. The mAP value of 99.5% also indicates good performance in detecting and localizing the stenosis lesions in the images.

Conclusion:

From table 2 and figure 4, the experimental results show that deep learning based proposed approach providing the promising results for detection of heart disease from Xray angiography images. From above results, it is also clear that the performance of proposed approach includes, precision is 99.4%, recall is 100.0%, and mAP is 99.5% as well as f1 score is 99.7%. In future soft computing approaches may be applied for betterment of the current work.

Reference:

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