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RESEARCH

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The value of CCTA combined with machine learning for predicting angina pectoris in the anomalous origin of the right coronary artery

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Abstract

Background: Anomalous origin of coronary artery is a common coronary artery anatomy anomaly. The anomalous origin of the coronary artery may lead to problems such as narrowing of the coronary arteries at the beginning of the coronary arteries and abnormal alignment, which may lead to myocardial ischemia due to the compression of the coronary arteries. Clinical symptoms include chest tightness and dyspnea, with angina pectoris as a common symptom that can be life-threatening. Timely and accurate diagnosis of anomalous coronary artery origin is of great importance. Coronary computed tomography angiography (CCTA) can provide detailed information on the characteristics of coronary arteries. Therefore, we combined CCTA and artificial intelligence (AI) technology to analyze the CCTA image features and clinical features of patients with anomalous origin of the right coronary artery to predict angina pectoris and the relevance of different features to angina pectoris.

Methods: In this retrospective analysis, we compiled data on 15 characteristics from 126 patients diagnosed with anomalous right coronary artery origins. The dataset encompassed both CCTA imaging attributes, such as the positioning of the right coronary artery orifices and the alignment of coronary arteries, and clinical parameters including gender and age. To identify the most salient features, we employed the Chi-square feature selection method, which filters features based on their statistical significance. We then focused on features yielding a Chi-square score exceeding a threshold of 1, thereby narrowing down the selection to seven key variables, including cardiac function and gender. Subsequently, we evaluated seven classifiers known for their efficacy in classification tasks. Through rigorous training and testing, we conducted a comparative analysis to identify the top three classifiers with the highest accuracy rates.

Results: The top three classifiers in this study are Support Vector Machine (SVM), Ensemble Learning (EL), and Kernel Approximation Classifier. Among the SVM, EL and Kernel Approximation Classifier-based classifiers, the best performance is achieved for linear SVM, optimizable Ensembles Learning and SVM kernel, respectively. And the corresponding accuracy is 75.7%, 75.7%, and 73.0%, respectively. The AUC values are 0.77, 0.80, and 0.75, respectively.

Conclusions: Machine learning (ML) models can predict angina pectoris caused by the origin anomalous of the right coronary artery, providing valuable auxiliary diagnostic information for clinicians and serving as a warning to clinicians. It is hoped that timely intervention and treatment can be realized to avoid serious consequences such as myocardial infarction.

Keywords: Anomalous origin of coronary artery, Angina pectoris, Computed tomography, Machine learning

Introduction

Anomalous origin of coronary artery (AOCA) is an anatomical anomaly in the opening of the coronary artery, which is caused by abnormal development or incomplete development of the coronary artery during the embryonic period. This anomaly can lead to problems such as the beginning narrowing of the coronary arteries and abnormal travel in front of the pulmonary arteries, which can lead to myocardial ischemia when the coronary arteries are squeezed by the surrounding tissues. The clinical manifestations include chest pain, chest tightness, and dyspnea, of which angina pectoris is a common manifestation, and in severe cases, sudden death may even occur [1]. The right coronary artery (RCA) anomalous openings include openings in the aorta, left coronary sinus, pulmonary artery, and left anterior descending coronary (LAD) [1, 2]. The right coronary artery originating from the left coronary sinus is a high-risk subtype, and sudden cardiac death and infarction have been reported in the literature, but mostly in individual cases or small samples [3, 4].

Invasive coronary angiography (ICA) is the gold standard for assessing the anatomy and stenosis of coronary arteries, but it is invasive and expensive. In contrast, coronary CT angiography (CCTA) is mostly used in the clinic as a non-invasive technique [5–7], which can be used for screening and cardiac function analysis of coronary artery diseases [8]. Patients with AOCA often develop angina pectoris (AP), which has a risk of myocardial infarction. Therefore, observation of CCTA images can provide more timely and accurate information on whether patients with AOCA develop angina pectoris or not, but this requires professional physicians and is influenced by the physician's experience. In recent years, artificial intelligence (AI) has achieved extraordinary progress in multiple aspects of coronary artery diagnosis, and CCTA combined with AI technology can provide a fast and efficient method for screening and diagnosis of AOCA.

Currently, most scholars' studies are based on artificial intelligence techniques for constructing coronary heart disease prediction models or identifying calcified plaques in coronary arteries. Babaoglu et al. [9] constructed a coronary heart disease (CHD) prediction model based on the Support Vector Machine algorithm (SVM) mining 23 clinical data features, which achieved a diagnostic accuracy of 79.71%. Takxet et al. [10] used an ML-based supervised classification system for automated coronary artery calcification (CAC) scoring of low-dose, non-contrast-enhanced, non-ECG-gated chest CT. They found that the method had acceptable reliability and consistency compared to a manually determined CAC scoring reference standard. Desai et al. [11] introduced a method for automated diagnosis of myocardial infarction using ECG beats, employing four ensemble learning classifiers based on decision trees. Among these, ROF was diagnosed with $99.51 \pm 0.31\%$ accuracy, $98.82 \pm 1.04\%$ sensitivity and $99.83 \pm 0.15\%$ specificity. This demonstrates its potential utility in screening for myocardial infarction. In addition, Kang [12] and Denzinger et al. [13] used machine learning methods to assess coronary stenosis and to analyze calcified plaque in coronary arteries on CCTA, respectively. We found that all of the above studies were performed on patients with CHD and did not find any relevant studies based on the anomalous origin of coronary arteries. However, in our study, we utilized seven types of classical machine learning algorithms, and the model results demonstrated high accuracy. Additionally, this research involves a long-term case collection that is clinically significant for predicting the occurrence of angina pectoris in AOCA patients.

In this study, the patients with AOCA included all had anomalous origin of the RCA, and the incidence of these cases is low, so this study data were collected over a long period. Machine learning has been widely applied to practical problems because of its strong self-learning and ability to handle nonlinear problems [14, 15]. Most domestic and international scholars have used machine learning to predict calcification scores or prognosis of coronary heart disease. In this study, the patients with AOCA included had the right coronary artery with anomalous origin. This study used a feature selection algorithm to filter CCTA image features and clinical features of AOCA patients and use these data in machine learning algorithms to find high-precision algorithms that can be used to diagnose angina pectoris, as well as to analyze which features are associated with angina pectoris.

Results

Baseline characteristics

One hundred and twenty-six patients, including 71 males and 55 females, were screened as the study population. Based on the presence of angina pectoris, AOCA patients were divided into 2 cohorts, namely angina pectoris ($n = 37$, age: 64.0 ± 14.1) and non-angina pectoris ($n = 89$, age: 53.7 ± 10.5). In this study, a total of 15 features were used as initial features, including CCTA image features and clinical baseline features. Clinical baseline data included sex and age. CCTA image features included the location of the opening of the right coronary artery, direction of course, and angle between the starting segment and the aorta.

Feature selection and model construction

The study performs feature selection by the Chi algorithm. Based on the weight of each feature, an appropriate p-value of the Chi test statistics is selected to exclude features with weights below this threshold. The p-value of the Chi test statistics value selected for this study was 1.0. Finally, seven features were selected and are marked in bold in Fig. 1.

The selected features are imported into seven classifiers better suited for the classification task. Table 1 shows the experimental results for the seven classifiers. Through the study, we found that the best performers among DT, Logistic Regression, Naive Bayesian, SVM, Kernel Approximation, Ensembles Learning, and Neural Network models were Optimizable Tree, Logistic Regression, Kernel Naive Bayesian, Linear SVM, SVM Kernel, Optimizable Ensemble, and Narrow Neural Network, respectively. The top three classifiers with the highest accuracy among the included classifiers were screened and are shown in bold in Table 1. The top three classifiers are Linear SVM, Optimizable

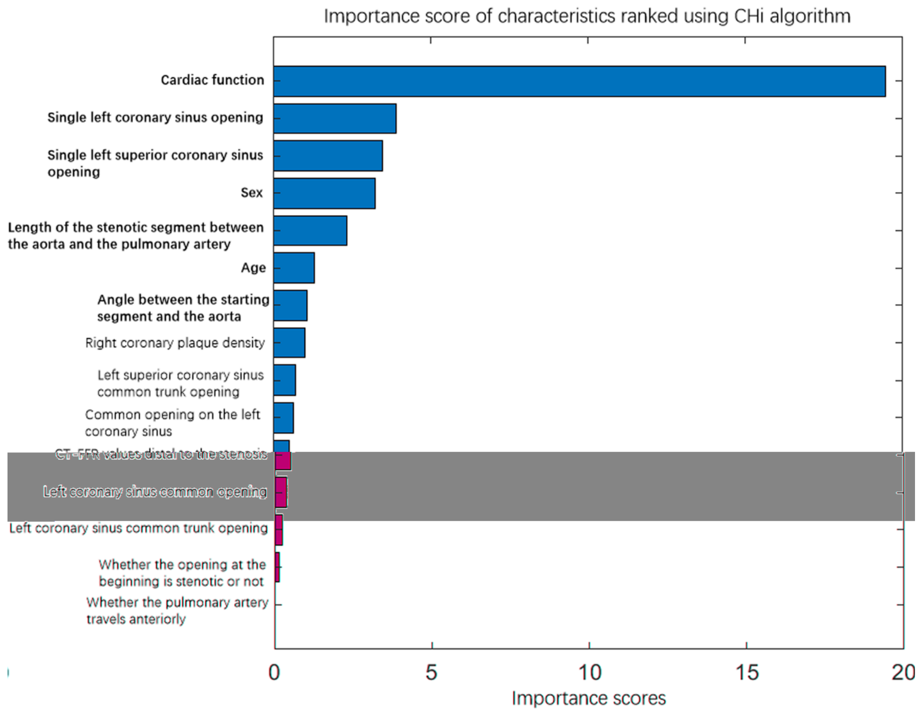

Fig. 1 The feature scores based on Chi feature selection. Note: Bolded characteristics are those that were included in the study after making the feature selection (*p*-value of the Chi test statistics > 1)

Table 1 The experimental results for the seven classifiers

Classifier	Training cohort				Test cohort			
	ACC (%)	AUC	SPE (%)	NPV (%)	ACC (%)	AUC	SPE (%)	NPV (%)
Optimizable Tree	77.50	0.61	96.80	77.20	70.30	0.49	96.20	71.40
Logistic Regression	64.00	0.65	73.00	75.40	67.60	0.60	84.60	73.30
Kernel Naive Bayes	73.00	0.69	90.50	76.00	62.20	0.63	84.60	68.80
Linear SVM	85.40	0.85	98.40	83.80	75.70	0.77	96.20	75.80
SVM Kernel	73.00	0.64	96.80	73.50	73.00	0.75	100.00	72.20
Optimizable Ensembles Learning	77.50	0.73	88.90	81.20	75.70	0.80	88.50	79.30
Narrow Neural Network	76.40	0.76	88.90	80.00	70.30	0.68	88.50	74.20

The bolded classifiers are the top three classifiers in performance among the seven classifiers

Ensembles Learning and SVM Kernel Classifier. By observation, the accuracy of linear SVM, Optimizable Ensembles Learning and SVM Kernel were 75.70%, 75.70% and 73.00%, respectively. The AUC values were 0.77, 0.80, and 0.75, respectively. Figure 2 shows the confusion matrix of the top three classifiers. Figure 3 shows the ROC curves for the top three classifiers.

Discussion

Anomalous origin of the coronary artery is an abnormal development of the coronary artery that makes the coronary artery originate in an anomalous location. AOCA patients may appear the beginning of the right coronary artery opening narrowing, and abnormal travel in front of the pulmonary artery, which leads to the right

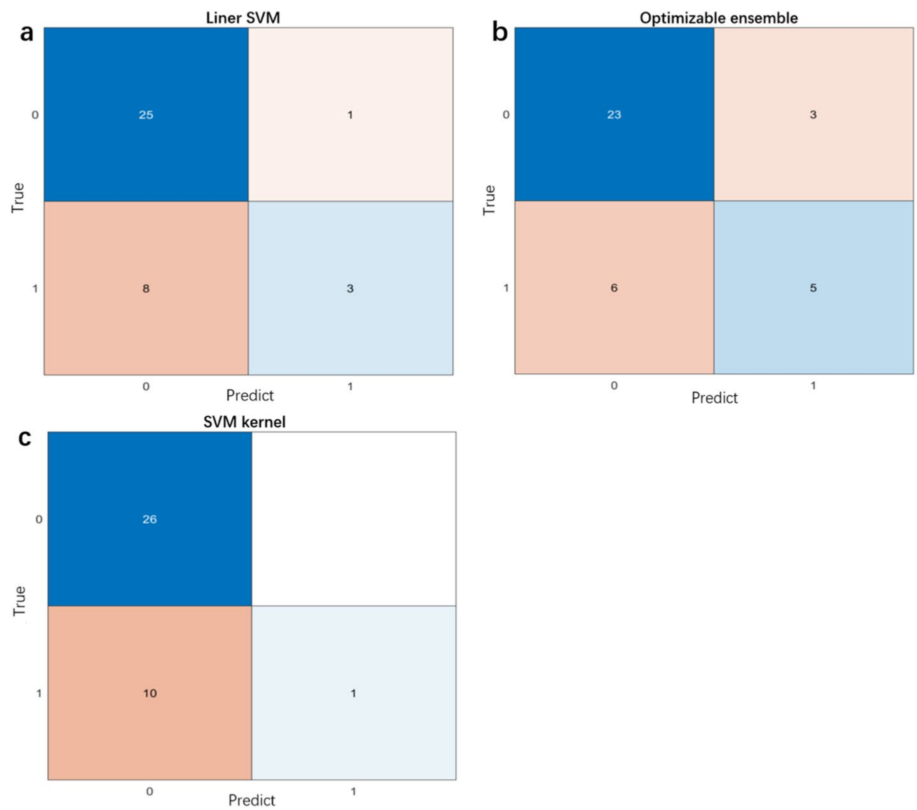

Fig. 2 The confusion matrix of the top three classifiers. **a** Confusion matrix of liner SVM; **b** confusion matrix of optimizable ensemble; **c** confusion matrix of SVM kernel

coronary artery by the surrounding tissues of the pressure caused by myocardial ischemia and other manifestations, so it is easy to develop angina pectoris, is a common clinical symptom of AOCA patients, which can be divided into stable angina pectoris and unstable angina pectoris [16]. Stable angina pectoris is an AP caused by an imbalance in the supply and demand of oxygen to the heart muscle; unstable angina pectoris is a clinical syndrome between stable angina pectoris and acute myocardial infarction [17]. In this study, the included AOCA patients had anomalous origins of the right coronary artery, and the incidence of such AOCA cases is low [18–21]. Such coronary anomalies of the RCA originating from the left coronary sinus can usually be observed with the narrowing of the opening of the initiating segment and a small angle between it and the aorta. The features incorporated in the study included whether or not the opening at the beginning was narrowed and the angle between the starting segment and the aorta, both of which are clinically considered to be more associated with the occurrence of AP [22, 23]. In general, the narrower the opening at the beginning, the higher the potential for AP to occur. Similarly, the smaller the angle between the starting segment and the aorta, the higher the potential for AP to occur. Coronary angiography is the gold standard of clinical diagnosis of coronary artery disease [24, 25]. However, coronary angiography is an invasive procedure and expensive. In contrast, CCTA could use prospective or retrospective ECG gating to collect the optimal phase to reconstruct the images at any heart

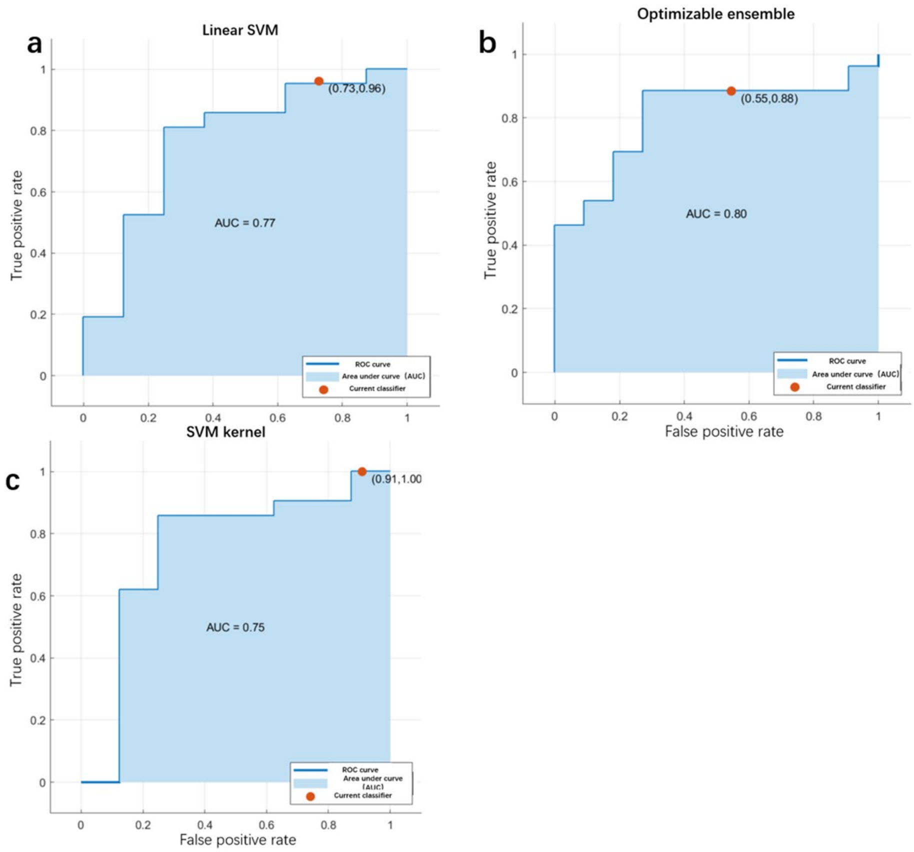

Fig. 3 The ROC curve results for the top three classifiers. **a** ROC curve of linear SVM; **b** ROC curve of optimizable ensemble; **c** ROC curve of SVM kernel

rate, showing the major branches of the coronary artery in multiple directions and analyzing the diseased vessels [26]. Therefore, CCTA is the best choice for clinical screening of coronary artery disease [27, 28]. In this study, we aim to utilize machine learning algorithms for early screening to promptly detect angina in AOCA patients. This approach will offer valuable diagnostic support to clinicians, contributing to the prevention of AP and improved patient follow-up. However, due to the subjectivity of radiologists' diagnosis, and the rapid development of artificial intelligence in the medical field, it provides us with new methods to diagnose diseases by combining AI with CCTA.

Machine learning algorithms have been used to develop intelligent diagnostic models for coronary heart disease. Both Kathleen et al. [29] and Hassannataj et al. [30] have used machine learning techniques to predict coronary heart disease and achieved good model performance. Among them, the randomized tree model proposed in Hassannataj's study incorporated the 40 most important features. This model had the best performance. Therefore, collecting more patient features is beneficial for model performance and can reveal potential links between diseases and features or between features. Desai et al. [31] employed Higher-Order Statistics (HOS) to distinguish and diagnose CHD and Normal Sinus Rhythm (NSR) heart beats. The research combined Random Forest (RAF) and Rotated Forest (ROF) classifiers for the principal component classification of medically significant features ($p < 0.05$). The study's findings highlighted the robustness of the proposed system. In addition, several studies have also reported AI algorithms for automatically detecting atherosclerotic plaques from CCTA images. For example, Kang et al. [12] proposed an ML algorithm that was applied to a dataset of 42 CCTA patients. Compared with expert readers using visual identification of narrow lesions. The proposed ML algorithm had high sensitivity (93%), specificity (95%), and accuracy (94%) with an AUC of 0.94. Yoneyama et al. [32] used an artificial neural network (ANN) for the detection of coronary stenoses from hybrid images of CCTA. The results prove that this model is useful for detecting culprit coronary arteries, achieving comparable results with nuclear medicine physicians. All the above studies achieved good model performance, but the small amount of data is a common problem, and most of the incorporated features belong to CCTA, so the inclusion of more comprehensive features is a future research direction.

Most of the current cardiac AI applications aim to assist radiologists in routine tasks, increasing efficiency and improving patient care [33]. The data can be mined by AI algorithms, which can not only improve the accuracy of diagnosis, but also identify some potential risk factors associated with the development of coronary artery disease through the data. In this study, we proposed a computer-aided diagnosis (CAD) model to analyze whether or not the anomalous origin of coronary artery patients produces angina pectoris, selected the Chi feature selection algorithm to improve model computational efficiency and evaluated the performance of different classifiers in angina pectoris identification. This study extracted 15 features, including CCTA image features and clinical features, and used the Chi algorithm for feature screening. The screened features are then analyzed using machine learning to select a method with high accuracy and applicability.

In this study, seven features were selected for model construction by the Chi algorithm, of which, as can be seen in Fig. 1, the Chi score of cardiac function was close to 20 points, and the three features of single left coronary sinus opening, single left superior coronary sinus opening and sex reached more than 3 points, while the other features were about one or two points. Due to more patients without angina pectoris in this study, there was a majority of patients with cardiac class I function. Cardiac function grading is a clinical method to assess the degree of impaired cardiac function, according to its grading that reflects the severity of the disease, which in this study was mainly grade I (total of four grades). Angina pectoris is caused by insufficient coronary artery blood supply, temporary myocardial ischemia and hypoxia, and is a manifestation of impaired cardiac function. Therefore, in the Chi algorithm, cardiac function is the most important feature in judging angina pectoris. In the meantime, a total of seven classifiers were used in this study, but the top three classifiers were Support Vector Machine (SVM), Ensemble Learning (EL), and Kernel Approximation Classifier. SVM is a binary classification algorithm that works well when dealing with linearly separable small sample data. EL classifiers can combine classifiers with independent decision-making ability, which can solve the three problems of small training data, small hypothesis space, and local optimum of a single classifier. The Kernel Approximation Classifier is a general linear programming SVM classifier, which is represented by using a minimum number of sample data points. It can be observed that all the above three classifiers are more advantageous in dealing with small sample datasets. In this study, only single-center data were collected and it was a retrospective study, so the data size was small and the incorporated features were not comprehensive. Therefore, SVM, EL, and Kernel Approximation Classifier were better at predicting angina pectoris.

Two limitations in this study should be noted here: the first limitation is the small number of patients, so there may be problems of data imbalance and overfitting. In addition, this study is a retrospective study. Another limitation is that this study was a single-center study and was not validated on an external dataset, and thus the proposed model may have poor generalization ability. In future studies, more AOCA patient data and more comprehensive features will be collected to improve the model's performance.

Conclusions

This study developed a CAD model to assess the risk of angina pectoris in patients with AOCA. This model improves the diagnostic accuracy of patients with AOCA who develop angina pectoris, provides clinician alerts to achieve timely therapy, and facilitates the interpretation of CCTA images of AOCA. In future studies, we will collect a large number of anomalous origins of coronary artery images and hope to introduce deep learning (DL) techniques to further improve the performance of the CAD model.

Methods

Patient data

The Institutional Review Board of Affiliated Zhoupu Hospital of Shanghai University of Medicine and Health Sciences approved this study, and the need for patient-informed consent was waived. This study was conducted following relevant guidelines and regulations. This was a retrospective study that analyzed the cases of AOCA patients from Affiliated Zhoupu Hospital, Shanghai University of Medicine and Health Sciences between January 2014 and December 2022. To effectively control the study bias and to ensure the operability of the study, the accuracy of the data, and the reliability of the results. Thus, scientific inclusion and exclusion criteria were established. The criteria for inclusion in this study were (1) clear diagnosis of anomalous origin of coronary artery by ICA; (2) ICA confirmed the right coronary artery with the anomalous origin; (3) complete CCTA image data and clinical information; (4) all were examined by 256-row spiral CCTA and coronary DSA at our hospital. The exclusion criteria were (1) patients with poor CCTA image quality, 3D reconstruction image blurring, existing motion artifacts, and cannot be diagnosed; (2) AI cannot be recognized or recognized incorrectly; (3) patients who are not suitable for CCTA examination: including iodine allergy, acute and chronic infections, severe cardio-cerebral, hepatic and renal disorders, blood disorders, and severe arrhythmia, etc.

A total of 126 patients were included in this study, of which 71 were male and 55 were female. The mean age was 55.8 ± 11.7 years, with a range of 25 to 89 years. The corresponding CCTA images of 126 patients with anomalous origin of coronary artery were collected, including 37 patients with angina pectoris and 89 patients without angina pectoris. Two experienced senior radiologists use CCTA images to judge the origin of major coronary arteries, as well as to perform post-processing and measurements. These

Table 2 Distribution of the dataset

	Patient number [AP (+)]	Patient number [AP (−)]	Sum of numbers
Training cohorts	26	63	89
Test cohorts	11	26	37
Sum of numbers			126

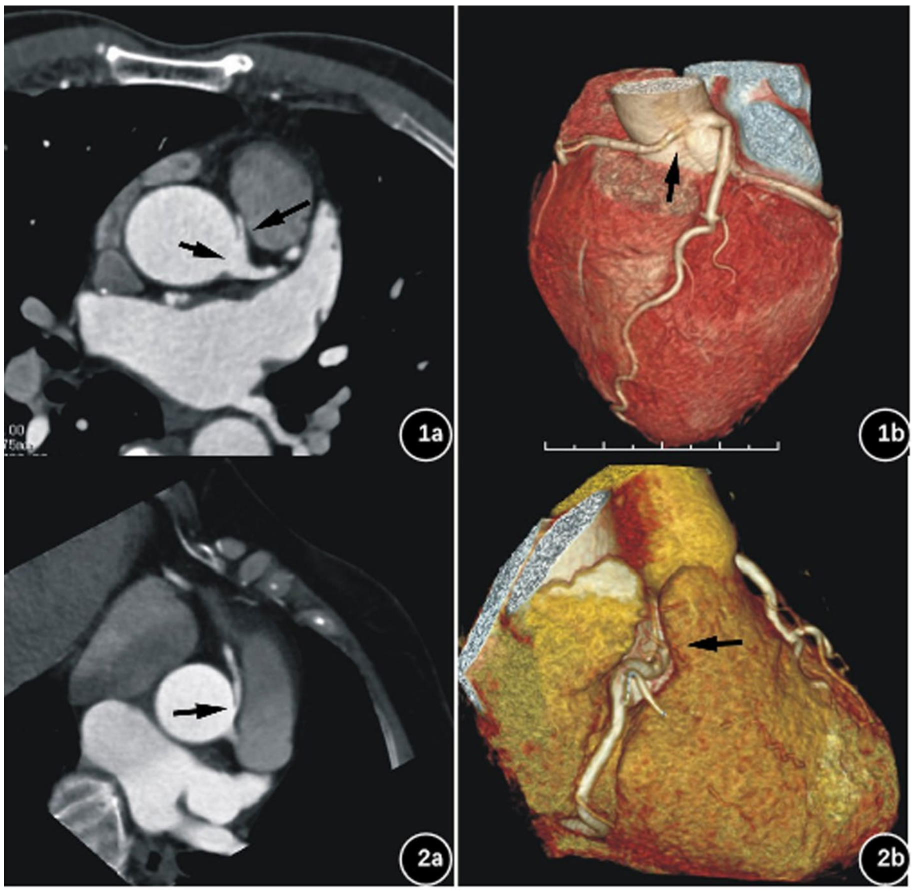

Fig. 4 Examples of CCTA images and VR images of AOCA patients. **1a** CCTA image shows that the right coronary artery opens into the left coronary sinus and the beginning segment is narrowed (long arrow) and forms an opening together with the left main coronary artery (short arrow); **1b** VR image for 1a image and the stenosis of its beginning segment is obvious (arrow). **2a** CCTA image shows the right coronary artery (arrow) opening in the left coronary sinus; **2b** VR image for 1a image, showing the right coronary artery (arrow) opening in the left coronary sinus

cases were divided into AP (+) or AP (−) groups in both the training and test cohorts. Firstly, randomly divided angina patients and non-angina patients into training and test cohorts in the ratio of 7:3, respectively. Then the two groups of patients were combined for the corresponding training and testing cohorts. The final training and test cohorts required for the study were formed. Table 2 shows the distribution of the total dataset in the training and test cohorts. Figure 4 shows CCTA and VR images of the right coronary artery with anomalous origin.

CCTA examination process

The patient takes the supine position, the foot is advanced, the center line is placed in the sternoclavicular joint, the hands are raised to hold the head, and deep inhalation at the end of the breath-holding, to prevent artifacts. The location of the electrode sheet: yellow electrode sheet is located in the right midline of the clavicle, under the clavicle; black electrode sheet is located in the left midline of the clavicle, under the clavicle; green electrode sheet is located in the right midline of the clavicle, the sixth intercostal space or below; red electrode sheet is located in the left midline of the clavicle, the sixth intercostal space or below. When connecting the ECG leads, make sure to avoid the electrode tabs and lead wires in the scanning area to minimize interference, thus ensuring the stability of the ECG signal and avoiding spurious interference.

A 256-row GE Revolution-CT (GE Healthcare, America) was used to perform a CT examination of the coronary arteries. The scanning range of the coronary artery was as follows: the upper boundary was located at the level of 2 cm below the tracheal crest, the lower boundary was to the diaphragmatic surface of the heart, and the left and right sides each exceeded the cardiac margins by 10–20 mm. The scanning parameters were as follows: tube voltage 100 kV; tube current 300–600 mAs; automatic milliampere-seconds; matrix size 512×512; slice thickness 0.625 mm; layer spacing 0.625 mm; pitch 0.992:1; field of view 250 mm $\times$ 250 mm. For coronary CTA examinations, 60 ml of non-ionic contrast agent (iohexol, 350 mg I/ml) was injected at a flow rate of 4.5 ml/s and followed by 40 ml of saline solution for each patient. In the present study, CCTA operation was performed using the trigger method. The ascending aortic root layer was set as the continuous exposure layer, and the descending aorta was selected as the observation region of interest (ROI). After contrast injection, continuous exposure was used to observe the region of interest in real-time, and the scan was triggered automatically when the CT value of the ROI exceeded 100 HU. The final volume rendering (VR) images of the coronary arteries were processed for image reconstruction using a ShuKun 618 workstation (Shukun Technology, China) and a GECTAW post-processing workstation (GE Healthcare, America), with corrections made by a professional radiographer.

Feature selection

Feature selection as a key content of machine learning is to filter out the main features from all the features. After collecting and analyzing the CCTA image and clinical data, we applied a machine learning algorithm to evaluate the presence of angina pectoris in AOCA. As shown in Fig. 5, the algorithm consists of three main steps: feature selection, model training, and model testing. A total of 126 patients with AOCA were obtained from CCTA images and clinical data, including 37 cases with AP and 89 cases without AP.

In this study, the important features were selected to improve the prediction accuracy of whether AOCA generated angina pectoris or not. The features were selected based on the entire dataset (a total of 126 patients, including 37 patients with angina pectoris and 89 patients without angina pectoris). In this study, a total of 15 features of AOCA patients were collected, including clinical baseline data and CCTA image features of AOCA patients. The clinical baseline data included two indicators of age

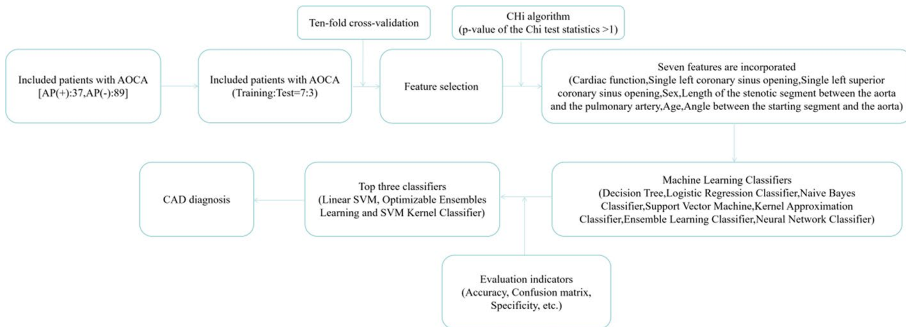

Fig. 5 The flowchart of the computer-aided model to detect AOCA causing AP

and gender, and the CCTA image features included the location of the right coronary artery opening, direction of travel, and cardiac function level. The CCTA image features were chosen because we found through clinical practice that these features were more closely related to angina pectoris, so we used these features in this study. In addition to this, there was no strong correlation between the features.

In this study, the Chi-square test (Chi) for feature selection. The Chi feature selection algorithm is one of the popular feature selection methods mainly used for correlation and relevance analysis of categorical variables (discrete variables) [34]. The basic idea: firstly the null hypothesis of Chi test is that two discrete components are independent of each other. Thus, when applied to label and feature discrimination, it determines whether a feature and label are independent or not. If they are independent, it suggests that the feature is not useful for predicting the label. In this study, the Chi-square value signifies the degree of deviation between features and labels, with the formula for calculating this deviation presented in Formula 1 (provided by the classification learner of the MATLAB software):

$$X^2 = \sum \frac{(\text{feature} - \text{label})^2}{\text{label}} \tag{1}$$

Chi algorithm was sorted by repeated iterations for selection and selected the top 7 variables (p-value of the Chi test statistics > 1) for model prediction based on their p-value of the Chi algorithm. This study's feature data are discrete, so the Chi algorithm is more suitable for constructing models. The Chi algorithm is simple, efficient and easy to implement, more suitable for our small dataset. The reason for the selection of the p-value of the Chi test statistic is that the experimental results found that the features with a p-value greater than 1 have a strong correlation with angina pectoris, while the features with a p-value less than 1 have a weak correlation. So, the features with a p-value greater than 1 are kept as a way to improve the accuracy of the model and reduce redundancy. The importance scores of the features are shown in Fig. 1. The final variables used for anomalous origin of coronary artery angina pectoris prediction were the top 7 features indicated in bold font in Fig. 1.

Construction of machine learning-based predictive models and performance evaluation

This study uses classifiers in MATLAB (Version 9.12, R2022a) to conduct the experiments and select a total of seven classifiers, including Decision Tree (DT), Logistic Regression Classifier (LR), Naive Bayes Classifier, Support Vector Machine (SVM), Kernel Approximation Classifier, Ensemble Learning Classifier, and Neural Network Classifier. For example, DT classifiers are suitable for nonlinear problems and easy to understand [35], are more applicable to our dataset, and are therefore included in the study. Meanwhile, SVM has the same ability to solve nonlinear and small sample datasets [36], as well as LR computationally cost is small and easy to understand and implement. This model uses accuracy (ACC), specificity (SPE) and AUC value to evaluate the applicability and effectiveness of the algorithm, and also uses tenfold cross-validation to verify the stability of the model.

The tenfold cross-validation method effectively prevents model overfitting and underfitting. It involves randomly splitting the dataset into ten parts, using one for testing and the remaining nine for training. This process is repeated ten times, ensuring each sample serves as both training and test data, thus eliminating bias. The final model evaluation is the average of these ten tests. Consequently, combining evaluation metrics with this method enhances the reliability and generalization performance of the experimental results.

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Author contributions
P.WX conceived and designed the research, W.Y wrote the main manuscript text and prepared the legends, Y.MY collected the data, W.MX polished the manuscript. All authors reviewed the manuscript.

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Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The study was approved by the Institutional Review Boards of Affiliated Zhoupu Hospital of Shanghai University of Medicine and Health Sciences. The informed consent was waived by the Institutional Review Boards of Affiliated Zhoupu Hospital of Shanghai University of Medicine and Health Sciences.

Consent for publication
None.

Competing interests
The authors declare no competing interests.

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