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Deep learning analysis in coronary computed tomographic angiography imaging for the assessment of patients with coronary artery stenosis

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ABSTRACT

Background and Objective: Recently, deep convolutional neural network has significantly improved image classification and image segmentation. If coronary artery disease (CAD) can be diagnosed through machine learning and deep learning, it will significantly reduce the burdens of the doctors and accelerate the critical patient diagnoses. The purpose of the study is to assess the practicability of utilizing deep learning approaches to process coronary computed tomographic angiography (CCTA) imaging (termed CCTA-artificial intelligence, CCTA-AI) in coronary artery stenosis.

Materials and Methods: A CCTA reconstruction pipeline was built by utilizing deep learning and transfer learning approaches to generate auto-reconstructed CCTA images based on a series of two-dimensional (2D) CT images. 150 patients who underwent successively CCTA and digital subtraction angiography (DSA) from June 2017 to December 2017 were retrospectively analyzed. The dataset was divided into two parts comprising training dataset and testing dataset. The training dataset included the CCTA images of 100 patients which are trained using convolutional neural networks (CNN) in order to further identify various plaque classifications and coronary stenosis. The other 50 CAD patients acted as testing dataset that is evaluated by comparing the auto-reconstructed CCTA images with traditional CCTA images on the condition that DSA images are regarded as the reference method. Receiver operating characteristic (ROC) analysis was used for statistical analysis to compare CCTA-AI with DSA and traditional CCTA in the aspect of detecting coronary stenosis and plaque features.

Results: AI significantly reduces time for post-processing and diagnosis comparing to the traditional methods. In identifying various degrees of coronary stenosis, the diagnostic accuracy of CCTA-AI is better than traditional CCTA ($AUC_{AI} = 0.870$, $AUC_{CCTA} = 0.781$, $P < 0.001$). In identifying $\geq 50\%$ stenotic vessels, the accuracy, sensitivity, specificity, positive predictive value and negative predictive value of CCTA-AI and traditional method are 86% and 83%, 88% and 59%, 85% and 94%, 73% and 84%, 94% and 83%, respectively. In the aspect of identifying plaque classification, accuracy of CCTA-AI is moderate compared to traditional CCTA ($AUC = 0.750$, $P < 0.001$).

Conclusion: The proposed CCTA-AI allows the generation of auto-reconstructed CCTA images from a series of 2D CT images. This approach is relatively accurate for detecting ≥50% stenosis and analyzing plaque features compared to traditional CCTA.

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1. Introduction

Coronary computed tomographic angiography (CCTA) is the heart imaging test that assists to determine whether plaque buildup narrows the coronary arteries, the blood vessels that supply the heart. CCTA can detect coronary artery stenosis noninvasively, so it is often used to identify suspected patients with

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coronary heart disease. It is currently the most frequently used noninvasive method to diagnose coronary artery disease (CAD). CCTA can not only assess coronary artery anatomy and coronary artery stenosis that can cause myocardial ischemia, but also characterize the nature of plaques, detect high-risk plaques for prediction of adverse cardiac events [1]. However, interpreting CCTA is subjective and has significant observational variability.

Deep learning is a series of machine learning algorithms. It uses supervised or unsupervised strategies to automatically learn features by executing multi-layered hierarchies, so as to achieve the purpose of classification [2]. For wide computer vision tasks, convolutional neural networks (CNN) have been proven to be strong tools. Since 1996, it has been applied to medical image processing [3-6]. However, in the field of imaging diagnosis of CAD, although some excellent studies focus on the performance of artificial intelligence (AI) in the CCTA image automatic segmentation and centerline extraction [7-11], the application of AI in the diagnosis of CAD is deficient in general. If AI can be applied to medical imaging diagnosis of CAD, the efficiency, quality and performance of diagnosis will be greatly improved.

CCTA-AI has been adopted in diagnosing coronary heart disease in recent studies [12-15], but they are compared with CCTA alone. It is generally well known that CCTA has limited diagnostic value in some areas, such as blooming artifacts due to calcified plaques, which make it difficult to accurately reflect the extent of coronary stenosis of CAD, despite the use of some approaches including image subtraction and use of post-processing methods to reduce the influence of heavy calcification on assessment of coronary stenosis. The reported specificity of CCTA was between 19 and 53% in patients with highly calcified plaques according to the assessment of coronary lumen stenosis and it was improved to some extent with use of different approaches of suppressing the effect of calcification [16-19]. Despite improved diagnostic performance, CCTA is still in limited in assessing calcified plaques.

In this study, we sought to compare the consistency of diagnosis between CCTA-AI and digital subtraction angiography (DSA), CCTA and DSA, and evaluate diagnostic efficiency of AI and CCTA in diagnosing coronary stenosis. Furthermore, we briefly compared the post-processing time between the two methods and evaluated the diagnostic value of CCTA-AI in evaluating the type of coronary plaque. The objective of this study was to determine the diagnostic value of deep learning algorithms for identification and characterization of coronary stenosis and plaques based on CCTA images in terms of efficiency and accuracy compared with the reference method.

2. Materials and methods

2.1. Patients population

Patients with suspected CAD who underwent CCTA and DSA examinations from June to December 2017 in our Hospital were retrospectively reviewed. One hundred randomly selected subjects were trained in CCTA-AI and evaluated in the remaining 50 subjects. Of these patients, the median age was 61 years (range, 31–91 years), and 64 years (range, 40–79 years) for the training and test groups, with corresponding men and women being 58 and 42, 29 and 21, respectively. The patient' demographics were shown in Table 1. The Medical Ethics Committee of Beijing Friendship Hospital approved this study. Informed consent was obtained from all individual participants included in the study.

2.2. CCTA, DSA and CCTA-AI

The CCTA images used to train and test the model were obtained with 256-slice GE Revolution CT (Revolution CT, GE Healthcare). The reconstruction thickness and the interval were 0.625 mm. The weight of iterative reconstruction (ASIR-V) was selected at 60% [20,21]. The reconstruction matrix is 512 × 512. Tube voltage was 120 kVp, with automatic tube current modulation applied and the range of smart mA was 200–700 mA. The preset Noise Index (NI) was 22. The rotation speed of frame was 0.28 s. At the same time, the Snapshot Freeze (SSF) technique was used to improve the time resolution to 29 ms [22,23]. Fifty mL of Iopromide (370 mg I/mL) was injected with a flow rate of 5 mL/s. Then 40 mL saline (flow rate 5 mL/s) was injected. The region of interest (ROI) is defined as the ascending aorta at the bifurcation level of the trachea with 150 HU as the triggering threshold to initiate the scan.

Table 1
Demographics of the study participants.

	Training group	Testing group
Male	58	29
Female	42	21
Median age (years old)	61	64
Total	100	50
	Diagnosis from DSA in the testing group	
Segments had lesions		179
≥50% stenotic vessels (segment)		68
≥50% stenotic vessels occur in LAD (segment)		29
≥50% stenotic vessels occur in LCX (segment)		8
≥50% stenotic vessels occur in RCA (segment)		12
≥50% stenotic vessels occur in small branches (segment)		19

DSA was performed according to the standard approach by using Philips Allura Xper FD digital subtraction angiography system. The injection rate of contrast medium was 2–3 ml/s and the dosage was 4–20 ml.

CCTA-AI system used is “CoronaryDoc clinical decision Support Platform V1.0″ from Shukun (Beijing) Technology Co.,Ltd. This system is based on CT axial images of coronary artery. It simulates 3-dimension volume rendering (3D VR), curved planar formation (CPR), vessel probe (VP), vessel straightening reconstruction from a series of images (Fig. 1). CCTA-AI can automatically identify the branches and segments of each coronary artery, distinguish the plaque feature according to the CT value of the plaque, and calculate the degree of coronary artery stenosis caused by atherosclerotic plaque.

2.3. Coronary segment, assessment of stenosis severity and classification of plaque

Coronary segments, naming standard and quantitative assessment of stenosis severity were proposed by the Society of Cardiovascular Computed Tomography (SCCT) according to the 18-segment model (Table 2) [24]. A standardized approach to coronary segmentation improves description and communication of findings. The standard American Heart Association (AHA) segmentation [25] initially proposed in 1975 has been used in many long-term outcome studies relating the location of stenoses to major adverse coronary events. This model has been adapted for coronary CTA with minimal alterations for clarity. Recommended stenosis grading: 0-Normal: no plaque, no luminal stenosis; 1-Minimal: <25% stenosis, 2-Mild: 25% to 49%, 3-Moderate: 50% to 69%, 4-Severe: 70% to 99%, 5-Occluded [24]. In this study, coronary artery segments with stenosis ≥ 50% were considered to be positive. And this study involved only blood vessels larger than 1.5 mm in diameter. The classification of plaque in CCTA: Calcified plaque-

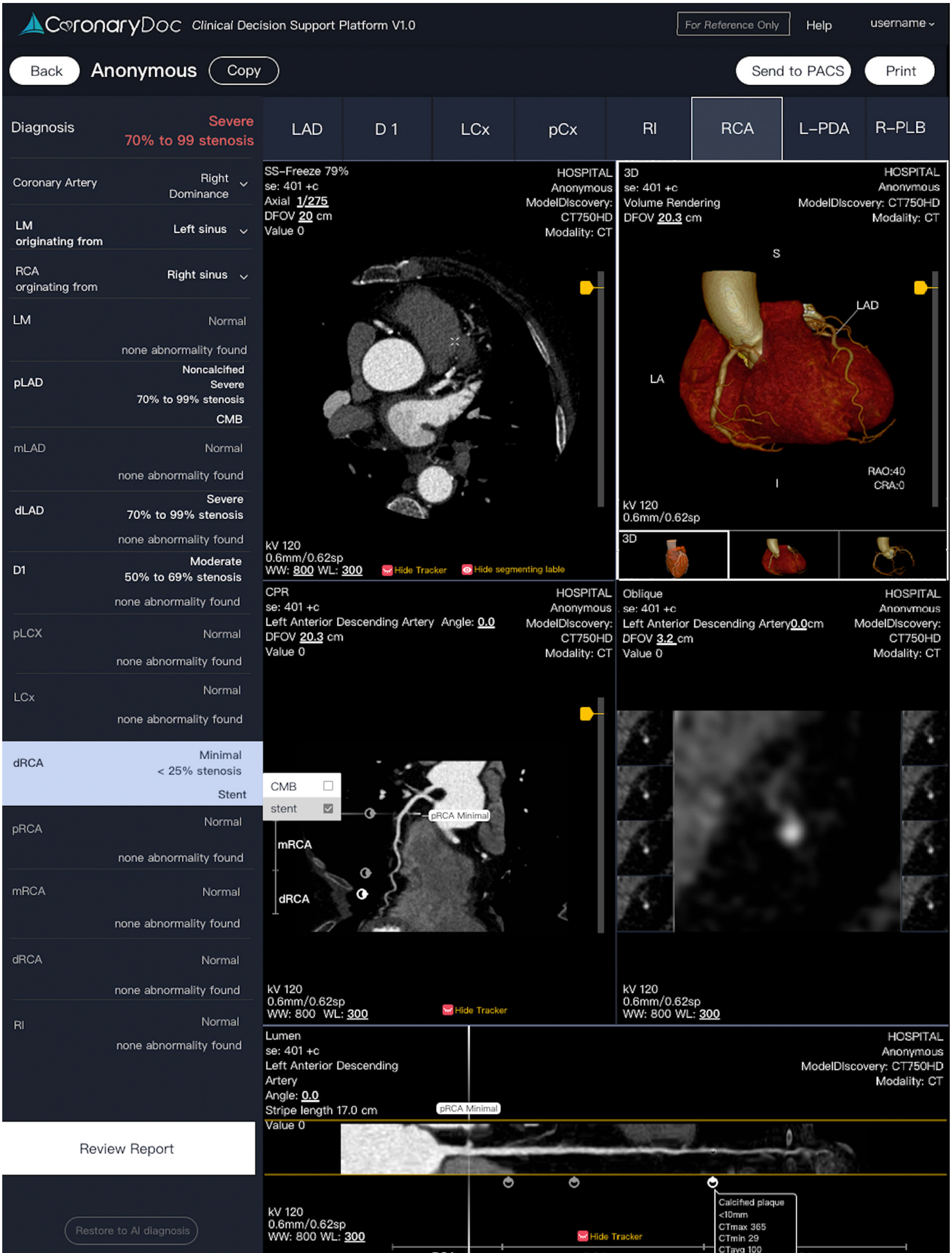

Fig. 1. CCTA-AI is based on CT axial images of coronary artery and simulates 3-dimension volume rendering (3D VR), curved planar reformation (CPR), vessel probe (VP), vessel straightening reconstruction to form a series of images.

Table 2
Coronary segments for assessment in the study participants.

Segment	Abbreviation	Description
Proximal right coronary artery (RCA)	pRCA	Ostium of the RCA to one-half the distance to the acute margin of heart
Mid RCA	mRCA	End of proximal RCA to the acute margin of heart
Distal RCA	dRCA	End of mid RCA to origin of the PDA (posterior descending artery)
PDA-R	R-PDA	PDA from RCA
Left main (LM)	LM	Ostium of LM to bifurcation of LAD (left anterior descending artery) and LCx (left circumflex artery)
Proximal LAD	pLAD	End of LM to the first large septal or D1 (first diagonal; >1.5 mm in size) whichever is most proximal
Mid LAD	mLAD	End of proximal LAD to one-half the distance to the apex
Distal LAD	dLAD	End of mid LAD to end of LAD
D1	D1	First diagonal branch D1
D2	D2	Second diagonal branch D2
Proximal LCx	pCx	End of LM to the origin of the OM1 (first obtuse marginal)
OM1	OM1	First OM1 traversing the lateral wall of the left ventricle
Mid and distal LCx	LCx	Traveling in the atrioventricular groove, distal to the OM1 branch to the end of the vessel or origin of the L-PDA (left PDA)
OM2	OM2	Second marginal OM2
PDA-L	L-PDA	PDA from LCx
PLB-R	R-PLB	PLB from RCA
Ramus intermedius	RI	Vessel originating from the left main between the LAD and LCx in case of a trifurcation
PLB-L	L-PLB	PLB from LCx

PLB, posterior-lateral branch. Additional nomenclature may be added, for example, D3, R-PDA2, saphenous vein graft.
Definitions derived, adopted, and adjusted from the report by Austen et al. [25].

The whole plaque appears as calcium density; partially calcified plaque- There are 2 visible plaque components, one of which is calcified; noncalcified plaque-The whole plaque is short of calcium density [26].

2.4. Assessments of image quality

Subjective score of CCTA images was based on an 18-segment model using a 4-point Likert scale, with a score of 1 corresponding to the worst image quality and 4 the best image quality.

Objective image quality assessment was determined by the CT mean value and standard deviation (SD) which was measured at the aortic root with a circular region of interest of 20 mm^2.

Two radiologists with more than 5 years of experience (CJH and XY), who evaluated CCTA, and two cardiologists with more than 5 years of experience (LN and LD), who evaluated DSA participated in image evaluation. They were neither involved in data selection nor were provided with any information of the subjects, and independently evaluated all images. Furthermore, the radiologists were blinded to the results of DSA images and the cardiologists were blinded to the results of CCTA. If there are different opinions, the superior physicians were consulted to resolve any discrepancy.

2.5. Inclusion criteria and exclusion criteria

The inclusion criteria for this study were: (1) The age of the patients is over 18 years old; (2) CCTA and DSA were carried out successively within six months; (3) The diameter of main branch and small branch of coronary artery is larger than 1.5 mm.

The exclusion criteria for this study were: (1) Coronary artery stenting or coronary artery bypass grafting (CABG); (2) Coronary artery anatomic abnormality; (3) CCTA image quality does not meet diagnostic requirements: Subjective score > 1;CT mean value < 300 HU and SD >30HU measured at the aortic root in objective assessment; CCTA-AI misidentification of coronary artery branches and segments due to various reasons such as motion artifacts.

2.6. Deep learning model

Our model is based on CNN, which are made up of neurons that have learnable and adjustable weights and biases [27]. The primary advantage of CNNs is that they use pre-processing compared to the other image classification algorithm. A typical CNN consists of an input layer and an output layer as well as one or more convolutional layers, pooling layers and followed by one or more fully connected layers. Every layer transform data to another layer through a differentiable function. Input layer of a neural network consists of artificial input neurons that contains the image pre-processing algorithm and brings the initial image data into the system for further processing. The convolutional layers receive the inputs and are used for feature extraction and recognition of image. The pooling layers are used for progressively reducing the spatial size of the representation to reduce the amounts of parameters and computation in the network. In the end, fully connected layers will generate the result.

The crucial component of our model is Semantic Segmentation Network (SSN). The deep learning framework consists of the image segmentation and the detection of stenosis. In the image segmentation, U-Net Convolutional Networks for BiomedicalImage Segmentation (U-net) was used. First, the conventional and pooling dowsampling was taken to the input image, and get the low-resolution feature map. Then, upsampling was taken to these features and get a high-resolution segmentation prediction. In the detection of stenosis, V-net Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation (V-net) was used. The input image received by the neural network model comes from a part of the cut image on the straightened image. The input image needs to maintain a fixed size. The result of the model calculation is a one-dimensional matrix, which contains the probability of each stenosis along the long axis of the vessel in the input image. The narrow position information can be obtained by threshold processing to the probability matrix.

The technical route is illustrated in Fig. 2. We first input a set of well-marked CCTA images as the training set, in which the all vessels and lesions have already been correctly marked by hand, then the training set is transferred to the CNN, where the data is analyzed and learnt. The CNN will automatically learn the basic rules and regulations for identifying vessels and lesions in the traditional CCTA images. The well-trained CNN is able to get segmentation image and prediction of stenosis from original images according to what it has learnt from the training set.

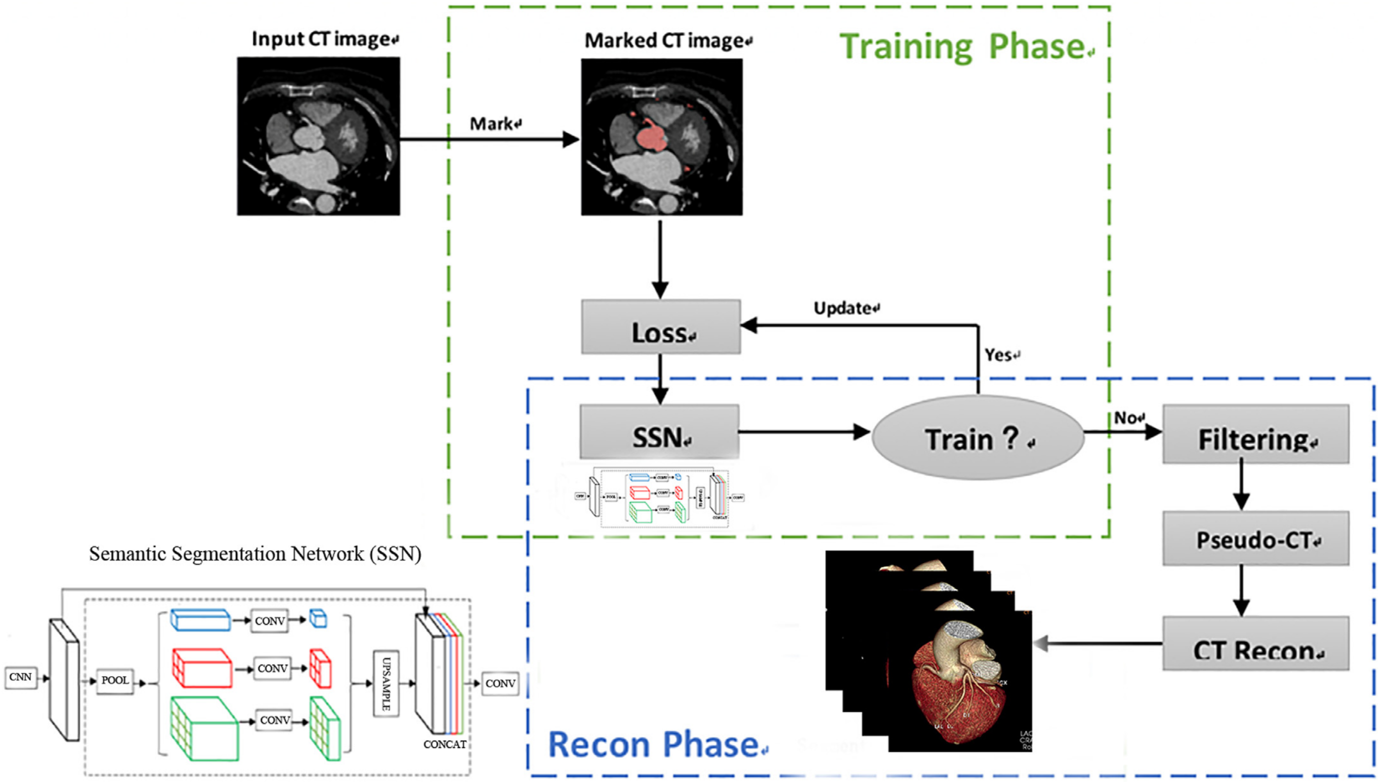

Fig. 2. The CNN learns rules and regulations from the marked CTA images, then it is able to process CTA images by automatically.

2.7. Experimental settings

In one of our previous studies, a CNN has been trained to identify coronary artery branch vessels, coronary lumen with more than 10,000 CCTA cases, which was treated as the Coronary BASE model. Based on the BASE model, in this study, retrospective CCTA images of 100 patients diagnosed with CAD by DSA were divided into a training data set, and further learned characteristics of calcified plaque, partially calcified plaque, non-calcified plaque and various degrees of coronary stenosis from traditional CCTA by transfer learning to train a new deep learn model. Another 50 CAD patients were divided into an independent testing dataset to further confirm the effectiveness of our proposed new deep learning model by comparing the accuracy of the new model and the traditional method to identify coronary artery stenosis and plaque type, with DSA as the reference method.

2.8. Statistical analysis

Statistical analysis was carried out using SPSS version 22.0 (SPSS Inc., Chicago, USA). The diagnostic efficacy of CCTA-AI and traditional CCTA in identifying $\geq$ 50% stenotic vessels was evaluated including sensitivity, specificity, accuracy, mistake diagnostic rate, omission diagnostic rate, positive predictive value and negative predictive value.

Receiver operating characteristic (ROC) analysis was employed to test the accuracy of AI and traditional CCTA with DSA as the reference method in identifying coronary stenosis including minimal stenosis, mild stenosis, moderate stenosis, severe stenosis and occlusion. ROC analysis was also employed to test accuracy of CCTA-AI in identifying plaque classification. $P < 0.05$ was considered to have significant difference. The area under curve (AUC) = 0.50 was considered valueless diagnosis, $0.50 < \text{AUC} \leq 0.7$ was low diagnostic accuracy, $0.7 < \text{AUC} \leq 0.9$ was moderate, $0.9 < \text{AUC} < 1.0$ was good.

3. Results

CCTA-AI images of 50 CAD patients were evaluated. Every segment of coronary artery in 50 patients was an observation object. In identifying stenosis, DSA was executed in 396 coronary segments of 50 patients. In identifying plaque classification, 793 coronary segments of these patients were evaluated.

3.1. Efficiency of AI compared to CCTA image generation

In the process of traditional image reconstruction, it takes average 15–20 min to perform CCTA post-processing for each patient. AI takes only 2–3 min in average to do it and reduces time by 85%. In the process of traditional CCTA diagnosis, it takes average 5–10 min for a patient by manual approach of image reading and interpretation, while AI takes only 1–2 minutes in average for each case and reduces time by 80%.

3.2. Accuracy of CCTA-AI in identifying coronary vessels

The diagnostic efficacy of CCTA-AI and traditional manual interpretation of CCTA in identifying stenotic vessels are shown in Table 3. With DSA as the reference method, in identifying various degrees of coronary stenosis, the diagnostic accuracy of AI is better than traditional CCTA ($AUC_{AI} = 0.870$, $AUC_{CCTA} = 0.781$, $P<0.001$, Fig. 3). In identifying $\geq$ 50% stenotic vessels, sensitivity, accuracy, mistake diagnostic rate and negative predictive value of CCTA-AI were 88%, 86%, 14.7% and 94%, which were respectively higher than traditional CCTA. Specificity, omission diagnostic rate and positive predictive value of CCTA-AI were 85%, 12.5%, and 73%, which were lower than those of traditional manual interpretation.

Table 3
The diagnostic efficacy of CCTA-AI and CCTA in identifying ≥50% stenotic vessels.

	CCTA-AI	CCTA
Sensitivity	88%	59%
Specificity	85%	94%
Accuracy	86%	83%
Mistake diagnostic rate	14.7%	6.5%
Omission diagnostic rate	12.5%	40.6%
Positive predictive value	73%	81%
Negative predictive value	94%	83%

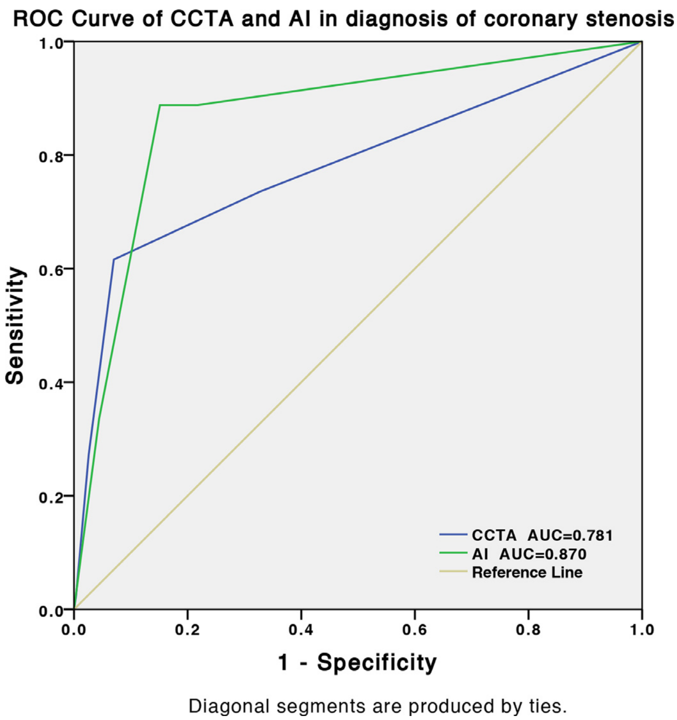

Fig. 3. In identifying stenotic ≥ 50% vessels, the diagnostic accuracy AI is better than traditional artificial CCTA (AUC_{AI} = 0.870, AUC_{CCTA}= 0.781, P = 0.000<0.001) with DSA as the gold standard.

3.3. The ability of CCTA-AI to identify plaque classification

With traditional CCTA as the reference method, the diagnostic accuracy of CCTA-AI in identifying plaque classification is shown in Table 4 and Fig. 4 (AUC = 0.750, P < 0.001). The accuracy is moderate. The diagnostic efficacy of AI in identifying calcified plaque, partially calcified plaque and noncalcified plaque is shown in Table 5. The consistency between them in identifying noncalcified plaque is relatively better than identifying calcified plaque and partially calcified plaque. The specificity, accuracy and negative predictive value of CCTA-AI in identifying every plaque classification are very good, the sensitivity (64%), mistake diagnostic rate (8.5%) in identifying calcified plaque is higher and the omission diagnostic rate (97%) in identifying partially calcified plaque is higher.

4. Discussion

The main findings of this analysis are that AI based on CCTA reduces 85% time to reconstruct images and 80% time to diagnose CAD comparing with traditional artificial image reconstruction and diagnosis. With DSA as the reference method, diagnostic accuracy of CCTA-AI is better than traditional CCTA images in identifying plaque classification, and the accuracy of CCTA-AI is moderate.

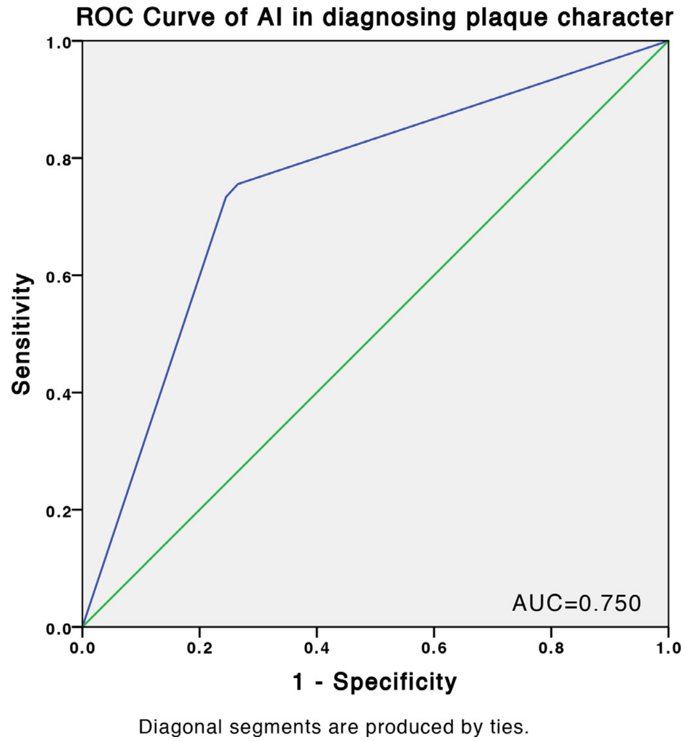

Fig. 4. In identifying plaque classification, the diagnostic accuracy of AI is moderate (AUC = 0.750, P < 0.001) with traditional artificial CCTA regarded as the gold standard.

So far, CNN has acquired many outstanding achievements in detection, segmentation and identification of objects and regions within images [13,28]. And some studies have been able to automatically extract coronary artery centerline in CCTA [29–32]. In this study, we explored and proved the feasibility of using a deep learning method for CCTA (CCTA-AI) which combined the method of automatically extracting the center line with the anatomical characteristics of each branch of the coronary artery to make the computer automatically identify the branches and segments of each coronary artery and simulate 3D VR, CPR, VP, vessel straightening reconstruction. In the past, computer-aided diagnostic equipment could only identify four major coronary artery vessels [33]. However, our AI workstation can not only identify major coronary artery vessels, but also branches larger than 1.5 mm in diameter. And it greatly reduces the time spent on post-processing. Furthermore, this system has a new algorithm that can be optimized through learning continuously and data accumulation. In this study, AI auto-reconstructed images fully complies with the manual reconstructed images of CCTA, and there are only errors in automatic identification.

In addition, we expounded and proved that a deep learning model trained by retrospective analysis of CCTA images is applicable to diagnosis of CAD, demonstrating the advantages, flexibility, and prospects of deep learning methods. In this study, comparing the time of AI and traditional artificial diagnosis, the results are different due to the different severity of the disease. The more severe the lesion, the longer it takes to diagnose artificially, but the diagnosis of AI can be obtained almost instantaneously. In this study, coronary artery diseases of patients undergoing DSA are relatively severe, thus AI shows dominant role in the diagnosis time.

Motwani et al. showed the machine learning (ML) greatly increased prediction rate of death by comparing with the Framingham Risk Score, segment stenosis score (SSS), segment involvement score (SIS), modified Duke index (DI) [12]. Rosendael et al.

Table 4
The comparison of CCTA-AI and CCTA in identifying plaque classification.

Plaque classification		CCTA				Total
		calcified plaque	partially calcified plaque	noncalcified plaque	no plaque	
CCTA-AI	calcified plaque	32	27	12	24	95
	partially calcified plaque	0	2	1	1	4
	noncalcified plaque	8	13	35	20	76
	no plaque	10	22	17	569	618
Total		50	64	65	614	793

The total accuracy is 80.4%.

Table 5
The diagnostic efficacy of CCTA-AI in identifying plaque classification.

	Calcified plaque	Partially calcified plaque	Noncalcified plaque
Sensitivity	64%	3.1%	54%
Specificity	91.5%	99.7%	94.4%
Coincidence	89.8%	91.9%	91.0%
Mistake diagnostic rate	8.5%	0.3%	5.6%
Omission diagnostic rate	36%	97%	46.2%
Positive predictive value	33.7%	50%	46%
Negative predictive value	97.4%	92.1%	95.8%

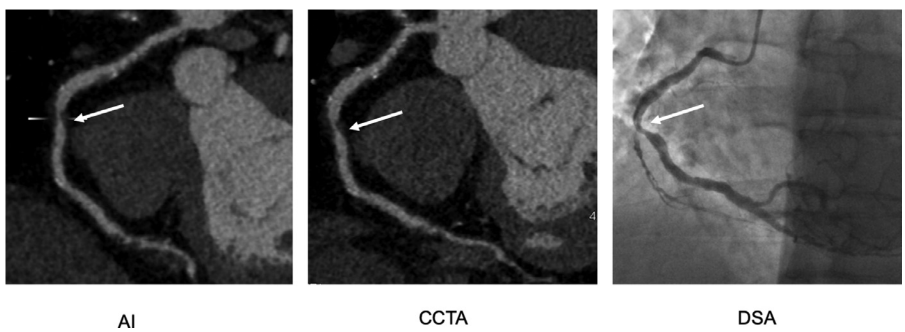

Fig. 5. 56-year-old female, moderate stenosis in the middle segment of the right coronary artery (RCA) due to non-calcified plaque. The diagnosis of CCTA-AI is consistent with that of traditional artificial CCTA and DSA.

demonstrated that a ML score provides increased risk stratification compared with conventional CCTA based risk scores [14]. However, they did not evaluate in detail the accuracy and cause of errors in detecting coronary artery stenosis and different types of plaque by the two examinations. In a similar study, Zreik et al. proposed an automatic recognition method for plaque and stenosis features. They showed that the accuracy of this method in identifying stenosis at the level of segment, artery and patient was 0.80, 0.76 and 0.75, and the linear weights were 0.68, 0.66 and 0.67, respectively [15]. However, they only compared ML with CCTA, which would lead to inaccurate diagnosis because of the inevitable limitations of CT. In our study, we compared CCTA-AI, CCTA and DSA, and compared the accuracy of ML and CCTA in detecting vascular stenosis with DSA as the reference method. In identifying $\geq$ 50% stenotic vessels, the sensitivity, accuracy, mistake diagnostic rate and negative predictive value of CCTA-AI are respectively higher than traditional CCTA, and specificity, omission diagnostic rate and positive predictive value of CCTA-AI are lower than traditional CCTA. Diagnostic consistency of CCTA-AI and DSA is better than that of traditional CCTA and DSA (shown in Figs. 5 and 6). To a certain extent, the use of CCTA-AI can improve the sensitivity to individual lesions in diagnosis and reduce the omission diagnostic rate. And it reduces the errors caused by the human eye in judging coronary artery stenosis and makes the diagnosis more accurate to 1%, whereas human eye can only reach one range. The lower specificity and higher mistake diagnostic rate may be associated with the false positive caused by the origin of coronary artery branches and beam hardening artifacts in original CT images (Figs. 7 and 8). Beam hardening artifacts caused by calcified plaques can be reduced by CT subtraction technology. In the future, we will use AI combined with CT subtraction technology to further explore the assessment of coronary heart disease, which is expected to be more accurate.

In addition, Zreik et al. showed the accuracy of this method in identifying plaque characteristics at the level of segment was 0.77 with unweighted of 0.61 [15]. In our study, AI achieved the total segment-level accuracy of 80.4% with AUC of 0.750, which is better than the previous study. It may be the result of continuous optimization of an algorithm. In our study, we also compared the accuracy of detecting various types of plaques. The recognition of calcified and non-calcified plaques is relatively better than partial calcified plaques. The partial calcified plaques are often recognized as calcified plaques, which is probably because the density of calcified plaques is significantly different from that of soft tissues, and the sensitivity of calcified plaques is higher. It was proved in evaluation of the diagnostic efficacy of CCTA-AI in identifying plaque classification (Table 5). However, the diagnostic mistake rate is relatively higher. This may be because AI recognizes some noise as calcified plaques, and this should be solved in future researches with the improvement of AI performance.

For a deep learning approach, despite CCTA-AI shows its benefit in identification of CAD, this study does have several limitations. First, CCTA-AI identifies coronary arteries in axial images by spatially registering to templates representing the particular anatomy. This requires that the anatomical structure of each subject is almost normal. However, this is often not the case in reality. Therefore, the method needs to be improved in subjects with abnormal anatomy. Second, in evaluating the diagnostic performance of

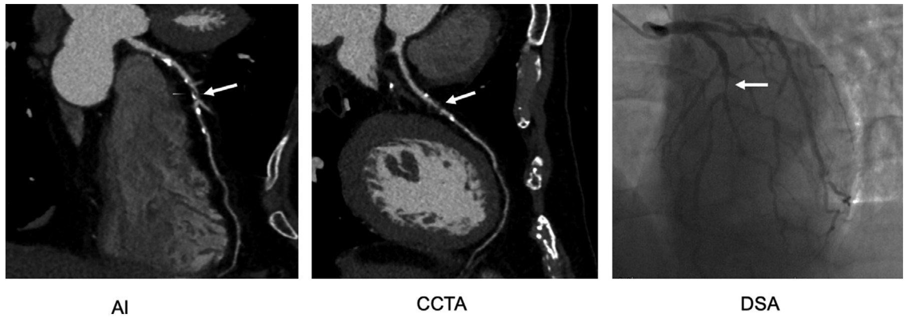

Fig. 6. 64-year-old male, severe stenosis in the mid-segment of the left anterior descending coronary artery (LAD) due to mixed plaque. The diagnosis of CCTA-AI is consistent with that of traditional artificial CCTA and DSA.

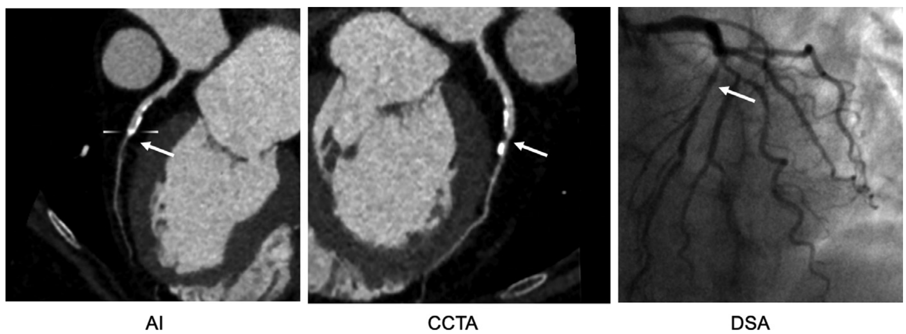

Fig. 7. 45-year-old male, at the origin of the middle segment of LAD, the diagnosis of CCTA-AI is moderate stenosis, while the DSA and traditional artificial CCTA are normal. The false stricture may be caused by the origin of coronary artery branches.

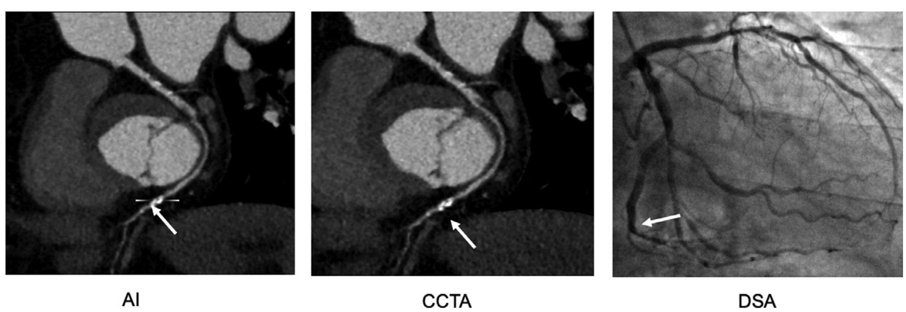

Fig. 8. 59-year-old male, at the distal segment of left circumflex, the diagnoses of CCTA-AI and traditional artificial CCTA are severe stenosis due to calcified plaque, while the DSA shows normal. The discrepancy between CCTA and DSA is due to beam hardening artifacts caused by calcified plaques which affect the determination of lumen stenosis in the original CT images.

CCTA-AI and CCTA, only ≥50% stenotic vessels were considered to be positive instead of exact stenosis grading vessels. AI's ability to distinguish between moderate and severe stenosis is not excellent, but its ability to recognize more than moderate stenosis is good enough. More than 50% of coronary stenosis can be diagnosed as coronary heart disease clinically, so this result was also very meaningful [34]. AI will perform better and better with the increase of data and the update of algorithm. In addition, the number of cases is too small, and the selection of patients is biased. The coronary artery lesions in patients undergoing DSA are usually severe with highly significant stenosis, so the value of this new method cannot be fully evaluated. AI may perform better in patients with mild stenosis and without coronary artery lesions. This requires expanding the database of deep learning and constantly iterating and updating algorithms. Patients with CABG or coronary stents were excluded in this study, however, future studies could be conducted to explore the clinical value of AI in detecting coronary stents, in particular, in-stent restenosis compared to CCTA.

In conclusion, as an automatic approach for coronary stenosis detection in clinical routine, CCTA-AI has tremendous potential. It omits some CCTA reconstruction steps to some extent, reduces time for reconstruction and diagnosis, and reduces the error of human eyes in assessing the degree of coronary stenosis compared with traditional artificial diagnosis. Unfortunately, AI has limited value in identifying the plaque feature exactly yet. At the present stage, AI still can't replace human beings in interpreting CCTA images, as it only changes the way of human beings work and improves the work efficiency. In daily work, it can provide a powerful reference for inexperienced doctors in local or regional hospitals, but sometimes it is still inseparable from the explanations of experienced doctors. In the future research, we will continue to improve the algorithm to increase the accuracy of AI to evaluate plaque types, and study the characteristics of bifurcated lesions, and explore the ability of AI to provide preoperative guidance and postoperative complications prediction for percutaneous coronary intervention in the analysis of bifurcated lesions.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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