

# Deep Learning Network-based Assessment of Stent Effectiveness and In-Stent Restenosis in Coronary Intervention Therapy

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**Abstract:** Objective: To explore the application value of deep learning network based stent effect assessment and in-stent restenosis assessment in coronary intervention therapy. Methods: Combining the image data related to coronary interventional therapy, a deep learning model was constructed, based on two-dimensional stent and vessel images without and with contrast, and after pre-processing such as image segmentation and registration, feature parameters such as the diameter of the stent and the vessel were extracted, the images with tent and image with angiography vessels are overlaid in the same image, and the rate of vascular restenosis was calculated, and the performance of the segmentation model was evaluated by DSC (Dice Similarity Coefficient). Data pertaining to 500 patients receiving stent implantation were analyzed and contrasted with clinical assessments. Results: The DSC values of the deep learning model for stent and vessel segmentation were  $0.89 \pm 0.04$  and  $0.92 \pm 0.03$ , respectively, and the segmentation error was controlled within the range of  $0.12 \pm 0.05$  mm. In 50 patients, the model had a detection rate of 90.0% for ISR (Kappa value = 0.82), and the stenosis rate measurement results were highly consistent with clinical evaluation (Pearson correlation coefficient  $r = 0.94$ ,  $P < 0.001$ ). Stratified analysis by vascular location showed that the evaluation rates of the anterior descending artery, circumflex artery, and right coronary artery were 92.9%, 83.3%, and 90.0%, respectively. Conclusion: The deep learning network can effectively segment the stent and angiography vessels, and the registration method without ECG signal can match the stent and vessel very well. The automatic assessment of the in-stent restenosis has good clinical application prospects.

**Keywords:** coronary intervention; stent; in-stent restenosis; deep learning; image evaluation

## 1. Introduction

Coronary intervention (PCI) has become a core means of coronary revascularization by virtue of its advantages of less trauma and faster recovery, and stent implantation is a key part of PCI <sup>[1]</sup>. However, after stent implantation, whether the stent effect is ideal or not, and whether in-stent restenosis (ISR) occurs or not,

are directly related to patients' subsequent therapeutic decisions and prognostic regression, and accurate assessment is of great significance to improve the quality of patients' long-term survival <sup>[2-4]</sup>.

Traditional assessment methods rely on physicians' visual analysis of coronary angiography, CT angiography, and other images, which have been used in clinical practice for many years, but the consistency and accuracy of the assessment results are often affected by the differences in physicians' experience, visual fatigue, and subjective judgment bias <sup>[5,6]</sup>. In recent years, deep learning technology has emerged in the field of medical imaging, and by building complex neural networks, it can automatically mine the hidden subtle features and laws in the images to achieve efficient and accurate image recognition and analysis. In the scenarios of lung nodule diagnosis, brain tumor segmentation, etc., deep learning has demonstrated the advantages beyond the traditional manual reading of films, bringing revolutionary changes to medical image evaluation <sup>[7-9]</sup>.

The aim is to construct a deep learning-based assessment model, with the help of algorithms to deeply analyze stent and vascular images, break through the limitations of manual assessment, provide more objective and accurate assessment tools for the clinic, and help optimize the post-PCI management strategy of patients with coronary heart disease, ultimately improve the prognosis of the patients, and promote the accurate diagnosis and treatment of cardiovascular diseases to a new height.

## 2 Data and Methods

### 2.1 Subjects

500 patients who underwent coronary intervention and stent implantation in our hospital from December 2023 to December 2024 were collected, all patients met the indications for coronary intervention and relevant imaging examinations were performed after the operation. Inclusion Criteria: ①Coronary stent implantation; ②Postoperative imaging data were complete and of good quality: coronary angiography or coronary CT angiography (CCTA) was performed at 1 month, 3 months, 6 months and 12 months after the operation, and the images should clearly show the stent and the vessel morphology; ③Informed consent of the patients and their family members. Exclusion criteria: ①Combined with severe hepatic and renal insufficiency; ②Obvious artifacts in the imaging data; ③Other serious cardiac diseases affecting the evaluation results; ④Serious acute complications after stent implantation.

### 2.2 Instruments and methods

A Siemens Artis zee series digital subtraction angiography machine was used to acquire two-dimensional vascular images with artifacts, paired with a Medtronic Dragonfly optical coherence tomography (OCT) system to acquire two-dimensional stent images without artifacts . Before the examination, the

patients were prepared routinely, and the images were acquired according to the operation standard of the equipment to ensure the image quality.

## 2.3 Image pre-processing and data set division

### 2.3.1 Image Acquisition and Initial Screening

Acquisition of 2D stent images without contrast (acquired by intravascular ultrasound, optical coherence tomography and other non-contrast modalities, clearly presenting the shape of the stent metal structure) and 2D vascular images with contrast (acquired by coronary angiography or CT angiography, accurately displaying the lumen of the blood vessel and the lesion contour) at different points in time after coronary interventional therapy (**Figure 1**). Two attending physicians with more than 10 years of experience in diagnostic coronary imaging performed primary screening based on image quality criteria (eg, no obvious motion artifacts or metal artifacts, image resolution  $\geq 512 \times 512$  pixels). First Image segment of catheter, stent and vessels. Then registration according to the catheter in the images of stent and vessels. (**Figure 2**).

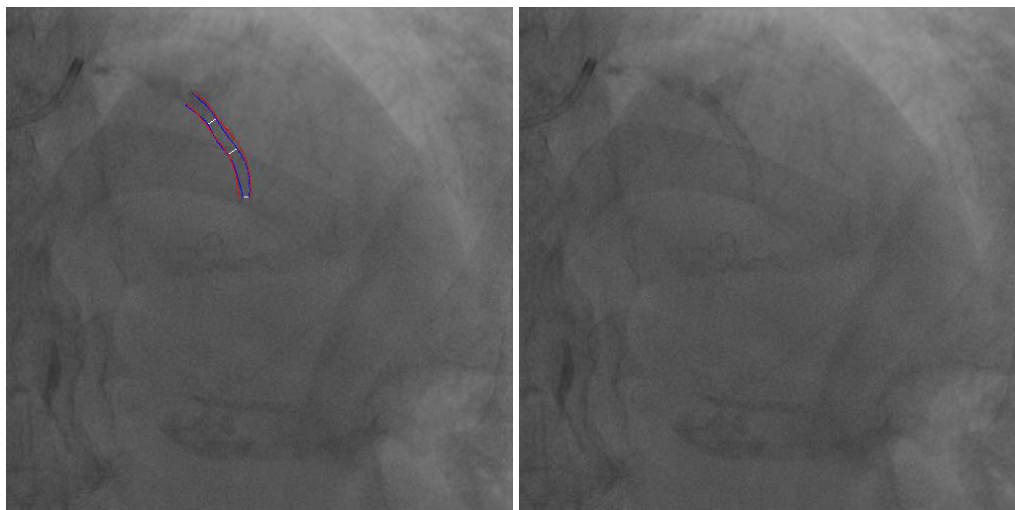


**Figure 1** 2D stent images the right image is the series with stent only; the left image is the result with stent and part of the vessel overlaid

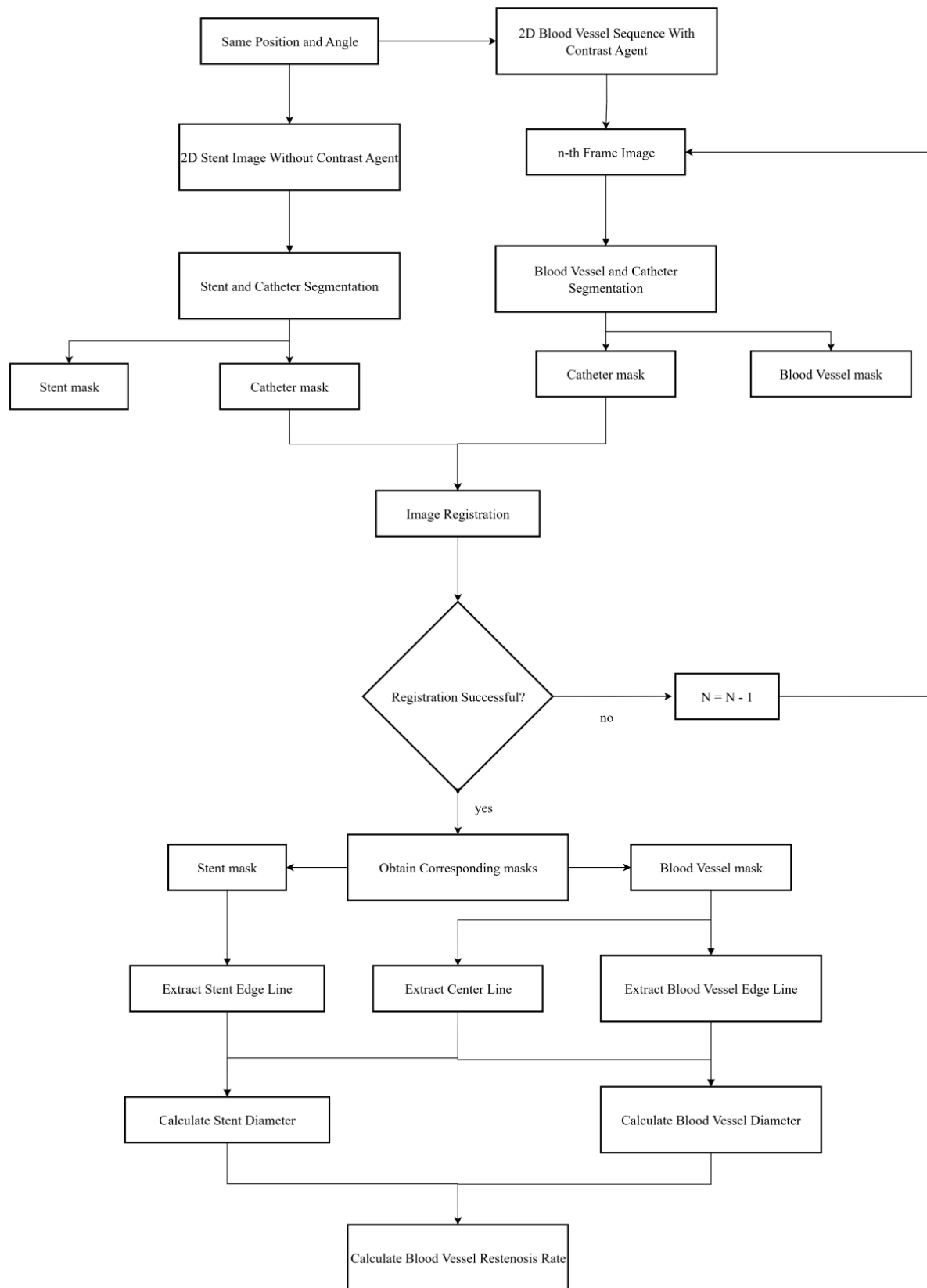


**Figure 2.** Specific flow chart of image preprocessing and analysis

### 2.3.2 Image Segmentation

The segmentation of the aligned images was performed under the PyTorch framework using the U-Net improved deep learning segmentation model. A training set of 10000 labeled stent and vessel images (80% for model training and 20% for validation) was constructed, and the labeling was done by the two physicians mentioned above, clearly dividing the stent area (stent mask) and vessel lumen area (vessel mask). During model training, the network parameters were optimized with the Dice loss function, and the image features were extracted through the convolutional layer, and then precisely segmented by up-sampling and down-sampling operations. After segmentation, the mask is post-processed using morphological operations (e.g., open/close operations) to remove small noise and fill in voids to ensure that the stent boundary line and vessel boundary line are continuous and accurate, which lays the foundation for subsequent feature extraction.

### 2.3.3 Image Registration

For Image registration, the ECG signal is not applied. While the catheter is employed to obtain the motion cycle of the heart and its vessels. Based the motion cycle, the image registration is executed and part of the vessels(Blue line) and stents (Purple line)are overlaid in the same image (**Figure 3**).



**Figure 3.** Image after adjustment, registration and segmentation

### 2.3.4 Feature extraction

From the segmented stent mask, an edge detection algorithm (Canny algorithm) is used to extract the stent boundary line, and the stent centerline is obtained based on the skeleton extraction technique (Zhang-Suen algorithm); similarly, the blood vessel boundary line and centerline are extracted from the blood vessel mask. Based on the information of these lines, the diameters were calculated with 5 equally spaced sampling points (evenly distributed in the stent/vessel length direction): a straight line was made perpendicular to the center line, and the distance between the intersection points with the boundary line was the

diameter of the point, and the average of the 5 points was taken as the stent diameter () and the vessel diameter () (**Fig. 4**), which was used for the subsequent calculation of restenosis rate (), where was the preoperative reference diameter of the same vessel segment).

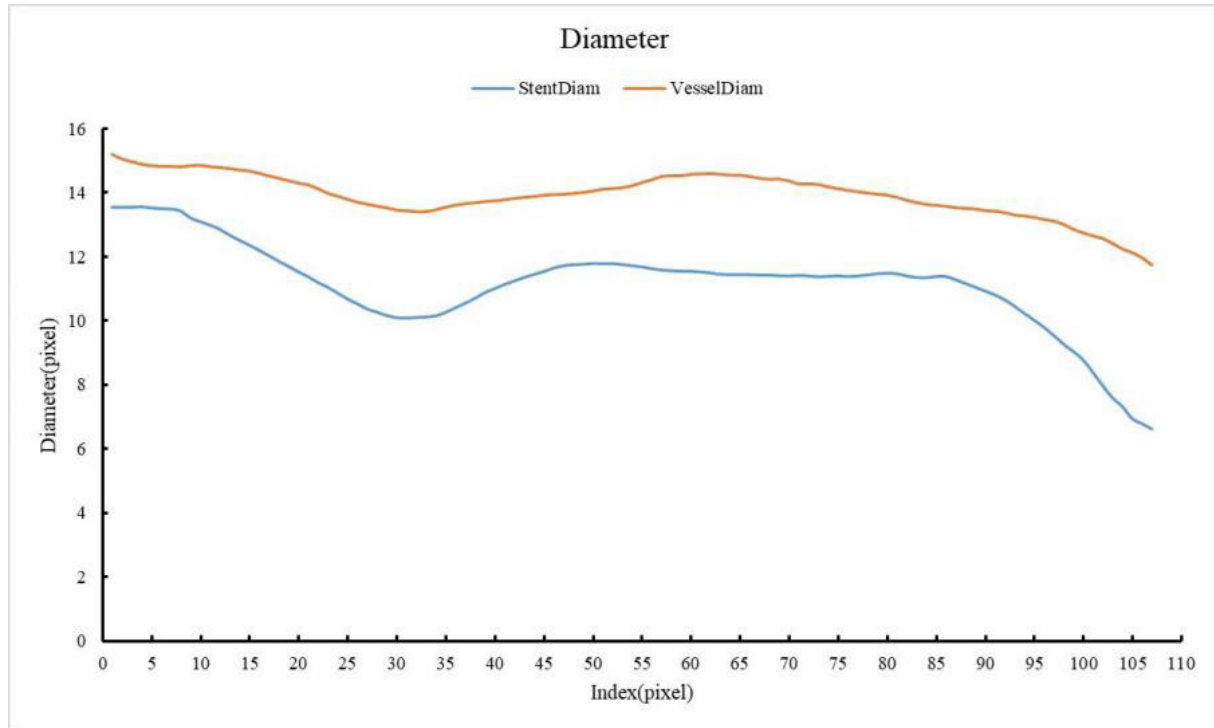


**Fig 4.** Diameter folding diagram

## 2.4 Deep Learning Model Construction

Build a deep learning model based on the preprocessed image data. The PyTorch framework is utilized for model construction, and since the processed images are two-dimensional images, they are adjusted to a format suitable for model input. Enhancement processes such as random angle rotation ( $-15^{\circ}\sim 15^{\circ}$ ), random horizontal and vertical flipping are performed on the dataset to improve the generalization ability of the model. The initial learning rate was set to 0.00001, the period 200, the batch size 64, the cross-entropy loss function and Adam optimizer were used, and a 24GB Nvidia RTX A5000 graphics card was used for model training.

## 2.5 Model Evaluation Metrics

The DSC (Dice Similarity Coefficient) was used to evaluate the performance of the segmentation model. The closer the DSC value is to 1, the better the consistency between the segmentation result and the actual situation. The evaluation results of the deep learning model were compared with the clinical evaluation results to verify the effectiveness of the model in the evaluation of in-stent restenosis.

### 3 Results

#### 3.1 Clinical data

Of the 150 patients included in this study, 29 were male and 21 were female, aged 45-78 years, with a mean age of (62.3±8.5) years. All patients successfully completed coronary stent implantation and imaging examination, and the general clinical data of different genders, ages, and underlying diseases (hypertension, diabetes mellitus) were compared among the training set, test set and validation set, and the differences were not statistically significant ( $P>0.05$ ), and were comparable.

#### 3.2 Performance of the deep learning model

The segmentation results of the deep learning model for stents and blood vessels showed that the Dice Similarity Coefficient (DSC) for stent segmentation was  $0.89\pm0.04$ , and for vessel segmentation was  $0.92\pm0.03$ , both meeting clinical application-level accuracy. The segmentation error at the vessel lumen boundary was controlled within  $0.12\pm0.05$  mm, providing a reliable foundation for diameter measurements required for stenosis assessment (**Table 1**).

**Table 1.** Segmentation performance of the deep learning model for stents and blood vessels

| Segmentation Target | Mean DSC $\pm$ SD | 95% Confidence Interval | Maximum Error (mm) |
|---------------------|-------------------|-------------------------|--------------------|
| Stent Structure     | $0.89\pm0.04$     | 0.87-0.91               | 0.21               |
| Vessel Lumen        | $0.92\pm0.03$     | 0.90-0.93               | 0.15               |

#### 3.3 Comparison of Stenosis Assessment Results

(1) Consistency in Restenosis Detection:

Among 50 patients, clinical evaluation confirmed restenosis (stenosis rate  $\geq 50\%$ ) in 12 cases. The deep learning model detected 11 cases, including 10 true positives, 1 false positive, and 1 false negative. The diagnostic agreement rate was 90.0%, with a Kappa value of 0.82 (**Table 2**).

**Table 2.** Model Performance in Restenosis Assessment

| Evaluation Method | Clinically Confirmed Restenosis (12 cases) | Clinically Excluded Restenosis (38 cases) |
|-------------------|--------------------------------------------|-------------------------------------------|
| Model-Positive    | 10 (True Positive)                         | 1 (False Positive)                        |
| Model-Negative    | 1 (False Negative)                         | 37 (True Negative)                        |

(2) Quantitative Comparison of Stenosis Severity:

For the 12 patients with restenosis(**Figure 5**), the stenosis rate measured by the deep learning model was  $(68.5\pm12.3)\%$ , while the clinical measurement was  $(67.8\pm11.5)\%$ . The mean difference was  $0.7\pm3.2\%$ , with a Pearson correlation coefficient of  $r = 0.94$  ( $P < 0.001$ ).

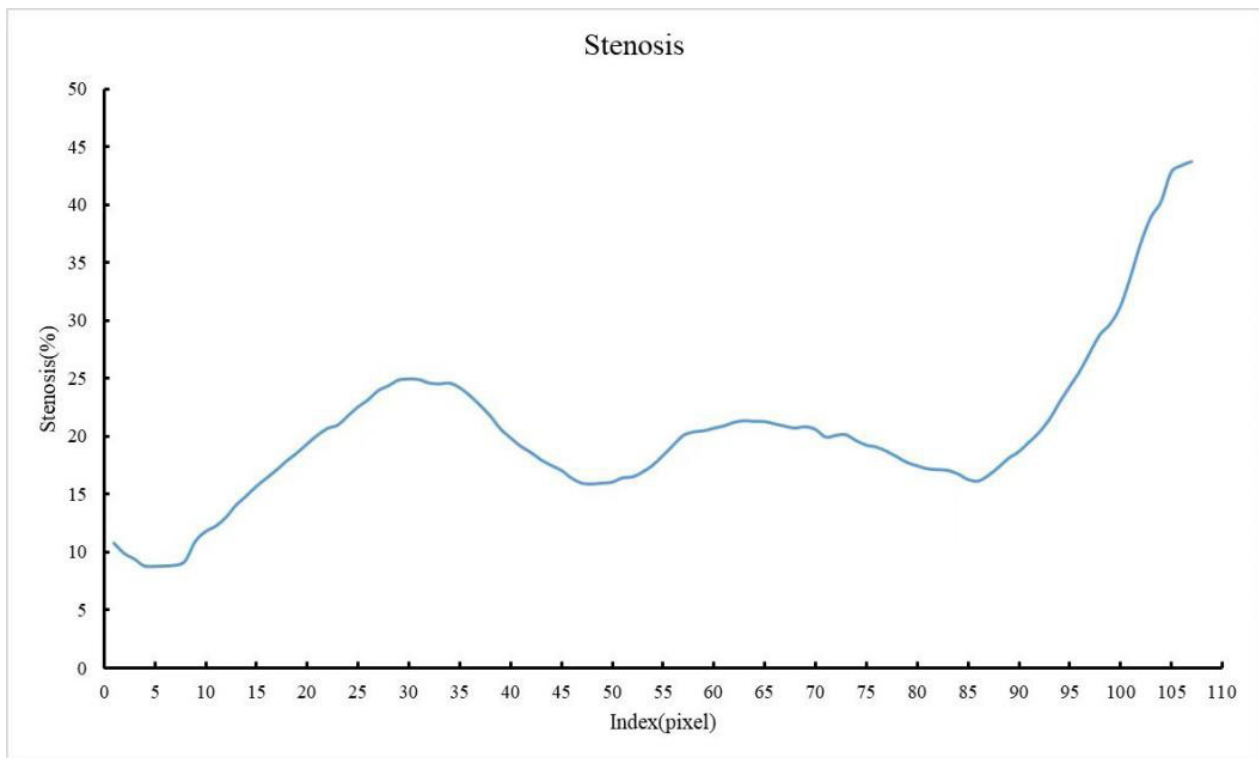


**Fig 5.** Line graph of stenosis rate

### (3) Stratified Analysis by Stent Location:

The agreement rates for stenosis assessment in the left anterior descending (LAD), left circumflex (LCX), and right coronary artery (RCA) were 92.9% (26/28), 83.3% (10/12), and 90.0% (9/10), respectively, demonstrating stable model performance across different vascular segments.

## 4. Discussion

In this study, an automatic assessment model of stent effect and ISR was constructed based on a deep learning network, and the results showed that the Dice similarity coefficient (DSC) of the model in stenting and vessel segmentation reached 0.89 and 0.92, respectively, and the compliance rate of stenosis assessment was 90.0%, which was in high agreement with the clinical results (Kappa value = 0.82). This result provides a new technical tool for accurate assessment of coronary interventions and also lays the foundation for further development of related research.

The core innovation of this study is the use of deep learning techniques to realize automatic segmentation and alignment of stents and vessels, and to quantify the stenosis rate by combining images without and with contrast. The study by Min et al <sup>[10]</sup> also demonstrated the powerful potential of deep learning, in which they predicted stent under-expansion based on pre-procedural intravascular ultrasound (IVUS) images by convolutional neural network (CNN) at both the frame level and lesion level with a prediction accuracy of 94% and a corre-

lation coefficient of 0.832, respectively. This result complements the accuracy of the postprocedural assessment in this study, suggesting that deep learning can be used not only for postprocedural assessment, but also to provide an important reference for clinical decision-making in the preprocedural period. Lopez and Sonka<sup>[11]</sup> further showed that deep learning combined with IVUS guidance can significantly improve PCI prognosis, for example In the IVUS-XPL trial, the target lesion revascularization rate decreased from 5.0% to 2.5%. Together, these studies confirm the value of deep learning in the entire process of coronary intervention, from pre-procedure planning to post-procedure follow-up.

In terms of ISR detection, the results of this study are consistent with the study by Kawai et al<sup>[12]</sup>, who used deep learning reconstruction technique (PIQE) to improve the diagnostic accuracy of CT angiography for restenosis of small stents (<3.0 mm diameter) with specificity and image quality scores that were significantly better than those of conventional methods. This suggests that deep learning is pervasive in multimodal imaging and enables highly accurate stenosis assessment, whether based on contrast images or CT images. In addition, a study by Giacoppo<sup>[13]</sup> emphasized that although drug-eluting stents (DES) significantly reduced the incidence of ISR, their treatment is still challenging, with target lesion revascularization rates as high as 38%-56% at 10 years. Therefore, early accurate assessment through deep learning (as modeled in this study) is important to improve the long-term prognosis of patients.

The results of this study are not only clinically useful, but also provide support for related theoretical studies. Shi et al<sup>[14,15]</sup> constructed a multi-physics field model by physical information neural network (PINN) to simulate the mechanism of ISR progression by combining biological constraints and drug release effects. Their study provided a theoretical framework for the quantification of stenosis rate in this paper, revealing the complex relationship between ISR and multiple biomechanical factors. For example, dynamic changes in factors such as platelet-derived growth factor (PDGF) and transforming growth factor (TGF- $\beta$ ) are closely related to the occurrence of ISR. Future studies may try to integrate such biological parameters into deep learning models to further improve the accuracy of prediction.

In addition, Nguyen et al<sup>[16]</sup> found that laminar flow in stent segments reduced the risk of ISR by 80% from a hemodynamic point of view, whereas turbulent flow was significantly associated with the occurrence of ISR. This finding, combined with the assessment results of this study stratified by vessel site (e.g., 92.9% compliance rate for anterior descending branches), suggests that blood flow characteristics may be an important factor influencing ISR. The inclusion of hemodynamic parameters (e.g., blood flow velocity, shear stress, etc.) may be considered in future model optimization for a more comprehensive assessment of stent effectiveness and ISR risk.

Despite the good results obtained in this study, there are some limitations. First, the small sample size (only 50 patients) may affect the generalization abil-

ity of the model. In the future, the dataset can be expanded through multicenter collaborations and more complex cases (e.g., bifurcation lesions, chronic completely occluded lesions, etc.) can be included to validate the broad applicability of the model. Second, this study is mainly based on two-dimensional images, while coronary lesions have three-dimensional characteristics, and future attempts can be made to incorporate three-dimensional reconstruction techniques to enhance the comprehensiveness of the assessment. Finally, the real-time nature of the model has not yet been validated in a clinical setting, and subsequent studies could explore integrating it into the workflow of the catheterization laboratory to achieve intraoperative real-time assessment.

## 5. Conclusions

In this study, an automatic assessment model of stent outcome and ISR after coronary intervention was successfully constructed based on deep learning network, and the results showed that it has high accuracy and clinical applicability. Combined with the relevant studies in recent years, deep learning shows a broad application prospect in the field of coronary intervention, covering the whole process of pre-procedure, intra-procedure and post-procedure. Despite certain limitations, the performance of the model is expected to be further improved through multicenter cooperation, multimodal data integration, and real-time optimization. Overall, deep learning provides new solutions for precise and individualized management of coronary interventions, which is expected to improve patient prognosis and promote the development of cardiovascular disease diagnosis and treatment.

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