Radiology

ORIGINAL RESEARCH • CARDIAC IMAGING

Deep Learning–based Prediction of Percutaneous Recanalization in Chronic Total Occlusion Using Coronary CT Angiography

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Conflicts of interest are listed at the end of this article.

See also the editorial by Pundziute-do Prado in this issue.

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Background: CT is helpful in guiding the revascularization of chronic total occlusion (CTO), but manual prediction scores of percutaneous coronary intervention (PCI) success have challenges. Deep learning (DL) is expected to predict success of PCI for CTO lesions more efficiently.

Purpose: To develop a DL model to predict guidewire crossing and PCI outcomes for CTO using coronary CT angiography (CCTA) and evaluate its performance compared with manual prediction scores.

Materials and Methods: Participants with CTO lesions were prospectively identified from one tertiary hospital between January 2018 and December 2021 as the training set to develop the DL prediction model for PCI of CTO, with fivefold cross validation. The algorithm was tested using an external test set prospectively enrolled from three tertiary hospitals between January 2021 and June 2022 with the same eligibility criteria. All participants underwent preprocedural CCTA within 1 month before PCI. The end points were guidewire crossing within 30 minutes and PCI success of CTO.

Results: A total of 534 participants (mean age, 57.7 years ± 10.8 [SD]; 417 [78.1%] men) with 565 CTO lesions were included. In the external test set (186 participants with 189 CTOs), the DL model saved 85.0% of the reconstruction and analysis time of manual scores (mean, 73.7 seconds vs 418.2–466.9 seconds) and had higher accuracy than manual scores in predicting guidewire crossing within 30 minutes (DL, 91.0%; CT Registry of Chronic Total Occlusion Revascularization, 61.9%; Korean Multicenter CTO CT Registry [KCCT], 68.3%; CCTA-derived Multicenter CTO Registry of Japan (J-CTO), 68.8%; $P < .05$) and PCI success (DL, 93.7%; KCCT, 74.6%; J-CTO, 75.1%; $P < .05$). For DL, the area under the receiver operating characteristic curve was 0.97 (95% CI: 0.89, 0.99) for the training test set and 0.96 (95% CI: 0.90, 0.98) for the external test set.

Conclusion: The DL prediction model accurately predicted the percutaneous recanalization outcomes of CTO lesions and increased the efficiency of noninvasively grading the difficulty of PCI.

Supplemental material is available for this article.

Chronic total occlusion (CTO) of the coronary arteries is characterized by significant atherosclerotic vessel narrowing that results in complete interruption of antegrade blood flow (thrombolysis in myocardial infarction grade 0 flow) for at least 3 months (1), which is encountered in approximately one-fifth of patients suspected of having coronary artery disease referred for invasive coronary angiography (ICA) (2). Because of its complexity, CTO recanalization remains challenging, leaving a substantial proportion of patients to be cared for medically or referred for coronary artery bypass graft surgery rather than percutaneous coronary intervention (PCI) (3,4). The availability of convenient indexes to evaluate the guidewire manipulation time and PCI success rate for CTO on a lesion-by-lesion basis may be valuable in helping physicians alleviate procedural uncertainty and select the best treatment options.

Since the introduction of 64-detector row scanners in 2003, coronary CT angiography (CCTA) has been widely used to evaluate coronary artery disease (5,6). The ability of CCTA to depict the complete coronary tree and nonenhanced occlusion segment makes it highly effective in the detection of obstructive lesions (7–9), especially for CTO lesions (all areas under the receiver operating characteristic curve [AUCs] > 0.85) (10). Coronary CT angiography is superior to ICA in the evaluation of CTO and

Abbreviations

AUC = area under the receiver operating characteristic curve, CCTA = coronary CT angiography, CTO = chronic total occlusion, CT-RECTOR = CT Registry of Chronic Total Occlusion Revascularization, DL = deep learning, ICA = invasive coronary angiography, J-CTO = Multicenter CTO Registry of Japan, KCCT = Korean Multicenter CTO CT Registry, PCI = percutaneous coronary intervention

Summary

Compared with manually derived coronary CT angiography scores for chronic total occlusion lesions, a deep learning model had better performance and image analysis efficiency in predicting 30-minute guidewire crossing and percutaneous coronary intervention outcomes.

Key Results

- A deep learning (DL) model, trained and tested with multicentric chronic total occlusion data sets, had higher accuracy than manual coronary CT angiography (CCTA)–based scores in predicting guidewire crossing within 30 minutes (DL, 91.0%; CCTA-based, 61.9%–68.8%) and percutaneous coronary intervention success (DL, 93.7%; CCTA-based, 74.6%–75.1%) ($P < .05$ for all).
- The DL-based prediction model had higher image reconstruction and analysis efficiency than the manual CCTA-based scores (mean time, 73.7 seconds vs 418.2–466.9 seconds; $P < .001$ for all).

provides valuable CTO characteristics, such as lesion length, calcium burden, stump morphology, and tortuosity (11–13). Preprocedural CCTA improves the revascularization outcome compared with ICA-guided PCI (14); thus, a number of CCTA-based prediction scores have emerged to predict guidewire crossing within 30 minutes, which minimizes operator-related bias, and PCI success of CTO lesions; these include the CT Registry of Chronic Total Occlusion Revascularization (CT-RECTOR) (15), Korean Multicenter CTO CT Registry (KCCT) (16), and CCTA-derived Multicenter CTO Registry of Japan (J-CTO) (17) scores. However, manual reconstruction and calculation of CCTA-based scores is time consuming and subjective and has less consistent predictive accuracy in external cohorts, thereby requiring further validation (18,19).

Recently, deep learning (DL)–assisted medical image processing and analysis have made considerable progress, demonstrating potential for image reconstruction (20), structural segmentation (21), lesion detection (22), and disease diagnosis (23). Moreover, artificial intelligence has played a role in automatic segmentation and CT reconstruction of CTO (24); however, to our knowledge, the performance of artificial intelligence in predicting PCI outcomes for CTO has not yet been reported.

In this study, we aimed to develop a DL model to predict guidewire crossing and PCI outcomes for CTO using CCTA and to evaluate its performance compared with manual prediction scores.

Materials and Methods

Study Sample

The study protocol was approved by the institutional review board of each participating center. All participants provided written informed consent.

For the training set, consecutive participants with CTO lesions from one tertiary hospital between January 2018 and December 2021 were prospectively identified. The inclusion criteria were as follows: *(a)* participants suspected of having coronary artery disease who underwent CCTA before PCI, *(b)* participants with ICA-confirmed CTO lesions, and *(c)* participants who underwent attempted PCI. The exclusion criteria were as follows: *(a)* history of acute myocardial infarction within 3 months, *(b)* interval between CCTA and PCI of more than 1 month, *(c)* a history of implanted stents or coronary artery bypass graft, and *(d)* nondiagnostic images with severe noise or artifacts and blurred vessel margin.

For the external test set, participants with CTO lesions were prospectively enrolled from three tertiary hospitals between January 2021 and June 2022 using the same eligibility criteria.

The reference values and definitions used for cardiovascular risk factors (hypertension, diabetes, and hyperlipidemia) are presented in Appendix S1.

CCTA Protocol

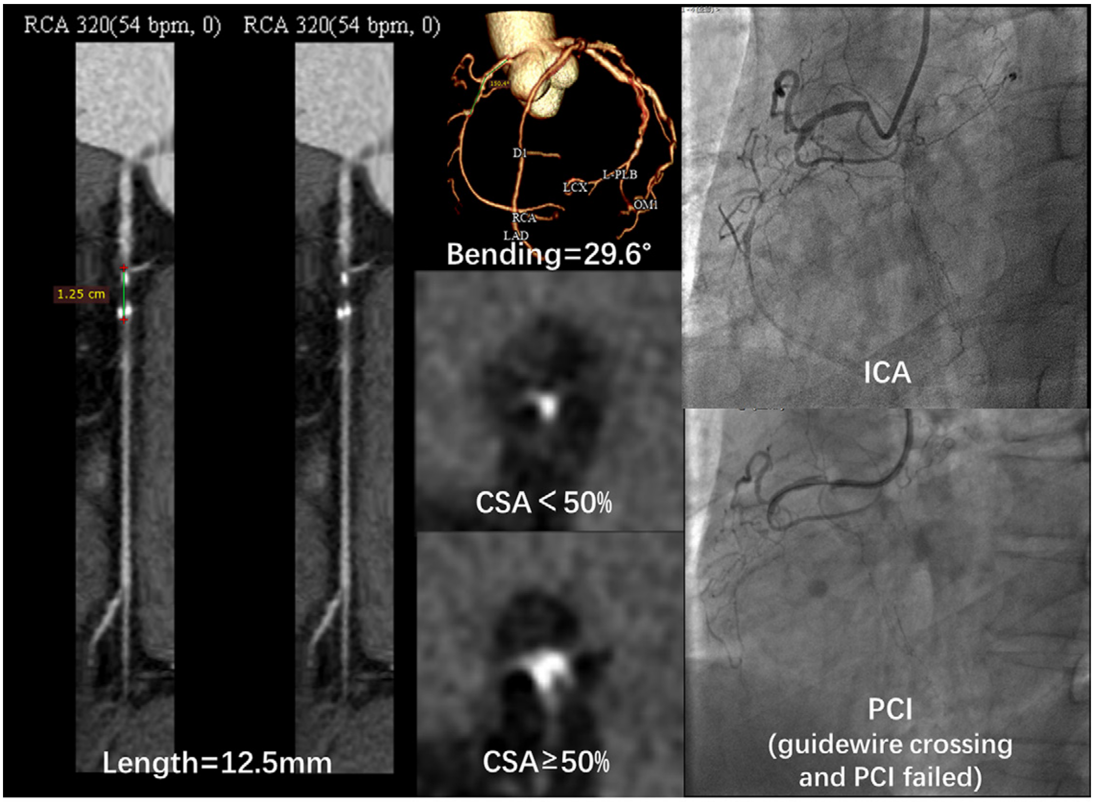
All enrolled participants were scanned using three types of multidetector CT scanners. Scan parameters were set according to the Society of Cardiovascular Computed Tomography guidelines (6). Details are provided in Appendix S2. The estimated radiation dose was determined based on the recommended conversion factors ($k = 0.014$ mSv · mGy^{-1} · cm^{-1}) (25).

CCTA Analysis

CCTA analysis was randomly performed using a commercial workstation (Vitrea fX, version 3.0; Canon Medical Systems) by two radiologists (Z.Z., N.Z.; both with 5 or more years of experience in cardiovascular image interpretation) who were blinded to clinical data and PCI results. To evaluate CTO, CCTA was performed using volume rendering, curved planar reformation, multiplanar reformation, and cross-sectional analysis (Fig 1). The CT-RECTOR (15), KCCT (16), and CCTA-derived J-CTO (17) scores were independently calculated by the same two radiologists, and disagreements were resolved by consensus or by adjudication from a third senior radiologist (L.X., >15 years of experience). The total analysis time was measured as the interval between the beginning of image loading and the end of the measurement of all parameters.

DL Model for Predicting Guidewire Crossing within 30 Minutes and PCI Success of CTO Lesions

Figure 2 shows the workflow of the proposed DL framework. An automated end-to-end network was proposed to predict guidewire crossing within 30 minutes and PCI success of CTO lesions. Coronary segmentation, CTO detection, and feature extraction were consecutively performed based on CCTA images. Before training the network, data preprocessing was performed by applying a minimum-maximum normalization method to standardize the image data. In segmentation stage, Patch-UCTNet was introduced to reconstruct the three-dimensional structure of the coronary arteries. Morphologic operations, including skeletonization



CT-RECTOR Score	multiple occlusions (1 point)	blunt stump (1 point)	bending >45° (1 point)	severe calcium (1 point)	reattempted PCI at CTO (1 point)	occlusion duration ≥12 months or unknown (1 point)			Total Score	**Predicting outcomes** GW crossing > 30min or failed GW crossing
	0	1	0	1	0	1			**3**	
KCCT Score	blunt proximal entry (1 point)	proximal side branch (1 point)	CTO segment bend >45° (1 point)	occlusion length ≥15 mm (1 point)	calcification including severe peripheral calcification (1 point)	calcification including severe central calcification (2 point)	reattempted PCI at CTO (1 point)	CTO duration of ≥12 months or unknown (1 point)	**4**	1) GW crossing > 30min or failed GW crossing 2) failed PCI
	1	1	0	0	1	0	0	1		
CCTA-derived J-CTO Score	previously failed lesions (1 point)	blunt type of entry (1 point)	bending>45° (1 point)	calcification (1 point)	occlusion length≥20 mm (1 point)				**2**	1) GW crossing≤30min 2) Successful PCI
	0	1	0	1	0					
DL Model	Predicting outcomes output									failed GW crossing and failed PCI

Figure 1: Example of the image reconstruction and analysis in the prediction of percutaneous coronary intervention (PCI) outcomes for chronic total occlusion (CTO) lesions by the deep learning (DL) model and manual coronary CT angiography (CCTA)-based prediction scores. BPM = beats per minute, CSA = cross-sectional area, CT-RECTOR = CT Registry of Chronic Total Occlusion Revascularization, GW = guidewire, ICA = invasive coronary angiography, J-CTO = CTO Registry of Japan, KCCT = Korean Multicenter CTO CT Registry, RCA = right coronary artery.

and expansion, were performed to detect CTO lesions. Subsequently, the Swin Transformer network *(https://github.com/microsoft/Swin-Transformer)*was applied to extract CTO features from CCTA images and candidate CTO lesion masks and generate prediction results: successful PCI with guidewire crossing of 30 minutes or less, successful PCI with guidewire crossing of more than 30 minutes, or failed PCI with failed guidewire crossing. Fivefold cross validation was used to determine the optimal model (26). The total analysis time of the DL model was measured as the interval between the beginning of automated image loading and the end of the output of prediction outcomes. Details are shown in Appendix S3. The code and model are available at *https://github.com/FSciencer/CTO-model*.

Coronary Intervention and End Point

Invasive coronary angiography and PCI were performed by experienced operators who were blinded to the results of the DL model and manual scores. Different guidewire approaches were performed according to lesion characteristics and guidance from the Asia Pacific CTO Club (27). Guidewire crossing time was defined as the time from the initial insertion of the guidewire into the coronary lumen to the time of successful wire crossing beyond the lesion into the distal vessel (4). PCI success was defined as successful opening of the total occlusion, post-PCI thrombolysis in myocardial infarction flow grade 3 (complete perfusion, defined as antegrade flow into the bed distal to the obstruction and quick clearance) (28), and residual stenosis of less than 25% (29).

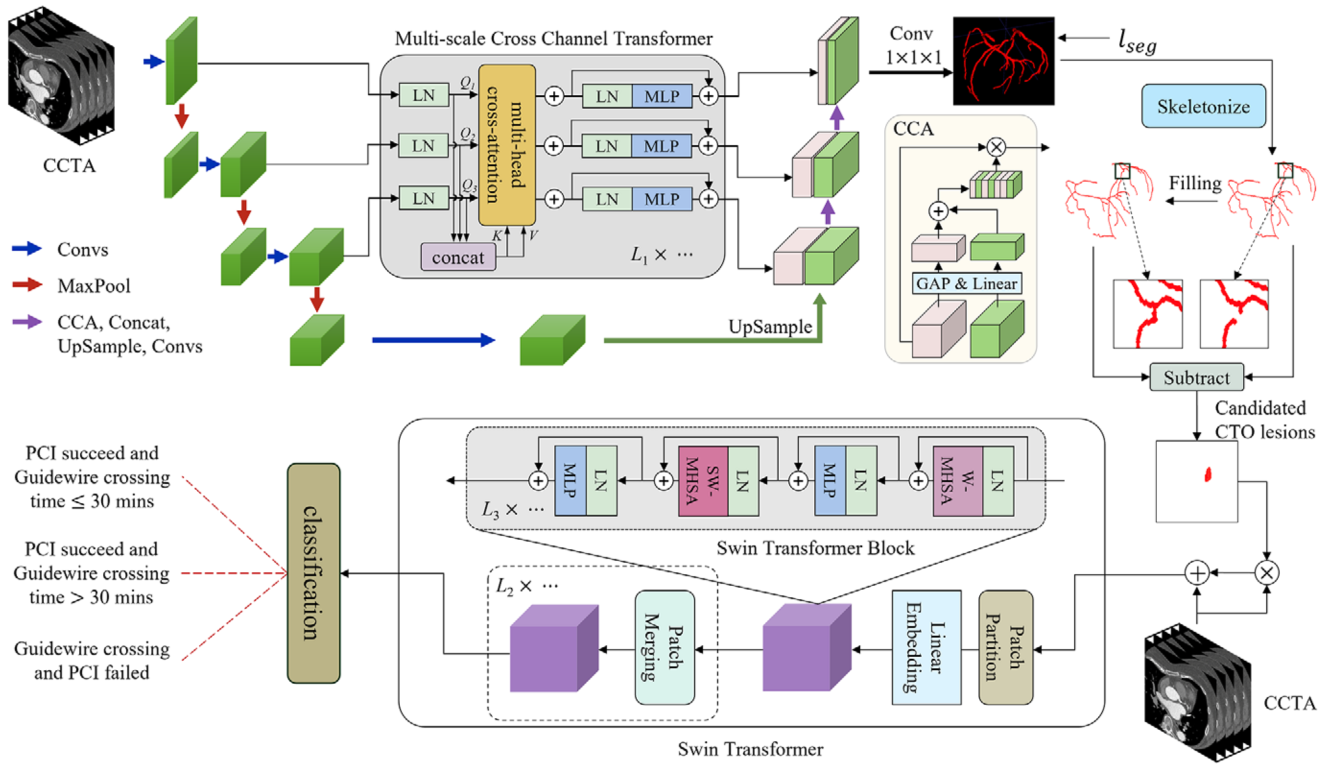


Figure 2: Overview of the workflow of the proposed deep learning–based prediction model of percutaneous recanalization outcomes for chronic total occlusion (CTO) lesions. CCA = channel-wise cross-attention, CCTA = coronary CT angiography, GAP = global average pooling, PCI = percutaneous coronary intervention, SW-MHSA = multihead self-attention with shifted windowing, W-MHSA = multihead self-attention with regular windowing.

The primary end point was guidewire crossing within 30 minutes, which is considered the most objective index of procedural difficulty for CTO and minimizes operator-related bias (30). The secondary end point was PCI success, which is a more relevant end point from a clinical perspective (17).

Statistical Analyses

Statistical analysis was performed by a statistician (Z.G.) using SPSS Statistics, version 20.0 (IBM). Continuous variables are presented as means ± SDs if normally distributed and as medians and IQRs otherwise. Categorical variables are presented as numbers and percentages. Continuous data were compared using two-sample t tests. The performance of the DL model and manual scores was compared using the McNemar test. The receiver operating characteristic curve was used to evaluate the performance of the DL model. Differences in categorical data were analyzed using the χ^2 test. The sample size was calculated using the AUC (Appendix S4). Intra- and interobserver agreements were assessed using intraclass correlation coefficient. Two-sided $P < .05$ indicated a significant difference.

Results

Clinical Characteristics of the Study Sample

Of the overall 2188 participants, after exclusion (ICA-confirmed non-CTO lesions, n = 651 [29.8%]; those not undergoing attempted PCI, n = 215 [9.8%]; interval between CCTA and PCI >1 month, n = 38 [1.7%]; history of acute myocardial infarction within 3 months, n = 16 [0.7%]; history of previously implanted stents or coronary artery bypass graft, n = 669 [30.6%]; and impaired CCTA image quality, n = 65 [3.0%]), 534 participants with 565 CTO lesions were included in this study and were divided into a training set of 348 participants with 376 CTO lesions and an external test set of 186 participants with 189 CTOs (Fig 3). Participant and lesion characteristics of the training and external test sets are presented in Table 1. In the training set, 275 (79%) participants were men and 73 (21%) were women, with a mean age of 57.3 years ± 10.5 (SD). In the external test set, 142 (76%) participants were men and 44 (24%) were women, with a mean age of 58.2 years ± 11.2. Except for body mass index (calculated as weight in kilograms divided by height in meters squared: training vs external test set, 26.5 ± 3.4 vs 25.8 ± 3.4; P = .04), there was no significant difference in left ventricular ejection fraction and cardiovascular risk factors between the training and external test sets.

Procedural Outcomes

In regard to procedural techniques, PCI was successfully performed using the antegrade approach in 351 of 565 (62.1%) participants, the parallel-wire technique in 85 of 565 (15.0%) participants, and the retrograde approach in 129 of 565 (22.8%) participants. The mean effective radiation dose of the CT examination was 3.1 mSv ± 2.0. Excellent intraobserver (observer A: intraclass correlation

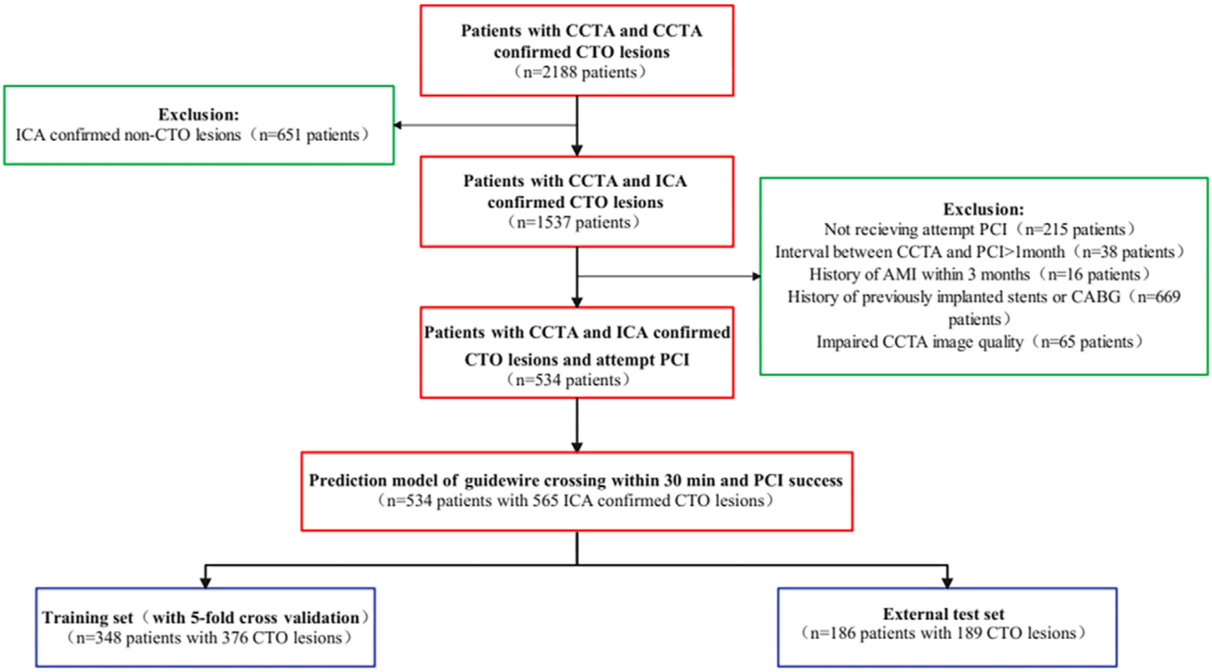


Figure 3: Study enrollment flowchart. AMI = acute myocardial infarction, CABG = coronary artery bypass graft, CCTA = coronary CT angiography, CTO = chronic total occlusion, ICA = invasive coronary angiography, PCI = percutaneous coronary intervention.

Table 1: Participant Demographic Data

Parameter	Training Set	External Test Set	*P* Value
No. of participants	348	186	…
Age (y)	57.3 ± 10.5 (25–92)	58.2 ± 11.2 (31–82)	.42
Sex			
Male	275 (79)	142 (76)	.52
Female	73 (21)	44 (24)	.52
BMI (kg/m^2)	26.5 ± 3.4	25.8 ± 3.4	.04
LVEF	59.7 ± 7.2	59.7 ± 7.2	.99
Cardiovascular risk factor			
Smoking	188 (54.0)	93 (50.0)	.35
Alcohol consumption	63 (18.1)	29 (15.6)	.48
Hypertension	202 (58.0)	103 (55.4)	.56
Diabetes mellitus	104 (30.0)	54 (29.0)	.82
Hyperlipidemia	205 (58.9)	116 (62.4)	.41
Myocardial infarction	49 (14.1)	25 (13.4)	.76
Family history of CAD	7 (2.0)	6 (3.2)	.56
CTO lesions	376	189	…
LAD artery	158 (42.0)	81 (42.9)	…
LCX artery	49 (13.0)	26 (13.8)	…
RCA artery	165 (43.9)	79 (41.8)	…
Other artery	4 (1.1)	3 (1.6)	…

Note.—Continuous variables are presented as means ± SDs, and categorical variables are presented as numbers of patients, with percentages in parentheses. BMI = body mass index (calculated as weight in kilograms divided by height in meters squared), CAD = coronary artery disease, CTO = chronic total occlusion, LAD = left anterior descending, LCX = left circumflex, LVEF = left ventricular ejection fraction, RCA = right coronary artery.

coefficient = 0.91 [95% CI: 0.83, 0.95], 0.89 [95% CI: 0.77, 0.94], and 0.92 [95% CI: 0.84, 0.95]; observer B: intraclass correlation coefficient = 0.90 [95% CI: 0.83, 0.94], 0.91 [95% CI: 0.80, 0.94], and 0.88 [95% CI: 0.78, 0.93]) and interobserver (intraclass correlation coefficient = 0.87 [95% CI: 0.78, 0.92], 0.90 [95% CI: 0.79, 0.95], and 0.89 [95% CI: 0.81, 0.93]) reproducibility were demonstrated when quantifying the CT-RECTOR, KCCT, and CCTA-derived J-CTO scores, respectively.

DL Prediction of Guidewire Crossing within 30 Minutes and PCI Success for CTO Lesions

Training set.—The prediction model of guidewire crossing within 30 minutes and PCI success for CTO was trained using 376 CTO lesions with PCI treatments. Of those, 237 (63.0%) achieved guidewire crossing within 30 minutes, and 294 (78.2%) achieved PCI success. The Dice similarity coefficient of coronary delineation in the segmentation phase was 0.93, while the fracture areas of suspected CTOs were all recognized. With fivefold cross validation, the averaged sensitivity, specificity, positive predictive value, negative predictive value, and accuracy of the DL prediction model for guidewire crossing within 30 minutes in the training set were 94.4%, 94.3%, 96.5%, 91.1%, and 94.4%, respectively (Table 2), and those for PCI success for CTO were 96.6%, 95.3%, 98.6%, 89.2%, and 96.3%, respectively (Table 3). The AUC of the DL model for predicting guidewire crossing within 30 minutes and PCI success of CTO lesions in the training set was 0.97 (95% CI: 0.89, 0.99) (Fig 4).

Table 2: Predicting Outcomes of the DL Model and Manual CCTA-based Prediction Scores for Guidewire Crossing within 30 Minutes of CTO Lesions

Predicting Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	*P* Value
DL model with fivefold cross validation	Training Set (*n* = 376)			
Fold 1	95.7	96.4	96.0	...
Fold 2	93.6	92.9	93.3	...
Fold 3	95.7	96.4	96.0	...
Fold 4	95.7	92.9	94.7	...
Fold 5	91.5	92.9	92.0	...
Averaged	94.4	94.3	94.4	...
Manual CCTA-based prediction scores	External Test Set (*n* = 189)			
DL model	89.4	93.9	91.0	...
CT-RECTOR score	82.9	22.7	61.9	<.001
KCCT score	83.7	39.4	68.3	<.001
CCTA-derived J-CTO score	80.5	47.0	68.8	.003

Note.—Prediction performance comparison: deep learning (DL) model versus CT Registry of Chronic Total Occlusion Revascularization (CT-RECTOR) score; DL model versus Korean Multicenter CTO CT Registry (KCCT) score; DL model versus coronary CT angiography (CCTA)–derived Multicenter CTO Registry of Japan (J-CTO) score. CTO = chronic total occlusion.

Table 3: Predicting Outcomes of the DL Model and Manual CCTA-based Prediction Scores for PCI Success of CTO Lesions

Predicting Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	*P* Value
DL model with fivefold cross validation	Training Set (*n* = 376)			
Fold 1	96.6	94.1	96.0	...
Fold 2	94.8	94.1	94.7	...
Fold 3	98.3	100	98.7	...
Fold 4	98.3	94.1	97.3	...
Fold 5	94.8	94.1	94.7	...
Averaged	96.6	95.3	96.3	...
Manual CCTA-based prediction scores	External Test Set (*n* = 189)			
DL model	95.2	88.1	93.7	...
KCCT score	82.3	47.6	74.6	.007
CCTA-derived J-CTO score	79.6	59.5	75.1	<.001

Note.—Prediction performance comparison: deep learning (DL) model versus Korean Multicenter CTO CT Registry (KCCT) score; DL model versus coronary CT angiography (CCTA)–derived Multicenter CTO Registry of Japan (J-CTO) score. CTO = chronic total occlusion, PCI = percutaneous coronary intervention.

External test set.—Overall, 189 CTO lesions were used in the external test set, of which 123 (65.1%) achieved guidewire crossing within 30 minutes and 147 (77.8%) achieved PCI success. The Dice similarity coefficient of coronary delineation was 0.92, and 98.0% of fracture areas were recognized. As shown in Tables 2 and 3, the sensitivity, specificity, positive predictive value, negative predictive value, and accuracy of the DL prediction model for guidewire crossing within 30 minutes in the external test set were 89.4%, 93.9%, 96.5%, 82.7%, and 91.0%, respectively, and those for PCI success for CTO were 95.2%, 88.1%, 96.6%, 84.1%, and 93.7%, respectively. The AUC of the DL model for predicting guidewire crossing within 30 minutes and PCI success of CTO lesions in the external test set was 0.96 (95% CI: 0.90, 0.98) (Fig 4).

Manual Prediction of the Procedural Outcomes for CTO Lesions

The probability of successful guidewire crossing within 30 minutes (96.1% reduced to 23.4% for the CT-RECTOR score, 95.5% reduced to 26.8% for the KCCT score, and 96.3% reduced to 30.5% for the CCTA-derived J-CTO score) and PCI success (95.5% reduced to 57.1% for the KCCT score and 98.1% reduced to 51.7% for the CCTA-derived J-CTO score) decreased consistently with increasing values of the CT-RECTOR, KCCT, and CCTA-derived J-CTO scores (Fig 5).

The sensitivity, specificity, and accuracy of the manual CCTA-based prediction scores in predicting guidewire crossing within 30 minutes and PCI success, based on the optimal cutoff value of the CT-RECTOR score of less than 3, KCCT

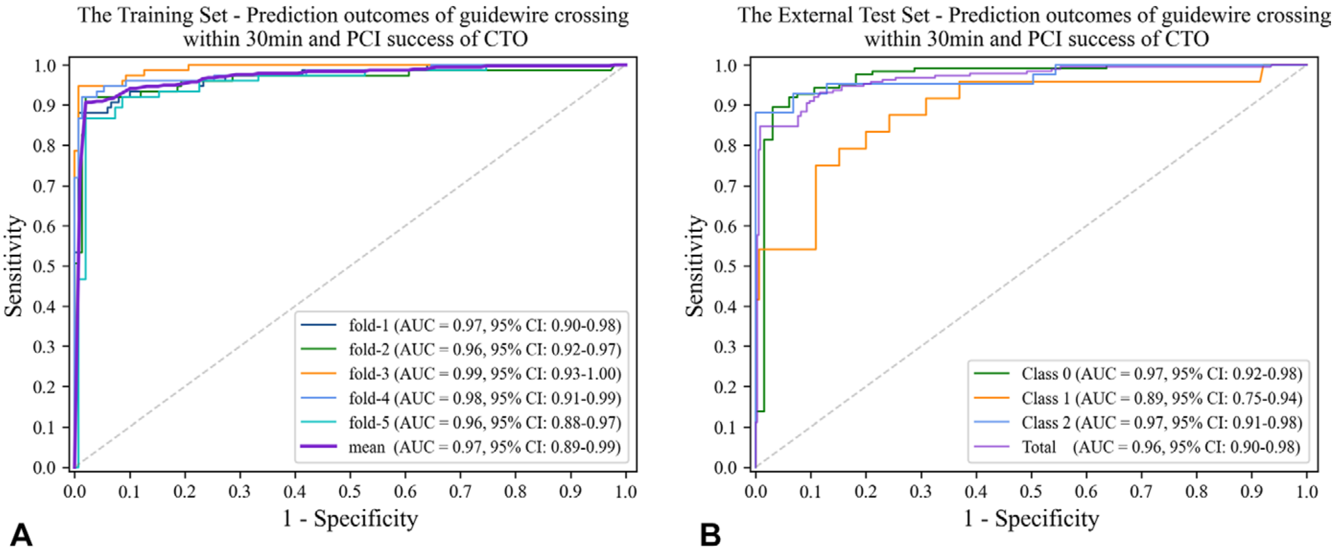


Figure 4: The receiver operating characteristic curves of the training set **(A)** and the external test set **(B)**. Fold denotes the result of each fold in fivefold cross validation. Class 0, percutaneous coronary intervention (PCI) succeeded and guidewire crossing of 30 minutes or less; class 1, PCI succeeded and guidewire crossing of more than 30 minutes; class 2, guidewire crossing and PCI failed. AUC = area under the receiver operating characteristic curve, CTO = chronic total occlusion.

score of less than 4, and CCTA-derived J-CTO score of less than 3, are shown in Tables 2 and 3.

Comparison of the DL Model versus Manual CCTA-based Prediction Scores

The DL-based prediction model had higher image analysis efficiency than manual CCTA-based scores and saved 85.0% of the reconstruction and analysis time of manual scores (DL model vs CT-RECTOR vs KCCT vs CCTA-derived J-CTO: mean, 73.7 seconds ± 5.0 vs 426.2 seconds ± 25.6 vs 466.9 seconds ± 22.9 vs 418.2 seconds ± 17.1; all $P < .001$).

The DL model outperformed the manual CCTA-based prediction scores in predicting both guidewire crossing within 30 minutes (all $P < .05$, Table 2) and PCI success (all $P < .05$, Table 3), as well as the sensitivity (DL model vs CT-RECTOR score, KCCT score, and CCTA-derived J-CTO score: $P = .008$, $P = .02$, and $P < .001$ for predicting guidewire crossing within 30 minutes; DL model vs KCCT score and CCTA-derived J-CTO score: all $P < .001$ for predicting PCI success) and the specificity (all $P < .001$ for predicting guidewire crossing within 30 minutes and PCI success).

Discussion

Despite marked advances in endovascular techniques and devices, percutaneous coronary intervention (PCI) for chronic total occlusion (CTO) lesions remains a challenge with unpredictable procedural success (31). PCI outcomes for CTO on a lesion-by-lesion basis may be valuable in helping physicians alleviate procedural uncertainty, but manual prediction scores are labor intensive and subjective and have less consistent accuracy. In this preliminary study, we developed a deep learning (DL) prediction model with better performance in predicting guidewire crossing within 30 minutes (accuracy, 91.0% vs 61.9%–68.8%; all $P < .05$) and PCI success (accuracy, 93.7% vs 74.6%–75.1%; all $P < .05$) for CTO lesions and higher efficiency (mean image analysis time, 73.7 seconds vs 418.2–466.9 seconds; all $P < .001$) than manual prediction scores.

Because of the complexity of the CTO, the successful rate of CTO recanalization remains low. In this study, only 63.7% of the enrolled CTO lesions achieved guidewire crossing within 30 minutes, and 78.1% achieved PCI success; these results were similar to those of previous studies, such as the study of CT-RECTOR (55% and 65%) (15), the KCCT score (51% and 71%) (16), and the J-CTO score (48% and 86%) (17).

To grade the difficulty of PCI for CTO, Morino et al (4) established the ICA-based J-CTO score using five independent predictors. However, the J-CTO score was invasive and possibly underestimated multiple occlusions and severe calcification.

With the ability to visualize the occluded segment, CCTA has emerged as an accurate noninvasive tool with which to assess morphology of occluded coronaries and has been recommended as a complement to ICA to guide CTO revascularization (32). The CT-RECTOR score was the first CCTA-based prediction score for predicting PCI outcomes of CTO, which yielded four CCTA-based factors and two clinical factors (15). The KCCT score further classified the severity of calcification into ternary categories, highlighting the negative effect of the calcification degree (16). Fujino et al (17) also calculated and compared the J-CTO score using both CCTA and ICA. Although these manual scores are helpful in guiding revascularization of CTO, their predictive performance varies, and the manual calculation of these scores is time consuming (18,19). Therefore, an objective, efficient, and accurate prediction system for PCI of CTO lesions is urgently required.

Deep learning has been successful for automated segmentation and quantification of cardiac and coronary structures (20,21), assisted diagnosis (22,23), and risk stratification of cardiovascular diseases (33). Owing to the technical challenges of vessel tracing and image analysis in case of coronary CTO, the application of DL in CTO lesions is rare and mainly

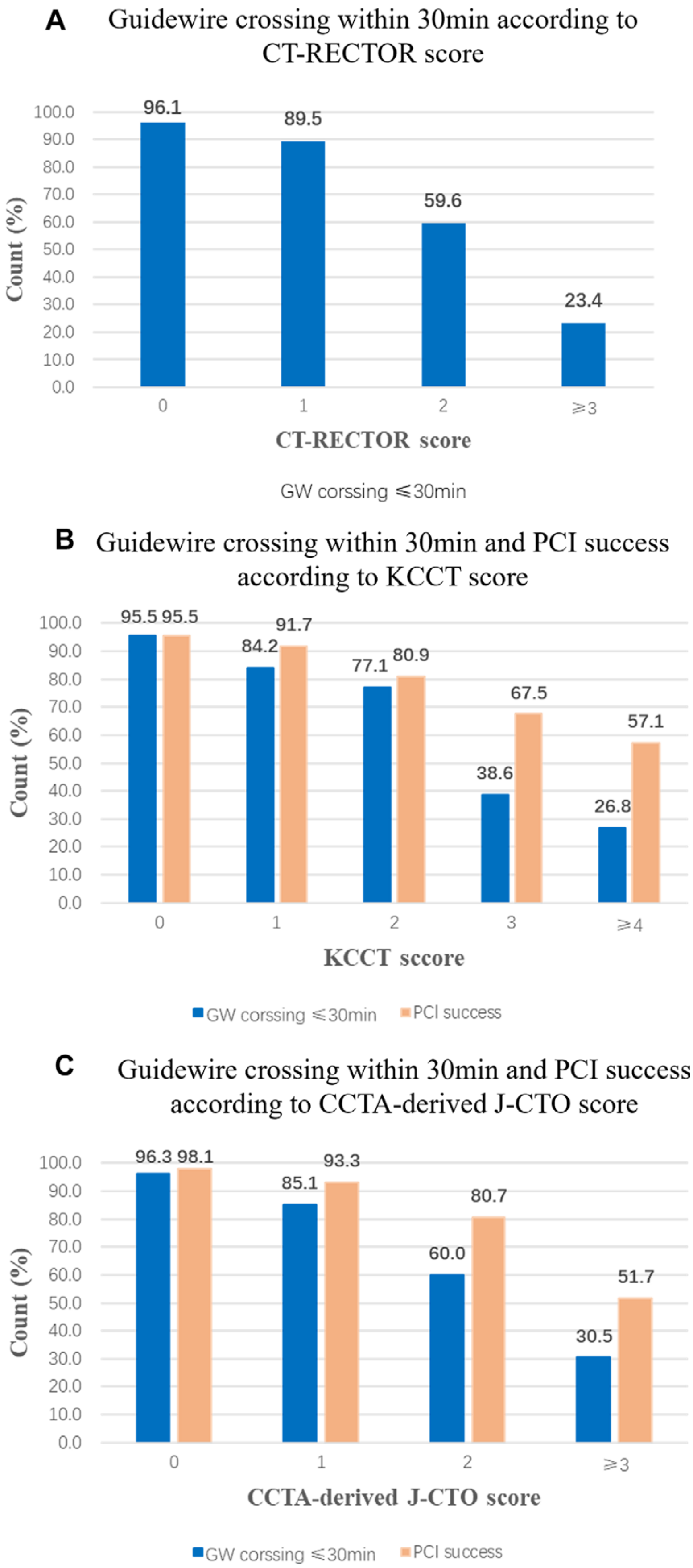


Figure 5: The relationship between the manual coronary CT angiography (CCTA)–based prediction scores and percutaneous recanalization results of chronic total occlusion (CTO) lesions. According to the manual CCTA-based prediction scores, the probability of successful guidewire (GW) crossing within 30 minutes and percutaneous coronary intervention (PCI) success rate decreased consistently with the increasing values of the manual CCTA-based prediction scores. **(A)** CT Registry of Chronic Total Occlusion Revascularization (CT-RECTOR) score, with the optimal cutoff value of less than 3. **(B)** Korean Multicenter CTO CT Registry (KCCT) score, with the optimal cutoff value of less than 4. **(C)** CCTA-derived Multicenter CTO Registry of Japan (J-CTO) score, with the optimal cutoff value of less than 3.

focused on automated segmentation and reconstruction (24). There is still no reported evidence of DL predicting PCI outcomes for CTO lesions.

In our study, an automated end-to-end DL model was developed to predict guidewire crossing within 30 minutes and PCI success of CTO lesions based on CCTA images, and we consecutively performed coronary segmentation, CTO detection, and feature extraction. Our prediction network proved effective in expediting CTO lesion preprocedural prediction without compromising accuracy, which could automatically load and analyze images and output outcomes.

Our results support the use of DL in predicting CTO procedural outcomes. In terms of guidewire crossing within 30 minutes and PCI success for CTO lesions, our DL model had better prediction performance than manual prediction scores (all $P < .05$). Our DL model, which minimizes operator-related bias, is more objective than manual scores. Our DL model will be helpful in choosing an adequate operator and CTO-specific devices based on the difficulty of evaluation before PCI of the CTO lesions. We propose the application of this DL model for forecasting PCI outcomes and alleviating physicians' concerns about the CTO procedure, which may be integrated into artificial intelligence–based CCTA diagnostic software to provide not only anatomic information but also guidance for PCI of CTO lesions.

Our study had some limitations. First, operator, site, and resource selection biases are inevitable, although guidewire crossing within 30 minutes was set as the primary end point to minimize operator-related bias. Second, different procedural approaches (ie, antegrade or retrograde) were performed according to CTO characteristics, and their impact needs to be further evaluated. Third, in-stent occlusion and bridging vessel occlusion were excluded because the characteristics of these occlusive lesions differed from those of de novo CTO. Stent artifacts may affect the predictive performance, which needs further exploration. Fourth, the DL model may not extract discriminative features of specific tasks when applying data from low-quality CCTA images. We will further explore the feasibility of adding a denoising module to this model to improve its robustness and generalization in low-quality CCTA images. All analyses were performed at the lesion level to predict PCI outcomes of CTO lesions; however, this approach may create a minor issue in the possible lack of independence for participants with multiple lesions. More participants with multiple CTO lesions are needed to further test our DL model. Finally, owing to the small sample size of CTOs, we used a cross-validation strategy, which may have some weaknesses. Larger multicenter samples are needed to further validate and test our model.

In conclusion, the proposed deep learning prediction model was efficient and performed well in predicting the percutaneous coronary intervention (PCI) outcomes of chronic total occlusion (CTO) lesions, which is helpful for grading the difficulty of PCI and selecting appropriate treatment strategies for CTO lesions.

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References

1. Stone GW, Kandzari DE, Mehran R, et al. Percutaneous recanalization of chronically occluded coronary arteries: a consensus document: part I. Circulation 2005;112(15):2364–2372.
2. Galassi AR, Brilakis ES, Boukhris M, et al. Appropriateness of percutaneous revascularization of coronary chronic total occlusions: an overview. Eur Heart J 2016;37(35):2692–2700.
3. Wu EB, Brilakis ES, Mashayekhi K, et al. Global Chronic Total Occlusion Crossing Algorithm: JACC State-of-the-Art Review. J Am Coll Cardiol 2021;78(8):840–853.
4. Morino Y, Abe M, Morimoto T, et al. Predicting successful guidewire crossing through chronic total occlusion of native coronary lesions within 30 minutes: the J-CTO (Multicenter CTO Registry in Japan) score as a difficulty grading and time assessment tool. JACC Cardiovasc Interv 2011;4(2):213–221.
5. Haase R, Schlattmann P, Gueret P, et al. Diagnosis of obstructive coronary artery disease using computed tomography angiography in patients with stable chest pain depending on clinical probability and in clinically important subgroups: meta-analysis of individual patient data. BMJ 2019;365:l1945.
6. Abbara S, Blanke P, Maroules CD, et al. SCCT guidelines for the performance and acquisition of coronary computed tomographic angiography: A report of the society of Cardiovascular Computed Tomography Guidelines Committee: Endorsed by the North American Society for Cardiovascular Imaging (NASCI). J Cardiovasc Comput Tomogr 2016;10(6):435–449.
7. Budoff MJ, Dowe D, Jollis JG, et al. Diagnostic performance of 64-multidetector row coronary computed tomographic angiography for evaluation of coronary artery stenosis in individuals without known coronary artery disease: results from the prospective multicenter ACCURACY (Assessment by Coronary Computed Tomographic Angiography of Individuals Undergoing Invasive Coronary Angiography) trial. J Am Coll Cardiol 2008;52(21):1724–1732.
8. Miller JM, Rochitte CE, Dewey M, et al. Diagnostic performance of coronary angiography by 64-row CT. N Engl J Med 2008;359(22):2324–2336.
9. Meijboom WB, Meijs MF, Schuijf JD, et al. Diagnostic accuracy of 64-slice computed tomography coronary angiography: a prospective, multicenter, multivendor study. J Am Coll Cardiol 2008;52(25):2135–2144.
10. Choi JH, Kim EK, Kim SM, et al. Noninvasive Discrimination of Coronary Chronic Total Occlusion and Subtotal Occlusion by Coronary Computed Tomography Angiography. JACC Cardiovasc Interv 2015;8(9):1143–1153.
11. Li M, Zhang J, Pan J, Lu Z. Coronary total occlusion lesions: linear intrathrombus enhancement at CT predicts better outcome of percutaneous coronary intervention. Radiology 2013;266(2):443–451.
12. Zhang J, Li Y, Li M, Pan J, Lu Z. Collateral vessel opacification with CT in patients with coronary total occlusion and its relationship with downstream myocardial infarction. Radiology 2014;271(3):703–710.
13. Li M, Zhang J, Pan J, Lu Z. Obstructive coronary artery disease: reverse attenuation gradient sign at CT indicates distal retrograde flow–a useful sign for differentiating chronic total occlusion from subtotal occlusion. Radiology 2013;266(3):766–772.
14. Hong SJ, Kim BK, Cho I, et al. Effect of Coronary CTA on Chronic Total Occlusion Percutaneous Coronary Intervention: A Randomized Trial. JACC Cardiovasc Imaging 2021;14(10):1993–2004.
15. Opolski MP, Achenbach S, Schuhbäck A, et al. Coronary computed tomographic prediction rule for time-efficient guidewire crossing through chronic total occlusion: insights from the CT-RECTOR multicenter registry (Computed Tomography Registry of Chronic Total Occlusion Revascularization). JACC Cardiovasc Interv 2015;8(2):257–267.
16. Yu CW, Lee HJ, Suh J, et al. Coronary Computed Tomography Angiography Predicts Guidewire Crossing and Success of Percutaneous Intervention for Chronic Total Occlusion: Korean Multicenter CTO CT Registry Score as a Tool for Assessing Difficulty in Chronic Total Occlusion Percutaneous Coronary Intervention. Circ Cardiovasc Imaging 2017;10(4):e005800.
17. Fujino A, Otsuji S, Hasegawa K, et al. Accuracy of J-CTO Score Derived From Computed Tomography Versus Angiography to Predict Successful Percutaneous Coronary Intervention. JACC Cardiovasc Imaging 2018;11(2 Pt 1):209–217.
18. Achenbach S, Tröbs M. Coronary Computed Tomographic Angiography Can Predict Chronic Total Occlusion Recanalization Success: Where Do We Go From Here? JACC Cardiovasc Imaging 2018;11(2 Pt 1):218–220.
19. Werner GS, Hecht H, Stone GW. Utility of CT Angiography to Guide Coronary Intervention of CTO. JACC Cardiovasc Imaging 2015;8(7):814–816.
20. Koetzier LR, Mastrodicasa D, Szczykutowicz TP, et al. Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects. Radiology 2023;306(3):e221257.
21. Wolterink JM, van Hamersvelt RW, Viergever MA, Leiner T, Išgum I. Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier. Med Image Anal 2019;51:46–60.
22. Kolossváry M, De Cecco CN, Feuchtner G, Maurovich-Horvat P. Advanced atherosclerosis imaging by CT: Radiomics, machine learning and deep learning. J Cardiovasc Comput Tomogr 2019;13(5):274–280.
23. Xu L, He Y, Luo N, et al. Diagnostic Accuracy and Generalizability of a Deep Learning-Based Fully Automated Algorithm for Coronary Artery Stenosis Detection on CCTA: A Multi-Centre Registry Study. Front Cardiovasc Med 2021;8:707508. [Published correction appears in Front Cardiovasc Med 2022;9:920738.]
24. Li M, Ling R, Yu L, et al. Deep Learning Segmentation and Reconstruction for CT of Chronic Total Coronary Occlusion. Radiology 2023;306(3):e221393.
25. Shrimpton PC, Hillier MC, Lewis MA, Dunn M. National survey of doses from CT in the UK: 2003. Br J Radiol 2006;79(948):968–980. [Published correction appears in Br J Radiol 2007;80(956):685.]
26. Jung Y, Hu J. A *K*-fold Averaging Cross-validation Procedure. J Nonparametr Stat 2015;27(2):167–179.
27. Harding SA, Wu EB, Lo S, et al. A New Algorithm for Crossing Chronic Total Occlusions From the Asia Pacific Chronic Total Occlusion Club. JACC Cardiovasc Interv 2017;10(21):2135–2143.

28. TIMI Study Group. The Thrombolysis in Myocardial Infarction (TIMI) trial. Phase I findings. N Engl J Med 1985;312(14):932–936.
29. Kim BK, Shin DH, Hong MK, et al. Clinical Impact of Intravascular Ultrasound-Guided Chronic Total Occlusion Intervention With Zotarolimus-Eluting Versus Biolimus-Eluting Stent Implantation: Randomized Study. Circ Cardiovasc Interv 2015;8(7):e002592.
30. Galassi AR, Boukhris M, Azzarelli S, Castaing M, Marzà F, Tomasello SD. Percutaneous Coronary Revascularization for Chronic Total Occlusions: A Novel Predictive Score of Technical Failure Using Advanced Technologies. JACC Cardiovasc Interv 2016;9(9):911–922.
31. Grantham JA, Marso SP, Spertus J, House J, Holmes DR Jr, Rutherford BD. Chronic total occlusion angioplasty in the United States. JACC Cardiovasc Interv 2009;2(6):479–486.
32. Brilakis ES, Grantham JA, Rinfret S, et al. A percutaneous treatment algorithm for crossing coronary chronic total occlusions. JACC Cardiovasc Interv 2012;5(4):367–379.
33. Motwani M, Dey D, Berman DS, et al. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. Eur Heart J 2017;38(7):500–507.