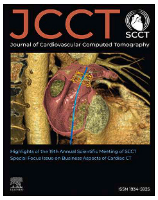
Journal of Cardiovascular Computed Tomography 19 (2025) 725–726

Contents lists available at ScienceDirect

Journal of Cardiovascular Computed Tomography

journal homepage: www.JournalofCardiovascularCT.com



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Coronary computed tomography angiography radiomics for predicting major adverse cardiovascular events after percutaneous coronary interventions

ARTICLE INFO

Keywords
Radiomics
Artificial intelligence
Coronary computed tomography angiography
Chronic coronary syndrome
Major adverse cardiovascular events

Radiomics, which leverages advanced image analysis to extract quantitative data, holds promise for improving risk stratification in cardiovascular imaging.[1] While artificial intelligence has demonstrated utility in the cardiovascular field,[2] the potential of coronary computed tomography angiography (CCTA) radiomics for predicting post-PCI clinical outcomes remains unclear. We recently reported that the coronary artery calcium (CAC) score in CCTA effectively predicts clinical events following percutaneous coronary intervention (PCI).[3] Building upon this finding, we further investigated whether incorporating a radiomics approach into CAC scoring could enhance the prediction of major adverse cardiovascular events (MACE) within one year after PCI in patients with chronic coronary syndrome (CCS).

This study was approved by the institutional review board and the Ethics Committee of the University of Miyazaki (No. O-1636). We retrospectively analyzed 253 consecutive CCS patients who underwent pre-PCI CCTA at Miyazaki Prefectural Nobeoka Hospital. The primary endpoint was one-year MACE, defined as all-cause death, myocardial infarction (MI), stroke, and heart failure rehospitalization.

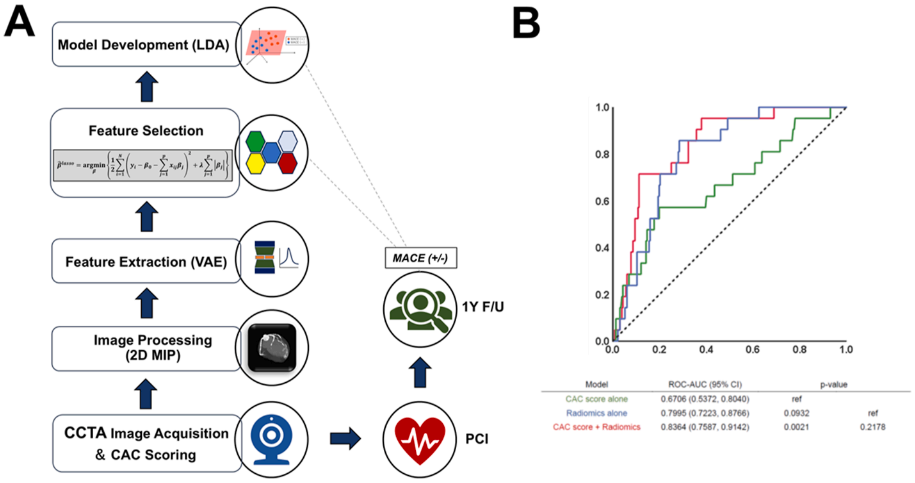
The radiomics workflow (Figure A) included: 1) generating two-dimensional maximum intensity projection (MIP) images from 3D CCTA data; 2) training a variational autoencoder on the MIP images to create a 50-dimensional latent space representation; 3) utilizing Lasso regression to identify axes within this latent space associated with MACE; 4) developing a predictive model via linear discriminant analysis using the selected five-dimensional axis values as radiomics features; and 5) employing leave-one-out cross-validation. Predictive performances of the models using the CAC score, radiomics features, and their combination were evaluated using receiver operating characteristic curve analysis, with the area under the curve (AUC) comparison.

During the follow-up, 21 patients experienced MACE (eight all-cause deaths, including three cardiac deaths; nine MIs; one stroke; and three heart failure rehospitalizations). All models showed statistically significant predictive performance for MACE: the CAC score model yielded an AUC of 0.6706 (95 % CI: 0.5372–0.8040, $p < 0.01$); the radiomics model achieved an AUC of 0.7995 (95 % CI: 0.7223–0.8766, $p < 0.001$); and the combined model yielded the highest AUC of 0.8364 (95 % CI: 0.7587–0.9124, $p < 0.001$) (Figure B). Notably, even when the outcomes were limited to cardiac death and MI, the radiomics model maintained robust predictive ability (AUC = 0.832, 95 % CI: 0.755–0.910, $p < 0.001$). Although the radiomics model demonstrated better predictive accuracy than the CAC score model, the difference did not reach statistical significance ($p = 0.0932$). However, the combined model significantly outperformed the CAC score alone ($p = 0.0021$) (Figure B). These findings suggest that incorporating radiomics into conventional CAC scoring in CCTA provides a promising, non-invasive, and quantitative tool for predicting post-PCI clinical outcomes in CCS patients. The improved predictive performance from adding radiomics features to the CAC score might stem from their ability to capture previously overlooked imaging characteristics, such as vessel shape and calcification distribution. However, the complex relationships identified by radiomics remain challenging to interpret. Future research should focus on developing explainable radiomics models to facilitate clinical adoption.

This study has several limitations, including its single-center design and relatively small number of MACE events, which may affect generalizability. Additionally, the retrospective design might introduce potential biases. Larger, prospective studies are necessary to validate these results and refine the radiomics model for clinical implementation.

In conclusion, radiomics can enhance the prediction of clinical outcomes after PCI, facilitating more effective management and monitoring of patients with CCS.

https://doi.org/10.1016/j.jcct.2025.06.008
Received 14 April 2025; Received in revised form 6 June 2025; Accepted 23 June 2025
Available online 1 July 2025



Model	ROC-AUC (95% CI)	p-value	
CAC score alone	0.6706 (0.5372, 0.8040)	ref	
Radiomics alone	0.7995 (0.7223, 0.8766)	0.0932	ref
CAC score + Radiomics	0.8364 (0.7587, 0.9142)	0.0021	0.2178

Figure. CCTA radiomics workflow and comparison of the ROC curves for the MACE prediction
A: Radiomics workflow. The radiomics workflow begins with acquiring coronary computed tomography angiography (CCTA) images and generating two-dimensional maximum intensity projection (MIP) images. A variational autoencoder (VAE) receives training with MIP images, enabling feature extraction. Lasso regression was utilized to select radiomics features, and a predictive model was developed with linear discriminant analysis. In the indicated formula, y_i represents the MACE information of the i-th patient, while x_j denotes the radiomics feature. The term β_j corresponds to the coefficient and β_0 is the constant term. The parameter $\lambda \geq 0$ serves as a complexity control factor that regulates the degree of reduction, with p representing the total number of radiomics features.
B: Model Performance Verification. Receiver operating characteristic (ROC) curves and area under the curves (AUC) of three predictive models and their performances: a model using the CAC score alone (green line), a model using radiomics alone (blue line), and a model incorporating radiomics into the CAC score (red line). CI: confidence interval, ref: reference.

Disclosures

All authors have nothing to disclose.

Funding

None.

Declaration of competing interest

All authors have no COI to disclose.

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