

Shear-Wave Elastography-Based Radiomics Nomogram for the Prediction of Cardiovascular Disease in Patients with Diabetic Kidney Disease

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Background: Diabetic kidney disease (DKD) patients have a high risk of suffering from cardiovascular disease (CVD), placing a heavy cost on the public health system. In this study, we intended to develop and validate a shear-wave elastography (SWE)-based radiomics nomogram for predicting the development of CVD in DKD patients. This approach allows extensive use of the valuable information contained in ultrasound images, thus helping clinicians to identify CVD in DKD patients.

Methods: Totally 337 and 145 patients constituted the training and validation cohorts, respectively. The radiomics features of the segmented kidney in ultrasound images were extracted and selected to generate the rad-score of each patient. These rad-score, as well as the predictors of risk of CVD occurrence from the clinical characteristics, were included in the multivariate analysis to develop a nomogram. It was further assessed in the training and validation cohorts.

Results: Patients with CVD accounted for 30.9% (104/337) in the training cohort and 31.0% (45/145) in the validation cohort. The rad-score was calculated for each patient using 6 features extracted from the ultrasound images. The radiomics nomogram was built with the rad-score, age, systolic blood pressure (SBP), low-density lipoprotein cholesterol (LDL-C). It was superior to the clinical nomogram developed without the rad-score and demonstrated promising discrimination, calibration, and clinical utility in both training and validation cohorts.

Conclusion: We developed and validated an SWE-based radiomics nomogram to predict CVD risk in patients with DKD. The model was demonstrated to have a promising prediction performance, showing its potential to identify CVD in DKD patients and assist decision-making for appropriate early intervention.

Keywords: radiomics, nomogram, shear-wave elastography, cardiovascular disease, diabetic kidney disease

Introduction

Type 2 diabetes mellitus (T2DM), characterized by hyperglycemia, is a big health challenge around the world that has attracted a lot of attention.¹ Diabetic kidney disease (DKD), a common microvascular complication of T2DM, may lead to end-stage renal disease which shortens life expectancy and decreases quality of life.^{2,3} Inflammation, endothelial dysfunction, electrolyte disturbances, etc. play important roles in the pathogenesis of DKD, which are also the leading causes of the development of cardiovascular disease (CVD).^{4,5} DKD patients have a high risk of suffering from CVD, placing a heavy cost on the public health system.^{4,6} Decreased renal function is regarded as an independent predictor of CVD; hence, DKD patients are more likely to develop CVD than the general population, leading to worse functional outcomes and mortality.⁷⁻¹⁰ At the same time, they suffer from under-treatment due to lack of knowledge of CVD risks. However, the mechanisms underlying the development of CVD in DKD patients have not been completely elucidated, and the individual prognosis are usually heterogeneous. Therefore, identifying risk factors of CVD in DKD patients and intervening early in high-risk patients may lead to improved prognosis.

In the evaluation of DKD, there is an effort to find reliable histologic or biochemical markers. Apart from these markers, reliable imaging evaluation methods are essential. Elastography is an ultrasound-based technique for evaluating

tissue elasticity by measuring the speed of shear waves entering the tissue generated by an external stimulus, and is primarily used for the non-invasive evaluation of liver fibrosis,^{11,12} spleen stiffness,¹³ prostate lesions,¹⁴ and so on. Among the different elastographic methods, shear wave elastography (SWE) technique has been shown in previous studies to be helpful for the kidney.^{15,16} A low speed means soft, while a high speed represents a stiff medium. However, SWE parameters have a lack of high-dimensional characteristics from various frequency scales. Radiomics is a new method based on high-throughput extraction of medical image features, providing a quantitative and objective basis for standardized analysis.^{17,18} Recently, radiomics has been used for the analysis of ultrasound images of fibrosis,^{19–21} which may offer a new approach to elucidating the relationship between SWE and DKD, and also present an alternative to kidney biopsy for predicting DKD progression.

In this study, we intended to develop and validate a SWE-based radiomics nomogram for predicting the development of CVD in DKD patients. This approach allows extensive use of the valuable information contained in ultrasound images, thus helping clinicians to identify CVD in DKD patients.

Methods

Ethics Statement

This retrospective study was approved by medical ethics committee of Xuan Cheng City Central Hospital (No. 2023027) and conducted in accordance with the Declaration of Helsinki. Written informed consents were obtained from patients.

Study Population

From February 2018 to February 2022, 506 patients with DKD from Xuan Cheng City Central Hospital were screened in this study. Inclusion criteria: (i) age > 18 years old; (ii) with T2DM; (iii) diagnosed with DKD (defined as estimated glomerular filtration rate [eGFR] < 60 mL/min/1.73m² and/or urinary albumin/creatinine ratio [UACR] ≥ 30 mg/g for more than 3 months); (iv) no less than 2 hospitalizations, which enabled us to document baseline data prior to the CVD event (if any). Exclusion criteria: (i) other types of kidney function injury such as nephrotic syndrome and interstitial kidney disease; (ii) patients with acute infection, malignant tumors, and hypertension; (iii) loss of research information; (iv) with a history of CVD. After screening on the basis of inclusion and exclusion criteria, 482 patients were enrolled in this study. The data (145 patients) recorded between February 2018 and April 2019 were assigned to the validation cohort, and the data (337 patients) obtained between May 2019 and February 2022 were named the training cohort (Figure 1). Patients with CVD accounted for 30.9% (104/337) in the training cohort and 31.0% (45/145) in the validation cohort. Referring to the rule to have at least 10 outcome events per variable,^{22,23} we ensured less than 10 features retained for the model in order to avoid overfitting.

The baseline clinical data were obtained from the medical records, including age, gender, Body mass index (BMI), smoking status, drinking status, systolic blood pressure (SBP), diastolic blood pressure (DBP), duration of diabetes, diabetic retinopathy, low-density lipoprotein cholesterol (LDL-C), high-density lipoprotein cholesterol (HDL-C), total cholesterol (TC), triglyceride (TG), serum creatinine (SCr), glycated hemoglobin (HbA1c), hemoglobin.

Cardiovascular Outcomes

According to the International Classification of Diseases 10th Revision (ICD-10), the definition of cardiovascular outcomes was coronary heart disease, congestive heart failure, cerebrovascular disease, and peripheral artery disease.

Workflow of Radiomic Analysis

The ultrasound radiomics workflow included the following: (i) image acquisition for radiomics; (ii) image segmentation and feature extraction; (iii) feature selection and radiomic score (rad-score) development; (iv) construction and validation of the radiomics nomogram (Figure 2).

Step I: Image Acquisition for Radiomics

Kidney ultrasound-based SWE was conducted using the Philips EPIQ 7 ultrasound system. The region of interest (ROI) was located in the kidney cortex.

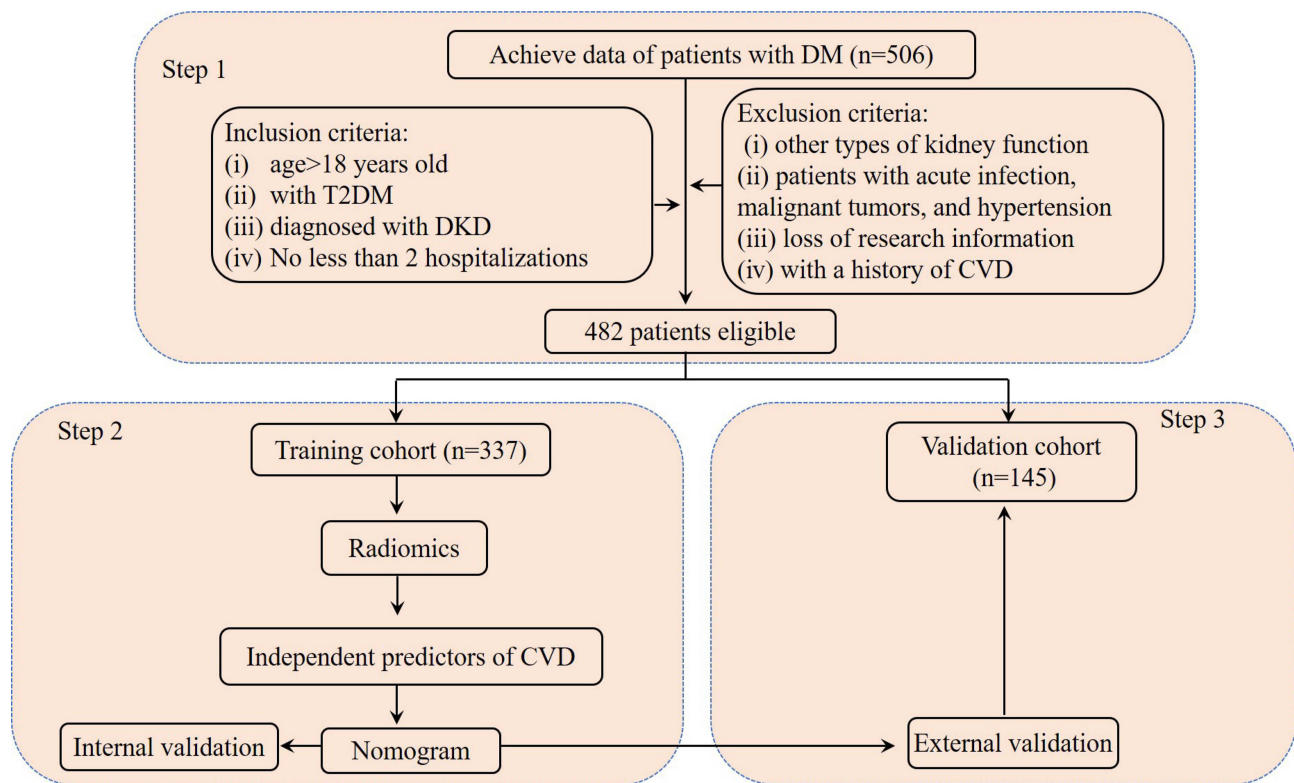


Figure 1 Summary of patient flow diagram.

Abbreviations: DM, diabetes mellitus; T2DM, type 2 diabetes mellitus; DKD, diabetic kidney disease; CVD, cardiovascular disease; Step 1: Patient screening; Step 2: Model construction; Step 3: Model validation.

Step 2: Image Segmentation and Feature Extraction

Utilizing ITK-SNAP software (<http://www.itksnap.org/pmwiki/pmwiki.php>), ROIs were manually accomplished by an experienced ultrasonographer, which was confirmed by another ultrasonographer (with >10 years of experience). All extractions of radiomics signatures of each ROI were performed by PyRadiomics (v3.7). In total, 6 image types and 6 feature classes were extracted.

Step 3: Feature Selection and Rad-Score Development

Before developing the nomogram model, three feature selection steps were conducted to prevent overfitting. First, the interclass correlation coefficients (ICCs) >0.8 were regarded as acceptable agreement. Next, the *t*-test was used for each feature between patients with CVD and non-CVD. Then, the using the least absolute shrinkage and selection operator (LASSO) logistic regression with 10-fold cross validation, CVD related features with non-zero coefficients were chosen from those with P-values <0.05 in the *t*-test. A linear combination of selected features weighted by the LASSO algorithm was used to generate a rad-score for every patient.

Step 4: Construction and Validation of the Radiomics Nomogram

To develop radiomic nomogram, the univariate logistic analysis was initially used to evaluate clinical data, features identified by ultrasound, and rad-score to explore the predictors associated with the occurrence of CVD. Subsequently, the multivariate logistic regression analysis was used to analyze all statistically significant variables from the univariate analysis. Then, a radiomics nomogram including all predictors was conducted in the training cohort, and validated in both the training and validation cohorts.

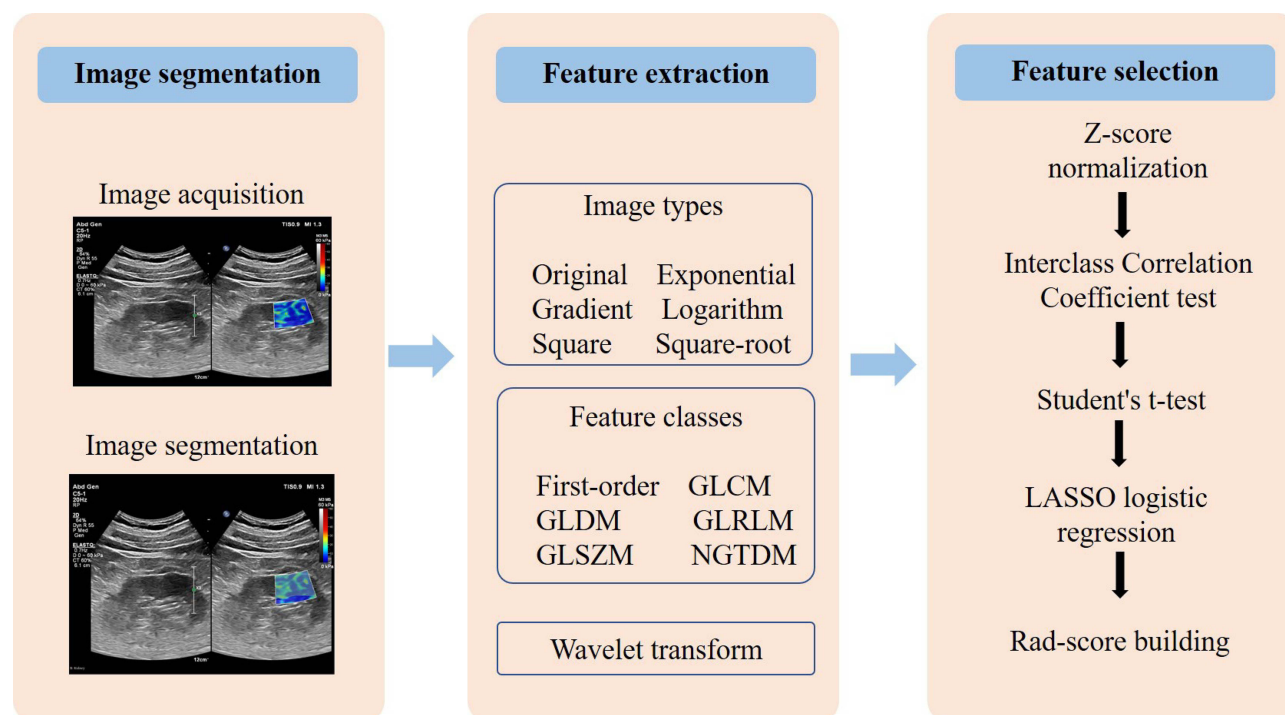


Figure 2 Workflow of the critical steps in constructing an ultrasound imaging-based rad-score for a patient with diabetic kidney disease. Kidney tumor is first manually segmented on ultrasound images to extract radiomics features. After normalization, a three-step feature selection method (Interclass Correlation Coefficient test, Student's *t*-test, and LASSO logistic regression) was performed to recognize the key radiomics features associated with the development of CVD and incorporate them into the rad-score.

Abbreviations: CVD, cardiovascular disease; GLCM, gray-level co-occurrence matrix; GLDM, gray-level dependence matrix; GLRLM, gray-level run length matrix; GLSZM, gray-level size zone matrix; NGTDM, neighbouring grey tone difference matrix; LASSO, least absolute shrinkage and selection operator; rad-score, radiomics score.

Statistical Analysis

Statistical analyses were performed using R statistical software (V4.2.1), IBM SPSS Statistics (V21.0), and Python programming software (V3.7.1). The normally distributed variables were recorded as mean (standard deviation), and compared using the Student's *t*-test. All non-normally distributed variables were recorded as [interquartile range (IQR)], and compared using Mann–Whitney *U*-test. The categorical characteristics were recorded as number (percentage), and compared using the χ^2 test. A two-sided $P < 0.05$ was regarded as the statistically significant difference. In the validation of the nomogram model, the receiver operating characteristic (ROC) curve, calibration curve with 1000 bootstrap samples, Hosmer–Lemeshow (HL) test, and decision curve analysis (DCA) was used to evaluate the discrimination, calibration, goodness-of-fit, and clinical usefulness of the nomogram model, respectively.

Results

Patient Summary

The clinical data of 337 patients in the training cohort and 145 patients in the validation cohort were evaluated. Patients with CVD accounted for 30.9% (104/337) in the training cohort and 31.0% (45/145) in the validation cohort. No statistically significant differences in CVD distribution, clinical characteristics, and rad-score between the two cohorts were observed (all P values > 0.05). The details of the two cohorts were shown in Table 1.

Radiomics Analyses for Rad-Score

A total of 1313 radiomics features were extracted and normalized from each ultrasound image in the training cohort. Sixty-eight (5.2%) features with intra-observer ICC ≥ 0.8 were chosen for the next Student's *t*-test. Finally, 6 CVD occurrence-related features with non-zero coefficients were chosen using a LASSO logistic regression model (Figures 3A and B). The rad-score was calculated for each patient using these 6 features and their weights, which was the correlation between the

Table I Comparisons of the Clinical Characteristics and Rad-Score Between the Training and Validation Cohorts

Variable	Training Cohort (N=337)	Validation Cohort (N=145)	P value
Age, years, median (IQR)	53.0 (47.0, 58.0)	53.0 (46.0, 60.0)	0.815 ^{\$}
Gender, n (%)			1.000 [#]
Male	233 (69.1)	100 (69.0)	
Female	104 (30.9)	45 (31.0)	
BMI, kg/m ² , median (IQR)	25.2 (22.4, 27.9)	25.2 (22.4, 28.6)	0.421 ^{\$}
Smoking status, n (%)			0.805 [#]
Never	279 (82.8)	117 (80.7)	
Previous	23 (6.8)	10 (6.9)	
Current	35 (10.4)	18 (12.4)	
Drinking status, n (%)			0.996 [#]
Never	236 (70.0)	102 (70.3)	
Previous	30 (8.9)	13 (9.0)	
Current	71 (21.1)	30 (20.7)	
SBP, mmHg, mean (SD)	129.0 (20.5)	132.2 (22.8)	0.134*
DBP, mmHg, median (IQR)	77.0 (68.0, 90.0)	77.0 (69.0, 90.0)	0.714 ^{\$}
Duration of diabetes, years, median (IQR)	10.5 (7.3, 12.8)	9.7 (7.1, 13.2)	0.699 ^{\$}
Diabetic retinopathy, n (%)			1.000 [#]
Yes	152 (45.1)	65 (44.8)	
No	185 (54.9)	80 (55.2)	
LDL-C, mmol/L, median (IQR)	2.4 (2.1, 2.7)	2.4 (2.1, 2.8)	0.756 ^{\$}
HDL-C, mmol/L, median (IQR)	1.0 (0.7, 1.4)	1.2 (0.8, 1.5)	0.085 ^{\$}
Total cholesterol, mmol/L, median (IQR)	4.4 (2.8, 5.6)	3.7 (2.5, 5.8)	0.071 ^{\$}
TG, mmol/L, median (IQR)	1.3 (0.8, 1.9)	1.4 (0.8, 2.1)	0.726 ^{\$}
SCr, μ mol/L, median (IQR)	82.5 (60.5, 101.6)	80.8 (58.7, 103.4)	0.809 ^{\$}
HbA1c, %, median (IQR)	8.0 (6.5, 9.4)	7.7 (6.3, 9.2)	0.117 ^{\$}
Hemoglobin, g/L, median (IQR)	108.0 (94.0, 125.0)	104.0 (90.0, 123.0)	0.124 ^{\$}
Rad-score, mean (SD)	0.4 (0.2)	0.4 (0.2)	0.447*

Notes: *For independent sample t-test; [#]For chi-square test; ^{\$}For Mann-Whitney U-test.

Abbreviations: IQR, inter-quartile range; BMI, body mass index; SBP, systolic blood pressure; SD, standard deviation; DBP, diastolic blood pressure; LDL-C, low-density lipoprotein cholesterol; HDL-C, high-density lipoprotein cholesterol; TG, triglyceride; SCr, serum creatinine; HbA1c, glycosylated hemoglobin; Rad-score, radiomic score.

CVD occurrence status and the features (Figure 3C). Supplemental Appendix 1 shown its calculation formula. A significant difference in rad-score was found between patients with and without CVD (0.34 [0.18, 0.50] vs 0.58 [0.39, 0.84]; $P < 0.001$). ROC curve analysis indicated that the rad-score exhibited a moderate predictive efficacy for the prediction of the occurrence of the CVD, with the area under the curve (AUC) of 0.791 (Figure 3D).

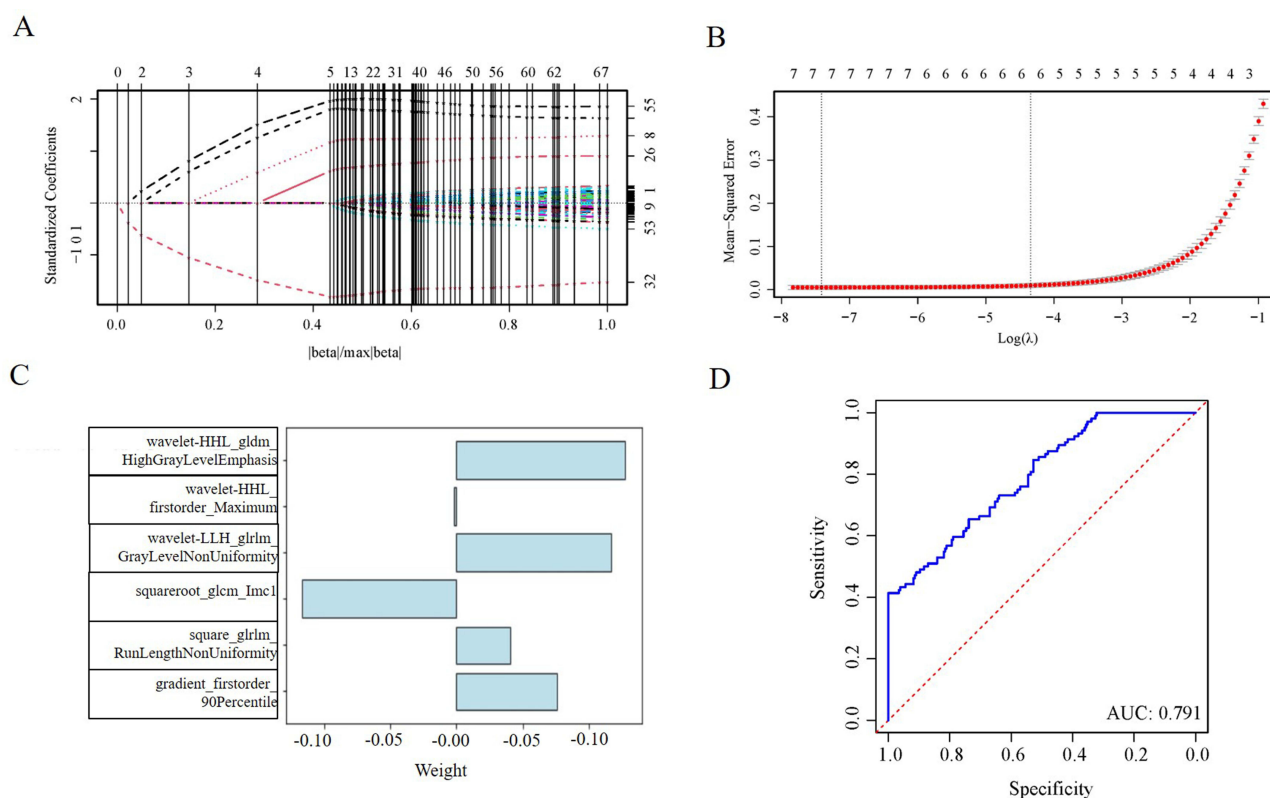


Figure 3 Radiomics feature selection using LASSO logistic regression for establishing the rad-score. **(A)** LASSO coefficient distribution of the 67 radiomics features. **(B)** Selection of the tuning parameter (λ) using 10-fold cross validation via the minimum criteria (λ_{\min}) and the 1-standard error of the minimum criteria (λ_{1-SE}). The optimal λ results in 6 features with nonzero coefficients. **(C)** The weights of the selected radiomics features. **(D)** ROC curve of the rad-score for predicting the occurrence of CVD. **Abbreviations:** LASSO, least absolute shrinkage and selection operator; λ , penalty regularization parameter; AUC, area under the curve; ROC, receiver operating characteristic; CVD, cardiovascular disease.

Radiomics Nomogram Development

To establish the radiomics nomogram, multivariate logistic regression followed by univariate logistic regression was used to evaluate clinical characteristics and the rad-score (Table 2). The result showed that the occurrence of CVD was independently related to age, SBP, LDL-C, and rad-score (all $P < 0.05$). The occurrence of CVD was more prevalent in patients with older age, higher SBP, higher LDL-C level, and higher rad-score (odds ratio [OR]: 1.081, 1.035, 1.876, and 5.531, respectively). The radiomics nomogram was developed with these 4 independent predictors to visualize the likelihood of CVD in patients with DKD (Figure 4).

Model Validation

The ROC curves of the clinical nomogram (without the rad-score) and radiomics nomogram in the training and validation cohorts were compared in Figure 5A and B, respectively. The discrimination of the radiomics model was significantly enhanced in both the training cohort (AUC: 0.888 vs 0.798; $P < 0.001$) and the validation cohort (AUC: 0.894 vs 0.792; $P = 0.002$), respectively. It suggested that the radiomics nomogram in both cohorts obtained better predictions than the model without the rad-score.

The calibration curves showed excellent agreement between the radiomics nomogram-predicted and the observed occurrence of CVD in both cohorts (Figures 6A and B). The HL test indicated good calibration of the radiomics nomogram in both the training ($\chi^2 = 12.019$, $P = 0.150$) and validation ($\chi^2 = 9.504$, $P = 0.302$) cohorts.

The DCA of the radiomics nomogram was shown in Figure 7. The plots revealed more net benefit of using radiomics nomogram to predict the occurrence of CVD than the treat-all or treat-none scheme.

Table 2 Univariate and Multivariate Logistic Regression Analyses for the Independent Correlates of the Occurs of CVD

Variable	Univariate Logistic Regression			Multivariable Logistic Regression		
	P value	OR	95% CI	P value	OR	95% CI
Age, years	<0.001	1.070	1.042–1.101	<0.001	1.081	1.045–1.123
Gender						
Female	Reference					
Male	0.981	1.006	0.613–1.672			
BMI, kg/m ²	0.005	1.107	1.032–1.190	0.147	1.074	0.976–1.183
Smoking status						
Never	Reference					
Previous	0.974	1.016	0.379–2.474			
Current	0.397	1.372	0.645–2.819			
Drinking status						
Never	Reference					
Previous	0.917	0.957	0.399–2.132			
Current	0.993	1.003	0.557–1.763			
SBP, mmHg	<0.001	1.039	1.026–1.053	<0.001	1.035	1.019–1.052
DBP, mmHg	0.306	1.008	0.993–1.023			
Duration of diabetes, years	0.363	1.015	0.982–1.049			
Diabetic retinopathy						
No	Reference					
Yes	0.983	1.005	0.630–1.599			
LDL-C, mmol/L	<0.001	2.207	1.642–3.111	<0.001	1.876	1.328–2.755
HDL-C, mmol/L	0.135	1.546	0.874–2.749			
Total cholesterol, mmol/L	0.248	1.080	0.948–1.231			
TG, mmol/L	0.183	1.245	0.903–1.722			
SCr, mmol/L	0.337	0.995	0.985–1.005			
HbA1c, %	0.647	0.969	0.846–1.109			
Hemoglobin, g/L	0.084	0.988	0.975–1.001			
Rad-score	<0.001	4.538*	1.105–22.021	<0.001	5.531*	1.094–34.432

Note: *Denotes a specific OR value, indicating that the risk increases by 0.01 unit increments.

Abbreviations: CVD, cardiovascular disease; BMI, body mass index; SBP, systolic blood pressure; DBP, diastolic blood pressure; LDL-C, low-density lipoprotein cholesterol; HDL-C, high-density lipoprotein cholesterol; TG, triglyceride; SCr, serum creatinine; HbA1c, glycosylated hemoglobin; Rad-score, radiomic score; OR, odds ratio; CI, confidence interval.

Example of the Radiomics Nomogram

For example, a 65-year-old patient with DKD had an SBP of 150 mmHg, an LDL-C of 4.5 mmol/L, and a rad-score of 0.5. The corresponding scores were: 37 points for age, 34 points for SBP, 39 points for LDL-C, and 50 points for rad-score. The total score was 160 points, and the risk of developing CVD is close to 90%.

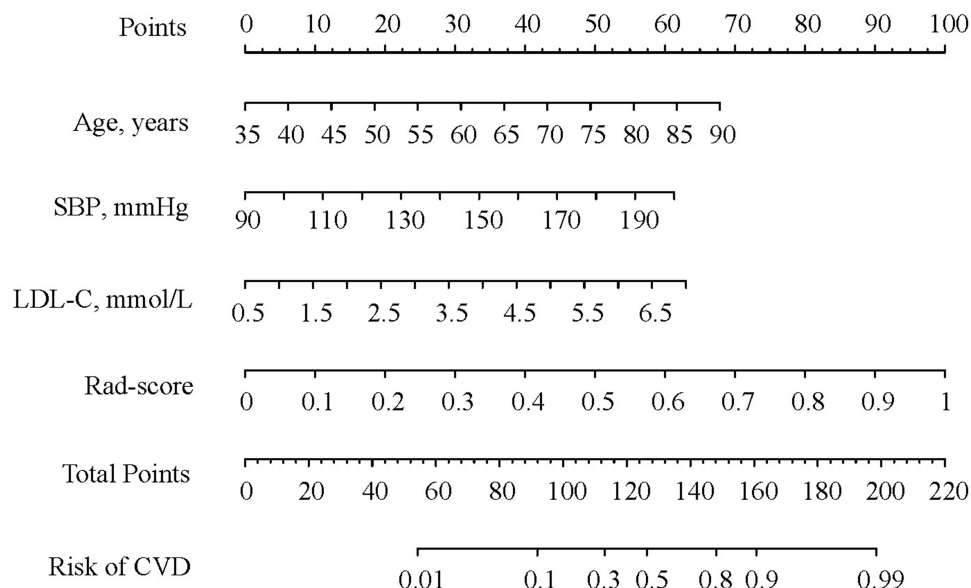


Figure 4 Radiomics nomogram for predicting CVD risk in patients with DKD.

Abbreviations: SBP, systolic blood pressure; LDL-C, low-density lipoprotein cholesterol; Rad-score, radiomics score; CVD, cardiovascular disease; DKD, diabetic kidney disease.

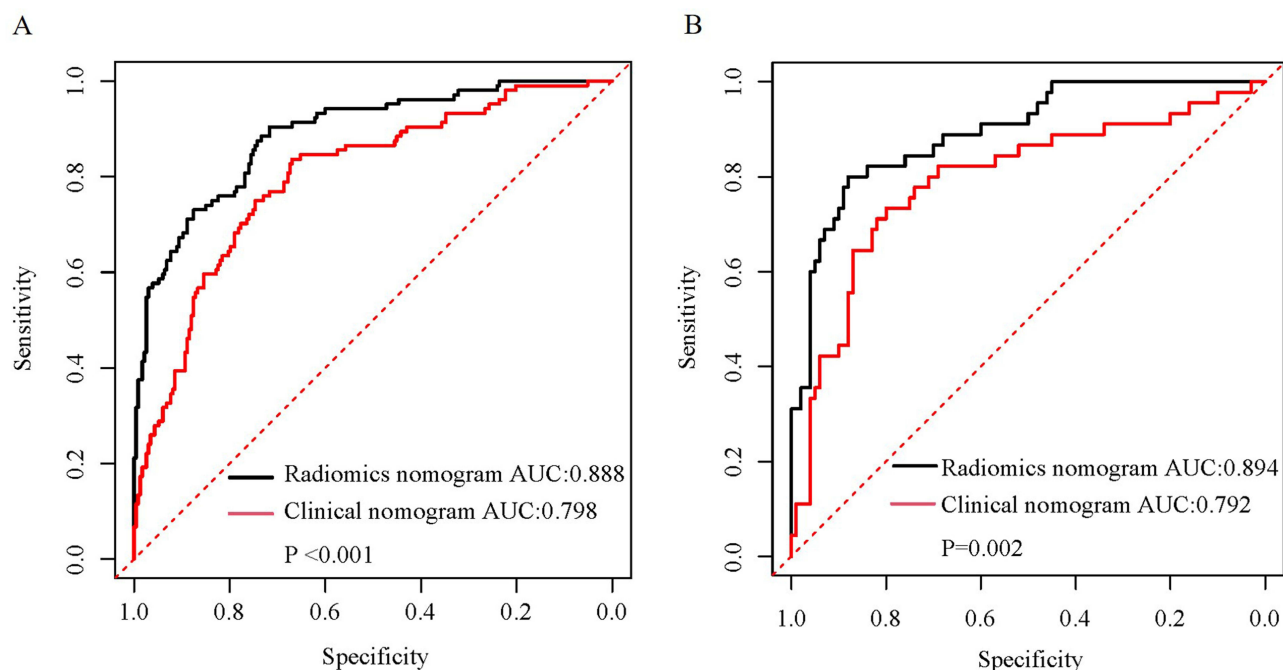


Figure 5 Assessment of the discrimination in training and validation cohorts. (**A** and **B**) demonstrate the ROC curves in the training and validation cohorts, respectively, for comparing the discrimination of radiomics nomogram and clinical nomogram (without the rad-score). The discrimination of the radiomics nomogram is higher than that of the clinical nomogram in both cohorts.

Abbreviations: ROC, receiver operating characteristic; rad-score, radiomics score.

Discussion

The occurrence of CVD is a crucial factor in the poor outcomes of patients with DKD.²⁴ In this study, an SWE-based radiomics nomogram including the baseline clinical characteristics and rad-score was developed and validated as a new tool to predict the development of CVD in patients with DKD. It was superior to the clinical nomogram developed

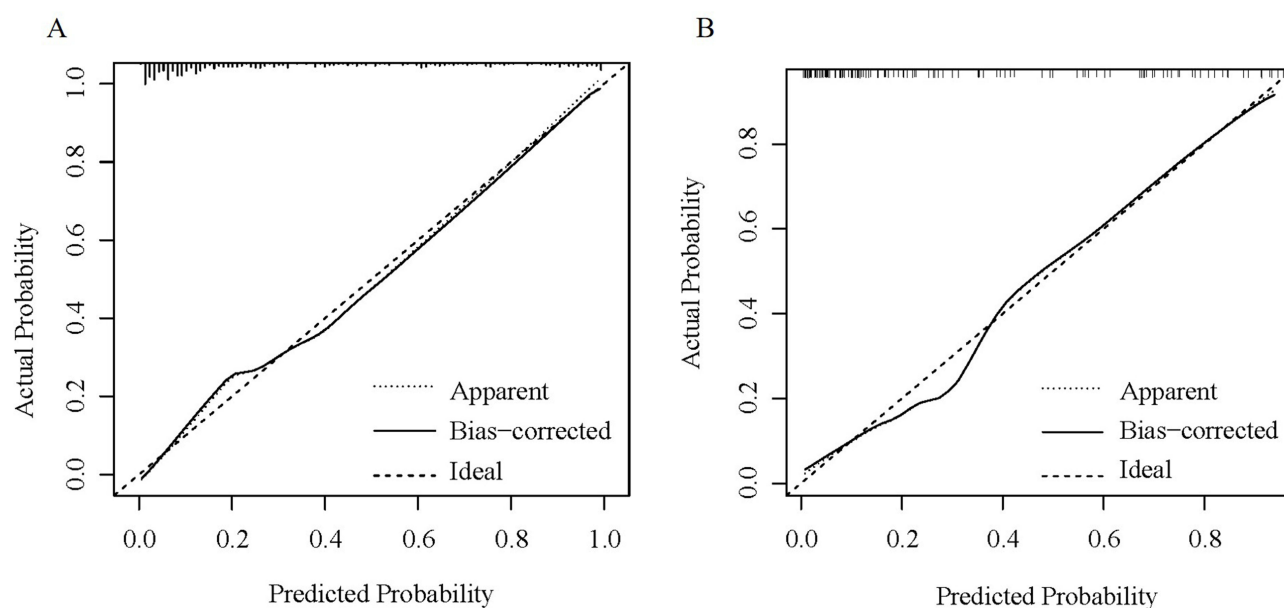


Figure 6 Assessment of the calibration in training and validation cohorts. (A and B) demonstrate the calibration curves of the radiomics nomogram in the training and validation cohorts, respectively.

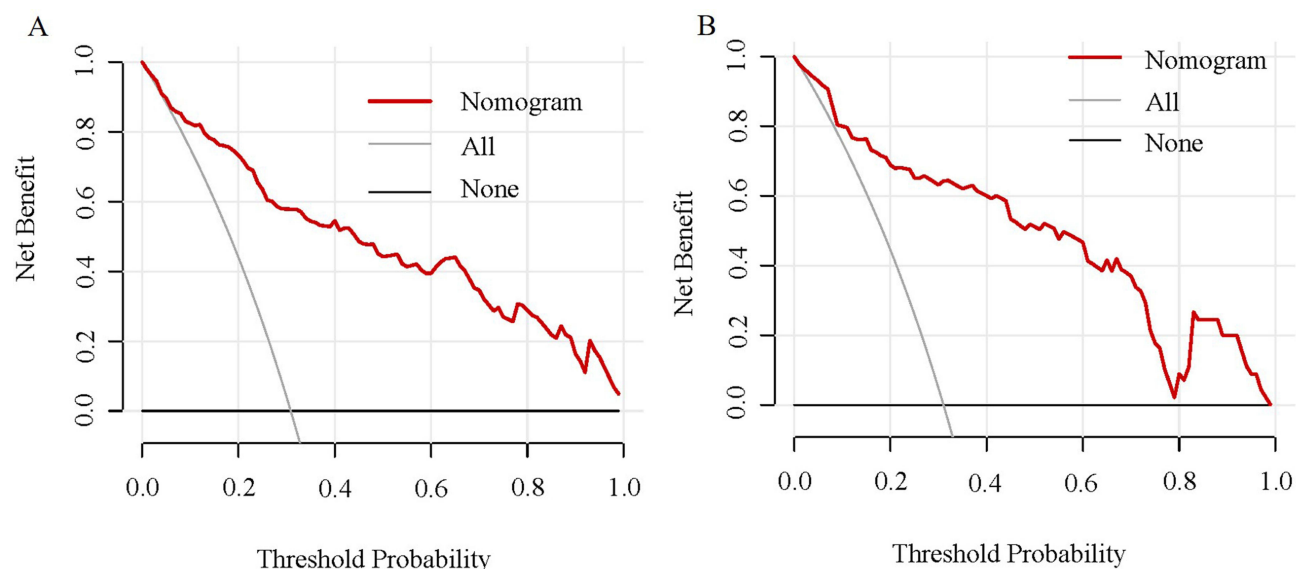


Figure 7 DCA of the radiomics nomogram for predicting CVD risk in patients with DKD in the training and validation cohorts. Both (A) (training cohort) and (B) (validation cohort) show that using the radiomics nomogram to predict CVD risk adds more net benefit than the treat-all or treat-none scheme.

Abbreviations: DCA, decision curve analysis; CVD, cardiovascular disease; DKD, diabetic kidney disease.

without the rad-score and demonstrated promising discrimination, calibration, and clinical utility in both training and validation cohorts. As a result, clinicians can select the most appropriate treatment strategy according to the results of risk stratification to perform individualized management and even achieve a better CVD outcome.

Many risk factors have been shown to be associated with a high incidence of CVD in patients with DKD. In this study, we also proved 3 recognized traditional risk factors, including age, SBP, and LDL-C, in agreement with previous studies.²⁵ A meta-analysis has revealed that these traditional risk predictors have been demonstrated in classical predictive models for the general population.²⁶ Age is a widely accepted risk factor for CVD.²⁷ In the aging process,

fundamental cardiomyocyte often leads to structural changes and functional dysfunction of the heart.²⁸ Hypertension is very common in patients with chronic kidney disease (CKD) and is widely considered to be a risk factor for the occurrence of CVD.^{29,30} Lowering blood pressure is an essential treatment strategy that not only slows the development of renal failure but also reduces the risk of CVD.³¹ Previous reports indicated that LDL-C is a potential risk marker for DKD. Regardless of the relationship with DKD, dyslipidemia is strongly associated with overall cardiovascular risk, so controlling dyslipidemia, especially LDL-C, is critical for patients with diabetes. Increased awareness of traditional risk factors for CVD is important for early intervention and effective treatment of patients with DKD.

Pálsson et al³² reported that patients with DKD have a much higher risk of developing CVD compared with patients with diabetes without CKD. The mechanisms underlying this association between DKD and cardiovascular risk are largely unknown. The increased risk in patients with diabetes cannot be fully explained by the common traditional risk factors. Therefore, there is an urgent need to explore other factor to predict the presence of CVD in patients with DKD. Elastography can evaluate increased tissue stiffness due to injury in breast, prostate and kidney.³³ We utilized a relatively novel SWE method to evaluate kidney stiffness. An ultrasound image is made up of pixels, and image texture analysis reveals the characteristics, spatial distribution and mutual relationships of pixel gray values of an image, as well as the features of pixel changes, and acquires quantitative data of these texture characteristics. In the present study, by evaluating the textural features of ultrasound images of the kidneys in patients with DKD, we found that SWE-based radiomics features could play an active role in predicting the occurrence of CVD in patients with DKD. In our study, the rad-score was developed on the basis of 6 image types, 6 feature classes, and wavelet transform extracted from ultrasound images, suggesting that it is associated with the occurrence of CVD in DKD patients.

The SWE-based radiomics nomogram developed in this study demonstrated good performance for the risk of developing CVD in patients with DKD. However, we must be aware of the limitations of this study. First, this study was a retrospective design. The prospective studies are needed to check the generalizability and validity of the nomogram. Second, the small number of patients enrolled was also a limitation of our study. Studies in larger sample sizes are needed to verify the superior predictive potential. Finally, this study only enrolled the Chinese population and further validation is required to ensure whether it can be extended to other ethnicities.

Conclusions

We developed and validated an SWE-based radiomics nomogram to predict CVD risk in patients with DKD. The model was demonstrated to have a promising prediction performance, showing its potential to identify CVD in DKD patients and assist decision-making for appropriate early intervention.

Abbreviations

T2DM, Type 2 diabetes mellitus; DKD, Diabetic kidney disease; CVD, Cardiovascular disease; SWE, Shear wave elastography; eGFR, Estimated glomerular filtration rate; UACR, Urinary albumin/creatinine ratio; BMI, Body mass index; SBP, Systolic blood pressure; DBP, Diastolic blood pressure; LDL-C, Low-density lipoprotein cholesterol; HDL-C, High-density lipoprotein cholesterol; TC, Total cholesterol; TG, Triglyceride; SCr, Serum creatinine; HbA1c, Glycated hemoglobin; Rad-score, Radiomic score; ROI, Region of interest; ICC, Interclass correlation coefficient; LASSO, Least absolute shrinkage and selection operator; IQR, Interquartile range; ROC, Receiver operating characteristic; HL, Hosmer-Lemeshow; DCA, Decision curve analysis; AUC, Area under the curve; CKD, chronic kidney disease.

Data Sharing Statement

All data generated or analysed during this study are included in this article. Further enquiries can be directed to the corresponding author.

Ethical Approval

This retrospective study was approved by medical ethics committee of Xuan Cheng City Central Hospital (No. 2023027) and conducted in accordance with the Declaration of Helsinki.

Informed Consent

Data collection was performed after written informed consents were obtained from subjects.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Funding

There is no funding to report.

Disclosure

The authors have no conflicts of interest to declare in this work.

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