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Original Article

Development and validation of an ECG-based nomogram for early diagnosis of dilated cardiomyopathy

Tongping Huang[1], Xiaojuan Lv[2], Tao Yu[1], Xiaojun Wang[3], Guidong Cai[3]

[1]Cardio-Thoracic Surgery, Lanzhou First People's Hospital, No. 1 Wujiayuan West Street, Qilihe District, Lanzhou 730050, Gansu, China; [2]Magnetic Resonance Room, Lanzhou First People's Hospital, No. 1 Wujiayuan West Street, Qilihe District, Lanzhou 730050, Gansu, China; [3]Cardiovascular Surgery, Baoji Central Hospital, No. 8 Jiangtan Road, Baoji 721008, Shaanxi, China

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Abstract: Objective: To develop a nomogram based on electrocardiogram (ECG) parameters to predict the early diagnosis of dilated cardiomyopathy (DCM), enhancing diagnostic accuracy and enabling earlier clinical intervention. Methods: A retrospective analysis was conducted on ECG data from 168 DCM patients and 130 healthy controls (N-DCM), diagnosed between October 2022 and August 2024. Lasso regression identified 11 significant ECG features (e.g., QTc interval, PR interval, QRS duration), and a nomogram model was constructed. Model performance was evaluated using ROC curves, calibration curves, decision curves, and clinical utility curves. Results: Significant differences in ECG parameters were observed between DCM and N-DCM groups, with DCM patients showing elevated values across multiple parameters. The nomogram demonstrated high predictive accuracy, achieving an AUC of 0.928 in the training group and 0.862 in the validation group. Calibration and decision curve analyses confirmed good calibration and clinical utility. Conclusion: The ECG-based nomogram provides an effective tool for early DCM diagnosis, with strong predictive accuracy and clinical benefits. It shows promising applicability for large-scale screenings, contributing to earlier detection and improved patient outcomes.

Keywords: Dilated cardiomyopathy, electrocardiogram, Lasso regression, nomogram, early diagnosis

Introduction

Dilated Cardiomyopathy (DCM) is a prevalent form of heart disease characterized by ventricular dilation, myocardial hypertrophy, and impaired cardiac contractility [1]. It is a leading cause of chronic heart failure and sudden cardiac death, with multifactorial pathogenesis involving genetic, environmental, and immune factors [2]. Early-stage DCM symptoms, such as fatigue, shortness of breath, chest pain, and edema, are often nonspecific, which complicates diagnosis and may lead to misdiagnosis with other cardiovascular conditions [3]. Early detection and accurate diagnosis of DCM are crucial for improving patient outcomes.

Electrocardiogram (ECG) has long been recognized as a cost-effective and convenient tool for providing critical insights into cardiac electrophysiology, aiding in the early identification of DCM [4]. Wang et al. [5] suggested that combining ECG screening with relevant biomarkers could improve early diagnosis rates for DCM. In line with this, Finocchiaro et al. [6] emphasized that ECG not only detects electrophysiological abnormalities but also helps differentiate between DCM subtypes. Currently, DCM diagnosis relies on a combination of clinical symptoms, physical signs, imaging techniques (such as echocardiography), ECG, and cardiac magnetic resonance imaging [7].

Studies have shown that combining ECG with echocardiography (UCG) improves diagnostic sensitivity and helps identify asymptomatic DCM patients in the early stages [8]. These findings further confirm ECG's value in early screening for DCM. Pezzato et al. [9] highlighted that ECG features play a key role in diagnosing non-

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ischemic dilated cardiomyopathy (NIDCM), particularly in assessing cardiac electrophysiological function. ECG assists clinicians in detecting conduction abnormalities, especially regarding QRS complex width and ST segment changes. In DCM patients, ECG not only identifies conduction abnormalities but also offers critical early diagnostic clues [10]. Typical ECG findings in DCM patients, such as prolonged QT interval, increased QRS width, and ST segment deviations, are strongly linked to structural heart changes, heart failure, and electrophysiological dysfunction [6]. Prolonged QRS duration, in particular, correlates with a decline in heart function in DCM patients, serving as a key marker for assessing heart failure risk [11]. Changes in QRS width and ST segment can indicate alterations in cardiac structure and function, providing valuable information for early screening and clinical intervention [12].

Given the limitations of traditional ECG analysis, developing a predictive model based on multiple ECG features is essential for enhancing early DCM diagnosis. Integrating multiple ECG parameters enables a more comprehensive evaluation of cardiac health, ultimately improving early detection rates and diagnostic accuracy. Han et al. [13] demonstrated that multi-lead ECG features can effectively differentiate DCM from other cardiovascular diseases, thus improving screening accuracy. The Lasso regression model (Least Absolute Shrinkage and Selection Operator) is widely used for feature selection and predictive modeling in high-dimensional data [14]. By applying Lasso regression with L1 regularization, the most predictive variables are selected, preventing overfitting and improving model performance.

In this study, we developed a nomogram model based on ECG features selected using Lasso regression. The model aims to provide an accurate, convenient tool for early DCM diagnosis, aiding clinicians in identifying high-risk patients at an earlier stage and enabling timely intervention.

Materials and methods

Case selection

This retrospective study collected data from 168 patients diagnosed with DCM between October 2022 and August 2024 at Lanzhou First People's Hospital, along with 130 healthy individuals serving as the non-DCM group during the same period. The study was approved by the Ethics Committee of Lanzhou First People's Hospital, and all procedures adhered to ethical guidelines to ensure compliance with medical ethics.

Inclusion criteria: Patients were included if they met the diagnostic criteria for DCM [15]. All enrolled patients had undergone both surface electrocardiogram (ECG) and echocardiography, with complete and recorded test results.

Exclusion criteria: Patients were excluded if they had any of the following conditions: hypertensive heart disease, congenital heart disease, valvular heart disease, hypertrophic cardiomyopathy, ischemic heart disease (coronary artery stenosis > 50%), metabolic and endocrine-related heart diseases (e.g., hyperthyroidism, diabetes, amyloidosis, hereditary neuromuscular disorders), systemic disease-related heart diseases (e.g., systemic lupus erythematosus, rheumatoid arthritis), toxic or other types of cardiomyopathy (e.g., allergic myocarditis, toxic myocarditis, cardiomyopathy associated with muscular dystrophy, mitochondrial myopathy, drug-induced cardiomyopathy), myocarditis, ectopic arrhythmias, or patients with a permanent pacemaker.

Sample size calculation

Following the approach by Wang et al. [5], logistic regression analysis was used to select 5 valid ECG parameters as independent predictors. According to the empirical rule, at least 15 events are required for each independent variable, resulting in a minimum of 75 events for this study (5 variables × 15 events = 75). Therefore, at least 75 events were necessary for analysis. To ensure sufficient events in each group (DCM and non-DCM), the final sample size was determined based on clinical data collection.

Data sources and collection

Data were sourced from the ECG room and clinical records of the Cardiovascular Department at Lanzhou First People's Hospital. ECG data were measured and stored using the GE MUSE cardiology information management system (model: GE MUSE Cardiology System), support-

ed by GE Healthcare, USA. Experienced technicians collected all ECG data to ensure accuracy and integrity. Clinical data, including patients' age, sex, medical history, and laboratory test results, were obtained from the hospital's electronic medical record system. Basic patient information includes age, gender, body mass index (BMI), smoking history, alcohol consumption, and past medical history (e.g., diabetes, hypertension). ECG parameters such as QTc interval, PR interval, QRS duration, V1SA, V2SA, V3SA, V5RA, V6RA, DIRA, aVLRA, DIIRA, aVFRA, and DIIIRA were measured and analyzed using the GE MUSE ECG system. All ECG data were collected upon patient admission to capture comprehensive heart electrical activity.

Outcome measurements

Primary outcome: Develop a diagnostic model for DCM based on ECG parameters and assess the model's clinical and diagnostic value by splitting the data into a training group (67%) and a validation group (33%).

Secondary outcome: Compare ECG parameter differences between DCM patients and healthy individuals, and analyze ECG parameter variations between the training and validation groups.

Statistical analysis

Statistical analyses were performed using SPSS 25.0 and R 4.3.2 software. Raw data were cleaned to ensure completeness, and missing data were addressed through imputation. Outliers were identified using boxplots and standard deviation methods and were either corrected or excluded as needed. For continuous variables, normality was assessed, with independent sample t-tests used for normally distributed data and the Mann-Whitney U test for non-normally distributed data. Descriptive statistics were used to calculate means, standard deviations, frequencies, and percentages to summarize the study sample. Differences in ECG parameters and clinical variables between the DCM and non-DCM groups were analyzed using t-tests or rank sum tests. Chi-square tests were applied for categorical variables. Pearson correlation analysis explored the relationships between clinical variables and ECG parameters. Lasso regression analysis was employed to select ECG parameters most closely associated with DCM and optimize model accuracy. Receiver operating characteristic (ROC) curves were used to evaluate the model's sensitivity, specificity, and area under the curve (AUC). Calibration curves assessed the predictive accuracy of the nomogram model, showing the fit between actual and predicted values. Decision curve analysis (DCA) and clinical utility curves (CIC) evaluated the clinical benefit of the model across various risk thresholds. The training and validation sets were divided in a 67:33 ratio, with model performance evaluated using AUC, accuracy, sensitivity, and specificity.

Results

Comparison of baseline data between DCM and non-DCM groups

We compared the baseline data between the two patient groups. The results showed no significant differences in any of the variables (all *p*-values > 0.05). Specifically, age (P = 0.484), gender (P = 0.055), body mass index (BMI) (P = 0.220), smoking history (P = 0.449), alcohol consumption (P = 0.315), diabetes history (P = 0.356), hypertension history (P = 0.682), marital status (P = 0.126), and education level (P = 0.736) did not differ significantly between the DCM and non-DCM groups (see **Table 1**).

Comparison of ECG parameters between DCM and non-DCM groups

ECG parameters were compared between the DCM and non-DCM groups. The results revealed significantly higher values in the DCM group for several ECG parameters, including QTc interval, PR interval, QRS duration, V6RA, aVLRA, DIIRA, aVFRA, DIIIRA, V1SA, V2SA, and V3SA (all P < 0.001). In contrast, no significant differences were observed for V5RA (P = 0.756) and DIRA (P = 0.871) (see **Table 2**).

Comparison of ECG parameters between the training and validation groups

ECG parameters were compared between the training and validation groups. No significant differences were observed between the two groups for any of the variables (all *p*-values > 0.05). Specifically, QTc interval (P = 0.868), PR interval (P = 0.542), QRS duration (P = 0.456), V6RA (P = 0.236), aVLRA (P = 0.502), DIIRA (P

Table 1. Comparison of baseline data between DCM and Non-DCM

Variable	Total	DCM (n = 168)	Non-DCM (n = 130)	Statistic Value	*P*-value
Age					
≥ 50 years	157	92	65	0.667	0.414
< 50 years	141	76	65		
Gender					
Male	199	109	90	0.625	0.429
Female	99	59	40		
Body Mass Index					
≥ 25 kg/m^2	88	45	43	1.394	0.238
< 25 kg/m^2	210	123	87		
Smoking History					
Yes	168	91	77	0.764	0.382
No	130	77	53		
History of Alcohol Consumption					
Yes	30	20	10	1.436	0.231
No	268	148	120		
Diabetes					
Yes	27	18	9	1.278	0.258
No	271	150	121		
High Blood Pressure					
Yes	50	30	20	0.321	0.571
No	248	138	110		
Marital Status					
Married	277	160	117	3.070	0.080
Other	21	8	13		
Educational Level					
≥ High School	108	59	49	0.210	0.647
< High School	190	109	81		

Note: DCM, Dilated cardiomyopathy; N-DCM, No-Dilated cardiomyopathy.

Table 2. Comparison of ECG parameters between DCM and non-DCM

Variable	DCM (n = 168)	Non-DCM (n = 130)	Statistic Value	*P* Value
QTc (ms)	448.91±19.76	432.18±13.43	8.684	< 0.001
PR Interval (ms)	171.88±13.65	161.26±9.51	7.909	< 0.001
QRS Time Limit (ms)	99.89±14.63	90.54±5.52	7.612	< 0.001
V5RA (mV)	1.54 [1.12, 2.06]	1.59±0.34	-0.311	0.756
V6RA (mV)	1.62±0.46	1.33±0.25	7.084	< 0.001
DIRA (mV)	0.73±0.22	0.73±0.13	0.162	0.871
aVLRA (mV)	0.59±0.30	0.35±0.15	8.605	< 0.001
DIIRA (mV)	0.55±0.16	0.64±0.18	-4.426	< 0.001
aVFRA (mV)	0.30±0.14	0.42 [0.24, 0.56]	-4.751	< 0.001
DIIIRA (mV)	0.18 [0.11, 0.26]	0.24 [0.14, 0.35]	-3.947	< 0.001
V1SA (mV)	0.96±0.44	0.64 [0.52, 0.79]	6.493	< 0.001
V2SA (mV)	1.56±0.70	1.07±0.31	8.08	< 0.001
V3SA (mV)	1.09 [0.59, 1.53]	0.82±0.25	3.897	< 0.001

Note: DCM, Dilated cardiomyopathy; Non-DCM, Non-Dilated cardiomyopathy; ECG, Electrocardiogram; QTc, Corrected QT interval, PR Interval, PR interval; QRS Time Limit, QRS duration; V5RA, Voltage in lead V5; V6RA, Voltage in lead V6; DIRA, Voltage in lead DI; aVLRA, Voltage in lead aVL; DIIRA, Voltage in lead DII; aVFRA, Voltage in lead aVF; DIIIRA, Voltage in lead DIII; V1SA, Voltage in lead V1; V2SA, Voltage in lead V2; V3SA, Voltage in lead V3.

Table 3. Comparison of ECG parameters between training and validation groups

Variable	Training Group (n = 198)	Validation Group (n = 99)	Statistic Value	*P* Value
QTc (ms)	441.74±19.94	441.35±17.56	0.167	0.868
PR Interval (ms)	166.10 [157.55, 176.35]	165.40 [158.30, 172.75]	0.609	0.542
QRS Time Limit (ms)	93.00 [87.70, 102.20]	93.10 [89.00, 101.50]	0.745	0.456
V6RA (mV)	1.45 [1.24, 1.77]	1.40 [1.16, 1.71]	1.186	0.236
aVLRA (mV)	0.43 [0.29, 0.65]	0.43 [0.29, 0.64]	0.671	0.502
DIIRA (mV)	0.58 [0.44, 0.71]	0.57 [0.48, 0.66]	0.398	0.690
aVFRA (mV)	0.32 [0.20, 0.46]	0.35 [0.24, 0.51]	1.331	0.183
DIIIRA (mV)	0.20 [0.12, 0.30]	0.20 [0.13, 0.32]	0.559	0.576
V1SA (mV)	0.81 [0.58, 1.07]	0.72 [0.54, 0.96]	1.403	0.161
V2SA (mV)	1.29 [0.92, 1.79]	1.24 [0.90, 1.56]	0.988	0.323
V3SA (mV)	0.85 [0.66, 1.23]	0.85 [0.60, 1.26]	0.225	0.822
DCM				
Yes	115	53	0.486	0.486
No	89	46		

Note: ECG, Electrocardiogram; QTc, Corrected QT interval; PR Interval, PR interval; QRS Time Limit, QRS duration; V6RA, Voltage in lead V6; aVLRA, Voltage in lead aVL; DIIRA, Voltage in lead DII; aVFRA, Voltage in lead aVF; DIIIRA, Voltage in lead DIII; V1SA, Voltage in lead V1; V2SA, Voltage in lead V2; V3SA, Voltage in lead V3; DCM, Dilated Cardiomyopathy.

Table 4. Comparison of ECG parameters in the training group

Variable	DCM (n = 115)	N-DCM (n = 84)	Statistic Value	*P* Value
QTc (ms)	448.71±20.68	432.20±14.22	6.668	< 0.001
PR Interval (ms)	171.77±14.16	162.14±9.87	5.65	< 0.001
QRS Time Limit (ms)	99.09±14.69	90.06±5.12	6.105	< 0.001
V6RA (mV)	1.62±0.47	1.36±0.24	5.303	< 0.001
aVLRA (mV)	0.59±0.30	0.36±0.14	7.02	< 0.001
DIIRA (mV)	0.55±0.17	0.65±0.20	-3.527	< 0.001
aVFRA (mV)	0.30±0.15	0.40 [0.21, 0.51]	-2.482	0.013
DIIIRA (mV)	0.18 [0.11, 0.27]	0.25±0.13	-2.724	0.006
V1SA (mV)	0.98±0.44	0.64 [0.51, 0.83]	5.529	< 0.001
V2SA (mV)	1.63±0.72	1.04±0.30	7.826	< 0.001
V3SA (mV)	1.07 [0.58, 1.48]	0.84±0.22	2.673	0.008

Note: ECG, Electrocardiogram; QTc, Corrected QT interval; PR Interval, PR interval; QRS Time Limit, QRS duration; V6RA, Voltage in lead V6; aVLRA, Voltage in lead aVL; DIIRA, Voltage in lead DII; aVFRA, Voltage in lead aVF; DIIIRA, Voltage in lead DIII; V1SA, Voltage in lead V1; V2SA, Voltage in lead V2; V3SA, Voltage in lead V3; DCM, Dilated Cardiomyopathy.

= 0.690), aVFRA (P = 0.183), DIIIRA (P = 0.576), V1SA (P = 0.161), V2SA (P = 0.323), V3SA (P = 0.822), and DCM (P = 0.486) did not show significant differences between the groups (see **Table 3**).

Comparison of ECG parameters in the training group

ECG parameters were compared between DCM and non-DCM patients within the training group. The results showed that the DCM group exhibited significantly higher values than the non-DCM group for multiple ECG parameters, including QTc interval (P < 0.001), PR interval (P < 0.001), QRS duration (P < 0.001), V6RA (P < 0.001), aVLRA (P < 0.001), DIIRA (P < 0.001), aVFRA (P = 0.013), DIIIRA (P = 0.006), V1SA (P < 0.001), V2SA (P < 0.001), and V3SA (P = 0.008) (see **Table 4**).

Lasso regression model results

To identify the differential variables between DCM and non-DCM groups, we performed Lasso regression analysis on the training group

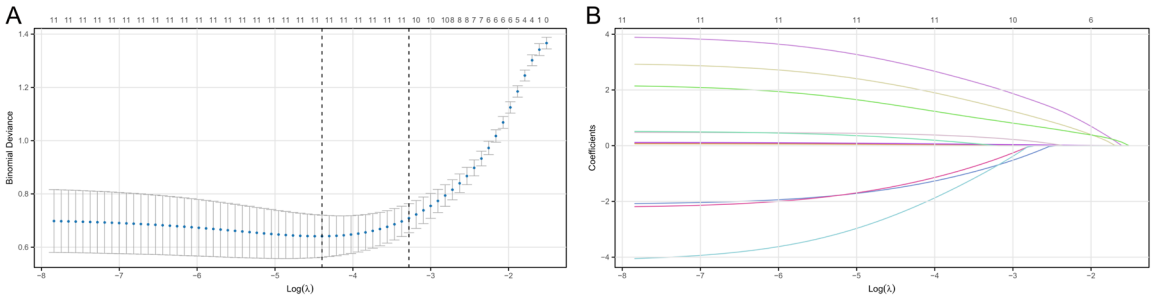

Figure 1. Lasso regression model results. A: Relationship between Lasso model's bias and complexity. B: Coefficient curves of each variable with changing λ. Note: Lasso, Least Absolute Shrinkage and Selection Operator.

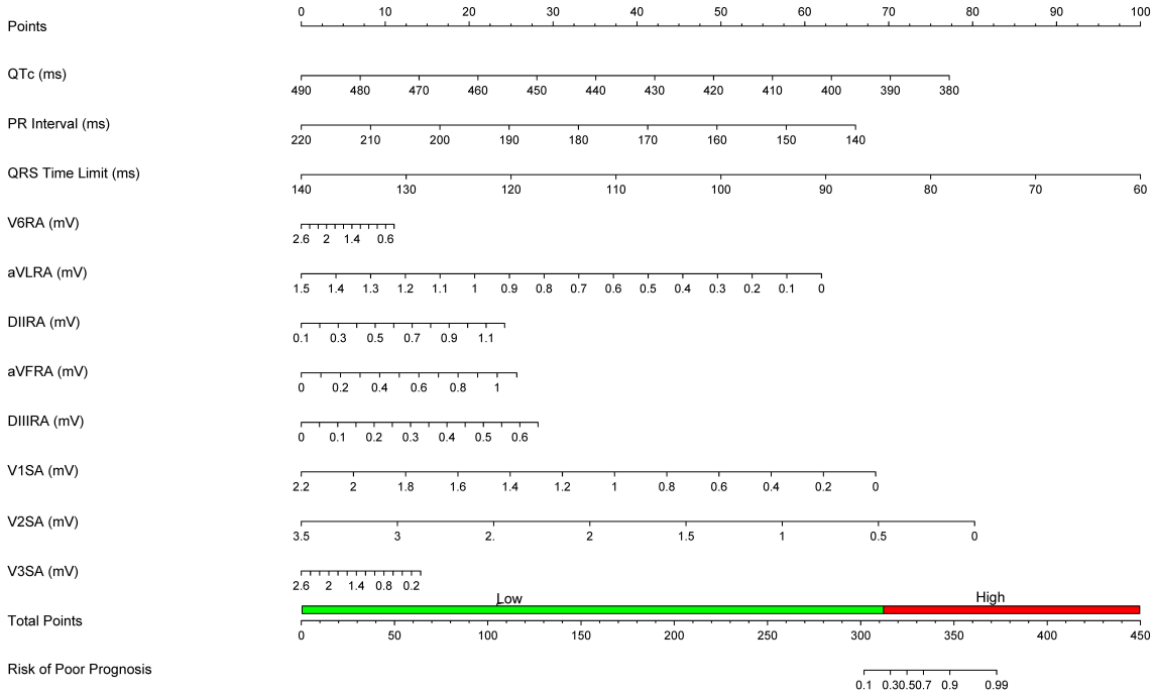

Figure 2. Nomogram model constructed from selected variables. Note: QTc, Corrected QT interval; PR Interval, PR interval; QRS Time Limit, QRS duration; V6RA, Voltage in lead V6; aVLRA, Voltage in lead aVL; DIIRA, Voltage in lead DII; aVFRA, Voltage in lead aVF; DIIIRA, Voltage in lead DIII; V1SA, Voltage in lead V1; V2SA, Voltage in lead V2; V3SA, Voltage in lead V3; DCM, Dilated Cardiomyopathy.

data. A Gaussian function was used for regression, and by adjusting the regularization parameter λ, we selected 11 significant variables when λ.min = 0.012322. These variables included QTc (ms), PR interval (ms), QRS duration (ms), V6RA (mV), aVLRA (mV), DIIRA (mV), aVFRA (mV), DIIIRA (mV), V1SA (mV), V2SA (mV), and V3SA (mV) (**Figure 1**).

Nomogram model based on selected variables

Using the 11 significant variables selected via Lasso regression, we constructed a Nomogram model to predict the risk of DCM (**Figure 2**). Each predictor variable corresponds to a score on the horizontal axis, and the total score is the sum of these values. The total score is then converted into the probability of DCM, helping to predict the likelihood of adverse outcomes. The 11 variables included in the model are: QTc (ms), PR interval (ms), QRS duration (ms), V6RA (mV), aVLRA (mV), DIIRA (mV), aVFRA (mV), DIIIRA (mV), V1SA (mV), V2SA (mV), and V3SA (mV). Among these, V6RA, aVLRA, and V1SA had a stronger impact, while DIIRA, DIIIRA, and V3SA had smaller weights. The model formula

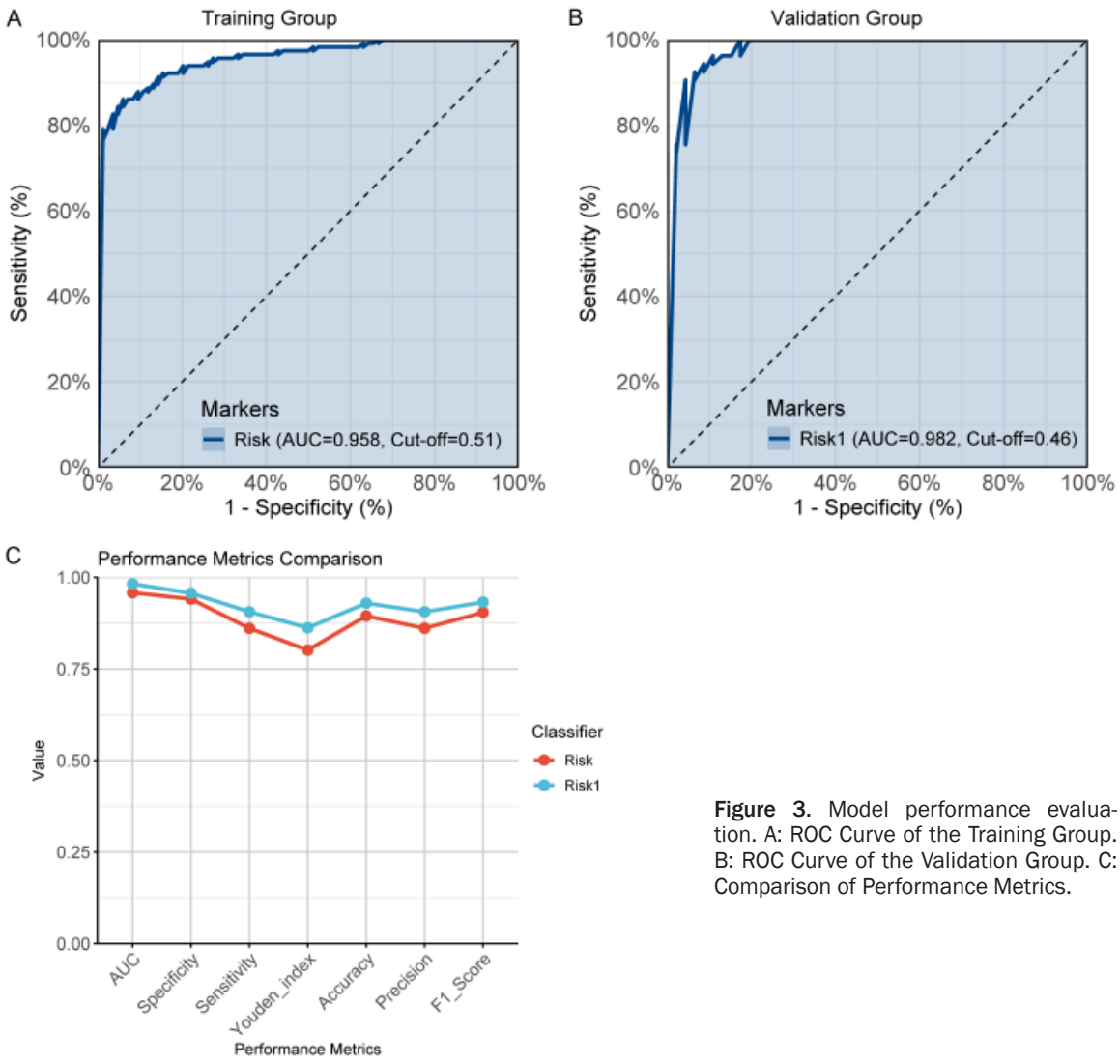

Figure 3. Model performance evaluation. A: ROC Curve of the Training Group. B: ROC Curve of the Validation Group. C: Comparison of Performance Metrics.

is as follows: Intercept = -4.045 + (QTc × 0.005) + (PRInterval × 0.0057) + (QRSDuration × 0.0084) + (V6RA × 0.0916) + (aVLRA × 0.448) + (DIIRA × -0.3389) + (aVFRA × -0.2898) + (DIIIRA × -0.3329) + (V1SA × 0.2923) + (V2SA × 0.1239) + (V3SA × 0.0637).

Nomogram evaluation and validation

ROC curve analysis for the training group (**Figure 3A**) and validation group (**Figure 3B**) showed that the model achieved an AUC of 0.928 (cut-off = 0.51) in the training group and 0.862 (cut-off = 0.46) in the validation group, indicating strong predictive performance in both groups. **Figure 3C** compares various performance metrics (e.g., accuracy, sensitivity, specificity) between the two groups, demonstrating high stability and effectiveness. Calibration curve analysis (**Figure 4A** and **4B**) indicated that the bias-corrected curve closely followed the ideal line, suggesting excellent calibration. In the training group, the likelihood ratio test's chi-square value was 170.11 (P < 0.001), with a C-index of 0.958 (95% CI: 0.934-0.983), showing excellent discrimination. The goodness-of-fit chi-square value was 3.9767 (P = 0.8592), indicating good calibration. In the validation group, the likelihood ratio test's chi-square value was 100.96 (P < 0.001), and the C-index was 0.982 (95% CI: 0.962-1.001), further confirming high discrimination, with a goodness-of-fit chi-square value of 5.0239 (P = 0.755).

DCA and CIC evaluation

DCA and CIC analyses were conducted to evaluate the clinical utility of the Nomogram. **Figure**

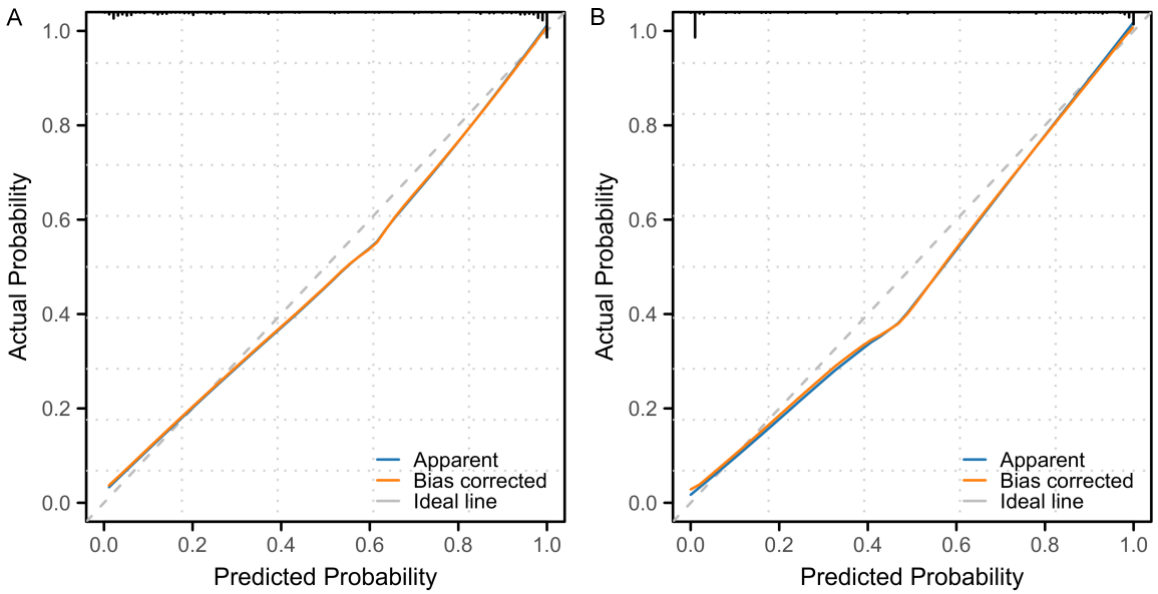

Figure 4. Calibration curves of the training and validation groups. A: Calibration Curve of the Training Group. B: Calibration Curve of the Validation Group.

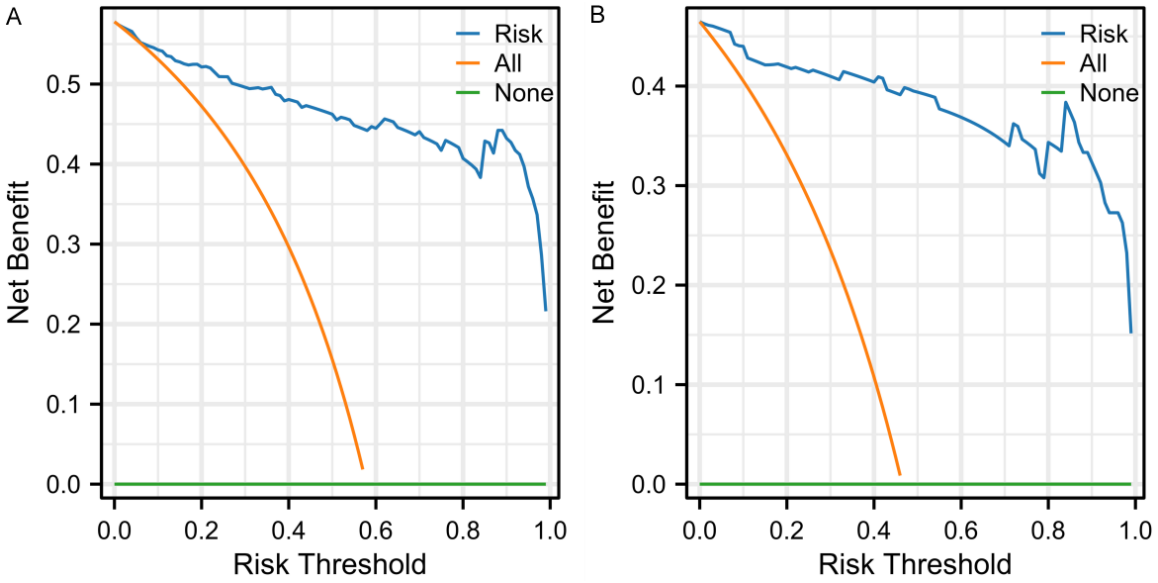

Figure 5. DCA of the training and validation groups. A: DCA Analysis of the Training Group. B: DCA Analysis of the Validation Group. Note: DCA, Decision Curve Analysis.

5 shows the DCA results, indicating net benefits across different risk thresholds. In the training group (**Figure 5A**), the highest net benefit was 57.78% across the 0-99% risk threshold range. In the validation group (**Figure 5B**), the highest net benefit was 46.46% across the 0-83% range. These results suggest that the model offers greater clinical benefit than full intervention or no intervention at various risk thresholds. CIC analysis revealed that when the risk threshold exceeded 50%, the Nomogram's clinical utility was high, effectively identifying high-risk populations for unplanned ICU admissions (**Figure 6**).

Discussion

DCM is a common form of cardiomyopathy, characterized by ventricular dilation, myocardi-

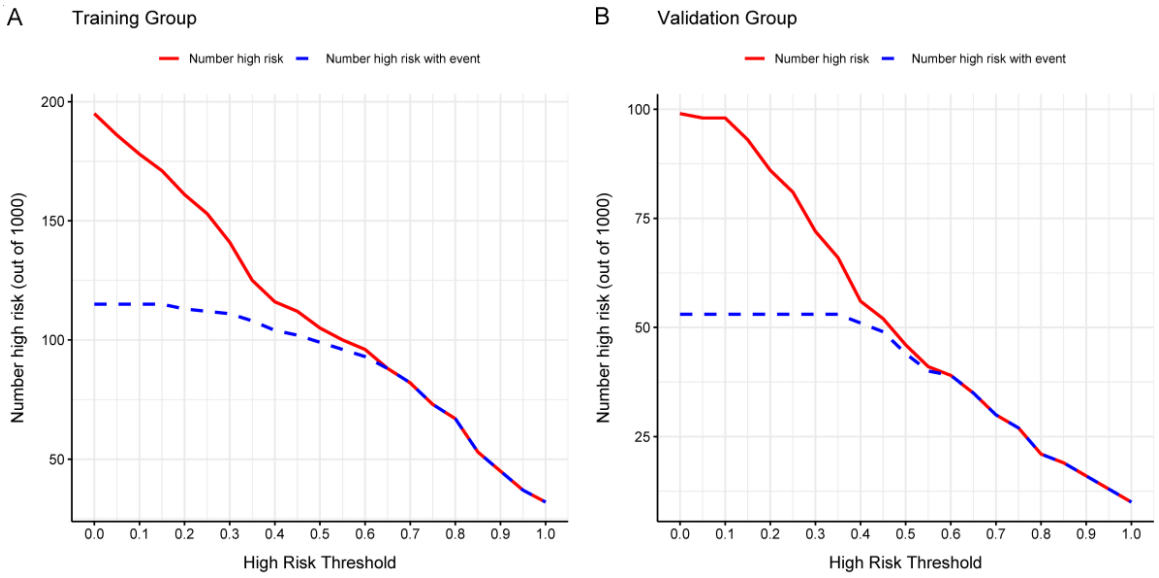

Figure 6. CIC of the training and validation groups. A: CIC Analysis of the Training Group. B: CIC Analysis of the Validation Group. Note: CIC, Clinical Utility Curve.

al hypertrophy, and impaired cardiac contractility [16]. It is a leading cause of chronic heart failure and sudden cardiac death, with a complex pathogenesis involving genetic, immune, and environmental factors [17]. Despite the availability of various diagnostic tools, early diagnosis of DCM remains challenging. Traditional ECG, being economical, convenient, and non-invasive, is widely used in cardiovascular disease diagnosis, particularly in early DCM detection [18].

ECG characteristics in DCM patients typically include prolonged QT interval, increased QRS width, and ST segment changes, often associated with electrophysiological dysfunction. Vidrio-Villaseñor et al. [19] highlighted that prolonged Tpe interval is closely linked to an increased risk of fatal arrhythmias in DCM patients, providing additional ECG markers for early screening. Similarly, Izquierdo et al. [20] found that combining radiomics with ECG could help differentiate DCM from other heart diseases, further supporting ECG's role in early diagnosis. Zavadovskij et al. [21] emphasized that ECG can assess left ventricular mechanical dyssynchrony, which is closely related to DCM prognosis, offering valuable information for clinical intervention.

This study aims to develop a predictive model using ECG parameters selected via Lasso regression analysis, resulting in a Nomogram designed to improve the accuracy of early DCM diagnosis. This model allows clinicians to identify high-risk patients before overt symptoms appear, enabling timely intervention and reducing the risk of heart failure and sudden cardiac death. Several studies have highlighted the utility of ECG in DCM. Wang et al. [5] proposed a simple ECG-based screening model, demonstrating that selecting ECG parameters and creating a Nomogram can significantly enhance early DCM detection. Finocchiaro et al. [6] emphasized the value of ECG in assessing cardiac electrophysiological function, making it an essential tool for DCM diagnosis.

In our study, we observed significant differences in ECG parameters between the DCM and non-DCM groups. Specifically, the QTc interval, PR interval, and QRS duration were significantly longer in the DCM group compared to the non-DCM group. These ECG characteristics are closely linked to the pathological changes seen in DCM, suggesting that ECG is a crucial tool for assessing electrophysiological abnormalities. Prolonged QTc intervals often indicate electrophysiological remodeling, potentially signaling an increased risk of arrhythmias [22]. Moreover, prolonged QRS duration and ventricular hypertrophy reflect structural and functional changes in the heart, providing critical evidence for early DCM diagnosis. Pezzato et al. [9] also

showed that ECG effectively reflects electrophysiological changes in NIDCM. DCM patients exhibit distinctive ECG characteristics that serve as crucial diagnostic markers of cardiac dysfunction. The prolongation of QTc interval, PR interval, and QRS duration reveals intricate electrophysiological remodeling and structural heart changes, providing clinicians with valuable insights into the pathological progression of dilated cardiomyopathy and enabling more targeted diagnostic strategies.

Lasso regression analysis identified 11 ECG parameters significantly associated with DCM, including QTc, PR interval, QRS duration, V6RA, and aVLRA. These variables not only show statistical significance but also offer clinical value. For instance, V6RA and aVLRA reflect left-sided electrical activity and are strongly correlated with structural and functional changes in the heart [23]. V1SA and V2SA, which reflect right ventricular electrical activity, provide important insights into electrical remodeling in the heart [24]. By systematically filtering and selecting 11 key variables, this study demonstrates statistical rigor while translating complex mathematical models into clinically meaningful diagnostic indicators with potential predictive and prognostic value.

A Nomogram model was developed based on 11 significant variables. The model's performance was evaluated using ROC curve analysis, calibration curves, and DCA. ROC curve analysis showed AUC values of 0.928 in the training group and 0.862 in the validation group, indicating strong predictive ability in both datasets. Calibration curve analysis demonstrated that predicted values closely matched observed values in both groups, confirming the model's excellent calibration and stability. DCA revealed significant net benefits across various risk thresholds, with substantial benefits observed between the 0-99% risk range, underscoring its practical value in clinical decision-making.

Additionally, this Nomogram model has substantial clinical utility. Zhao et al. [8] proposed that combining ECG with echocardiography could improve DCM screening by providing more diagnostic information. Li et al. [26] emphasized that Nomogram models based on multi-parameter analysis can enhance DCM diagnostic sensitivity and improve early identification rates. ECG, being simple, cost-effective, and non-invasive, can rapidly reflect changes in cardiac electrophysiological status, especially in the early stages of DCM. Xu et al. [27] also supported the use of ECG in DCM screening, particularly in linking lipid metabolism disorders with cardiac function changes. By applying this Nomogram, clinicians can quickly identify high-risk patients through ECG analysis, even before symptoms manifest. This is crucial for early intervention and improving patient outcomes. Moeinafshar et al. [2] found that early ECG screening helps identify high-risk patients, reinforcing its potential in clinical practice. Combining ECG with imaging techniques further enhances diagnostic accuracy, and integrating multiple ECG features with Lasso regression analysis in large-scale screenings can reduce misdiagnosis and missed diagnosis rates. Han et al. [13] demonstrated that ECG characteristics can distinguish DCM from other cardiovascular diseases, improving screening accuracy. The Nomogram model goes beyond traditional diagnostic methods by offering a sophisticated, non-invasive, and cost-effective approach to identifying high-risk DCM patients. By enabling early detection and risk stratification, this tool has the potential to transform clinical practice, facilitating proactive medical interventions, reducing sudden cardiac events, and improving patient outcomes and quality of life.

This study has some limitations. First, the data were collected from a single hospital, and the relatively small sample size may not fully represent broader patient populations. Therefore, multi-center validation studies with larger sample sizes are needed to confirm these findings. Second, while the study considered multiple ECG parameters, other unaccounted factors, such as genetic background and lifestyle, may also influence the model's accuracy. Future research should incorporate additional clinical variables to enhance the model's reliability. Furthermore, ECG sensitivity and specificity may vary depending on clinical conditions, particularly in the early stages of DCM. Combining ECG with other diagnostic methods, such as cardiac magnetic resonance or echocardiography, could further improve diagnostic accuracy. Future studies should focus on multi-center validation, integration with other diagnostic techniques, and exploration of long-term follow-

up effects. With advancements in artificial intelligence and deep learning, automated ECG analysis could improve screening efficiency and clinical decision support.

In conclusion, this study developed a Nomogram model based on ECG parameters selected through Lasso regression analysis, demonstrating high diagnostic accuracy and clinical utility for early DCM prediction. The model provides clinicians with a simple, cost-effective, and accurate tool for early identification of high-risk patients, enabling timely intervention and improved patient outcomes.

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Disclosure of conflict of interest

None.

Address correspondence to: Guidong Cai, Cardiovascular Surgery, Baoji Central Hospital, No. 8 Jiangtan Road, Baoji 721008, Shaanxi, China. E-mail: guidong2012@126.com

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