



# Prognostic prediction of left ventricular myocardial noncompaction using machine learning and cardiac magnetic resonance radiomics

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**Background:** Although there are many studies on the prognostic factors of left ventricular myocardial noncompaction (LVNC), the determinants are varied and not entirely consistent. This study aimed to build predictive models using radiomics features and machine learning to predict major adverse cardiovascular events (MACEs) in patients with LVNC.

**Methods:** In total, 96 patients with LVNC were included and randomly divided into training and test cohorts. A total of 105 cine cardiac magnetic resonance (CMR)-derived radiomics features and 35 clinical characteristics were extracted. Five different oversampling algorithms were compared for selection of the optimal imbalanced processing. Feature importance was assessed with extreme gradient boosting (XGBoost). We compared the performance of 5 machine learning classification methods with different sample:feature ratios to determine the optimal hybrid classification strategy. Subsequently, radiomics, clinical, and combined radiomics-clinical models were developed and compared.

**Results:** The machine learning pipeline included an adaptive synthetic (ADASYN) algorithm for imbalanced processing, XGBoost feature selection with a sample:feature ratio of 10, and support vector machine (SVM) modeling. The areas under the receiver operating characteristic curves (AUCs) of the radiomics model, clinical model, and combined model in the validation cohort were 0.87 (sensitivity 83.33%, specificity 64.29%), 0.65 (sensitivity 16.67%, specificity 78.57%), and 0.92 (specificity 33.33%, sensitivity 100.00%), respectively. The radiomics model performed similarly to the clinical and combined models ( $P=0.124$  and  $P=0.621$ , respectively). The performance of the combined model was significantly better than that of the clinical model ( $P=0.003$ ).

**Conclusions:** The machine learning-based cine CMR radiomics model performed well at predicting MACEs in patients with LVNC. Adding radiomics features offered incremental prognostic value over clinical factors alone.

**Keywords:** Machine learning; radiomics; left ventricular myocardial noncompaction (LVNC); magnetic resonance imaging; prognosis

Submitted Mar 22, 2023. Accepted for publication Jul 21, 2023. Published online Aug 23, 2023.

doi: 10.21037/qims-23-372

View this article at: <https://dx.doi.org/10.21037/qims-23-372>

## Introduction

Left ventricular noncompaction (LVNC) is a rare but widely recognized condition characterized by prominent trabeculations on the luminal surface of the ventricle, deep intertrabecular recesses communicating with the ventricular cavity, and a thin compacted myocardial layer (1). LVNC is remarkably heterogeneous in terms of its causes, clinical presentation, morphology, and prognosis. Despite several published studies on LVNC, its prognosis remains unclear, as many patients have a favorable prognosis (2,3); meanwhile, others may experience progression, with heart failure (HF), ventricular arrhythmias (VAs), and systemic embolisms (SEs) being the most frequent cardiovascular complications (4), and many even die (mortality rate 13.2–48%) (5,6). Although these potential adverse outcomes and factors that indicate illness severity and clinical outcomes have been well described, there remains an urgent need to develop predictive models that can identify and stratify patients with LVNC at risk of major adverse cardiovascular events (MACEs; including HF, VA, SE, and all-cause death) to thus facilitate the management of these patients.

Recent research into imaging analysis technology and artificial intelligence has made remarkable progress in a variety of medical fields, and applications for building discriminative models have been reported (7–10). Radiomics is an emerging analytical method that can extract quantitative pixel-level features from routinely acquired medical images. As the approach can obtain multiple quantifiers of tissue features with no need for additional image acquisitions or changes in protocol, radiomics shows great potential for improving diagnosis, prognosis, and clinical decision-making (11). In addition, an ensemble machine learning framework, which can reduce the bias in a single machine learning algorithm, may help to improve the predictive performance of radiomics methods (12). Cardiac magnetic resonance (CMR) is frequently used for the measurement of left ventricular (LV) function and the identification and assessment of the extent of trabeculations; it outperforms echocardiography in the precise and comprehensive assessment of the heart owing

to its higher spatial resolution and better field of view (13). Applications of radiomics based on cine CMR sequences have been reported for the diagnosis of acute, subacute, and chronic myocardial infarction (14,15) and etiologies of LV hypertrophy (16). However, to the best of our knowledge, the performance of cine CMR-based radiomics in predicting MACEs in patients with LVNC has not thus far been examined.

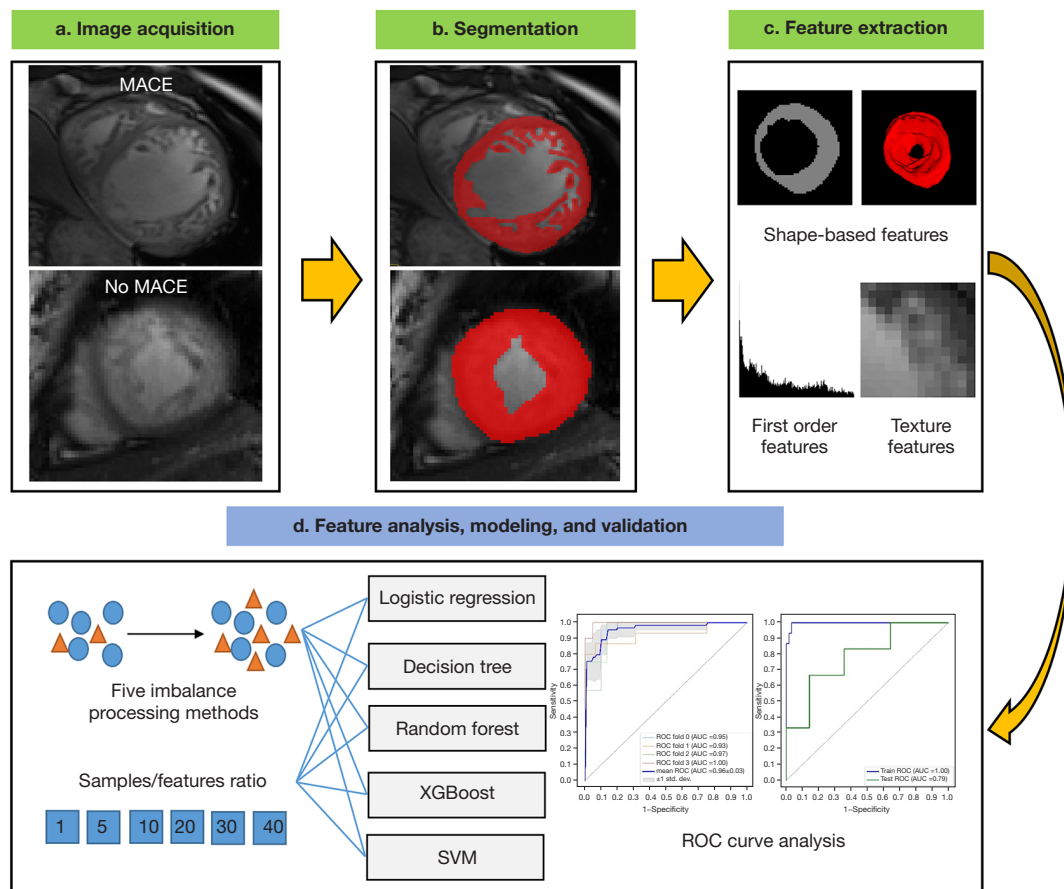
In this study, we aimed to extract and select radiomics features derived from cine CMR images and develop a predictive model using machine learning to predict MACEs in patients with LVNC. We further sought to develop and validate a combined model for predicting MACEs comprising the selected radiomics features and clinical factors to better stratify patients with LVNC.

## Methods

This study was conducted in accordance with the Declaration of Helsinki (as revised in 2013) and was approved by the Biomedical Research Ethics Committee of the West China Hospital of Sichuan University (No. 2022–1190). Individual consent for this retrospective analysis was waived. All personal information was kept strictly confidential and only used for research purposes. The study workflow included data acquisition, image segmentation, feature extraction, feature analysis, model construction, and model validation (see *Figure 1*).

### *Patient profiles and CMR image acquisition and analysis*

We retrospectively screened 129 consecutive patients with LVNC who had undergone CMR from May 2013 to May 2021. LVNC was diagnosed using the Petersen criteria (17). The exclusion criteria were as follows: congenital heart disease; severe valvular disease requiring surgical intervention; known coexisting acquired cardiomyopathy; age <12 years, pregnant women, or athletes; estimated glomerular filtration rate (eGFR) <30 mL/min; and poor image quality. Participants were followed up for MACEs,



**Figure 1** Radiomics workflow for predicting MACEs in patients with LVNC. MACE, major adverse cardiovascular event; XGBoost, extreme gradient boosting; SVM, support vector machine; ROC, receiver operator characteristic; AUC, area under the receiver operating characteristic curve; LVNC, left ventricular myocardial noncompaction.

including HF, VA, SE, and all-cause death (see [Table S1](#) for full details). The follow-up involved clinical visits or telephone interviews. The follow-up duration was not less than 2 months and was calculated as the date of CMR examination to the occurrence of an MACE or the last follow-up without an MACE. Of the 105 patients remaining after the application of the exclusion criteria, 9 were excluded due to being lost to follow-up (>2 months).

The 96 patients included in this study were divided into 2 cohorts, training and validation, in a ratio of 8:2 via simple randomization to construct and validate models, respectively. Thus, 76 patients (44 males and 32 females; mean age  $37.12 \pm 14.18$  years) were enrolled in the training cohort, including 61 non-MACE patients and 15 MACE patients; meanwhile, 20 patients (14 males and 6 females; mean age  $38.20 \pm 16.68$  years) were enrolled in the validation

cohort, including 14 non-MACE patients and 6 MACE patients. The patients' demographic characteristics and clinical data were collected from their electronic medical records. Medical treatments were performed by medical professionals according to the relevant clinical guidelines (18,19). The details of the CMR protocol and CMR image analysis are presented in [Appendix 1](#).

### Image segmentation

Segmentation was performed on serial short-axis slices at end diastole by 2 investigators with more than 3 years of CMR experience in consensus. A region of interest (ROI) of the LV myocardium (including trabeculations and excluding papillary muscles) was manually segmented using the pencil tool in ITK-SNAP software (<http://www.itksnap.org>).

Papillary muscles were treated as trabeculation when they were indistinguishable from trabeculation.

To evaluate the interobserver reproducibility of the radiomics features, 2 radiologists (readers 1 and 2) with at least 3 years of cardiology experience who were blinded to the patients' information independently performed the segmentations. To assess the intraobserver reproducibility of the radiomics features, reader 1 performed a second segmentation 1 month later.

### *Radiomics feature extraction*

Image normalization was implemented to eliminate the differences between cine CMR image signals, with a normalized scale of 100. Precropping was performed to reduce the memory footprint, and the bin size was 20. The details of the related parameters and features can be viewed online (<https://pyradiomics.readthedocs.io/en/latest/index.html>). Three-dimensional (3D) radiomics analysis was chosen, as it provides more comprehensive information than does the 2-dimensional (2D) approach. The radiomics features calculated from 8 to 12 short-axis cine images for each patient were introduced together. Following this, 105 quantitative radiomics features were extracted from each volume of interest (VOI) using Pyradiomics (version 3.0.1; <https://pyradiomics.readthedocs.io>) and SimpleITK (version 2.0.0; <https://simpleitk.org>). The detailed features are provided in [Table S2](#). The reproducibility of the extracted radiomics features was based on VOI delineation in interobserver and intraobserver comparisons. In addition, we compared the radiomic features of the 2 different magnetic resonance scanners.

### *Data analysis strategy*

The class imbalance of training samples (non-MACE:MACE ratio: 61:15) would have affected the processing effect of machine learning algorithms. To resolve this issue, we first balanced the MACE data in the training cohort by using oversampled algorithms to synthesize new MACE samples based on interpolation. The non-MACE and MACE samples were then balanced to a ratio of approximately 61:61 in the generated dataset, which served as the final training cohort. Finally, feature analysis and machine learning modeling were implemented in the training cohort, and their diagnostic performance was evaluated in the validation cohort. A radiomics model and clinical model with the top 12 importance-ranked

radiomics or clinical features were developed. We also built a combined radiomics-clinical combined model by integrating valuable radiomics features and clinical features. The performance of the prediction models was compared.

### *Feature analysis, modeling, and validation*

We compared 5 oversampling algorithms: the synthetic minority oversampling technique (SMOTE), adaptive synthetic (ADASYN) algorithm, borderline SMOTE, KMeans SMOTE, and support vector machine (SVM) SMOTE. We then used the extreme gradient boosting (XGBoost) algorithm to repeatedly build models and assess the importance of each feature. Previous studies have shown that each feature needs at least 10 samples that can yield reasonably stable estimates (11,20,21). To determine the optimal sample:feature ratio, we implemented 5 different sample:feature ratios (1, 5, 10, 20, 30, and 40) and compared their results. To identify the best-fitting method, the 5 most commonly used methods in the radiomics studies were adopted: logistic regression, decision tree, random forest, XGBoost, and SVM algorithms. Through these experiments, the optimal machine learning pipeline was determined.

Finally, we built the machine learning pipeline by using Python Jupyter Lab (version 3.0.14; <https://jupyter.org>) for further analysis. Based on the selected radiomics features, clinical features, and their combinations, the radiomics model, clinical model, and combined model were built using 4-fold cross-validation in the training cohort and evaluated in the validation cohort. The receiver operating characteristic (ROC) curves of the 3 models were plotted, and the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, accuracy, precision and F1 score of each were calculated. The point with the largest Youden index (equal to sensitivity + specificity - 1), was defined as the optimal cutoff on each ROC curve. The reported values of sensitivity and specificity were those at the best cutoff point.

### *Statistical analysis*

Statistical analyses were conducted in R (version 3.5.1; <https://www.r-project.org>) with RStudio (version 1.0.136, <https://www.rstudio.com>). The machine learning algorithms were implemented using Python (version 3.6.6, <https://www.python.org>). The Kolmogorov-Smirnov test was used to assess the normality of the distributions of the variables. Normally distributed continuous variables are presented as

the mean  $\pm$  standard deviation, and nonnormally distributed continuous variables are presented as the median with interquartile range (IQR). Categorical variables are presented as frequency (percentage). Student *t*-, Mann-Whitney, and the chi-squared tests were conducted, as appropriate. The intraclass correlation coefficient (ICC) was calculated to evaluate feature repeatability. ICC values were categorized as poor (ICC <0.40), fair (ICC =0.40–0.59), good (ICC =0.60–0.74), and excellent (ICC =0.75–1.0). Pearson correlation coefficient (*r*) was calculated between clinical variables and radiomics variables and was evaluated as follows:  $|r| \leq 0.2$ , no correlation;  $0.2 < |r| \leq 0.4$ , weak correlation;  $0.4 < |r| \leq 0.6$ , moderate correlation;  $0.6 < |r| \leq 0.8$ , strong correlation; and  $0.8 < |r| \leq 1.0$ , excellent correlation. The AUC was categorized as follows: AUC =0.5, no discrimination;  $0.5 \leq \text{AUC} < 0.7$ , poor discrimination;  $0.7 \leq \text{AUC} < 0.8$ , acceptable discrimination;  $0.8 \leq \text{AUC} < 0.9$ , excellent discrimination; and  $\text{AUC} \geq 0.9$ , outstanding discrimination. The DeLong test was used to assess the difference between ROC curves.  $P < 0.05$  indicated statistical significance.

## Results

### Patient characteristics

The median time to an MACE was 30.6 (IQR, 11.7–51.3) months. MACEs occurred in 21 (21.88%) patients, including 11 (11.46%) cases of HF, 6 (6.25%) of VAs, and 4 (4.17%) of all-cause death (Table S1). The incidence of MACEs was not significantly different between the training and validation cohorts (training:  $n=15$ , 19.7%; validation:  $n=6$ , 30.0%;  $P=0.494$ ). The baseline patient characteristics and CMR findings in the 2 cohorts are shown in Tables 1,2, respectively.

### The machine learning pipeline

Figure 2 shows the performance of the various machine learning models (mean AUC) when different oversampling methods were used in the training and validation cohorts. The diagnostic performance was mostly improved via the oversampling technique. The ADASYN algorithm showed the best performance, and ADASYN + SVM modeling had the highest AUC in both the training (AUC =0.97) and validation cohorts (AUC =0.87).

Figure 3 shows the performance of the mean AUC for various machine learning models when different

sample:feature ratios were used in the training and validation cohorts. The predictive performance was best when the sample:feature ratio was 10, which is consistent with findings from previous research (11).

Therefore, the final machine learning pipeline included ADASYN imbalanced processing, XGBoost feature selection with a sample:feature ratio of 10, and SVM modeling. The algorithm details are provided in Table S3.

### Feature analysis

The 12 most important radiomics features and 12 most important clinical features were selected for further modeling (Figure 4A,4B). Among all 12 radiomics features, first-order features ( $n=3$ ), shape-based features ( $n=3$ ), and gray-level size-zone matrix (GLSZM) features ( $n=3$ ) had greater importance. Among all clinical variables, the top 5 most important factors were as follows: age, left ventricular mass index (LVMI), body mass index (BMI), maximal noncompacted to compacted (NC:C) ratio, and presence of LV late gadolinium enhancement (LGE).

Figure 4C,4D display the correlations between the selected clinical factors and radiomics features in the training and validation cohorts. In the training cohort, LVMI showed strong correlations with GLSZM gray-level nonuniformity ( $r=0.73$ ), shape maximum 2D diameter row ( $r=0.79$ ), neighboring gray-tone difference matrix (NGTDM) coarseness ( $r=-0.62$ ), and gray-level co-occurrence matrix inverse difference normalized (GLCM Idn) ( $r=0.6$ ). Left ventricular ejection fraction (LVEF) had a strong correlation with the shape maximum of the 2D diameter row ( $r=-0.77$ ), and left ventricular end diastolic volume (LVEDV) showed an excellent correlation with the shape of the maximum 2D diameter row ( $r=0.85$ ). In the validation cohort, LVMI had an excellent correlation with GLSZM gray-level nonuniformity ( $r=0.9$ ) and NGTDM coarseness ( $r=-0.83$ ), and a strong correlation with the shape maximum of the 2D diameter row ( $r=0.7$ ) and GLCM Idn ( $r=0.6$ ). LVEF had strong correlation with the shape of maximum 2D diameter row ( $r=-0.79$ ) and NGTDM coarseness ( $r=0.61$ ). LVEDV showed excellent correlation with the shape of the maximum 2D diameter row ( $r=0.88$ ).

The intraobserver (ICC: 0.934–1.000) and interobserver (ICC: 0.917–0.999) reproducibility for the 12 most important radiomics features was excellent (Table S4). In addition, significant differences in several radiomics features were found between different magnetic resonance scanners (all  $P$  values <0.05) (Table S5).

**Table 1** Baseline characteristics in the training and validation cohorts

Characteristics	Training cohort (n=76)			Validation cohort (n=20)		
	Non-MACE (n=61)	MACE (n=15)	P	Non-MACE (n=14)	MACE (n=6)	P
Age (years)	34.00 (27.00, 46.00)	46.00 (29.00, 55.00)	0.083	34.50 (29.25, 40.00)	48.00 (20.75, 69.25)	0.141
Sex			0.564			1.000
Female	27 (44.3)	5 (33.3)		4 (28.6)	2 (33.3)	
Male	34 (55.7)	10 (66.7)		10 (71.4)	4 (66.7)	
Family history of cardiomyopathy	2 (3.3)	0 (0.0)	1.000	0 (0.0)	1 (16.7)	0.300
Hypertension	3 (4.9)	2 (13.3)	0.254	2 (14.3)	3 (50.0)	0.131
Dyslipidemia	2 (3.3)	0 (0.0)	1.000	1 (7.1)	1 (16.7)	0.521
Diabetes mellitus	3 (4.9)	0 (0.0)	1.000	1 (7.1)	2 (33.3)	0.202
Smoking	13 (21.3)	5 (33.3)	0.521	4 (28.6)	2 (33.3)	1.000
BMI (kg/m <sup>2</sup> )	23.19 (20.15, 26.33)	22.03 (20.03, 26.45)	0.749	22.70 (19.85, 25.63)	20.23 (18.76, 23.00)	0.269
Symptoms on admission						
Baseline NYHA functional class			0.002			0.034
I	45 (73.8)	6 (40.0)		12 (85.7)	2 (33.3)	
II	6 (9.8)	1 (6.7)		0 (0.0)	1 (16.7)	
III	8 (13.1)	3 (20.0)		0 (0.0)	2 (33.3)	
IV	2 (3.3)	5 (33.3)		2 (14.3)	1 (16.7)	
Stroke or systemic embolization	1 (1.6)	1 (6.7)	0.358	1 (7.1)	0 (0.0)	1.000
Arrhythmias	10 (16.4)	4 (26.7)	0.584	0 (0.0)	2 (33.3)	0.079
Cardiomyopathy phenotype						
Dilated phenotype	16 (26.2)	5 (33.3)	0.819	7 (50.0)	3 (50.0)	1.000
Hypertrophic phenotype	1 (1.6)	3 (20.0)	0.023	0 (0.0)	1 (16.7)	0.300
Restrictive phenotype	1 (1.6)	0 (0.0)	1.000	0 (0.0)	0 (0.0)	NA
Arrhythmogenic phenotype	0 (0.0)	1 (6.7)	0.197	0 (0.0)	0 (0.0)	NA
Co-existing RVNC	8 (13.1)	3 (20.0)	0.788	1 (7.1)	1 (16.7)	0.521
Medical therapy						
Beta-blocker	19 (31.1)	5 (33.3)	1.000	3 (21.4)	3 (50.0)	0.303
Angiotensin-converting enzyme inhibitor	5 (8.2)	0 (0.0)	0.576	0 (0.0)	1 (16.7)	0.300
Angiotensin receptor blockers	10 (16.4)	2 (13.3)	1.000	4 (28.6)	1 (16.7)	1.000
Diuretics	16 (26.2)	6 (40.0)	0.462	4 (28.6)	4 (66.7)	0.161
Ivabradine	2 (3.3)	1 (6.7)	0.488	1 (7.1)	0 (0.0)	1.000
Calcium antagonists	0 (0.0)	0 (0.0)	NA	0 (0.0)	1 (16.7)	0.300
Statins	2 (3.3)	0 (0.0)	1.000	1 (7.1)	1 (16.7)	0.521
Amiodarone	3 (4.9)	2 (13.3)	0.254	0 (0.0)	0 (0.0)	NA
Class 1C antiarrhythmic	1 (1.6)	0 (0.0)	1.000	0 (0.0)	0 (0.0)	NA
Oral anticoagulant therapy	3 (4.9)	3 (20.0)	0.160	0 (0.0)	0 (0.0)	NA

Data are presented as the median with interquartile range and n (%). MACE, major adverse cardiovascular event; BMI, body mass index; NYHA, New York Heart Association; NA, not applicable; RVNC, right ventricular noncompaction.

**Table 2** CMR findings in the training and validation cohorts

CMR variable	Training cohort (n=76)			Validation cohort (n=20)		
	Non-MACE (n=61)	MACE (n=15)	P	Non-MACE (n=14)	MACE (n=6)	P
LVEF (%)	47.36 (21.84, 57.59)	22.10 (16.80, 34.60)	0.010	44.36 (27.97, 55.07)	13.01 (10.48, 17.01)	0.001
LVEDV (mL)	176.87 (125.20, 279.53)	313.00 (182.90, 390.60)	0.016	199.71 (155.80, 283.37)	313.81 (258.80, 424.90)	0.016
LVESV (mL)	89.50 (59.86, 200.77)	273.60 (116.10, 299.30)	0.011	115.90 (68.44, 221.16)	272.71 (216.33, 381.40)	0.003
LVSV (mL/m <sup>2</sup> )	68.80 (58.50, 89.80)	59.20 (40.60, 77.50)	0.251	78.57 (67.46, 96.96)	42.35 (39.52, 48.82)	0.002
LVMI (g/m <sup>2</sup> )	52.98 (41.08, 70.47)	76.09 (68.99, 105.36)	0.001	62.34 (47.65, 74.09)	102.62 (62.13, 136.01)	0.013
Maximal NC:C ratio (%)	3.55 (2.77, 4.79)	4.57 (2.73, 6.69)	0.273	3.25 (2.77, 3.75)	4.67 (3.20, 6.21)	0.141
Number of noncompacted segments	9.00 (5.00, 12.00)	11.00 (7.00, 13.00)	0.614	9.50 (6.00, 11.00)	12.00 (9.00, 15.00)	0.205
RV abnormalities (low EF, dilation)	28 (45.9)	12 (80.0)	0.018	5 (35.7)	3 (50.0)	0.642
LGE	18 (29.5)	12 (80.0)	<0.001	5 (35.7)	4 (66.7)	0.336

Data are presented as the median with interquartile range and n (%). CMR, cardiac magnetic resonance; MACE, major adverse cardiovascular event; LVEF, left ventricular ejection fraction; LVEDV, left ventricular end diastolic volume; LVESV, left ventricular end systolic volume; LVSV, left ventricular stroke volume; LVMI, left ventricular mass index; NC:C, noncompacted to compacted ratio; RV, right ventricular; EF, ejection fraction; LGE, late gadolinium enhancement.

### **Radiomics, clinical, and combined radiomics-clinical feature models**

Based on the top 12 most important radiomics features, clinical features, and their combinations, the radiomics model, clinical model, and combined model were constructed via 4-fold cross-validation in the training cohort and validated in the validation cohort (Figure 5). Details of the machine learning pipeline and its parameters are shown in Table S3. The detailed diagnostic performances of the radiomics, clinical, and combined models are shown in Table 3.

The radiomics model yielded an AUC of 0.97 (sensitivity 100.00%, specificity 70.49%) in the training cohort and an AUC of 0.87 (sensitivity 83.33%, specificity 64.29%) in the validation cohort. For the clinical model, the AUC was 0.97 (sensitivity 100.00%, specificity 91.80%) in the training cohort and 0.65 (sensitivity 16.67%, specificity 78.57%) in the validation cohort. The combined model achieved an AUC of 0.99 (sensitivity 93.33%, specificity 93.44%) in the training cohort and an AUC of 0.92 (sensitivity 33.33%, specificity 100.00%) in the validation cohort.

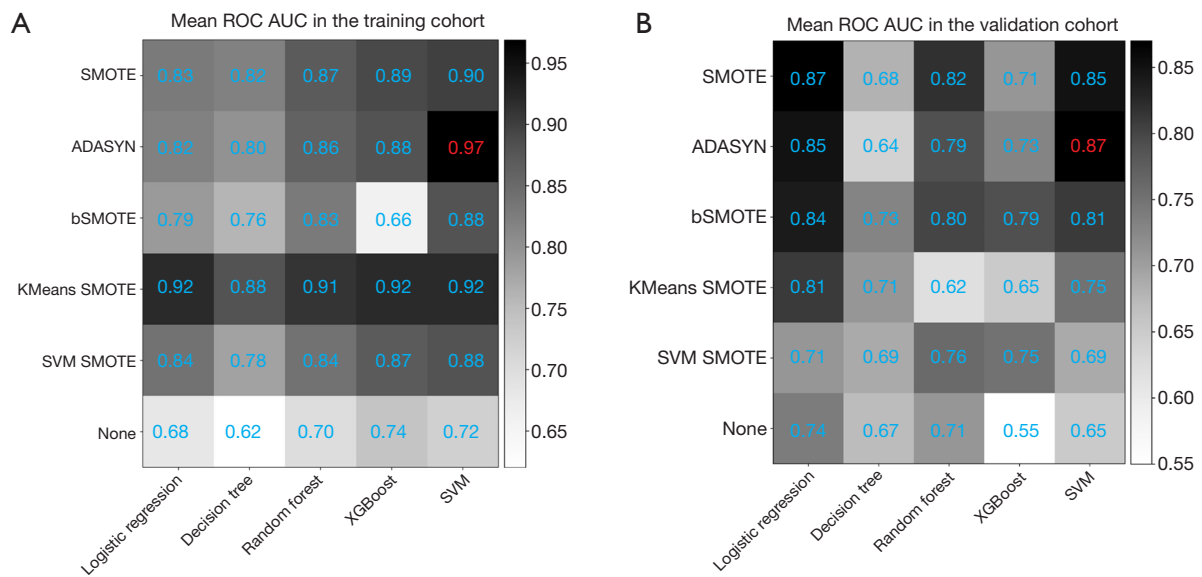
The combined radiomics-clinical feature model showed the best performance, with the highest predictive accuracy. There was no significant difference in the performance of the radiomics model and the clinical model or the combined model (P=0.124 and P=0.621, respectively).

The performance (AUC) of the combined model was significantly better than that of the clinical model (P=0.003).

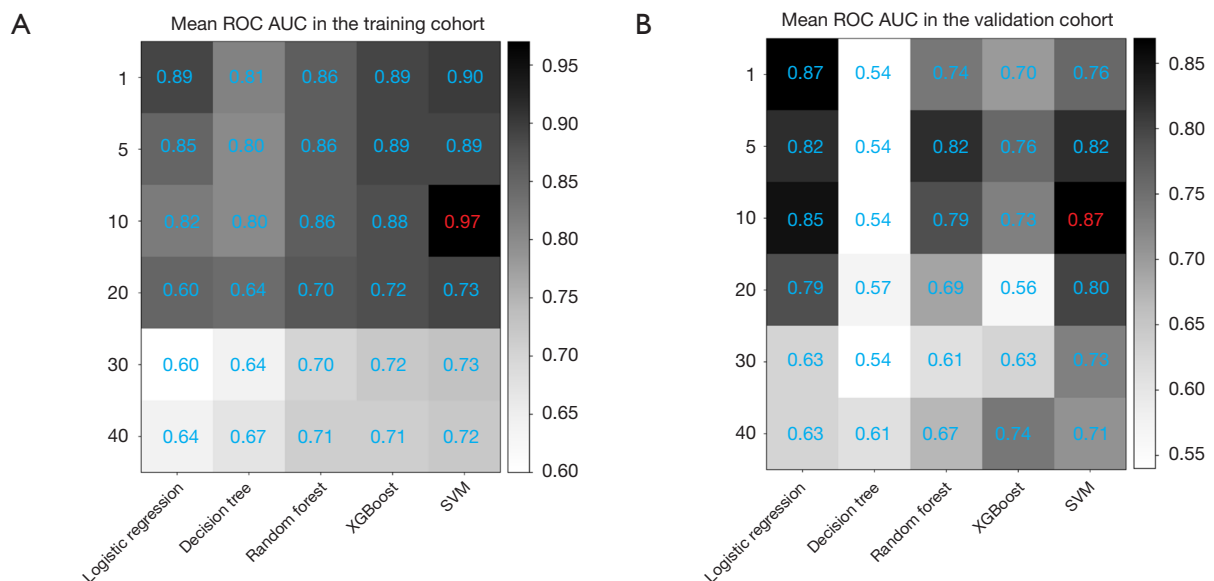
### **Discussion**

In this study, we assessed cine CMR-derived radiomics features and clinical risk factors using XGBoost and SVM algorithms in predicting MACEs in patients with LVNC. Our results showed the following: (I) radiomics analysis is feasible on cine CMR images, and the machine learning radiomics model performed considerably well in MACE prediction for patients with LVNC; (II) the combined radiomics-clinical feature model, integrating the radiomics features and clinical variables, showed a more competitive discrimination performance than did the clinical model. The combined model may facilitate personalized risk stratification and improve treatment decision-making for patients with LVNC.

Patients with LVNC experience different disease courses: many patients have a good prognosis, but some patients have an unfavorable prognosis. Therefore, identifying patients at risk for MACEs may be useful for guiding the frequency of clinical follow-up as well as the timing of interventions. Several studies (3,22-24) have explored predictors of poor outcomes, such as LVEF, presence

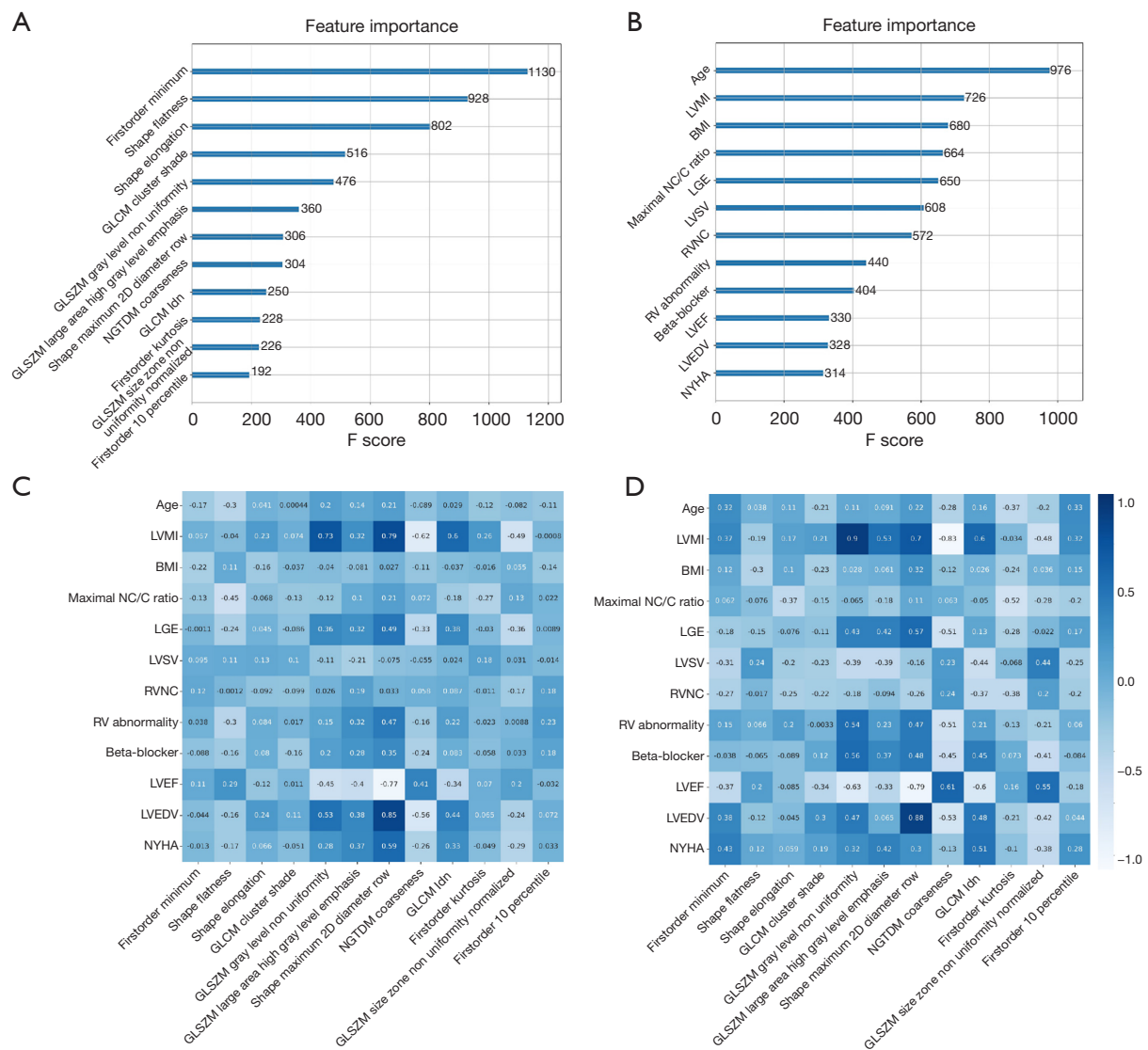


**Figure 2** Comparison of the performance of various machine learning models with different oversampling methods. (A) Comparison of the performance of various machine learning models with different oversampling methods in the training cohort. (B) Comparison of the performance of various machine learning models with different oversampling methods in the validation cohort. “None” refers to the baseline model. ROC, receiver operator characteristic; AUC, area under the receiver operating characteristic curve; SMOTE, synthetic minority oversampling technique; ADASYN, adaptive synthetic; bSMOTE, borderline synthetic minority oversampling technique; SVM, support vector machine; XGBoost, extreme gradient boosting.



**Figure 3** Comparison of the performance of various machine learning models with different sample:feature ratios. (A) Comparison of the performance of various machine learning models with different sample:feature ratios in the training cohort. (B) Comparison of the performance of various machine learning models with different sample:feature ratios in the validation cohort. ROC, receiver operator characteristic; AUC, area under the receiver operating characteristic curve; XGBoost, extreme gradient boosting; SVM, support vector machine.

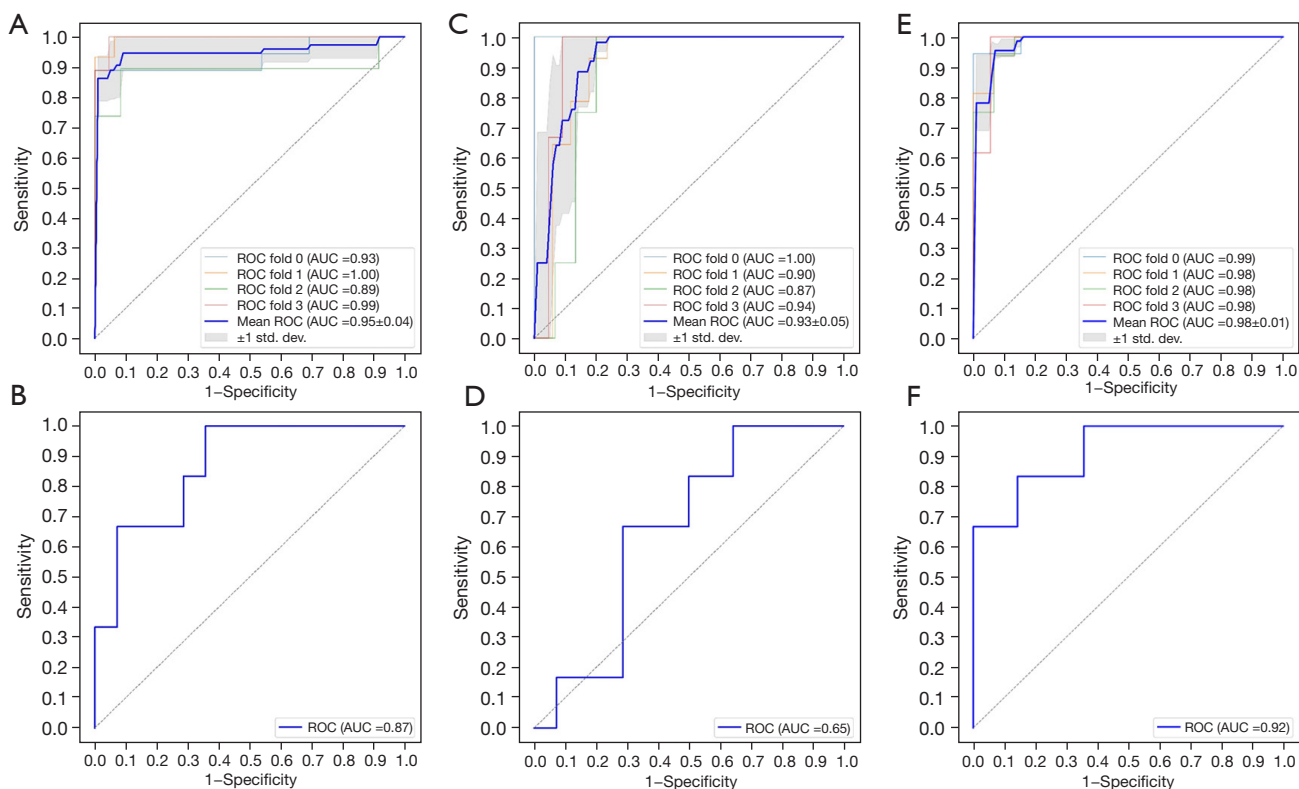




**Figure 4** The importance and correlation heatmaps of radiomics features and clinical characteristics. The 12 top-ranked important (A) radiomics and (B) clinical characteristics. (C,D) Correlation heatmap between selected radiomics features and clinical factors in the training and validation cohorts. GLCM, gray-level co-occurrence matrix; GLSZM, gray-level size-zone matrix; NGTDM, neighborhood gray-tone difference matrix; GLCM ldn, gray-level co-occurrence matrix inverse difference normalized; LVMI, left ventricular mass index; BMI, body mass index; NC/C, noncompacted to compacted ratio; LGE, late gadolinium enhancement; LVSV, left ventricular stroke volume; RVNC, right ventricular noncompaction; LVEF, left ventricular ejection fraction; LVEDV, left ventricular end diastolic volume; NYHA, New York Heart Association.

of LGE, LV end-diastolic dimension, LV posterior wall compaction, decreased strains, and HF at diagnosis, and reports on prognostic factors and a poor outcome of LVNC are numerous, but their indicators are varied and not entirely consistent. There is thus a need to establish models to predict poor outcomes in patients with LVNC, given the heterogeneities of their various risk factors.

Casas *et al.* (25) designed a risk score model using Cox regression based on variables [including age, sex, cardiovascular risk factors, abnormal electrocardiography signs, LVEF, and noncompaction cardiomyopathy (LVEF <50% and/or family aggregation)] associated with MACEs to improve the risk stratification of patients with LVNC, which showed good discrimination between score tertiles.



**Figure 5** ROC curves of the different models. (A,B) ROC curves of the radiomics model in the training and validation cohorts. (C,D) ROC curves of the clinical model in the training and validation cohorts. (E,F) ROC curves of the combined model in the training and validation cohorts. ROC, receiver operator characteristic; AUC, area under the receiver operating characteristic curve.

**Table 3** Model performance for predicting MACEs

Models	AUC	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	F1 score
<b>Radiomics model</b>						
Training	0.97	100.00	70.49	76.32	45.45	0.63
Validation	0.87	83.33	64.29	70.00	50.00	0.63
<b>Clinical model</b>						
Training	0.97	100.00	91.80	93.42	75.00	0.86
Validation	0.65	16.67	78.57	60.00	25.00	0.20
<b>Combined model</b>						
Training	0.99	93.33	93.44	93.42	77.78	0.85
Validation	0.92	33.33	100.00	80.00	100.0	0.50

MACE, major adverse cardiovascular event; AUC, area under the receiver operating characteristic curve.

In our study, using a machine learning pipeline, we found that conventional cardiac structure and function parameters (LVMI, LGE, LVSV, RV abnormality, LVEF, and LVEDV), myocardial morphology assessed with CMR (maximal

NC:C ratio, and right ventricular noncompaction), and clinical characteristics (age, BMI, beta-blocker usage, and baseline New York Heart Association functional class) constituted important values in the classification process.

However, the clinical model showed poor discriminative performance. This indicates that clinical factors alone are insufficiently predictive and that additional effective tools are needed to predict MACEs in patients with LVNC.

Radiomics has shown potential as a noninvasive and quantitative tool in diagnosis and prognosis via the extraction of effective imaging features (26-28). Izquierdo *et al.* (29) demonstrated the value of machine learning-based CMR radiomics in the differential diagnosis of LVNC, hypertrophic cardiomyopathy, and dilated cardiomyopathy. Our study further explored the ability of radiomics to risk-stratify patients with LVNC, and our results showed that the radiomics model using nonenhanced cine CMR images had good discriminative capacity comparable to that of the clinical model. Since CMR is becoming more commonly used for the clinical assessment of LVNC and cine imaging is a routine sequence in clinical practice (30), supplemental radiomics analyses could be easily implemented. In this study, although adding radiomics features improved the sensitivity of clinical factors alone to some extent, the sensitivity of both the clinical and combined models was low. This may be due to the low sensitivity of the clinical model itself. However, the combined model had high specificity and accuracy, demonstrating the potential of the model to predict MACEs. In addition, consistent with some radiomics studies (31,32), we found a strong correlation between the selected radiomics features extracted from cine CMR images and the conventional CMR-derived indicator, suggesting the biological interpretability of radiomics features. We also observed several differences in the radiomics features between different magnetic resonance scanners, which was consistent with Lee *et al.*'s study (33). Further studies are warranted to reduce or avoid this difference to minimize its impact on quantitative analyses.

In our study, the final machine learning pipeline was ADASYN processing, XGBoost feature selection, and SVM modeling. The SMOTE algorithm and SMOTE-based extensions are mature data-imbalance processing algorithms (34) that show good performance in biomedical data analysis (35-37). ADASYN can generate balanced samples depending on the estimate of the local distribution of the class, so it is suitable for generating harder-to-learn examples. In addition, SMOTE, bSMOTE, and KMeans SMOTE also demonstrated good performance, which can provide a reference for other imbalanced biomedical data processing. A recent study (38) reported that machine learning mining results using the SMOTE method were

largely consistent with the baseline patterns or trends, and synthetic data generated using machine learning have shown advantages in clinical modeling (39). XGBoost is a novel tree-based algorithm for sparse data processing that provides the gradient-boosted decision tree, which is widely recognized in data mining challenges and tasks (40,41). Some studies (42,43) have indicated that XGBoost performs better than do deep learning methods in tabular data analysis. The optimal sample:feature ratio is 10, which may be a universal conclusion in radiomics research. Our results also showed that the predictive performance was best and most robust under different conditions when the sample:feature ratio was 10. When the ratio approaches 1, almost all features are incorporated into machine learning modeling without selection. Most irrelevant and redundant features will hinder the learning effect as noise. When the ratio is very large, this is equivalent to only a few features being selected for modeling and may lack sufficiently useful information. Our study also tested multiple modeling approaches, and the comparisons of these modeling methods showed that SVM, which maximizes the separating margin (44,45), was the most powerful classifier with high accuracy and robustness.

Our results further indicated that the combined model, which integrated radiomics features and clinical risk factors, achieved a better prediction of MACEs than did the clinical model alone. These findings suggest that the combination of quantitative cine CMR image-based radiomics features with clinical characteristics can maximize the predictive performance for MACEs. This clinical parameter plus radiomics and machine learning pipeline may aid clinicians in deciding upon the appropriate management and early intervention for patients with LVNC. These results also indicate that radiomics yielded valuable information that provided complementary prognostic value in LVNC beyond routine clinical data. This may be because radiomics analyses obtained more information than that obtained with radiologists' conventional imaging interpretation. Larger studies are needed to verify the complementary values of the radiomics features in identifying patients with LVNC at high risk of MACEs. In addition, although the sensitivity was improved via the addition of radiomics features to clinical factors, it was still relatively low. However, the combined model yielded an outstanding AUC and specificity, while the radiomics model had good sensitivity but low specificity. The tradeoff between predictive models depends on the weight of the sensitivity or specificity in different clinical or research scenarios.

### Limitations

A few limitations to this study should be mentioned. First, we employed a single-center design, which might have introduced patient selection biases. Second, the small number of patients (especially those who experienced MACEs) is a limitation of the evaluation. Although we used data oversampling for data preprocessing, our results still need to be verified in a larger-sample study. Third, the types of CMR techniques and devices were limited in this single-center study. Evaluation of the different techniques and devices used across a number of centers can provide a more comprehensive understanding of the stability and heterogeneity of the radiomics features. Multicenter and multiscanner studies are needed to validate and generalize the performance of the proposed predictive models. Fourth, although the radiomics model and combined model performed well at predicting MACEs in this study, our future research is aimed at constructing predictive models for different adverse events in patients with LVNC for achieving a more effective prediction, thus allowing for individualized prevention and precise treatment.

### Conclusions

Machine learning-based radiomics of cine CMR images provided a useful quantitative prognostic tool for predicting MACEs in patients with LVNC. Integrating radiomics features with clinical risk factors of these patients can achieve a more accurate and individualized prediction of poor prognostic outcomes, which may assist in their management and surveillance.

### Acknowledgments

*Funding:* This work was supported by the 1-3-5 Project for Disciplines of Excellence, West China Hospital, Sichuan University (Nos. ZYGD18013 and ZYYC21004); and the Sichuan Science and Technology Program (No. 2020YJ0229).

### Footnote

*Conflicts of Interest:* All authors have completed the ICMJE uniform disclosure form (available at <https://qims.amegroups.com/article/view/10.21037/qims-23-372/coif>). The authors have no conflicts of interest to declare.

*Ethical Statement:* The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013) and was approved by the Biomedical Research Ethics Committee of the West China Hospital of Sichuan University (No. 2022-1190). Individual consent for this retrospective analysis was waived.

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**Cite this article as:** Han PL, Jiang ZK, Gu R, Huang S, Jiang Y, Yang ZG, Li K. Prognostic prediction of left ventricular myocardial noncompaction using machine learning and cardiac magnetic resonance radiomics. *Quant Imaging Med Surg* 2023;13(10):6468-6481. doi: 10.21037/qims-23-372