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Diffusion-Weighted Imaging–Based Radiomics Features and Machine Learning Method to Predict the 90-Day Prognosis in Patients With Acute Ischemic Stroke

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Objectives: The evaluation of the prognosis of patients with acute ischemic stroke (AIS) is of great significance in clinical practice. We aim to evaluate the feasibility and effectiveness of diffusion-weighted imaging (DWI) image-based radiomics features and machine learning methods in predicting 90-day prognosis among patients with AIS.

Patients and Methods: We enrolled a total of 171 patients with AIS in this study, including 134 patients with a good prognosis and 37 patients with a poor prognosis, and collected the patients' clinical and DWI image data. Radiomics features from manually sketched ischemic lesions were extracted using the Pyradiomics package of Python, and the best radiomics features were selected by a *t* test and the least absolute shrinkage and selection operator. The radiomics model and clinical model were constructed using support vector machine and logistic regression, respectively, and the predictive performance of each model was evaluated.

Results: We selected 9 features from a total of 851 radiomics features to build the final radiomics model. For predicting the poor prognosis of patients with AIS, the area under the curves, accuracy, sensitivity and specificity of the clinical model, radiomics model in the training set and radiomics model in the testing set were 0.865, 0.930 and 0.906, 81.3%, 92.0% and 90.0%, 81.1%, 76.0% and 75.0%, and 81.3%, 97.0% and 95.0%, respectively.

Conclusions: DWI image-based radiomics features and machine learning methods can accurately predict the 90-day prognosis of patients with AIS, and the radiomics model is superior to the clinical model in predicting prognosis.

Key Words: acute ischemic stroke, diffusion-weighted imaging, radiomics, machine learning, prognosis

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The authors declare no conflict of interest.

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Stroke is one of the top causes of disability and death worldwide.[1] Acute ischemic stroke (AIS) is the main type of stroke and accounts for 60% to 80% of all strokes.[2] According to the blood supply site, AIS occurs most frequently in the blood supply area of the middle cerebral artery, which is closely related to the main functional outcome. The rehabilitation of patients with AIS is a long-term process, adding to society's significantly higher health costs. The assessment of prognosis is conducive to selecting patients who may benefit from treatment, formulating individualized treatment plans, and optimizing management modes, which is one of the key research topics of patients with AIS.

Neuroimaging is crucial for the diagnosis and severity assessment of AIS. Clinicians can evaluate the prognosis of patients with AIS according to the characteristics of neuroimaging, but this is usually a visual evaluation method based on the gross anatomic structure, such as the infarction location, lesion volume, and space occupied, which is subjective and often qualitative, and cannot quantitatively obtain the microenvironmental information in the lesions that is reflected on the image. Medical image analysis technology can overcome the limitations of traditional evaluation methods and transform a subjective visual interpretation into an image data-driven objective evaluation.

Radiomics is a promising medical image analysis technology that can extract a large number of quantitative features from biomedical images in an objective, reproducible, and high-throughput way,[3] and these features can reveal the potential pathologic and physiological characteristics of the tissue. These features are selected and then trained into machine learning models for different evaluations and predictions.[3,4] As of now, radiomics is mainly used in the field of tumor research and has attained a research graduate through its application in analyzing tumor grades,[5] diagnosis and treatment,[6] survival prediction,[7] etc. Recently, researchers have applied radiomics to stroke research and found that the radiomics features of computed tomography (CT) or magnetic resonance imaging (MRI) can be used to judge the existence of early lesions in AIS,[8] determine AIS onset time,[9] and predict hemorrhagic transformation after infarction.[10] Diffusion-weighted imaging (DWI) is a common MRI sequence in the diagnosis of AIS and can show the infarct core in the hyperacute phase. Previous studies have indicated that DWI features can predict the prognosis of AIS. One study showed that DWI lesion patterns may help to identify possible differences in early endpoints after ischemic stroke,[11] and another study showed that low relative DWI signal intensity was well

correlated with a good prognosis after intravascular thrombectomy in patients with AIS.[12] However, it is rare to evaluate the prognosis of AIS based on the radiomics features of DWI.

The evaluation of the prognosis of patients with AIS is of great significance for the formulation of individualized treatment in clinical practice. The main purpose of this study is to investigate the feasibility and effectiveness of DWI image-based radiomics features and machine learning methods in predicting the 90-day prognosis among patients with AIS.

PATIENTS AND METHODS

Patients

The ethics committee of the authors' hospital approved this study, and the necessity for informed consent was waived in exchange for confirmation of patient data confidentiality by the ethics committee. Patients with AIS were retrospectively enrolled from The Second Affiliated Hospital of Guangxi Medical University from January 2021 to January 2023. We considered the following criteria for inclusion: (1) acute neurological deficit syndrome and new infarction on DWI, (2) the infarct site was the blood supply area of the unilateral middle cerebral artery, and (3) completed brain magnetic resonance (MR) examination within 3 days of the onset of symptoms. The exclusion criteria included the following: (1) the infarct diameter was ≤ 1 cm or the infarct focus on MRI was only a single plane, (2) there were posterior circulation infarctions, anterior cerebral artery infarctions or bilateral cerebral hemispheric infarctions at the same time, (3) there was cerebral infarction complicated with hemorrhage transformation, (4) there was a history of brain trauma, surgery, tumor, or radiotherapy, and (5) the clinical or imaging data were incomplete or had poor image quality. A complete flowchart of the patient selection process is illustrated in Figure 1.

We used the demographic and clinical data of patients, including sex, age, smoking, alcoholism, hypertension, diabetes, coronary heart disease, previous stroke, hospital complications (including pneumonia, deep venous thrombosis, gastrointestinal bleeding), low-density lipoprotein cholesterol, creatinine, glycosylated hemoglobin, National Institute of Health Stroke Scale (NIHSS) score on admission, modified Rankin score (mRS) before onset, and 90d-mRS; a poor prognosis was defined as a 90d-mRS > 2, and a good prognosis was defined as a 90d-mRS ≤ 2.[13] The visual image evaluation indexes included the white matter hyperintensity (WMH) Fazekas score,[14] cerebral small vessel disease (CSVD) load score[15] [susceptibility-weighted imaging was not a routine scan sequence for ischemic stroke; hence, CSVD load only counted WMH, lacunae and perivascular spaces, with 1 point for each of the following: (1) ≥ 1 lacunae, (2) in Fazekas score, deep WMH score ≥ 2 and/or paraventricular WMH score 3, and (3) moderate and severe perivascular space (grade: 2 to 4) in basal ganglia], and DWI Alberta Stroke Program Early Computed Tomography Score (DWI-ASPECTS).[16]

All patients received the standardized diagnosis and treatment process in the department of neurology. The treatment included antithrombotic therapy (patients with large artery atherosclerosis and small artery occlusion were administered antiplatelet aggregation therapy, whereas those with cardiogenic embolism were administered anticoagulation therapy), improving circulation, nourishing the nerves, protecting the brain, regulating lipids, and regulating the patient's blood pressure and blood sugar. Twenty-two patients received intravenous thrombolysis, whereas 5 patients received emergency interventional therapy.

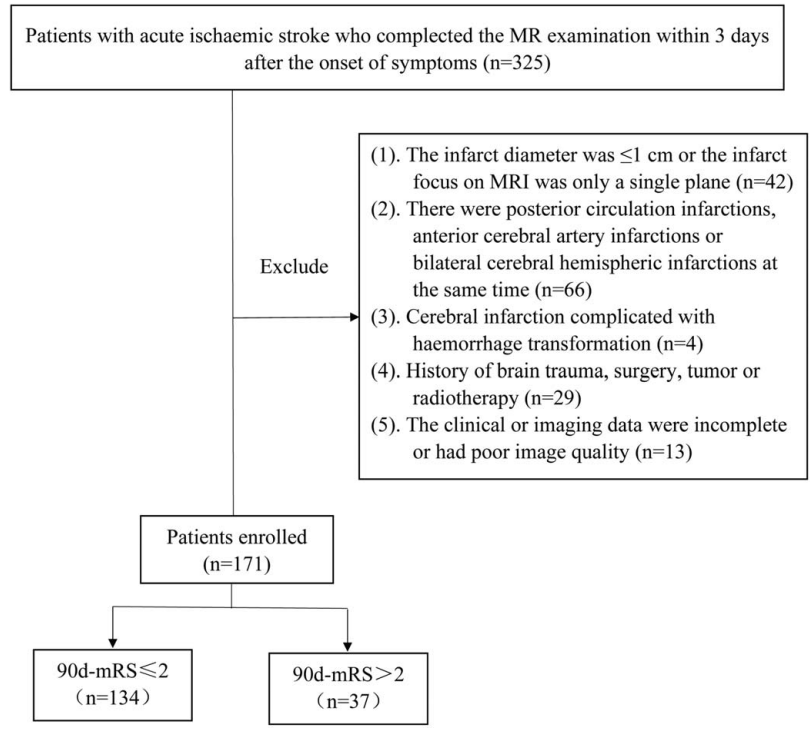

FIGURE 1. Flowchart of the patient selection process for this retrospective study. MR indicates magnetic resonance; MRI, magnetic resonance imaging; mRS, modified Rankin score.

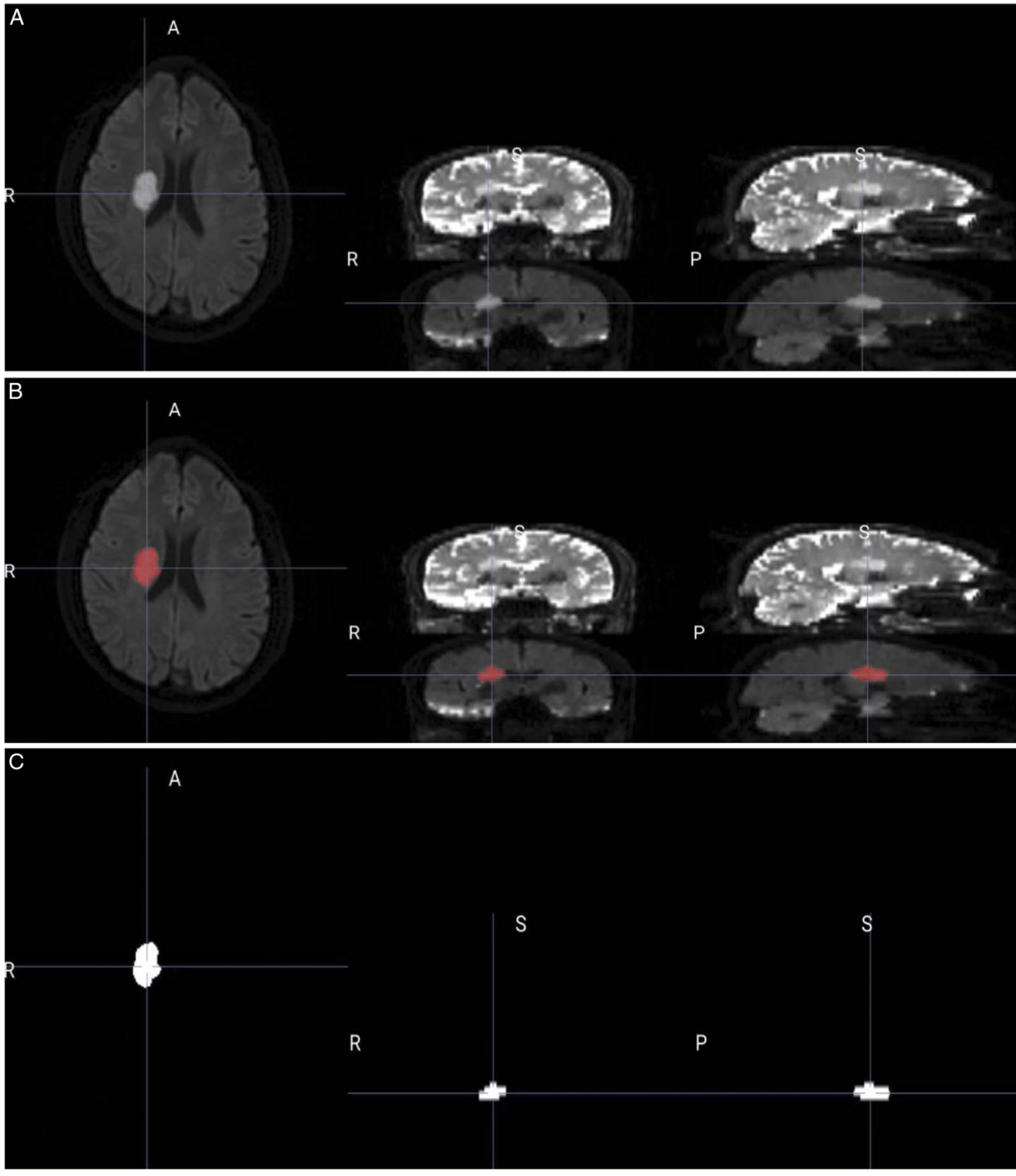

FIGURE 2. Lesion segmentation with MRIcroGL software. (A) A high signal lesion in the right coronal region on DWI images. (B) An ROI obtained by segmenting the high signal lesion on DWI images is shown in the red areas. (C) Obtained the ROI. DWI indicates diffusion-weighted imaging; ROI, region of interest.

Radiomic Analysis

Image Acquisition

All patients underwent a brain MR examination with 3.0 T GE Medical Systems MR scanning equipment [SIGNA Pioneer 3.0 T and (III class) DISCOVERY MR 750]. The imaging sequence included T1-fluid-attenuated inversion recovery(FLAIR), T2PROPELLER, T2-FLAIR, and DWI. The scanning parameters of the DWI sequences were as follows: slice thickness = 4 mm, slice spacing = 5 mm, imaging frequency = 127.76 MHz, pixel bandwidth = 1953.12, flip angle = 90 degrees, field of view = 240×240 mm, b = 0 and 1000 s/mm^2. SIGNA Pioneer 3.0 T: repetition time/echo time = 5986 ms/76.3 ms and acquisition matrix = 128×128. (III class) Discovery MR

TABLE 1. Distribution of Clinical Characteristics in Training Set and Testing Set, Good Prognosis Group and Poor Prognosis Group

Characteristics	Training set (n = 119)	Testing set (n = 52)	*P*	90d-mRS ≤2 (n = 134)	90d-mRS >2 (n = 37)	*P*
90d-mRS ≤2, n (%)	94 (79.0)	40 (76.9)	0.763	—	—	—
Sex (M), n (%)	87 (73.1)	33 (63.5)	0.205	90 (67.2)	30 (81.1)	0.101
Age (y)	61.96 ± 13.16	63.25 ± 10.68	0.534	61.44 ± 12.33	65.65 ± 12.46	0.068
Risk factors, n (%)						
Hypertension	89 (74.8)	39 (75.0)	0.977	101 (75.4)	27 (73.0)	0.766
Diabetes	25 (21.0)	12 (23.1)	0.763	30 (22.4)	7 (18.9)	0.65
Coronary heart disease	7 (5.9)	1 (1.9)	0.259	7 (5.2)	1 (2.7)	0.52
Smoking	40 (33.6)	20 (38.5)	0.541	43 (32.1)	17 (45.9)	0.118
Alcoholism	32 (26.9)	9 (17.3)	0.177	31 (23.1)	10 (27.0)	0.623
Previous stroke, n (%)	29 (24.4)	11 (21.2)	0.648	26 (19.4)	14 (37.8)	0.019*
Hospital complications, n (%)	22 (18.5)	11 (21.2)	0.684	17 (12.7)	16 (43.2)	< 0.001*
LDL-C (mmol/L)	3.00 ± 0.91	2.95 ± 0.97	0.764	3.02 ± 0.92	2.85 ± 0.94	0.317
Creatinine (mmol/L), median (IQR)	80 (69; 93)	81 (70; 90)	0.736	80 (69; 92)	83 (72; 90)	0.934
Glycosylated hemoglobin, median (IQR)	6.0 (5.6; 6.4)	6.1 (5.8; 6.5)	0.153	5.9 (5.6; 6.4)	6.1 (5.6; 6.6)	0.375
Fazekas score, median (IQR)	1 (1.0; 2.0)	1 (1.0; 2.0)	0.488	1 (1.0; 2.0)	1 (0.5; 2.0)	0.503
CSVD load score, median (IQR)	0 (0.0; 1.0)	0 (0.0; 1.0)	0.892	0 (0.0; 1.0)	0 (0.0; 1.0)	0.168
DWI-ASPECTS, median (IQR)	8 (7.0; 9.0)	8 (5.0; 9.0)	0.223	9 (7.0; 9.0)	6 (3.5; 7.0)	< 0.001*
Admission NIHSS score, median (IQR)	4 (2.0; 8.0)	4 (2.0; 7.0)	0.609	4 (2.0; 6.0)	10 (4.0; 12.5)	< 0.001*
mRS before onset, median (IQR)	0 (0.0; 0.0)	0 (0.0; 0.0)	0.396	0 (0.0; 0.0)	0 (0.0; 0.5)	0.019*
Intravenous thrombolysis	16 (13.4)	6 (11.5)	0.732	16 (11.9)	6 (16.2)	0.492
Mechanical thrombectomy	2 (1.7)	3 (5.8)	0.144	3 (2.2)	2 (5.4)	0.312

P value < 0.05 is considered statistically significant.
*$P < 0.05$.
CSVD indicates cerebral small vessel disease; DWI-ASPECTS, diffusion-weighted imaging-Alberta Stroke Program Early Computed Tomography Score; IQR, interquartile range; LDL-C, low-density lipoprotein cholesterol; mRS modified Rankin score; NIHSS, National Institute of Health Stroke Scale.

750T: repetition time/echo time = 4831 ms/65.8 ms and acquisition matrix = 160×160. The DWI imaging data in the DICOM format were copied from the imaging system for the radiomics analysis.

Region of Interest Segmentation

The DWI images were converted from a DICOM format into a NIFTI format using the SimpleITK package (version 2.1.1) of Python and then imported into MRIcroGL software for manual image segmentation. The region of interest (ROI) was manually delineated layer by layer at the edge of high signal lesions on DWI images (Fig. 2). Two physicians (one with 8 and another with 10 y of working experience) sketched the ROI of each patient and then compared the 2 ROIs of the same patient. If the 2 physicians agree that the 2 ROIs are basically the same, the ROI sketched by physician 1 will be used as the patient's ROI. If the 2 physicians evaluate that there is a certain difference between the two ROIs, each physician will sketch it 3 more times, and then evaluate in pairs, and take the ROI sketched by physician 1 in the closest ROI pair that the 2 physicians agree with as the patient's ROI.

Radiomics Feature Extraction

The Pyradiomics package (version 3.0.1) of Python was used for radiomics feature extraction. The radiomics features included the shape features and first, second, and high-order statistical measures.[3] The texture features included the gray level cooccurrence matrix, gray level dependent matrix, gray level size zone matrix, gray level run length matrix, and neighborhood gray-tone difference matrix.[17] The radiomic features are described in detail on the website (http://pyradiomics.readthedocs.io).

Feature Selection

To reduce the redundancy between radiomic features and improve the computational efficiency of machine learning models, feature selection is necessary. All the patients were randomly divided into a training set and a testing set at a ratio of 7:3.[18] In the training set, a *t* test was carried out first for feature selection, and then the least absolute shrinkage and selection operator (LASSO) was used for feature dimensionality reduction.[19] During the process of feature dimensionality reduction by LASSO, cross-validation was used to determine the optimized adjustment parameter λ,[19] and then the optimized λ was used in the LASSO equation to select the best radiomics features.

Model Building and Testing

The best radiomics features were incorporated into the support vector machine (SVM) for modeling. The SVM used the radial basis function (RBF) kernel, which was the representative and widely applied kernel function.[20] Two

TABLE 2. Multivariate Logistic Regression Analysis of Poor Prognosis in Patients With AIS (n = 171)

Characteristics	*P*	OR (95% CI)
Previous stroke	0.390	1.608 (0.545-4.747)
Hospital complications	0.488	1.467 (0.496-4.343)
DWI-ASPECTS	0.005*	0.748 (0.611-0.916)
Admission NIHSS score	0.002*	1.213 (1.074-1.371)
mRS before onset	0.052	1.966 (0.993-3.894)

AIS indicates acute ischemic stroke; DWI-ASPECTS, diffusion-weighted imaging-Alberta Stroke Program Early Computed Tomography Score; mRS, modified Rankin score; NIHSS, National Institute of Health Stroke Scale; OR, odds ratio.
*$P < 0.05$.

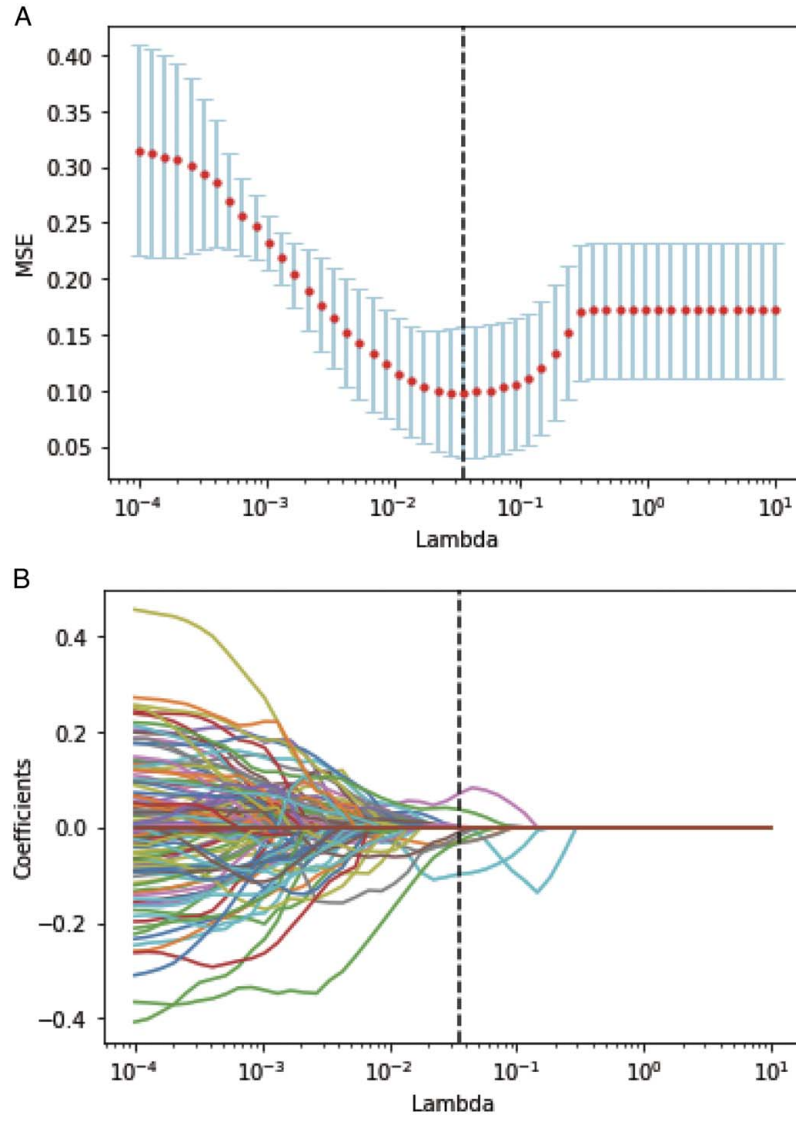

FIGURE 3. Using the LASSO model to select the best radiomics features (A) Selection of the adjustment parameter λ in the LASSO model. (B) The curve of the radiomics features coefficients changes with the λ value. LASSO indicates least absolute shrinkage and selection operator.

parameters γ and C of RBF were optimized by the GridSearchCV function, and the optimized parameters γ = 0.0625 and C = 0.5 were substituted into RBF for SVM modeling. The radiomics model developed with the data of the training set was tested on the testing set. Finally, the stability of the model was assessed by a 2-round, 5-fold cross-validation.

Statistical Analysis

IBM SPSS Statistics software (version 28.0) was used for statistical analyses, and a P value <0.05 ($P < 0.05$) was considered statistically significant. Univariate logistic regression analysis was applied to compare the differences in clinical characteristics between different groups, including the training set versus the testing set and the good prognosis group versus the poor prognosis group. Multicollinearity diagnosis was performed to explore the existence of multiple collinearities of the variables with statistical significance between the good prognosis group and the poor prognosis group. Binary logistic regression analysis was performed, and a clinical model was constructed. Receiver operating characteristic curves were used to evaluate the predictive performance of the radiomics model and the clinical model and calculate the area under the curve (AUC), accuracy, specificity, and sensitivity of each model.

RESULTS

Patient Characteristics

The clinical characteristics of the different groups are summarized in Table 1. Statistically, there was no significant difference found in the clinical characteristics between the training set and testing set ($P > 0.05$). Univariate logistic regression analysis between the good prognosis group and poor prognosis group showed that history of stroke, hospitalization complications, DWI-ASPECTS, admission

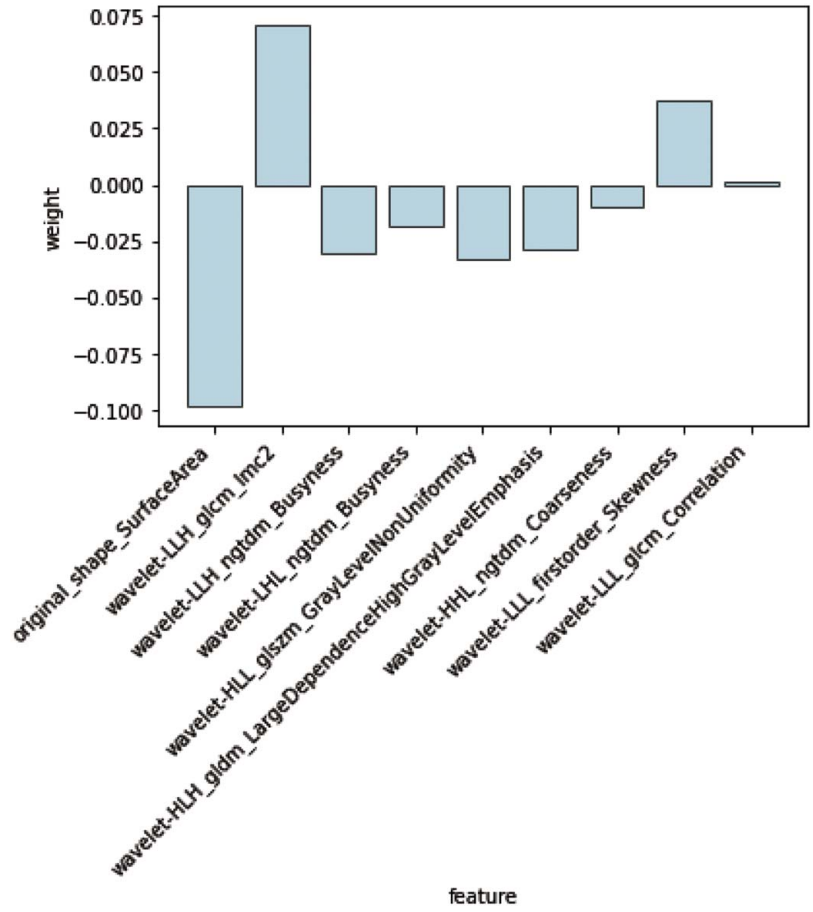

FIGURE 4. The weight map of the best radiomics features.

NIHSS score, and mRS before onset were correlated with a poor prognosis ($P < 0.05$), and the multicollinearity diagnosis results showed that the variance inflation factor and tolerance were 1.278 to 1.550 and 0.645 to 0.783, respectively, which showed no obvious collinearity. Multivariate logistic regression analysis showed that DWI-ASPECTS (odds ratio = 0.748, 95% CI: 0.611-0.916) and admission NIHSS score (odds ratio = 1.213, 95% CI: 1.074-1.371) were significantly correlated with a poor prognosis in patients with AIS ($P < 0.05$; Table 2).

Assessment of the Radiomics Features

We extracted a total of 851 radiomics features from each DWI image, and 485 features were selected using a *t* test. After feature dimensionality reduction by LASSO, 9 features were selected that were strongly correlated with a poor prognosis in AIS. These 9 features included (1) original_shape_SurfaceArea, (2) wavelet-LLL_firstorder_Skewness, (3) wavelet-LLH_glcm_Imc2, (4) wavelet-LLL_glcm_Correlation, (5) wavelet-HLH_gldm_LargeDependenceHighGrayLevelEmphasis, (6) wavelet-LLH_ngtdm_Busyness, (7) wavelet-LHL_ngtdm_Busyness, (8) wavelet-HHL_ngtdm_Coarseness, and (9) wavelet-HLL_glszm_GrayLevelNonUniformity. In the process of feature dimensionality reduction by LASSO, a λ (lambda) value with the minimum cross-verification error (MSE) was the optimal value of this model (Fig. 3). The weight map of the best radiomics features is shown in Figure 4.

Model Performance Evaluation

The results of the 2-round, 5-fold cross-validation showed that the 95% CI of the accuracy of the radiomics model was 0.847 to 0.917, indicating good stability of the radiomics model. The receiver operating characteristic curves of each model are shown in Figures 5 and 6. In terms of predicting the poor prognosis of patients with AIS, the AUCs, accuracy, sensitivity and specificity of the clinical model, radiomics model in the training set and radiomics model in the testing set were 0.865, 0.930 and 0.906, 81.3%, 92.0% and 90.0%, 81.1%, 76.0% and 75.0%, and 81.3%, 97.0% and 95.0%, respectively Table 3. These results indicated that the radiomics model possessed good predictive performance, and its efficiency was better than that of the clinical model.

DISCUSSION

This study used DWI images to extract radiomics features and developed a radiomics model for predicting the outcome of patients with AIS using the machine learning method. The radiomics model could accurately predict the 90-day prognosis of patients with AIS, and it was better at predicting a poor prognosis than the clinical model constructed using clinical features, indicating that the radiomics features of DWI images are stronger predictors of poor prognosis in AIS.

In this study, the clinical model was constructed based on the common clinical factors that affect the prognosis of

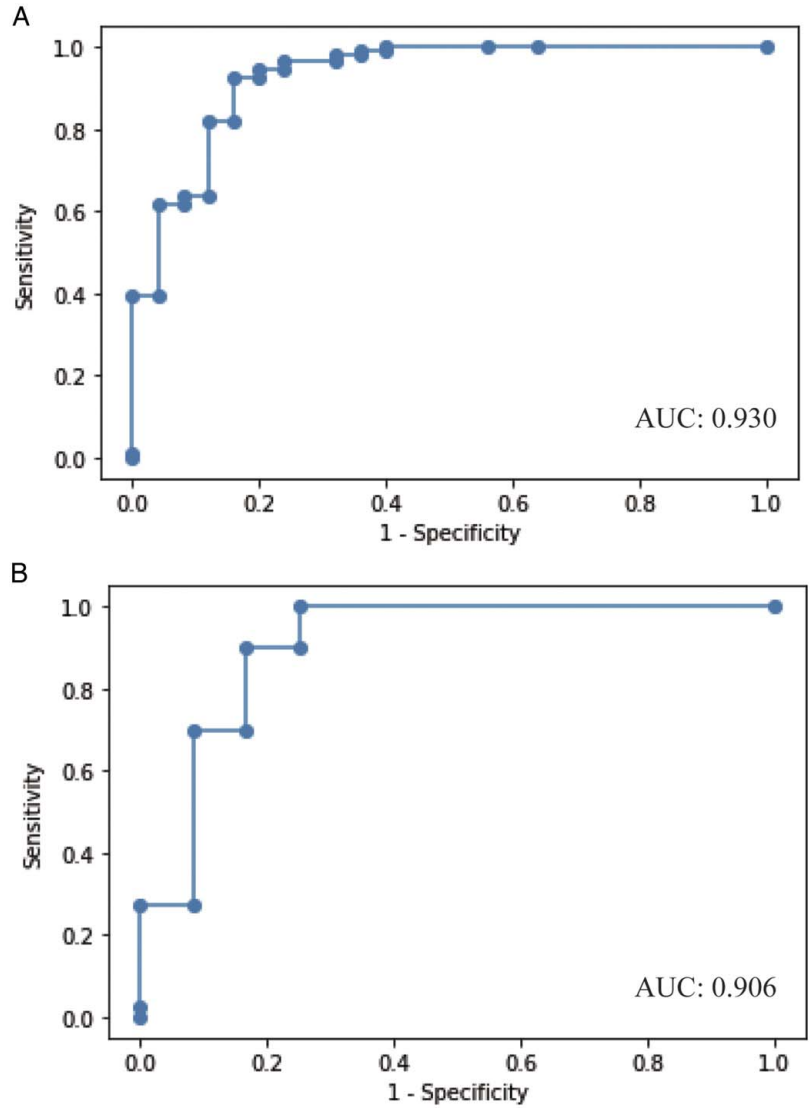

FIGURE 5. ROC curves and AUC values for the radiomics model [(A) training set; (B) testing set]. AUC indicates area under the curve; ROC, receiver operating characteristic.

patients with AIS through traditional statistical methods, which is relatively simple. There is a certain causal relationship between clinical factors and prognosis, but the evaluation of clinical factors is often subjective. While the radiomics features are objective, reproducible, and high-throughput. Machine learning can construct statistical models from massive data sets and continuously improve its own performance by acquiring new knowledge and reorganizing existing knowledge structures, which have artificial intelligence.

Radiomics features can reveal the subtle pathophysiological features and heterogeneity of lesions. One shape feature and 8 high-order statistical measures were most associated with the poor prognosis of patients with AIS in this study. According to previous studies, a large infarct volume contributes to the poor prognosis of patients with AIS,[21] but the shape feature that was selected in this study was the infarct surface area. One possible explanation is that with a larger infarct surface area when the infarct volume is equal, there is a greater impact on the connection between neurons or brain regions. It is possible to obtain texture features either from the original image or from the transformed image (such as the wavelet transform and Gaussian transform), which reflect the spatial distribution of voxel gray levels and could be used to measure lesion heterogeneity. However, there is some degree of uncertainty regarding which texture features reflect specific pathophysiological changes, for example, the best texture features to reflect the degree of edema.

Recently, machine learning has been gradually applied to medicine, where radiomics combined with machine learning has been the research focus, hoping that large amounts of medical imaging data will improve medical practice after computer learning and processing. Machine learning includes supervised learning and unsupervised learning. Common supervised machine learning models include random forest, SVM, Naïve Bayes, etc. Different types of machine learning algorithms have different

TABLE 3. The AUCs, Accuracy, Sensitivity, and Specificity of the Radiomics Model (Including the Training Set and the Testing Set) and Clinical Model

	Radiomics model		
Model	**Training set**	**Testing set**	**Clinical model**
AUC	0.930	0.906	0.865
Accuracy (%)	92.0	90.0	81.3
Sensitivity (%)	76.0	75.0	81.1
Specificity (%)	97.0	95.0	81.3

AUC indicates area under the curve.

characteristics. In the research of disease prediction, the SVM algorithm is used most frequently, and it has high accuracy, second only to random forest. SVM, first proposed by Vapnik and Lerner[22] in 1963, is a powerful and effective machine learning classifier. SVM can construct a hyperplane and provide the best separation boundary so that it can predict tags from one or more feature vectors.[23] This study used the powerful function of SVM to maximally distinguish between good and poor clinical outcomes, and it showed high accuracy in both the training set and testing set.

This study showed that DWI image-based radiomics features were strong predictors of poor prognosis in AIS. Similarly, other studies found that radiomics feature analyses based on CT, T2-FLAIR, apparent diffusion coefficient (ADC), etc, can also evaluate the prognosis of patients with AIS. Based on the CT-ASPECTS and the radiomics features of unenhanced CT and CT angiography, Wen et al[24] constructed a model to predict malignant middle cerebral artery infarction, and their study results showed that the model had good predictive performance in both the training set and verification set, with AUCs of 0.917 and 0.913, respectively. Wang et al[25] explored the feasibility of texture analysis based on T2-FLAIR and ADC images in the assessment of the severity and functional outcome of stroke, and their study results showed that texture features could be a biomarker in predicting the severity of a stroke, but not a functional outcome. A possible reason why it was insufficient to predict the functional outcome of ischemic stroke was that they recruited patients with ischemic stroke in the subacute stage when the pathophysiological changes tended to be stable. Compared with the study by Wang and colleagues, this study included patients with AIS within 3 days of the onset of symptoms and used DWI images for radiomics analysis, and it was found that the radiomics model could accurately predict the 90-day prognosis of patients with AIS.

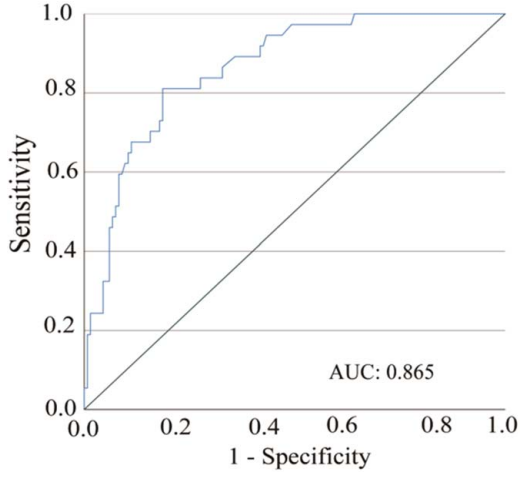

FIGURE 6. ROC curves and AUC values for the clinical model. AUC indicates area under the curve; ROC, receiver operating characteristic.

Many clinical factors play a part in determining the prognosis of patients with AIS, including the admission NIHSS score,[26] hospitalization complications, past stroke history, etc, and visual imaging performance also reflects the prognosis of AIS, such as the infarction location, DWI-ASPECTS,[27] and CSVD.[28] According to this study, the admission NIHSS score and the DWI-ASPECTS were independently associated with poor prognosis in patients with AIS, indicating that the more damage to brain tissue and the greater the degree of dysfunction after onset, the poorer the prognosis for patients. Recently, many studies have shown that CSVD has a certain impact on the prognosis of patients with AIS,[28,29] especially WHM and the total load of CSVD.[30,31] However, this study did not find that either of them had any significant impact on the prognosis of patients with AIS, which may be because most patients in this study did not have severe CSVD; perhaps when CSVD reaches a certain degree of severity, it can influence the prognosis of patients with AIS. Regarding whether adding clinical factors to the radiomics model can further improve the prediction efficiency, the results of the current studies were not the same. Quan et al[32] demonstrated that a comprehensive model combining the radiomics features of FLAIR and ADC with clinical and conventional image features can further enhance prediction accuracy. Conversely, Kassner et al[10] found that a comprehensive model combining texture features from enhanced MR images and conventional visual image assessments did not improve the overall prediction performance. The differences in these findings may be related to the fact that they chose different machine-learning models for modeling.

This study is limited by the fact that it is retrospective and the patient sample is relatively small. Second, in this study, the ROI was manually sketched and proofread by 2 physicians, which took a lot of time and was subjective. In this regard, using semiautomatic or fully automatic sketching has certain advantages. Third, there was an imbalance in our data set, which may be related to the low severity of most of the patients admitted to our center. In the future, we need to combine multicenter data and expand the sample size for further research and verification.

CONCLUSION

DWI image-based radiomics features and machine learning methods can accurately predict the 90-day prognosis of patients with AIS, and the radiomics model is superior to the clinical model in predicting prognosis, providing a basis for individualized treatment for patients with AIS.

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