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*Retrospective Study*

**Preoperative prediction of perineural invasion of rectal cancer based on an magnetic resonance imaging radiomics model: a dual-center study**

Radiomics for predicting perineural invasion in rectal cancer

Yan Liu, Bai-Jin-Tao Sun, Chuan Zhang, Bing Li, Xiao-Xuan Yu, Yong Du

**Abstract**

BACKGROUND

Perineural invasion (PNI) has been used as an important pathological indicator and independent prognostic factor for patients with rectal cancer(RC), preoperative prediction of PNI status is helpful for individualized treatment of RC. Recently, several radiomics studies have been used to predict the PNI status in RC, demonstrating a good predictive effect, but the results lacked generalizability. The preoperative prediction of PNI status is still challenging and needs further study.

AIM

To establish and validate an optimal radiomics model for predicting PNI status preoperatively in RC patients.

METHODS

This retrospective study enrolled 244 postoperative patients with pathologically confirmed RC from two independent centers. The patients underwent preoperative high-resolution MRI between May 2019 and August 2022. Quantitative radiomics

features were extracted and selected from oblique axial T2-weighted imaging (T2WI) and contrast-enhanced T1WI (T1CE) sequences. The radiomics signatures were built using logistic regression analysis and the predictive potential of various sequences was compared (T2WI, T1CE, and T2WI+T1CE fusion sequences). A clinical-radiomics (CR) model was established by combining the radiomics features and clinical risk factors. The internal and external validation groups were used to validate the proposed models. The area under the receiver operating characteristic (ROC) curves (AUCs), DeLong test, net reclassification improvement (NRI), integrated discrimination improvement (IDI), calibration curve, and decision curve analysis (DCA) were used to evaluate the model performance.

RESULTS

Among the radiomics models, the T2WI+T1CE fusion sequences model showed the best predictive performance, in the training and internal validation groups, the AUCs of the fusion sequence model were 0.839 (95%CI: 0.757–0.921) and 0.787 (95%CI: 0.650–0.923), which were higher than those of the T2WI and T1CE sequence models. Among all models, the CR model built by combining clinical risk factors had the best prediction performance, in the training and internal and external validation groups, the AUCs of the CR model were 0.889 (95%CI: 0.824–0.954), 0.889 (95%CI: 0.803–0.976) and 0.894 (95%CI: 0.814–0.974). Delong test, NRI, and IDI showed that the CR model had statistically significant differences from other models (P < 0.05). Moreover, calibration curves demonstrated good agreement, and DCA revealed significant benefits of the CR model.

CONCLUSION

The CR model based on preoperative MRI radiomics features and clinical risk factors can preoperatively predict the PNI status of RC non-invasively, which facilitates individualized treatment of RC patients.

**Key Words:** Rectal cancer; Perineural invasion; Magnetic resonance imaging; Radiomics; Nomogram

**Core Tip:** This study constructed radiomics prediction models, clinical prediction model and clinical-radiomics model(CR model) based on preoperative magnetic resonance imaging images of rectal cancer(RC), as well as independent clinical risk factors, to predict the preoperative perineural invasion(PNI) status of RC patients. The reliability and repeatability of the established prediction models were analyzed using internal and external validation groups. The results showed the CR model had the best stable neutral performance in both the internal and external validation group. Therefore, the CR model was able to predict the PNI status of RC noninvasively before the surgery, thereby providing support for the individualized treatment of RC patients.

## INTRODUCTION

Rectal cancer (RC) is one of the most common gastrointestinal malignancies worldwide, and its incidence is increasing annually. Most patients with RC are diagnosed in the middle and late stages[1]. Perineural invasion (PNI), a potential pathway for the metastatic spread of RC, has been used as an important pathological indicator and independent prognostic factor for patients with RC since the 7th edition of the cancer staging system developed by the American Joint Commission on Cancer (AJCC)[2].

PNI refers to the invasion of nerves by tumor cells, followed by the spread of tumor cells along the nerve sheath. It is categorized as tumor cell invasion of endoneural, neurinal sheath, and epineural membrane layers, or tumor cells surrounding the nerve and wrapping more than 33% of the epineural membrane[3].

Multiple studies have shown that the PNI status is correlated with postoperative recurrence rates and poor prognosis of RC[4-8]. Preoperative stratification of RC patients according to the PNI status facilitates individualized treatment and improves the prognosis of RC patients. Studies have shown that neoadjuvant chemoradiotherapy (nCRT) can significantly reduce the incidence of PNI[9-12]. Preoperative assessment of PNI is helpful in decision-making regarding nCRT, especially in patients with stage II RC. Currently, the use of nCRT for stage II patients is controversial. Because stage II RC is a heterogeneous disease, distinct clinicopathological features may lead to different clinical outcomes and should be treated differently[13]. The latest European Society of Medical Oncology RC Guidelines indicate that PNI is a key factor in determining whether stage II patients will benefit from nCRT and postoperative adjuvant chemotherapy[14,15]. In addition, nCRT combined with total mesorectum excision is regarded as the standard treatment for locally advanced RC. Although the local recurrence rate is reduced to less than 10%, the distant metastasis rate is still more than 20–30%. Postoperative adjuvant chemotherapy is used to prevent distant metastasis, and the PNI status is an indicator of postoperative adjuvant chemotherapy[14-16]. However, nCRT can significantly reduce the incidence of PNI in patients with RC, promoting the downward phase of the tumor. Therefore, the postoperative pathological conditions do not fully reflect the patient's status[17]. The preoperative evaluation of PNI is helpful for guiding the use of postoperative adjuvant chemotherapy for patients with locally advanced RC.

Currently, the PNI status cannot be assessed based on conventional preoperative biopsy or magnetic resonance imaging (MRI), but can only be determined through postoperative pathological examination. Conventional preoperative biopsy only obtains the mucosal and submucosal layers, whereas peripheral nerves mostly exist outside the mucosal muscle layer or even outside the intestinal wall. Additionally, MRI cannot display very small nerves. The efficiency and timeliness of postoperative pathological testing limit the use of PNI[13].

Radiomics can extract quantitative features that reflect tumor heterogeneity, allowing the extraction of deep mining data from images and analyzing non-invasive clinical predictors to provide detailed information for personalized treatment and patient management[18]. This technique is widely used for auxiliary diagnosis, pathological staging, prediction of treatment outcomes, and prognostication. Currently, several radiomics studies have been used to predict the PNI status in RC, demonstrating a good predictive effect. However, most studies were based on CT or single sequences of MRI and were conducted at single centers without external validation. Therefore, the results lacked generalizability[13, 19-23].

This two-center study aims to construct a radiomics prediction model for the PNI status of RC based on T2WI and T1CE sequences of high-resolution MRI and to systematically compare the performance of different radiomics prediction models. The optimal radiomics prediction model combined with PNI-related clinical features was selected to construct the final clinical-radiomics model, which provided the basis for individualized management strategies for RC patients.

## MATERIALS AND METHODS

### Patients

This two-center retrospective study was approved by the Ethical Review Committee of the Affiliated Hospital of North Sichuan Medical College (AHNSMC, file number: 2022ER431-1), which waived the need for informed consent from participants.

The study inclusion criteria were as follows: (1) postoperative pathologically confirmed RC; (2) high-resolution contrast-enhanced MRI of rectum performed using 1.5 Tesla MRI within 1 week before the operation, and a complete TNM staging report was obtained; and (3) preoperative peripheral blood carcinoembryonic antigen (CEA) and carbohydrate antigen 19-9 (CA19-9) levels were detected within 1 week before the operation.

The exclusion criteria included: (1) nCRT and other antitumor treatments were administered preoperatively; (2) the postoperative pathological report did not record

the PNI status; and (3) poor image quality, which makes it difficult to segment the image of the lesion.

A total of 613 patients who underwent surgical resection of rectal RC were recruited between May 2019 and August 2022. Finally, 244 patients from two independent centers were enrolled in the present study. Among them, 170 consecutive patients from Center 1 (Affiliated Hospital of North Sichuan Medical College) were randomly divided into a training group (n = 118) and an internal validation group (n = 52) at a ratio of 7:3, whereas 74 consecutive patients from Center 2 (Second Clinical School of North Sichuan Medical College) served as an external validation group. The detailed workflow of our study is presented in Figure 1.

The preoperative information on clinical and radiological variables was collected retrospectively from our medical records and Picture Archiving and Communication System. The clinical variables included age, gender, CEA level (< 5 or ≥ 5 ng/mL), CA19-9 Level (< 30 or ≥ 30 U/mL), histopathological grade, and clinical M (cM) stage. The radiological variables included the distance between the tumor and anal margin (DIS), MRI T (mT) stage, MRI N (mN) stage, clinical TNM (cTNM) stage, MRI-based circumferential resection margin (mCRM), and MRI-based extramural vascular invasion (mEMVI). PNI status data were derived from postoperative pathological analysis of hematoxylin and eosin (H-E)-stained sections and immunohistochemical analysis of the resected specimens.

**MRI Scans**

All patients in Center 1 were scanned using Siemens Aera 1.5T MRI, and all patients in Center 2 were scanned using GE Sigma HDxt 1.5T MRI. The sequences included high-resolution oblique axial T2WI and axial T1CE. Contrast-enhanced scans (T1CE sequences) were obtained after intravenous administration of gadolinium contrast agent using an MRI-compatible power injector at a rate of 2 mL/s and a dose of 0.2 mL/kg, followed by flushing 20 mL of saline using a high-pressure syringe. The detailed sequence parameters are presented in Table 1.

**Imaging Analysis and Segmentation**

MR images were derived from the Picture Archiving and Communication System in the Digital Imaging and Communications in Medicine format. Two experienced radiologists, with 8 and 10 years of work experience, independently evaluated the MRI images while being blinded to the postoperative pathological findings. Discrepancies among the readers were resolved through discussion. The diagnostic methods were based on the 8th AJCC staging system[24].

In cases with unknown pathological findings, Reader 1 used the 3D slicer software (version 4.11.2; https://www.slicer.org) to manually delineate the lesion layer-by-layer on oblique axial T2WI and axial T1CE sequences, thereby obtaining the volume of interest (VOI) of the tumor. Subsequently, the 3D mask of the tumor was exported. One month after completing the image segmentation of all patients by Reader 1, 30 patients were randomly selected, for whom Readers 1 and 2 independently performed repeated segmentation of the lesion and output masks. Repeatability analysis was conducted within and between observers to evaluate the stability of subsequent radiomics features.

**Radiomics Feature Extraction and Selection**

The Radiomics package of the 3D-Slicer software (version 4.11.2; https://www.slicer.org) was used for original image preprocessing and radiomics feature extraction. To minimize the image extraction of radiomics features using different MRI models, the preprocessing of the original images included the following steps: (1) voxel spacing was standardized, and all images were resampled to a volume of $1 \times 1 \times 1$ mm; and (2) the image noise and normalized voxel intensity were controlled, and the voxel intensity values were discretized using a fixed bin width (25 HU)[25].

All VOIs were imported into the 3D-Slicer software (version 4.11.2; https://www.slicer.org) for feature extraction. In total, 944 radiomics features were extracted for each VOI. The image types of the extracted radiomics features included the following: (1) a total of 107 radiomics features were extracted from the original image after image preprocessing [including shape features, first-order statistical

features, gray-level co-occurrence matrix (GLCM) features, gray-level dependence matrix features, gray-level run length matrix (GLRLM) features, gray-level size zone matrix (GLSZM) features, and neighboring gray tone difference matrix features]; (2) a total of 93 radiomics features of images were extracted (including first-order statistical, GLCM, gray-level dependence matrix, GLRLM, GLSZM, and neighboring gray tone difference matrix) using the Laplace operator of the Gaussian filter and the image derived from the transformation of $1\sigma$ (0.5); and (3) a total of 744 radiomics features were extracted from eight image types derived from wavelet transformation (including first-order statistical features, GLCM features, gray-level dependence matrix features, GLRLM features, GLSZM features, and neighboring gray tone difference matrix features). The specific radiomics feature types extracted based on the abovementioned images are shown in Supplementary Table 1. For further details, please refer to http://pyradiomics.readthedocs.io/en/Latest/features.html#.

Based on the training group data, the radiomics features were reduced and screened. First, dimensionality reduction, Z-score standardization, and maximum-minimum normalization of radiomics eigenvalues were used to remove irrelevant and redundant features. Then, radiomics features were screened using the following three steps: (1) the radiomics features with inter- and intra-class correlation coefficients > 0.75 were screened to ensure their stability; (2) the radiomics features with statistical differences ($P < 0.05$) were screened using univariate logistic regression analysis; (3) the LASSO regression algorithm was used to adjust the penalty parameters using 10-fold cross-validation, and the regression coefficients of each radiomics feature were compressed, according to the principle of the simplest model. Then, radiomics features with non-zero coefficients were screened to establish the Rad-score.

**Model Construction and Evaluation**

Based on the training group data, univariate logistic regression analysis was carried out for all clinical and MRI factors. According to our results and clinical practice, relevant factors were selected to be included in the multi-factor logistic regression analysis. Then, we constructed a clinical prediction model and three

radiomics prediction models, namely T2WI, T1CE, and T2WI+T1CE fusion sequence. Finally, the best radiomics prediction model was selected and combined with selected clinical and MRI risk factors to construct a radiomics-clinical combined prediction model.

The abovementioned prediction models were tested in the internal and external validation groups to determine their differentiation, calibration, and clinical effectiveness. The area under the ROC curves (AUC), Delong test, NRI, and IDI were used to compare the differentiation of each prediction model. Calibration curves were used to evaluate the calibration degree of each prediction model, i.e., the consistency between the predicted and actual results. DCA was used to evaluate the efficacy of each prediction model. Finally, the optimal model was selected to construct a nomogram and an online interactive nomogram. The detailed research process is presented in Figure 2.

**Statistical Analyses**

The clinical and MRI factors were statistically analyzed using SPSS software (version 26.0). Categorical variables are expressed as percentages and analyzed using chi-square tests or Fisher's exact tests. Continuous variables with normal data distribution are expressed as mean ± standard deviation, whereas those with non-normal distribution are expressed as median (interquartile range). P < 0.05 (two-tailed) was considered statistically significant. R software (version 4.2.1, http://www.r-project.org) was used for feature screening, construction, and evaluation of the prediction model. Several R packages were used for data analysis, including caret, irr, car, MASS, glmnet, pROC, nricens, rms, DynNom, rsconnect, rmda, plot, and ggplot2.

**RESULTS**

**Patient Characteristics**

In this study, 244 patients were enrolled and categorized into the training group (n = 118), internal validation group (n = 52), and external validation group (n = 74). Table 2 summarizes the detailed clinical and radiological characteristics of the patients. There were no significant differences in the proportion of PNI-positive patients

between the training group and the two validation groups (32.1, 32.7, and 33.8%, respectively; P > 0.05). There were no statistical differences between the training, internal validation, and external validation datasets (P > 0.05). In contrast, the training group dataset demonstrated significant differences between PNI-positive and PNI-negative patients in terms of CA19-9 Level, mN, mCRM, mEMVI, and histological grade (P < 0.05). Furthermore, in the internal validation group dataset, there were statistically significant differences in the CEA and CA19-9 Levels between the PNI-positive and PNI-negative patients (P < 0.05). In the external validation group dataset, there were statistically significant differences in CEA, mN, and mEMVI between PNI-positive and PNI-negative patients (P < 0.05).

**Model Construction and Evaluation**

In this study, 12 features were ultimately retained from the three sequences: T2WI (n = 5), T1CE (n = 2), and T2WI+T1CE fusion sequence (n = 5). The detailed information regarding these features is presented in Figure 3 and Supplementary Table 2. The radiomics scores were calculated by multiplying the selected features with the corresponding coefficients for each modality as follows:

T2WI_Rad-score = 14.86872 + (0.03702 × original_glcm_Correlation) + (0.10289 × original_glcm_MCC) + (8.2082 × original_glszm_ZoneEntropy) + (9.15542 × wavelet-LLL_glcm_MCC) + (-3.61471 × wavelet-LLL_glrlm_GrayLevelNonUniformityNormalized)

T1CE_Rad-score = -26.133 + (2.919 × original_shape_Maximum$^2$DDiameterSlice) + (22.566 × original_gldm_DependenceEntropy)

(T2WI+T1CE)_Rad-score = -7.0772 + (-0.1798 × T2WI_original_glcm_MCC) + (0.7251 × T2WI_original_glszm_ZoneEntropy) + (7.5941 × T2WI_wavelet-LLL_glcm_MCC) + (-4.442 × T2WI_wavelet-LLL_glrlm_GrayLevelNonUniformityNormalized) + (2.3265 × T1CE_original_shape_Maximum$^2$DDiameterSlice)

Three radiomics prediction models were constructed based on the Rad-score using logistic regression. In the training group, the AUCs of the T2WI sequence radiomics

prediction model, T1CE sequence radiomics prediction model, and T2WI+T1CE fusion sequence radiomics prediction model were 0.817, 0.798, and 0.839, respectively, and these values were 0.763, 0.689, and 0.787 in the internal validation group, respectively, and 0.759, 0.841, and 0.836 in the external validation group, respectively. Detailed information regarding the prediction models is presented in Table 3 and Figure 4.

Univariate and multivariate logistic regression analyses of training group data demonstrated that cTNM (odds ratio [OR]: 42.002; 95% confidence interval [CI]: 2.913–605.511; P = 0.006) and histological grade (OR: 0.113; 95%CI: 0.020–0.658; P = 0.015) were independent risk factors for PNI in RC. Further details are presented in Table 4. The AUCs of the clinical prediction models for the training, internal validation, and external validation groups were 0.804, 0.828, and 0.813, respectively. Further details are presented in Table 3.

The Delong test for the training group data showed no significant differences among the three radiomics prediction models (P = 0.476). However, the NRI and IDI indices demonstrated that the T2WI+T1CE fusion sequence radiomics prediction model had significantly higher prediction ability compared to the T2WI and T1CE sequence radiomics prediction models (NRI index > 0, IDI index > 0, P < 0.05). The T2WI+T1CE fusion sequence radiomics prediction model was superior to the T2WI and T1CE sequence radiomics prediction models. Further details are presented in Table 5. Finally, the (T2WI+T1CE)_Rad-score and independent clinical risk factors (cTNM and histological grade) were selected to construct a combined clinical-radiomics (CR) prediction model through logistic regression. The combined CR model demonstrated AUCs of 0.889, 0.889, and 0.894 in the training, internal validation, and external validation groups, respectively. Further details are presented in Table 3.

**Construction and Validation of Models**

Figure 4 shows the ROC curves of each model in the training, internal validation, and external validation groups. The CR model demonstrated the best discrimination ability in each group (Table 3).

Further comparisons were made between the CR, clinical prediction, and T2WI+T1CE fusion sequence radiomics prediction models. Based on the training group data, the Delong test showed no significant differences (P > 0.05) between the clinical prediction model and the T2WI+T1CE fusion sequence radiomics prediction model. The CR model demonstrated a statistically significant difference (P < 0.05) compared to the

clinical prediction model and the T2WI+T1CE fusion sequence radiomics prediction model. The NRI and IDI indices further revealed that the CR model had significantly higher predictive ability compared to the clinical prediction model and T2WI+T1CE fusion sequence radiomics prediction models (NRI index > 0, IDI index > 0, $P < 0.05$) (Table 6).

The calibration curves of the three models are shown in Figure 5. The results showed that the CR model had the best calibration ability in the training, internal validation, and external validation groups (i.e., the calibration curve was closest to the reference line). The DCA curve is shown in Figure 6. The CR model achieved the highest clinical net benefit compared to the clinical prediction model and the T2WI+T1CE fusion sequence radiomics prediction model.

Based on the final results of model construction and validation, the CR model with the best model performance was selected to construct a concise nomogram (Figure 7) and an online interactive dynamic web page nomogram (Figure 8) for visualization.

## DISCUSSION

Non-invasive assessment of the prognosis of RC is challenging and has always been a research hotspot[26,27]. Research has shown that PNI is not only characterized by tumor cell infiltration and growth along the nerves but also involves an interaction between various neurotrophic and chemotactic factors released from tumor cells and the surrounding microenvironment. This process induces tumor invasion, local recurrence, and metastasis, leading to a poor prognosis[28-30]. Preoperative prediction of PNI status is helpful for individualized treatment of RC. For example, PNI-positive RC patients should receive more aggressive treatment, such as nCRT[9-12].

The present study constructed radiomics prediction models, clinical prediction models, and CR models based on preoperative high-resolution MRI images of RC, as well as independent clinical risk factors (cTNM and histological grade), to predict the preoperative PNI status of RC patients. The reliability and repeatability of the established prediction models were analyzed using internal and external validation

groups. The results showed that, compared to the radiomics and clinical prediction models, the CR model had the best discrimination, calibration, and clinical net benefit, with stable neutral performance in both the internal and external validation groups.

Furthermore, in this study we constructed three radiomics prediction models based on T2WI and T1CE sequences: T2WI, T1CE, and T2WI+T1CE fusion sequence. In the training and internal validation groups, the AUCs of the fusion sequence model were 0.839 (95%CI: 0.757–0.921) and 0.787 (95%CI: 0.650–0.923), which were higher than those of the T2WI and T1CE sequence models. In the external validation group, the AUC of the fusion sequence model was 0.836 (95%CI: 0.735–0.937), which was slightly lower than that of the T1CE sequence model (0.841, 95%CI: 0.752–0.930). Although the AUCs of the fusion sequence models in the training group were higher than those of the T2WI and T1CE sequences, there were no significant differences between the models in the Delong test (P > 0.05). The contradictory results may be due to two reasons: first, the study sample size was not sufficiently large. Further research with larger sample sizes is needed. Second, there are inherent limitations of the Delong test. Although it is widely used to compare models, it may not be sufficiently sensitive to the incremental changes in the predictive ability of the model. Therefore, we also used the NRI and IDI indexes for evaluation[31]. The final results showed that the fusion sequence model had a significantly higher prediction ability compared to the T2WI and T1CE sequence models (NRI index > 0, IDI index > 0, P < 0.05). Therefore, a CR model was constructed using Rad-score fusion sequences and independent clinical risk factors.

The Rad-score value of the T2WI+T1CE fusion sequence radiomics prediction model consisted of five radiomics features, including one shape feature, two GLCM features, one GLRLM feature, and one GLSZM feature. The shape feature is the Maximum-2D-diameter-Slice based on the original image of the T1CE sequence, which reflects the tumor size. This may be because larger tumors have a relatively higher probability of contact with nerves, leading to a relatively higher probability of PNI[32,33]. The GLCM features include Matthews correlation coefficient (MCC) based on original T2WI images and wavelet transformation of T2WI sequence wavelet-LLL images. The

GLCM features mainly reflect the probability of voxel values appearing at a given direction and distance in the spatial arrangement relationship between voxel gray levels of an image. The MCC is primarily used to determine the binary classification, and it comprehensively considers true positive, true negative, true positive, true negative, false positive, and false negative cases, making it a relatively balanced indicator. The GLRLM feature is the Gray-Level Non-Uniformity Normalized (GLNN) based on the T2WI sequence wavelet-LLL image. This feature reflects the spatial arrangement of voxels in the image, and the voxel length with the same gray level continuously appearing in the specified direction. GLNN is primarily used to determine the similarity of gray-level intensity values in the image. The GLSZM feature is the Zone Entropy (ZE) based on the original T2WI images, which reflects the area of continuous voxel values quantified in the spatial arrangement of voxels and grayscales in the image. ZE represents the uncertainty or randomness of the measurement area and grayscale distribution. The higher the value, the greater the non-uniformity of the texture pattern.

Among the five radiomics features, two are wavelet-transformed features, which decompose the original image into different frequency domains and then extract features from each wavelet image individually. Therefore, multi-frequency domain and multi-scale image information can be obtained, allowing the obtained features to more effectively reflect the spatial heterogeneity of tumors. The selected GLCM and GLSZM features of MCC and ZE mainly reflect the heterogeneity of the extracted VOI, which is inconsistent with the specific features extracted by Guo *et al* and Huang *et al* [20,23]. These findings may be explained by the differences in scanning and reconstruction parameters, as well as inconsistencies between the methods of model construction. Nevertheless, our results demonstrated consistent results for some of the extracted radiomics features, reflecting tumor heterogeneity. Furthermore, this also confirms the results of previous studies, which found that the higher the tumor heterogeneity, the more aggressive the tumor is likely to be[34]. In addition, the GLRLM feature of GLNN

mainly reflects the tumor homogeneity, which is negatively correlated with the Rad-score, further confirming our conclusion.

Univariate and multivariate logistic regression analyses of the clinical prediction model showed that cTNM and histological grade were independent risk factors for the PNI status of RC, which is in line with the results of Alotaibi *et al* and Poeschl *et al*[32,33]. The explanation for these findings may be that a higher TNM stage and lower histological grade correlates with a more malignant and aggressive tumor that is more likely to invade the nerves around the tumors. Previous studies have also shown that a high T stage, high N stage, distant metastasis, positive CRM status, positive EMVI status, high CEA level ($\geq$ 5 ng/mL), and tumor budding are also independent risk factors for PNI. However, in the present study, the selection of patients and variables was biased due to the study design. Furthermore, multivariate logistic regression analysis did not reveal statistically significant results. Finally, the clinical prediction model based on cTNM and histological grade was selected, which demonstrated AUCs of 0.804 (95%CI: 0.727–0.881), 0.828 (95%CI: 0.719–0.937), and 0.813 (95%CI: 0.724–0.903) in the training, internal validation, and external validation groups, respectively, as well as satisfactory model stability. Compared with the T2WI+T1CE fusion sequence radiomics prediction model, the Delong test showed that there were no significant differences in the differentiation ability among the models. Therefore, the combined CR model was constructed, and the results show the best prediction performance, the AUCs of the CR model in the training and internal and external validation groups were 0.889 (95%CI: 0.824–0.954), 0.889 (95%CI: 0.803–0.976) and 0.894 (95%CI: 0.814–0.974).

Compared with previous similar studies, the present study had certain strengths. First, this study extracted 944 radiomics features from each sequence of the following images: raw images, Gaussian transformed images, and wavelet transformed images. The number of features was significantly higher than in previous studies, which may reflect the spatial heterogeneity of tumors more effectively. Second, this study used internal and external validation groups to evaluate the models, whereas previous studies were based on a single-center internal validation group, lacking independent

external validation. Third, the CR model demonstrated good stability in both the internal and external validation groups, with greater repeatability than models proposed in previous studies. Fourth, the PNI status of 244 RC patients was evaluated based on H-E staining and immunohistochemical analysis of postoperative resection specimens. A previous study demonstrated that immunohistochemical analysis can significantly improve the PNI detection rate, which is 2–3 times higher than the detection rate using H-E staining alone[5]. However, some previous studies did not provide a detailed explanation of their specimen analysis methods[13,19,21,22], whereas some other studies evaluated the PNI status based on H-E staining only of postoperative specimens[20,23].

There were certain limitations to this study. First, this was a retrospective study with possible selection bias. Second, although the external validation group included patients from an independent center based on strict eligibility criteria, further validation studies are needed to reduce the impact of data bias. Third, the VOI was manually delineated layer-by-layer, which takes a long time in clinical settings and may lead to inter-observer variability. Therefore, further studies are needed to determine the feasibility of applying deep learning to automatically delineate the VOI[35,36].

## CONCLUSION

In conclusion, the radiomics model constructed in this study based on preoperative MRI was found to be useful for predicting the PNI status in RC. Furthermore, the CR model combined with the clinical risk factors of PNI was able to predict the PNI status of RC noninvasively before the surgery, thereby providing support for the individualized treatment of RC patients.

## ARTICLE HIGHLIGHTS

*Research conclusions*

The CR model based on MRI radiomics features and clinical risk factors was able to predict the PNI status of RC noninvasively, showed stable performance, which can provide support for individualized treatment of RC patients.

### Research perspectives

Further external verification research is needed to optimize the mode, and explore the feasibility of applying deep learning to automatically describe volume of interest, reduce the difference between observers and improve the applicability of the model.

### Research results

Our study extracted 944 radiomics features from T2WI and contrast-enhanced T1WI sequences, combined with PNI-related clinical features (cTNM and histological grade) to construct the final clinical-radiomics (CR) model, and used internal and external validation groups to evaluate the models, The final CR model showed good performance to predict PNI status, the AUCs of the CR model in the training and internal and external validation groups were 0.889 (95%CI: 0.824–0.954), 0.889 (95%CI: 0.803–0.976) and 0.894 (95%CI: 0.814–0.974).

### Research methods

Our study enrolled 244 RC patients from two independent centers from May 2019 to August 2022. The patients from Center 1 were randomly divided into a training group (n = 118) and an internal validation group (n = 52), whereas 74 patients from Center 2 served as an external validation group. Extracted and selected quantitative radiomics features and clinical risk factors to establish and validate the radiomics prediction model and clinical-radiomics model.

### Research objectives

To evaluate the usefulness of a model based on preoperative magnetic resonance imaging (MRI) radiomics for predicting the perineural infiltration (PNI) status in

patients with rectal cancer (RC) and establish and validate an optimal nomogram model for predicting PNI status preoperatively in RC patients.

### Research motivation

Nowadays, the preoperative prediction of PNI status is still challenging and needs further study.

### Research background

Perineural invasion (PNI), a potential pathway for the metastatic spread of rectal cancer (RC), has been used as an important pathological indicator and independent prognostic factor for patients with RC, Preoperative stratification of RC patients according to the PNI status facilitates individualized treatment and improves the prognosis of RC patients.

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