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Retrospective Study

Magnetic resonance imaging-based lymph node radiomics for predicting the metastasis of evaluable lymph nodes in rectal cancer

Yong-Xia Ye, Liu Yang, Zheng Kang, Mei-Qin Wang, Xiao-Dong Xie, Ke-Xin Lou, Jun Bao, Mei Du, Zhe-Xuan Li

Abstract

BACKGROUND
Lymph node (LN) staging in rectal cancer (RC) affects treatment decisions and patient prognosis. For radiologists, the traditional preoperative assessment of LN metastasis (LNM) using magnetic resonance imaging (MRI) poses a challenge.

AIM
To explore the value of a nomogram model that combines Conventional MRI and radiomics features from the LNs of RC in assessing the preoperative metastasis of evaluable LNs.

METHODS
In this retrospective study, 270 LNs (158 nonmetastatic, 112 metastatic) were randomly split into training (n = 189) and validation sets (n = 81). LNs were classified based on pathology-MRI matching. Conventional MRI features [size, shape, margin, T2-weighted imaging (T2WI) appearance, and CE-T1-weighted
imaging (T1WI enhancement) were evaluated. Three radiomics models used 3D features from T1WI and T2WI images. Additionally, a nomogram model combining conventional MRI and radiomics features was developed. The model used univariate analysis and multivariable logistic regression. Evaluation employed the receiver operating characteristic curve, with DeLong test for comparing diagnostic performance. Nomogram performance was assessed using calibration and decision curve analysis.

RESULTS

The nomogram model outperformed conventional MRI and single radiomics models in evaluating LNM. In the training set, the nomogram model achieved an area under the curve (AUC) of 0.92, which was significantly higher than the AUCs of 0.82 ($P < 0.001$) and 0.89 ($P < 0.001$) of the conventional MRI and radiomics models, respectively. In the validation set, the nomogram model achieved an AUC of 0.91, significantly surpassing 0.80 ($P < 0.001$) and 0.86 ($P < 0.001$), respectively.

CONCLUSION

The nomogram model showed the best performance in predicting metastasis of evaluable LNs.

Key Words: Radiomics; Lymph node metastasis; Rectal cancer; Magnetic resonance imaging

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Core Tip: We have developed and validated a predictive model that combines radiomic features with conventional magnetic resonance imaging features. This model has shown promising results in preoperative assessment of lymph node metastasis (LNM), improving the accuracy of LNM evaluation by radiologists. Additionally, the study has focused on individual LNs and has the potential to provide information on both the quantity and location of metastatic LNs.

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INTRODUCTION

Rectal cancer (RC) ranks 8th among the 36 different types of cancer in terms of both new cases and deaths[1]. Lymph node metastasis (LNM) is correlated with advanced tumor staging and unfavorable prognosis (seer.cancer.gov). Accurate preoperative assessment of LNs is crucial for selecting the treatment plan. Magnetic resonance imaging (MRI) is the preferred method for the preoperative evaluation of RC, enabling the visualization of LNs with a diameter ≥ 5 mm. Guidelines highlight the assessment of LNM based on size, borders, and morphological characteristics[2]. However, importantly, > 90% of these LNs are nonmetastatic[3-5]. RC specimen studies show that only approximately 6% of total LNs can be evaluated[6], leading radiologists to primarily focus on these limited nodes for staging. The accuracy of assessing LNM based on MRI remains limited, as indicated by a meta-analysis reporting a sensitivity of approximately 73% and specificity of approximately 74% for MRI in diagnosing LNM[7-9]. Therefore, there is a risk of diagnostic insufficiency and overdiagnosis[10]. Evaluating LNs with a diameter < 5 mm is challenging, as they may not be visible on MRI, and the metastasis rate for all small LNs is less than 15%[11-14]. Importantly, there is no evidence suggesting that small LNs independently contribute to node staging beyond the evaluable LNs. Improving diagnostic accuracy is the crucial first step for radiologists in making accurate clinical decisions, considering the unique nature of evaluable LNs.

Radiomics extracts nonvisual information from medical images and transforms it into quantitative features that reveal pathophysiological potential[15]. Recent studies indicate that radiomics models can predict LNM using tumor information[16-19]. However, they only confirm the presence of LNM and do not provide precise details on quantity or location. To redress this insufficiency, it is paramount to prioritize the analysis of radiomics information specific to LNs. Presently, there is a lack of research targeting LN radiomics. The purpose of this study was to utilize MRI-based LN radiomics to predict the metastasis in evaluable LNs.

MATERIALS AND METHODS

Patients

This retrospective study received approval from the institutional review board, and a waiver of written informed consent was obtained. Between January 2018 and December 2022, we continuously enrolled 848 patients with resectable RC from

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Nanjing Medical University Affiliated Cancer Hospital. The inclusion criteria were as follows: (1) Confirmed diagnosis of rectal adenocarcinoma through histopathology; (2) undergoing curative surgery for RC; (3) an MRI examination 2 wk before surgery with the MRI report indicating N stage positivity; and (4) complete clinical data, including carcinoembryonic antigen and surgical approaches. The exclusion criteria were as follows: (1) Incomplete clinical data; (2) neoadjuvant therapy before surgery; (3) poor image quality of MRI; (4) pelvic LNs with a short diameter on MRI less than 5 mm; and (5) LNs unmatched between pathology and MRI. Finally, we enrolled 144 patients with RC. Patients were allocated to the training and validation sets in a 7:3 ratio (Table 1).

**LN histopathological assignment and grouping**

Patients underwent total mesenteric excision and were staged according to the 8th edition of the American Joint Committee on Cancer (AJCC) TNM staging system. Patients in the non-LN metastasis (NLNM) group had no regional LNM, while patients in the positive LN group had at least one regional LNM. Patients in the positive LN group underwent assessment by two gastrointestinal radiologists, namely, reader ZK, boasting 25 years of experience, and reader MQW, with 27 years of experience. These radiologists adhered to the guidelines[2], aiming to identify nonfused suspicious LNM on MRI with a short diameter of ≥ 5 mm. Subsequently, the identified suspicious LNM were compared with the number and location of regionally LNM mentioned in the pathology report, including the peritumoral area, superior rectal artery region, and lateral pelvic wall. Only the nodes that were manually matched and agreed upon by both radiologists were considered metastatic. Given the reliable correlation observed between LNs with a short axis exceeding 1 cm and metastasis on MRI[13], the analysis excluded 9 LNs with a diameter greater than 1 cm. A total of 270 LNs (158 nonmetastatic and 112 metastatic) were included and randomly allocated to training set (111 nonmetastatic and 78 metastatic) and validation set (47 nonmetastatic and 34 metastatic) at a 7:3 ratio (Table 1). The flowchart of LNs collection is illustrated in Figure 1.

**MRI scanning protocol**

Patients were instructed to observe a fasting period prior to the examination. To suppress intestinal peristalsis, a 10 mg dosage of anisodamine hydrochloride was administered via intramuscular injection 10 min before examination with the 3.0 T MR scanner (Ingenia; Philips Medical Systems, Best, Netherlands). The imaging protocols consisted of axial T1-weighted imaging (T1WI) with the following parameters: Repetition time (TR) of 594 ms, echo time (TE) of 10 ms, field of view (FOV) of 300, matrix size of 376 × 296, slice thickness of 4 mm, and slice gap of 0.4 mm. For oblique axial T2-weighted imaging (T2WI), the parameters were a TR of 4203 ms, a TE of 102 ms, an FOV of 220, a matrix size of 256 × 256, a slice thickness of 4 mm, and no slice gap. Axial contrast-enhanced imaging utilized a TR of 4.5 ms, a TE of 1.4 ms, an FOV of 230, a matrix size of 268 × 250, a slice thickness of 5 mm, and a slice gap of 1 mm. Contrast enhancement involved the intravenous administration of gadopentetate dimeglumine (Magnevist; Bayer Healthcare, Leverkusen, Germany) at a flow rate of 1.5 mL/s, with a dose of 0.2 mL/kg body weight. A high-pressure injector was used to administer a 20 mL saline flush; then the contrast-enhanced scan was performed 1 min after administration of the contrast agent.

**Imaging analyses**

Two radiologists (reader XDX, with 8 years of experience in diagnosing RC with MRI; reader YXY, with 5 years of similar experience) conducted a qualitative analysis of image features. Although the presence of rectal adenocarcinoma tumors was confirmed, the radiologists were not informed of the tissue pathology of postoperative LNs or the study design of the images. They independently evaluated the conventional MRI features of LNs on T2WI and CE-T1WI, including: (1) Size (short axis/Long axis), (2) shape (round, nonround); (3) margin smooth or nonsmooth (lobulated, spiculated and indistinct)[30]; (4) T2WI heterogeneous appearance (absent/present); and (5) enhancement appearance (homogeneous/heterogeneous). A flowchart of radiomics process is shown in Figure 2. Radiomics feature analyses were as follows: LNs in both datasets were manually segmented by Reader ZXL using ITK-SNAP (version 3.6.0; http://www.itksnap.org) software for radiomics feature extraction. The segmentation process was performed on T1WI and T2WI. To assess the variability of intrareader, interreader, and radiomics features, all LNs from the test set were subjected to repeated segmentation by Reader ZXL and segmentation by MD. The second segmentation was conducted 1 mo after the initial segmentation. The intrareader and interreader agreements were evaluated using the intraclass correlation coefficient. Both readers were unaware of the histopathologic classification of all LNs. The radiomics features were extracted from segmented MRI voxels using the PyRadiomics open-source Python package (version 3.1.0; Harvard Medical School). Before extraction of the features, z score normalization was applied to normalize the MRI images. The “N4ITK” bias field correction method was applied to correct the intensity inhomogeneity caused by variations in the magnetic field[21]. To ensure consistent scale and orientation during the extraction of three-dimensional features, the images were resampled with a voxel size of 1 mm × 1 mm × 1 mm. A total of 2000 features were extracted from the T1WI and T2WI sequences, including 14 shape features, 18 first-order statistics, 14 GLDM features, 22 GLCM features, 16 GLRLM features, 16 GLSZM features, and 688 wavelet features.

**Statistical analysis**

Categorical variables were compared using the Chi-square test or Fisher’s exact test, while the normality of data distribution was assessed using the Kolmogorov-Smirnov test. For quantitative data, an independent sample t test was utilized for comparisons. Univariate analysis was applied to examine the differences in conventional MRI features between nonmetastatic and metastatic LNs in the training set. The homogeneity of variance in radiomics features was evaluated using Levene’s test. Dimensionality reduction and optimal feature selection were conducted using the LASSO regression algorithm. The features with nonzero coefficients were linearly combined to calculate the radiomics
Table 1 Demographics of training and validation set

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>All patients</th>
<th>Training set</th>
<th>Validation set</th>
<th>P value</th>
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<td>n = 144</td>
<td>n = 100</td>
<td>n = 44</td>
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<tr>
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<td>59 ± 10</td>
<td>59 ± 9</td>
<td>60 ± 10</td>
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<tr>
<td>Sex</td>
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<td>97 (67.4)</td>
<td>68 (68.0)</td>
<td>29 (65.9)</td>
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</tr>
<tr>
<td>Female</td>
<td>47 (32.6)</td>
<td>32 (32.0)</td>
<td>15 (34.1)</td>
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<tr>
<td>CEA in ng/mL (^1)</td>
<td>4.0 (2.4, 7.8)</td>
<td>3.8 (2.3, 9.3)</td>
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<td>0.787</td>
</tr>
<tr>
<td>Location</td>
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<td>22 (22.0)</td>
<td>9 (20.5)</td>
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<tr>
<td>Middle</td>
<td>66 (45.8)</td>
<td>41 (41.0)</td>
<td>25 (56.8)</td>
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<tr>
<td>Lower</td>
<td>47 (32.6)</td>
<td>37 (37.0)</td>
<td>10 (22.7)</td>
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<td>Surgical approach</td>
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<td>0.489</td>
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<td>Dixon</td>
<td>120 (83.3)</td>
<td>82 (82.0)</td>
<td>38 (86.4)</td>
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<td>Miles</td>
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<td>15 (15.0)</td>
<td>6 (13.6)</td>
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<td>0 (0.0)</td>
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<td>Surgical specimen histological type</td>
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<td>Ulcerative</td>
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<td>28 (63.6)</td>
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<td>Infiltrative</td>
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<td>14 (31.8)</td>
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<tr>
<td>Differentiation</td>
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<td>0.689</td>
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<tr>
<td>Well</td>
<td>8 (5.6)</td>
<td>5 (5.0)</td>
<td>3 (6.8)</td>
<td></td>
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<tr>
<td>Moderate</td>
<td>86 (59.7)</td>
<td>62 (62.0)</td>
<td>24 (54.5)</td>
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<tr>
<td>Poor</td>
<td>50 (34.7)</td>
<td>33 (33.0)</td>
<td>17 (38.6)</td>
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<td>Pathological T stage</td>
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<tr>
<td>T1</td>
<td>7 (4.9)</td>
<td>4 (4.0)</td>
<td>3 (6.8)</td>
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</tr>
<tr>
<td>T2</td>
<td>39 (27.1)</td>
<td>29 (29.0)</td>
<td>10 (22.7)</td>
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<tr>
<td>T3</td>
<td>84 (58.3)</td>
<td>59 (59.0)</td>
<td>25 (56.8)</td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>14 (9.7)</td>
<td>8 (8.0)</td>
<td>6 (13.6)</td>
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<tr>
<td>Pathological N status</td>
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</tr>
<tr>
<td>Positive</td>
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<td>34 (34.0)</td>
<td>19 (43.2)</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>91 (63.2)</td>
<td>66 (66.0)</td>
<td>25 (56.8)</td>
<td></td>
</tr>
</tbody>
</table>

\(^1\)Data are n (%) or median (IQR).
CEA: Carcinoembryonic antigen.
Figure 1 Flowchart for the selection of evaluable lymph nodes with a short diameter of within 5-10 mm. LNs: Lymph nodes; NLNM: Non-lymph node metastasis; LNM: Lymph node metastasis.

RESULTS

Building the conventional MRI model
The conventional MRI features of and LNM groups are presented in Table 2. A significant difference was observed between the groups in terms of size, margin, T2WI heterogeneous appearance, and enhancement appearance (all P < 0.05) in the training set. Exceptionally, no significant difference was found in shape (P >0.05). Multivariable analysis showed that margin (OR = 4.184; 95%CI: 1.831, 10.105; P < 0.001) and enhancement appearance (OR = 7.709; 95%CI: 3.200, 20.561; P < 0.001) remained independent conventional MRI features predictors associated with LNM (Table 3).

Building the radiomics signature model
The T1WI-Radscore included 13 features, the T2WI-Radscore included 10 features, and the T1WI & T2WI-Radscore included 18 features (Supplementary Figure 1). The AUC for the T1WI & T2WI-Radscore was higher than that of the T1WI-Radscore and T2WI-Radscore in the training set (0.89 vs 0.83 and 0.89 vs 0.85, respectively) and validation set (0.86 vs 0.81 and 0.86 vs 0.84, respectively) (Figure 3 and Table 4).

Building the nomogram model and the performance of different models
The margin, enhancement appearance, and T1WI & T2WI-Radscore were integrated to build a nomogram model (Figure 4A). The nomogram model was obtained using the following equation: Nomogram model = -4.270 + (T1WI & T2WI-Radscore × 0.839) + (Margin × 1.278) + (enhancement appearance × 1.477). The DCA based on the three models is presented in Figure 4D. The diagnostic performances of the nomogram models are shown in Table 4 and Figure 4A and B. The AUC of the T1WI & T2WI-Radscore was higher than that of the conventional MRI model in the training set (0.89 vs 0.82, P < 0.001) and validation set (0.86 vs 0.80, P < 0.001). The AUC of the nomogram was higher than that of the conventional MRI model in the training set (0.92 vs 0.82, P < 0.001) and validation set (0.91 vs 0.80, P < 0.001). The AUC of the nomogram was higher than that of the T1WI & T2WI-Radscore in the training set (0.92 vs 0.89, P < 0.001) and validation set (0.91 vs 0.86, P < 0.001) (Figure 4).
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### Table 2 Baseline characteristics of lymph nodes in the training and validation sets

<table>
<thead>
<tr>
<th>Features</th>
<th>Training set</th>
<th>Validation set</th>
<th>P value</th>
<th>Training set</th>
<th>Validation set</th>
<th>P value</th>
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</thead>
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<tr>
<td></td>
<td>NLNM, n = 111</td>
<td>LNM, n = 78</td>
<td></td>
<td>NLNM, n = 47</td>
<td>LNM, n = 34</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short axis in mm</td>
<td>6.10 (5.40, 7.20)</td>
<td>7.80 (6.60, 9.00)</td>
<td>&lt; 0.001</td>
<td>5.70 (5.10, 7.40)</td>
<td>7.25 (6.57, 8.67)</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Long-axis in mm</td>
<td>7.63 ± 1.72</td>
<td>9.13 ± 1.94</td>
<td>&lt; 0.001</td>
<td>7.55 ± 1.79</td>
<td>8.67 ± 1.43</td>
<td>0.004</td>
</tr>
<tr>
<td>Shape</td>
<td></td>
<td></td>
<td>0.105</td>
<td></td>
<td></td>
<td>0.185</td>
</tr>
<tr>
<td>Non-round</td>
<td>82 (73.88)</td>
<td>29 (37.17)</td>
<td></td>
<td>31 (65.95)</td>
<td>27 (79.41)</td>
<td></td>
</tr>
<tr>
<td>Round</td>
<td>29 (26.12)</td>
<td>49 (62.83)</td>
<td></td>
<td>16 (34.04)</td>
<td>7 (20.59)</td>
<td></td>
</tr>
<tr>
<td>Margin</td>
<td></td>
<td></td>
<td>&lt; 0.001</td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>Clear</td>
<td>55 (49.54)</td>
<td>13 (16.67)</td>
<td></td>
<td>24 (51.00)</td>
<td>4 (14.70)</td>
<td></td>
</tr>
<tr>
<td>Unclear</td>
<td>56 (50.46)</td>
<td>65 (83.33)</td>
<td></td>
<td>23 (49.00)</td>
<td>30 (65.30)</td>
<td></td>
</tr>
<tr>
<td>T2WI heterogeneous signal</td>
<td></td>
<td></td>
<td>&lt; 0.001</td>
<td></td>
<td></td>
<td>0.029</td>
</tr>
<tr>
<td>Absent</td>
<td>63 (56.76)</td>
<td>17 (21.79)</td>
<td></td>
<td>25 (53.19)</td>
<td>5 (14.71)</td>
<td></td>
</tr>
<tr>
<td>Presrent</td>
<td>48 (43.24)</td>
<td>61 (78.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patterns of enhancement</td>
<td></td>
<td></td>
<td>&lt; 0.001</td>
<td></td>
<td></td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Homogeneous</td>
<td>65 (58.55)</td>
<td>8 (10.26)</td>
<td></td>
<td>32 (68.08)</td>
<td>8 (23.52)</td>
<td></td>
</tr>
<tr>
<td>Heterogeneous</td>
<td>46 (41.45)</td>
<td>70 (89.74)</td>
<td></td>
<td>15 (31.92)</td>
<td>26 (76.48)</td>
<td></td>
</tr>
<tr>
<td>Radiomics score</td>
<td>-1.28 ± 1.28</td>
<td>0.62 ± 1.41</td>
<td>&lt; 0.001</td>
<td>-1.29 ± 1.27</td>
<td>0.60 ± 1.60</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

1Data are n (%) or median (IQR).

LNM: Lymph node metastasis; NLNM: Non-lymph node metastasis; T2WI: T2-weighted imaging.

### Table 3 Risk factors of lymph node metastasis in lymph nodes

<table>
<thead>
<tr>
<th>Intercept and variable</th>
<th>Conventional MRI model</th>
<th>Nomogram model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Odds ratio (95%CI)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.429</td>
<td>0.002 (0.001, 0.012)</td>
</tr>
<tr>
<td>Short axis</td>
<td>0.478</td>
<td>1.612 (0.962, 2.745)</td>
</tr>
<tr>
<td>Long-axis</td>
<td>0.009</td>
<td>1.010 (0.679, 1.520)</td>
</tr>
<tr>
<td>Margin</td>
<td>1.431</td>
<td>4.184 (1.831, 10.105)</td>
</tr>
<tr>
<td>T2WI heterogeneous signal</td>
<td>0.309</td>
<td>1.362 (0.586, 3.120)</td>
</tr>
<tr>
<td>Patterns of enhancement</td>
<td>2.042</td>
<td>7.709 (3.200, 20.561)</td>
</tr>
<tr>
<td>Radiomics score</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Data are results of the multivariable regression analysis. The conventional magnetic resonance imaging model was developed based on independent factors of lymph node metastasis without the addition of radiomics signature. CI: Confidence interval; MRI: Magnetic resonance imaging; NA: Not available.

### DISCUSSION

In this study, we found that the optimal performance in preoperatively diagnosing LNM in patients with RC was provided by the nomogram model, followed by radiomics features alone. Meanwhile, both approaches outperformed conventional MRI model alone in both the training and validation set. These findings indicated that radiomics features derived from MRI could serve as an effective complement to MRI imaging features for the preoperative diagnosis of LNM in patients with RC.

Adequate morphological information is essential for the accurate diagnosis of LNM. Previous studies revealed specific characteristics observed in LNM, such as calcification and cystic changes, which contribute to heterogeneous enhancement[22,23]. Metastatic LNs typically exhibit irregular and indistinct borders with lobulated contours, resulting...
Table 4 Diagnostic performance of the conventional magnetic resonance imaging model, radiomics model, and nomogram

<table>
<thead>
<tr>
<th>Data set</th>
<th>Model</th>
<th>AUC (95%CI)</th>
<th>Sensitivity, %</th>
<th>Specificity, %</th>
<th>Accuracy, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training cohort</td>
<td>Conventional MRI model</td>
<td>0.82 (0.76, 0.87)</td>
<td>75.0</td>
<td>80.0</td>
<td>77.8</td>
</tr>
<tr>
<td></td>
<td>T1WI radiomics model</td>
<td>0.83 (0.79, 0.87)</td>
<td>59.5</td>
<td>82.6</td>
<td>73.5</td>
</tr>
<tr>
<td></td>
<td>T2WI radiomics model</td>
<td>0.85 (0.79, 0.91)</td>
<td>63.1</td>
<td>93.0</td>
<td>79.0</td>
</tr>
<tr>
<td></td>
<td>T1WI &amp; T2WI Radiomics model</td>
<td>0.89 (0.84, 0.93)</td>
<td>74.3</td>
<td>86.1</td>
<td>81.5</td>
</tr>
<tr>
<td></td>
<td>Nomogram model</td>
<td>0.92 (0.84, 0.99)</td>
<td>72.2</td>
<td>91.1</td>
<td>82.8</td>
</tr>
<tr>
<td>Validation cohort</td>
<td>Conventional MRI model</td>
<td>0.80 (0.76, 0.83)</td>
<td>71.0</td>
<td>78.8</td>
<td>75.7</td>
</tr>
<tr>
<td></td>
<td>T1WI radiomics model</td>
<td>0.81 (0.75, 0.86)</td>
<td>60.5</td>
<td>83.7</td>
<td>72.8</td>
</tr>
<tr>
<td></td>
<td>T2WI radiomics model</td>
<td>0.84 (0.80, 0.88)</td>
<td>62.2</td>
<td>87.0</td>
<td>77.2</td>
</tr>
<tr>
<td></td>
<td>T1WI &amp; T2WI Radiomics model</td>
<td>0.86 (0.79, 0.92)</td>
<td>65.8</td>
<td>90.7</td>
<td>79.0</td>
</tr>
<tr>
<td></td>
<td>Nomogram model</td>
<td>0.91 (0.81, 0.96)</td>
<td>81.6</td>
<td>86.7</td>
<td>84.7</td>
</tr>
</tbody>
</table>

AUC: Area under the receiver operating characteristic curve; CI: Confidence interval; MRI: Magnetic resonance imaging; T1WI: T1-weighted imaging; T2WI: T2-weighted imaging.

in a nonsmooth appearance[3,24,25]. LN heterogeneous T2WI signals have been recognized as indicators of LNM[23,26]. Our study also identified significant differences in both factors between the NLNM and LNM groups. However, it is intriguing to note that the heterogeneous T2WI signal did not exhibit independent predictive capability on its own. One possible explanation is that the influence of heterogeneous T2WI signals on LNM is encompassed by heterogeneous enhancement features. The heterogeneous enhancement feature exhibits a more stable impact in predicting LNM. Furthermore, our research results emphasize the significant clinical diagnostic value of using intravenous contrast agents as recommended in guidelines[27]. Multifactor logistic regression analysis revealed enhancement and boundary features as independent predictors for LNM, with a validation set AUC of 0.80. These findings align with previous research, which obtained a similar AUC of 0.82 for morphological evaluation in assessing LNM[2]. Despite the relatively low AUC values of the morphological model in both datasets, it still provides reasonably good classification performance.

Our research revealed that the AUC based on the LN T1WI & T2WI Radscore was consistently higher than the AUC based on the T1WI radscore and T2WI Radscore. This implies that combining radiological features of T1WI and T2WI imaging may provide more useful information for predicting LNM. Previous research has also demonstrated the superior predictive value of multiparametric MRI radiomics compared to single-parameter radiomics. In our study, we developed a model using T1WI and T2WI imaging, and it exhibited similar AUC values in both the training and validation datasets, indicating a high level of reproducibility for the model. This could be attributed to the inherent stability of LN features in T1WI and T2WI imaging, which are less susceptible to variations in scanning parameters, image preprocessing techniques, and ROI segmentation methods. The DWI sequence was not included in the study. In fact, DWI only aids in LN detection without providing predictive value for LNM[28]. Although some studies have affirmed the diagnostic value of tumor DWI radiomics in LNM[18,29], our preliminary exploration showed the poor ability of DWI LN radiomics for LNM. The matching rate between preoperative imaging and postoperative specimens of LNs in RC is notably low as demonstrated by a recent study that reported only 47% agreement[30]. Few studies have reported LN radiomics in predicting LNM in RC. Wang et al[31] found that LN CT radiomics outperformed morphological features in predicting lateral LNM. Zhu et al[32] showed that all visible LN MRI radiomics performed better than tumor radiomics in predicting LNM. We used MRI guidelines and pathology reports to correlate LNs and assess the predictive efficacy of MRI radiomics for LNM on a per-node basis. In our study, the LN T2WI-radscore was found to outperform morphological features in predicting LNM. This indicates that radiomics may capture some microscopic tumor characteristics of LNs that are not visible on MRI. Previous research has supported the superiority of integrating multiple predictive indicators in a nomogram for LNM compared to using a single Radscore[17,23]. Our study yielded similar results, with the nomogram demonstrating superior predictive efficacy in diagnosing LNM compared to the T1WI & T2WI Radscore. The integration of Conventional MRI features into the nomogram offers personalized risk evaluation for per-node metastasis. This holds immense importance for patients who have enlarged lateral LNs, as it has the potential to avoid genitourinary dysfunction resulting from unnecessary LN dissection in those with negative lateral LNs[34].

In our research, we found the nomogram combining Conventional MRI features and MRI radiomics, making up for the limitation of assessing Metastasis of Evaluable LNs only according to Conventional MRI features of the LN itself, could improve the accuracy of preoperative assessing metastasis of evaluable LNs; this improvement may be because MRI radiomics can reflect tumor microscopic characteristics in the evaluable LNs.
CONCLUSION

The nomogram model of conventional MRI features combined with radiomics features on T1WI and T2WI of RC-related evaluable LNs showed promising performance in assessing LNM preoperatively.
Figure 3 Receiver operating characteristic curves. A and B: Receiver operating characteristic curves of the T1-weighted imaging (T1WI)-Radscore, T2-weighted imaging (T2WI)-Radscore, T1WI & T2WI-Radscore in the training (A) and validation (B) set, respectively. AUC: Area under the curve; ROC: Receiver operating characteristic.

Figure 4 Performance of the final selected model to predict lymph node metastasis. A and B: Receiver operating characteristic curves of conventional magnetic resonance imaging (MRI) model, T1-weighted imaging (T1WI) & T2-weighted imaging (T2WI)-Radscore and nomogram to predict lymph node
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metastasis (LNM) with rectal cancer in training set (A), validation set (B); C: Predictive nomogram of LNM; D: Decision curve analysis of models to investigate the clinical usefulness in predicting LNM. It indicates both T1WI & T2WI-Radscore and nomogram obtain more benefit than “treat all”, “treat none”, and the Conventional MRI model when the threshold probability is > 15%. AUC: Area under the curve; ROC: Receiver operating characteristic.

ARTICLE HIGHLIGHTS

Research background
Lymph node (LN) staging in rectal cancer (RC) affects treatment decisions and patient prognosis. For radiologists, the traditional preoperative assessment of LN metastasis (LNM) using magnetic resonance imaging (MRI) poses a challenge.

Research motivation
The accuracy of assessing LNM based on MRI remains limited. A meta-analysis demonstrated a sensitivity of approximately 77% and specificity of approximately 71% when using MRI to diagnose metastasis in evaluable LNs. Therefore, there is a risk of diagnostic insufficiency and overdiagnosis.

Research objectives
To explore the value of a nomogram model that combines Conventional MRI and radiomics features from the LNs of RC in assessing the preoperative metastasis of evaluable LNs.

Research methods
A total of 270 LNs (158 LNM and 112 metastatic) were included and randomly allocated to training set (111 nonmetastatic and 78 metastatic) and validation set (47 nonmetastatic and 34 metastatic) at a 7:3 ratio. Radiomic features were extracted from T1-weighted imaging (T1WI) and T2-weighted imaging (T2WI) images of individual LN. The least absolute shrinkage and selection operator regression analysis was used for feature selection. Multivariate logistic regression analysis was used to develop the Rad-score and nomogram model. Receiver operating characteristic curves were constructed to evaluate the diagnostic performance of the models for predicting LNM. The performance of the nomogram was assessed using decision curve analysis (DCA).

Research results
The nomogram model outperformed conventional MRI and single radiomics models in evaluating LNM. In the training set, the nomogram model achieved an area under the curve (AUC) of 0.92, which was significantly higher than the AUCs of 0.82 (P < 0.001) and 0.89 (P < 0.001) of the conventional MRI and radiomics models, respectively. In the validation set, the nomogram model achieved an AUC of 0.91, significantly surpassing 0.80 (P < 0.001) and 0.86 (P < 0.001), respectively.

Research conclusions
The nomogram model showed the best performance in predicting metastasis of evaluable LNs.

Research perspectives
Radiomics holds great promise for transforming medical practice, especially for patients with RC. However, before its widespread adoption, challenges regarding sample size, model design, and robust multicenter validation sets must be addressed. To validate the proposed model externally, future prospective multicenter studies with larger sample sizes are crucial.

FOOTNOTES

Author contributions: Ye YX contributed to writing-review & editing, writing-original draft, validation, project administration, methodology, investigation, and data curation; Yang L contributed to conceptualization, writing-review & editing, supervision, and funding acquisition; Xie XD contributed to methodology, data curation and formal analysis; Zheng K contributed to investigation, validation and project administration; Wang MQ contributed to validation, resources and investigation; Lou KX contributed to resources and supervision; Li ZX contributed to investigation and visualization; Du M contributed to investigation; Bao J contributed to writing-review & editing, supervision, project administration and funding acquisition.

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Institutional review board statement: The study was reviewed and approved by the Affiliated Cancer Hospital of Nanjing Medical University & Jiangsu Cancer Hospital & Jiangsu Institute of Cancer Research Institutional Review Board (Approval No. AF-SOP026-01).
Informed consent statement: The informed consent statement has been exempted by the Affiliated Cancer Hospital of Nanjing Medical University & Jiangsu Cancer Hospital & Jiangsu Institute of Cancer Research Institutional Review Board.

Conflict-of-interest statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data sharing statement: Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Country/Territory of origin: China

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References


