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ORIGINAL RESEARCH

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Construction of a risk prediction model based on the analysis of MRI imaging features for patients with triple-negative breast cancer and validation of its efficacy

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Abstract

This study is aimed at constructing a risk prediction model for patients with triple-negative breast cancer based on the feature analysis of Magnetic Resonance Imaging (MRI) and verifying the efficacy of the model. 150 patients admitted to our hospital, who had been diagnosed with breast cancer by immunohistochemistry were recruited as our study subjects. For each patient, we collated a range of clinical data (age, tumor size, menopausal status and family history of breast cancer), pathological findings (tumor pathological type and grading), and MRI imaging characteristics. Then patients with triple-negative breast cancer were compared to patients with non-triple-negative cancers. We created a risk prediction model for patients with triple-negative breast cancer after identifying risk variables for the disease using single-factor and multi-factor logistic regression analysis. The Hosmer and Lemeshow test was used to assess the goodness-of-fit of the risk prediction model and a Receiver Operating Characteristic (ROC) curve was plotted by SPSS to evaluate the predictive value of the risk prediction model. The results of single factor analysis based on MRI imaging characteristics showed that there were statistically significant differences between triple-negative breast cancer patients and non-triple-negative breast cancer patients in terms of clear boundaries, increased blood vessels around the tumor, T2-weighted imaging (T2WI) signals, and enhancement mode ($p < 0.05$). The statistical model for predicting triple-negative breast cancer was: $P = 1/[1 + \exp(6.055 - 2.802X_2 - 1.904X_3 - 2.120X_4)]$. The Hosmer and Lemeshow test was used to test the goodness-of-fit for the statistical model ($\chi^2 = 7.993$, $p = 0.434$). ROC analysis showed that the area under the curve (AUC) was 0.916 and with a 95% confidence interval (CI) of 0.874–0.957.

Keywords

MRI imaging features; Triple-negative breast cancer patients; Risk prediction model; Efficacy verification

1. Introduction

Breast cancer is one of the most common malignant tumors in women. The incidence of this disease has increased over recent years with an increasing trend to affect younger patients. Consequently, the overall size of the patient population is increasing annually, thus generating a serious threat to the health and lives of women [1, 2]. Triple-negative breast cancer is a special type of breast cancer, which refers to the simultaneous negative expression of the estrogen receptor, progesterone receptor, and human epidermal growth factor receptor. The proportion of patients with triple-negative breast cancer ranges from 15% to 20% of all breast cancer patients [3, 4]. Patients with triple-negative breast cancer have a high degree of clinical malignancy and experience significant characteristics such as rapid progression, recurrence, metastasis, and poor prognosis. Therefore, it is important to identify triple-negative breast cancer at an early stage of development and provide early clinical interventions so that we can prolong the survival time and improve the quality of life of patients [5–7]. Immunohistochemistry is the gold standard for diagnosing triple-negative breast cancer, and magnetic resonance imaging (MRI) technology has significant advantages in diagnosing breast cancer-related diseases. MRI has superior soft tissue resolution when compared to mammography and ultrasound; it also offers a variety of imaging sequences such as T1WI, TIWI fat suppression, T2WI, T2WI fat suppression, and dynamic enhancement (DCE-MRI) sequences that can be used to analyze lesions from the perspectives of morphology, function, and hemodynamics. MRI also offers a variety of functional imaging sequences,

such as diffusion-weighted imaging (DWI) and its derivatives; susceptibility-weighted imaging (SWI), intravoxel incoherent motion (IVIM), and magnetic resonance spectroscopy (MRS). Not only do DWI and its derivatives, along with other rich functional imaging sequences, provide significant capability to distinguish between benign and malignant tumors, but they are also advantageous for the detection and diagnosis of small lesions of breast cancer; the diagnosis of axillary lymph nodes; visualizing tumor morphology and pathology; the molecular typing of tumors; the evaluation of therapeutic efficacy, and the prediction and assessment of prognosis. The development of artificial intelligence (AI) technologies has recently been aided by the internet and the rapid advancement of computer technology. With the help of AI, the diagnostic efficacy of MRI for breast cancer has been further enhanced.

Significant advancements have also been made in the detection of lesions, segmentation, diagnosis, pathological and molecular typing, disease prediction, and the evaluation of therapeutic efficacy, among other clinical needs. However, when considering earlier clinical studies [8–10], few studies have attempted to generate risk prediction models based on multifactorial analysis. Recently, some studies have attempted to build AI-based medical imaging analysis solutions. Studies targeted to the diagnosis of triple-negative breast cancer by MRI technology are mostly based on single-factor analysis. Furthermore, there is little clinical data to distinguish between triple-negative and non-triple-negative breast cancers [11, 12]. In this study, we enrolled 150 patients who were admitted to our hospital and had been immunohistochemically diagnosed with breast cancer. The characterization of MRI images was then used to build a risk prediction model for patients with triple-negative breast cancer.

2. Methods

2.1 Clinical data

We recruited 150 patients with breast cancer who were admitted to our hospital. These patients were grouped according to their immunohistochemical examination results. Patients diagnosed with triple-negative breast cancer were classified as the study group (n = 56) while the remaining patients were classified as the control group (n = 94).

2.1.1 Inclusion criteria

The inclusion criteria were as follows: (1) the patient met the clinical diagnosis criteria for breast cancer; (2) the patient had a complete set of MRI-related clinical information, and (3) the patient provided signed and informed consent.

2.1.2 Exclusion criteria

The exclusion criteria were as follows: (1) patients with poor MRI image quality; (2) patients who were breastfeeding or pregnant; (3) patients who had received endocrine therapy or chemotherapy, and (4) patients who were found to have metastatic lesions.

2.2 Methodology

Patients were evaluated by magnetic resonance imaging (MRI) with a Magnetom Avanto 1.5T (Siemens AG, Erlangen Town, Bavaria, Germany) superconducting MRI imaging system and breast-specific coils manufactured by Siemens. Patients were asked to fast for 4–6 hours before the examination, maintain a prone position during the examination, and place both breasts naturally down into the breast-specific coil. The relevant parameters were set as follows:

(1) For transverse fat-suppressed T2 imposition imaging, we used the following settings: T2WI, TR (repetition time): 11,271. 4 ms; TE (echo time): 74 ms; flip angle: 80 degrees; layer thickness: 4 mm; layer spacing: 0.8 mm; field-of-view (FOV): 320 mm × 320 mm; matrix: 576 × 403; excitation number: 1.

(2) For diffusion-weighted imaging in a transverse position, we used the following settings: DWI: TR: 3000 ms; TE: 70 ms; flip angle: 10 degrees; layer thickness: 5 mm; layer spacing: 2 mm; FOV: 340 mm × 340 mm; matrix: 192 × 192; excitation number: 1; b-value: 800 s/mm^2 and 1000 s/mm^2. The apparent diffusion coefficient (ADC) map was generated by self-contained software.

(3) For dynamic enhancement, we used the Vibe-T1WI technique with the following settings: TR: 5.16 ms; TE: 1.5 ms; flip angle: 10 degrees; layer thickness: 1.2 mm; layer spacing: 0.24 mm; FOV: 340 mm × 340 mm; matrix: 448 × 386; number of excitations: 4; image acquisition time: 70, 130, 190, 250 and 310 s before and after contrast injection.

(4) For sagittal fat suppression, T1WI was performed after dynamic enhancement examination with the following settings: TR: 26 ms; TE: 6.41 ms; flip angle: 10 degrees; layer thickness: 4 mm; layer spacing: 1 mm; FOV: 340 mm × 340 mm; matrix: 448 × 386; excitation: 1. The contrast agent was gadopentetate glucosamine (Gd-DTPA); this was administered intravenously in the forearm at a dose of 0.2 mL/kg and an injection flow rate of 2.5 mL/s.

2.3 Observation indices

We statistically analyzed a range of clinical data (age, tumor size, menopause status, and family history of breast cancer), pathological results (tumor pathological type and grading), and MRI imaging characteristics of the patients in both groups.

2.4 Statistical methods

Data were analyzed and processed by SPSS version 27.0 software (International Business Machines Corporation, Armonk, NY, USA). Measurement data were analyzed by the *t*-test while numerical data were analyzed by the χ^2 test. A binary logistic regression analysis model was used for multi-factor regression analysis and the Hosmer and Lemeshow was used to test the goodness-of-fit for the predictive model. SPSS was used to plot a ROC curve to evaluate the predictive value of the prediction model. $p < 0.05$ was considered to be statistically significant.

3. Results

3.1 Comparisons of clinical data between the two groups of patients

There were no significant differences between the two groups in terms of Body Mass Index (BMI), lesion diameter, and family history ($p > 0.05$). The age of patients in the study group was significantly lower than that of the control group ($p < 0.05$). Furthermore, the pathological type and grading differences between the two groups were also statistically significant ($p < 0.05$). Invasive ductal carcinoma and basal-like carcinoma accounted for a higher proportion of the pathological types in the study group than in the control group. In the study group, invasive ductal carcinoma and basal-like carcinoma accounted for a higher proportion than the control group; the pathological grading of patients in the study group was mainly grade III, while that of patients in the control group was mainly grade II. See Table 1.

3.2 Univariate analysis results based on MRI image features in patients with triple-negative breast cancer

The results of univariate analysis based on MRI imaging features showed that the differences between patients with triple-negative breast cancer and those with non-triple-negative breast cancer were statistically significant in terms of clear borders, increased peritumor vascularity, and T2WI signal and enhancement pattern ($p < 0.05$). See Table 2.

3.3 Results of logistic multi-factor regression analysis based on MRI image feature analysis in patients with triple-negative breast cancer

Next, we performed binary logistic regression analysis in which the dependent variable was whether the breast cancer patients had triple-negative breast cancer or not. The independent variables were a clear boundary, peritumoral vascularity, T2WI signal, and enhancement mode; these were all significantly different between the two groups in the previous analysis (Table 3). The binary logistic regression analysis was performed in SPSS software (Table 4) with a significant level of $p < 0.05$. This analysis showed peritumoral vascularity, T2WI signal (high), and enhancement mode (circumferential) were risk factors for the development of triple-negative breast cancer.

3.4 Probabilistic model for the development of triple-negative breast cancer based on the feature analysis of MRI images

Based on the three significant risk factors and their coefficients shown in Table 3, we constructed a binary logistic multi-factor regression analysis model, as follows:

$$Logit(P) = ln[P/(1-P)] = -6.055+2.802X_2+1.904X_3+2.120X_4$$

A probabilistic model for predicting the diagnosis of triple-negative breast cancer patients was also generated, as follows:

$$P = 1/[1 + exp(6.055 - 2.802X_2 - 1.904X_3 - 2.120X_4)]$$

TABLE 1. Comparison of clinical data between the two groups.

Indicators	Study group (n = 56)	Control group (n = 94)	Statistical value	*p* value
Age (yr)	45.36 ± 4.64	49.55 ± 4.45	5.495	<0.001
Body Mass Index (kg/m^2)	26.35 ± 1.95	26.44 ± 1.84	0.252	0.802
Lesion diameter (cm)	2.81 ± 0.29	2.83 ± 0.31	0.555	0.580
Family history (n, %)				
Yes	5, 8.93	9, 9.57	0.017	0.895
No	51, 91.07	85, 90.43		
Pathological type (n, %)				
Invasive ductal carcinoma	37, 66.07	78, 82.98	8.539	0.036
Invasive lobular carcinoma	10, 17.86	10, 10.64		
Invasive ductal carcinoma	6, 10.71	6, 6.38		
Intraductal carcinoma Basal-like carcinoma	3, 5.36	0, 0.00		
Pathological classification (n, %)				
Grade I	5, 8.93	1, 1.06	39.241	<0.001
Grade II	12, 21.43	69, 73.40		
Grade III	39, 69.64	24, 25.53		

TABLE 2. Results of univariate analysis of patients with triple-negative breast cancer based on MRI image feature analysis.

MRI imaging features	Study group (n = 56)	Control group (n = 94)	Statistical value	*p* value
Whether classified as single lesion (n, %)				
Yes	35, 62.50	65, 69.15	0.698	0.403
No	21, 37.50	29, 30.85		
Clear boundary (n, %)				
Yes	30, 53.57	24, 25.53	11.975	<0.001
No	26, 46.43	70, 74.47		
Tumor morphology (n, %)				
Round-like	13, 23.21	23, 24.47		
Foliated	29, 51.79	49, 52.13	0.061	0.970
Irregular	14, 25.00	22, 23.40		
Increased peritumor vascularity (n, %)				
Yes	45, 80.36	24, 25.53	42.465	<0.001
No	11, 19.64	70, 74.47		
T2WI signal (n, %)				
equal to low	13, 23.21	23, 24.47		
slightly high	7, 12.50	57, 60.64	44.767	<0.001
High	36, 64.29	14, 14.89		
Intensification mode (n, %)				
Uniform	8, 14.29	13, 13.83		
Uneven	7, 12.50	66, 70.21	54.840	<0.001
Ring-shaped	41, 73.21	15, 15.96		
TIC (n, %)				
Continuous	20, 35.71	22, 23.40		
Platform type	10, 17.86	16, 17.02	3.023	0.221
Outflow type	26, 46.43	56, 59.57		
ADC value ($\times 10^{-3}$ mm^2/s)	1.133 ± 0.092	1.109 ± 0.076	1.712	0.089

MRI: magnetic resonance imaging; ADC: apparent diffusion coefficient; T2WI: T2-weighted imaging; TIC: time-signal intensity curve.

TABLE 3. Variable assignments for binary logistic multifactorial regression analysis for triple-negative breast cancer.

Factors	B	Assignment situation
Triple-negative breast cancer	Y	Secondary variables: Yes: Assign 1; No: Assign 0
Clear border	X_1	Secondary variables: Yes: Assign 1; No: Assign 0
Increased peritumor vascularity	X_2	Secondary variables: Yes: Assign 1; No: Assign 0
T2WI signal	X_3	Ordered categorical variables: equal low: assigned 0; slightly high: assigned 1; high: assigned 2
Intensification pattern	X_4	Ordered categorical variables: Continuous: assigned 0; Platform: assigned 1; Outflow: assigned 2

T2WI: T2-weighted imaging.

TABLE 4. Results of binary logistic multi-factor regression analysis.

Factors	β	Standard Error	Wald	*p*	OR value	95% confidence interval of OR	
						Lower limit	Upper limit
Clear border	0.488	0.392	1.549	0.213	1.630	0.755	3.517
Increased peritumor vascularity	2.802	0.589	22.630	<0.001	16.477	5.194	52.270
T2WI signal	1.904	0.584	10.628	0.001	6.713	2.137	21.088
Intensification pattern	2.120	0.443	22.886	<0.001	8.329	3.495	19.849
Constants	−6.055	1.030	34.585	<0.001	0.002		

T2WI: T2-weighted imaging; OR: odds ratio.

3.5 Goodness-of-fit test for a probability model for the diagnosis of triple-negative breast cancer onset of triple-negative breast cancer based on the feature analysis of MRI images

The Hosmer and Lemeshow test was used to evaluate the goodness-of-fit of the probabilistic model (χ^2 = 7.993, p = 0.434); these data indicated a good fit for the probabilistic model (Table 5).

TABLE 5. Hosmer-Lemeshow test results for the probability model.

χ^2	Degrees of freedom	p
7.993	8	0.434

3.6 Predictive value analysis of the probability model for triple-negative breast cancer based on the feature analysis of MRI images

ROC curve analysis showed that the predictive model had significant predictive value ($p < 0.05$) with an AUC of 0.916 and a 95% CI of 0.874–0.957 (Fig. 1).

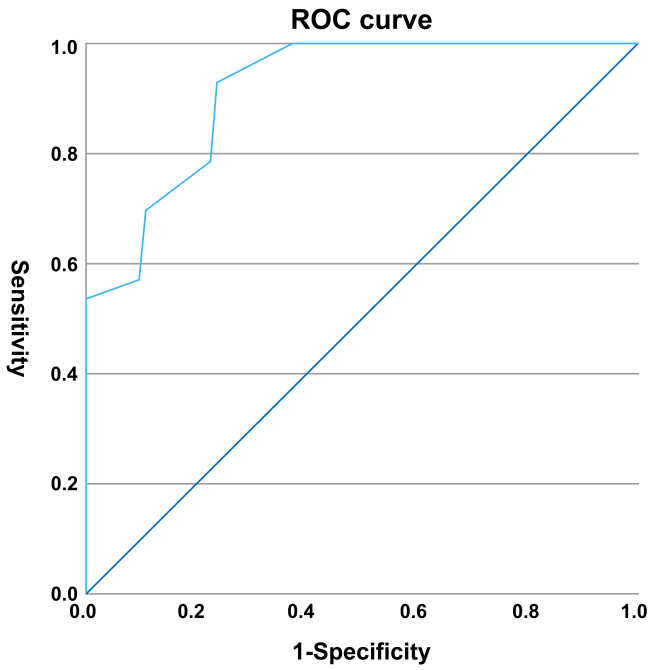

FIGURE 1. Receiver Operating Characteristic (ROC) curve for the probability model for triple-negative breast cancer based on the feature analysis of MRI images.

4. Discussion

Triple-negative breast cancer is a special type of breast cancer characterized by the simultaneous negative expression of the estrogen receptor, progesterone receptor, and human epidermal growth factor receptor. Therefore, triple-negative breast cancer differs significantly from non-triple-negative breast cancer in terms of immunophenotype and biological behavior, thus leading to a significant difference in the sensitivity to different treatments and the clinical prognosis of patients with triple-negative breast cancer when compared to those with non-triple-negative breast cancer [13]. Triple-negative breast cancer patients suffer from a higher degree of clinical malignancy, more rapid progression, a higher recurrence rate, and a worse prognosis. Early identification of triple-negative breast cancer patients is vital if we are to provide targeted early and aggressive treatment. This strategy is also significant in promoting the overall effect of clinical treatment for breast cancer.

Clinical studies have confirmed that MRI has obvious comparative advantages in the process of diagnosing breast cancer. Moreover, the use of MRI technology is more advantageous for the early diagnosis of triple-negative breast cancer in China due to the specific characteristics of dense breast cancer patients. At present, clinical studies referring to the application of MRI technology for the diagnosis of triple-negative breast cancer are mainly based on single-factor analysis methods. In addition, the main analytical studies focused predominantly on the pathology, morphology, and clinical prognosis of patients. Few studies have analyzed predictive models for triple-negative breast cancer based on MRI imaging features [14].

In the present study, we investigated the differences in MRI imaging features between triple-negative breast cancer patients and non-triple-negative breast cancer patients. Then, we used univariate and multifactorial logistic regression analysis to build a risk prediction model for the development of triple-negative breast cancer. Our analysis showed that the pathological grading was predominantly grade III in the group of patients with triple-negative breast cancer, while grade II was predominant in the group of patients with non-triple-negative breast cancer. This finding suggests that triple-negative breast cancer patients have a higher degree of malignancy, as described previously in other publications.

Multi-factorial logistic regression analysis further showed that increased peritumoral vascularity, T2WI signal (high), and enhancement pattern (circumferential), were significant risk factors for the development of triple-negative breast cancer. This finding is consistent with a previous report [15]. In terms of increased peritumoral vascularity, triple-negative breast cancers exhibit a higher degree of invasiveness due to a greater degree of malignancy and therefore have a richer blood supply around the associated focal tissue [16]. Due to their more efficient tumor cell replication, patients with triple-negative breast tumors exhibit higher T2WI signals, accelerated phagocytosis of healthy cells, and the infiltration of lymphocytes [17]. The primary causes of circumferential intensification are a high rate of vascular system generation, a greater proportion of necrotic areas at the center of the tumor, and higher levels of fibrosis. Patients with triple-negative breast cancer predominantly exhibit circumferential intensification in terms of intensification mode, which is closely related to the characteristics of their malignant lesions [18].

The present study constructed a binary logistic multi-factor regression analysis model based on three significant risk factors and their coefficients. The goodness-of-fit of the probabilistic model was tested by the Hosmer-Lemeshow test, and

the model's predictive value was analyzed by ROC curve analysis. Analysis showed that the model had a satisfactory goodness-of-fit and significant predictive value. Furthermore, when using the model to analyze the patients recruited for this study, we found that the model predicted 39 patients with triple-negative breast cancer and 83 patients with non-triple-negative breast cancer. The overall predictive accuracy of the model was 81.90% with a sensitivity of 78.71% and a specificity of 83.00%. These results confirmed the reliability of the novel prediction model.

This study has some limitations that need to be considered, including the number and source of patients. In future studies, the scope of the study population should be further broadened to address potential issues with data imbalance, feature selection, or generalizability in specific patient groups.

5. Conclusions

In this study, we identified several significant risk factors for the development of triple-negative breast cancer based on the feature analysis of MRI images, including increased peritumoral vascularity, high T2WI signals, and ring shape enhancement. Our findings suggest that the mutual integration of AI and medical imaging should be further strengthened, and the benefits of AI should be fully exploited to increase the predictive accuracy of the risk associated with breast cancer.

AVAILABILITY OF DATA AND MATERIALS

The authors declare that all data supporting the findings of this study are available within the paper and any raw data can be obtained from the corresponding author upon request.

AUTHOR CONTRIBUTIONS

CC, CZ and YJN—designed the study and carried it out; supervised the data collection, analyzed the data, interpreted the data, prepared the manuscript for publication, and reviewed the draft of the manuscript. All authors have read and approved the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Ethical approval was obtained from the Ethics Committee of The First Affiliated Hospital of Jinzhou Medical University (Approval no. 202395). Written informed consent was obtained from a legally authorized representative(s) for anonymized patient information to be published in this article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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