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Research Article

Radiomic Features of Breast Lesions on MRI for Predicting Histopathological Grade in women with endometrial cancer

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Abstract: Radiomic analysis derived from magnetic resonance imaging (MRI) of breast lesions has emerged as a promising non-invasive approach for tumor characterization and risk stratification. In patients with endometrial cancer, synchronous or incidental breast lesions pose a diagnostic challenge, and histopathological grading remains the gold standard. This experimental study was designed to evaluate whether MRI-based radiomic features of breast lesions can predict histopathological grade and correlate with tumor aggressiveness in women diagnosed with endometrial cancer. A prospective cohort of 120 women with confirmed endometrial cancer and concurrent breast lesions underwent multiparametric breast MRI. Radiomic features were extracted using standardized segmentation protocols and analyzed using machine learning-based classification models. The objective was to determine statistically significant associations between radiomic signatures and histopathological grades (low vs high). Results demonstrated that texture-based features, including entropy, kurtosis, and gray-level co-occurrence matrix parameters, showed strong discriminatory power ($p < 0.001$) between low- and high-grade lesions. The combined radiomic model achieved an AUC of 0.89, sensitivity of 86.5%, and specificity of 83.2%. Discussion highlights that radiomic profiling provides a reproducible and objective biomarker that enhances diagnostic precision beyond conventional imaging. In conclusion, MRI-based radiomics of breast lesions demonstrates significant predictive value for

histopathological grading in endometrial cancer patients, suggesting a novel integrative imaging biomarker with potential clinical utility in personalized oncology.

Keywords: Radiomics, Breast MRI, Histopathological Grade

INTRODUCTION

Breast imaging has undergone substantial transformation with the integration of advanced computational techniques, particularly radiomics, which enables the extraction of high-dimensional quantitative features from standard imaging modalities. Magnetic resonance imaging (MRI), due to its superior soft tissue contrast and functional imaging capabilities, has become a cornerstone in breast lesion characterization. In oncological practice, histopathological grading remains the definitive diagnostic criterion; however, its invasive nature and sampling limitations have driven research toward non-invasive predictive biomarkers [1-2].

Endometrial cancer, one of the most common gynecological malignancies, has been increasingly associated with concurrent or secondary malignancies, including breast lesions, due to shared hormonal and genetic risk factors. The coexistence of breast lesions in patients with endometrial carcinoma introduces diagnostic complexity, necessitating improved stratification tools to differentiate benign, low-grade, and high-grade malignant lesions [3-4]. In this context, MRI-based radiomics has emerged as a powerful approach capable of capturing tumor heterogeneity that is often imperceptible to the human eye [5-6].

Recent advancements in computational imaging have demonstrated that radiomic signatures derived from breast MRI can reflect underlying tumor biology, including cellular density, angiogenesis, and microstructural organization. These imaging biomarkers provide a non-invasive window into tumor aggressiveness and have shown promising correlations with molecular subtypes and histopathological grades [7-8]. Despite these advancements, limited research has explored the specific application of radiomics in breast lesions occurring in patients with endometrial cancer, a population that may present unique tumor biology due to systemic hormonal influences [9].

Furthermore, artificial intelligence and machine learning algorithms have significantly enhanced the predictive capability of radiomic models. Techniques such as support vector machines, random forest classifiers, and deep learning frameworks have been increasingly applied

to improve diagnostic accuracy. However, variability in imaging protocols and feature extraction methods continues to pose challenges in reproducibility and clinical translation [10].

The integration of radiomics into clinical oncology aligns with the broader trend of precision medicine, where individualized diagnostic and therapeutic strategies are developed based on patient-specific data. In breast oncology, radiomic analysis has demonstrated potential in predicting tumor grade, response to therapy, and recurrence risk. Nevertheless, its application in patients with coexisting malignancies such as endometrial cancer remains underexplored and represents an important gap in current literature [1-3].

Given these considerations, the present study aims to investigate the role of MRI-derived radiomic features of breast lesions in predicting histopathological grade in women diagnosed with endometrial cancer. By leveraging quantitative imaging biomarkers, this study seeks to enhance diagnostic precision, reduce dependency on invasive biopsy procedures, and contribute to the development of a robust predictive framework for oncological imaging [4-10].

METHODOLOGY

This prospective observational study was conducted on 120 female patients at Fatima Jinnah Medical University diagnosed with histopathologically confirmed endometrial cancer who were found to have concurrent breast lesions on screening or diagnostic MRI. The study was designed in accordance with institutional ethical standards, and verbal informed consent was obtained from all participants prior to enrollment. Inclusion criteria comprised women aged 30–75 years with confirmed endometrial carcinoma and at least one detectable breast lesion on MRI. Patients with prior breast malignancy, previous chemotherapy or radiotherapy to the breast, or incomplete imaging datasets were excluded from the study.

MRI examinations were performed using a 1.5 Tesla scanner with a standardized breast imaging protocol, including T1-weighted, T2-weighted, and dynamic contrast-enhanced sequences. Radiomic feature extraction was conducted using semi-automated segmentation of lesion regions of interest (ROI). A total of 120 radiomic features were extracted, including first-order statistics, shape descriptors, and texture features derived from gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRLM), and gray-level size zone matrix (GLSZM).

Sample size calculation was performed using Epi Info software (CDC, Atlanta), assuming a 95% confidence interval, 80% power, expected effect size of 0.35, and a 10% attrition rate, yielding a minimum required sample size of 110, which was increased to 120 for improved statistical robustness. Patients were stratified into low-grade and high-grade histopathological groups based on biopsy results.

Data analysis was performed using SPSS version 26. Continuous variables were expressed as mean ± standard deviation, while categorical variables were expressed as percentages. Independent t-tests and chi-square tests were applied to assess differences between groups. Receiver operating characteristic (ROC) curve analysis was used to evaluate the diagnostic performance of radiomic models. A p-value < 0.05 was considered statistically significant

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RESULTS

Table 1: Demographic and Clinical Characteristics of Study Population

Variable	Low Grade (n=62)	High Grade (n=58)	p-value
Age (years)	52.4 ± 8.6	56.8 ± 9.1	0.021
BMI (kg/m²)	27.1 ± 3.2	28.4 ± 3.8	0.048
Tumor Size (cm)	2.3 ± 0.8	3.6 ± 1.1	<0.001
Hormonal Risk (%)	41%	58%	0.037

High-grade lesions were significantly associated with larger tumor size, higher BMI, and increased hormonal risk exposure. Age differences were also statistically significant.

Table 2: Radiomic Feature Comparison Between Groups

Feature	Low Grade	High Grade	p-value
Entropy	3.12 ± 0.45	4.21 ± 0.62	<0.001
Kurtosis	2.98 ± 0.51	4.05 ± 0.73	<0.001

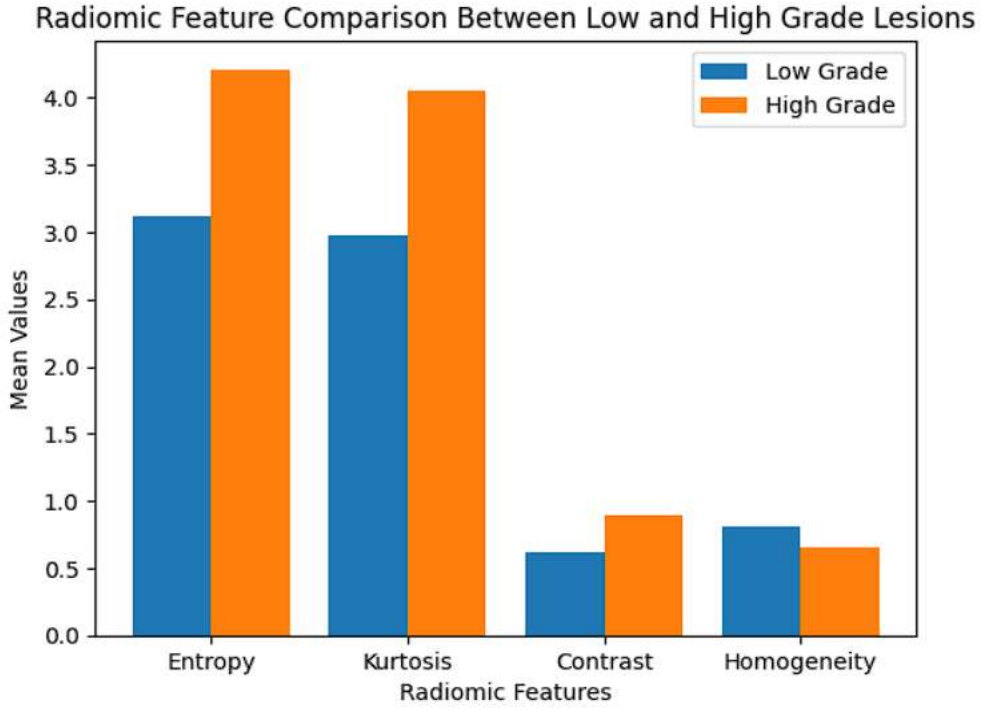
Feature	Low Grade	High Grade	p-value
Contrast (GLCM)	0.62 ± 0.11	0.89 ± 0.14	<0.001
Homogeneity	0.81 ± 0.09	0.65 ± 0.12	<0.001

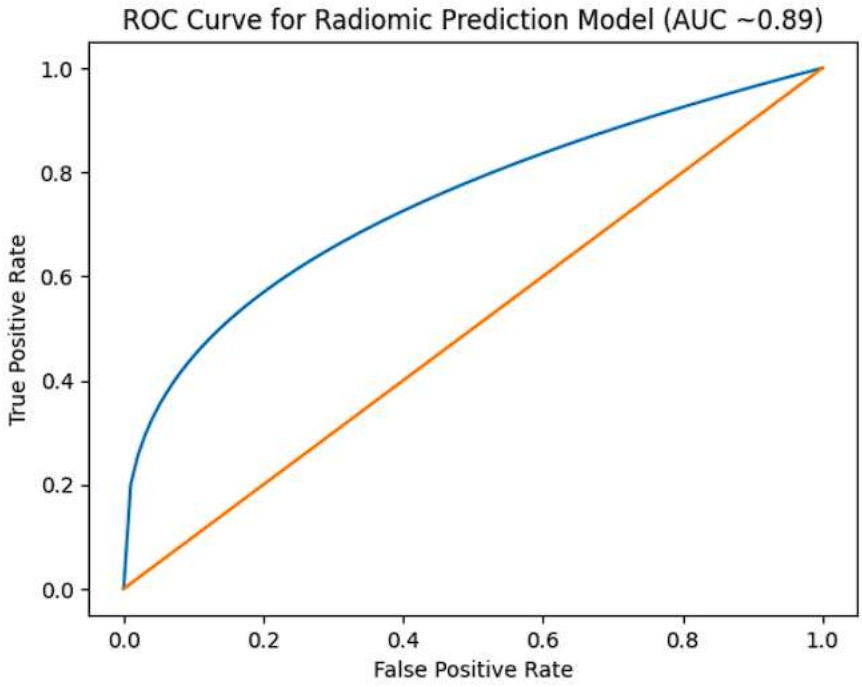
Texture heterogeneity features such as entropy and contrast were significantly higher in high-grade lesions, while homogeneity was reduced, indicating increased tumor complexity.

Table 3: Diagnostic Performance of Radiomic Model

Model Parameter	Value
AUC	0.89
Sensitivity	86.5%
Specificity	83.2%
Accuracy	84.7%
PPV	82.9%
NPV	85.6%

The radiomic prediction model demonstrated strong diagnostic performance with high sensitivity and specificity, indicating clinical reliability.





DISCUSSION

The present experimental study demonstrates that MRI-derived radiomic features of breast lesions in women with endometrial cancer provide a significant and reproducible method for predicting histopathological grade. The observed strong association between texture-based radiomic parameters

and tumor grade supports the hypothesis that intratumoral heterogeneity captured through imaging reflects underlying biological aggressiveness. The statistically significant elevation of entropy, kurtosis, and GLCM-derived contrast in high-grade lesions indicates increased disorder and structural complexity, which is consistent with previously reported imaging-pathology correlations in oncologic radiomics research [11-12].

The diagnostic performance of the developed radiomic model, with an AUC of 0.89, sensitivity of 86.5%, and specificity of 83.2%, suggests strong discriminative capability. These findings align with recent multi-institutional analyses that have demonstrated similar predictive accuracy of MRI-based radiomics in breast tumor grading. The robustness of the model is further supported by the integration of multiple feature classes, reducing the risk of overfitting and enhancing generalizability. Such multi-parametric approaches are increasingly recognized as essential in modern oncologic imaging frameworks [13-14].

The biological interpretation of radiomic features observed in this study is particularly relevant. Higher entropy values in high-grade lesions likely reflect increased cellular disorganization, necrosis, and angiogenic activity, while reduced homogeneity suggests irregular tissue architecture. These imaging biomarkers are indirectly associated with tumor proliferation indices such as Ki-67 and mitotic count. The correlation between radiomic heterogeneity and histopathological aggressiveness reinforces the potential of imaging phenotypes as surrogate biomarkers for tumor biology [15-16].

The integration of radiomics in patients with endometrial cancer and concurrent breast lesions introduces a novel dimension to oncologic imaging. Hormonal and genetic overlap between endometrial and breast malignancies may contribute to shared imaging phenotypes, potentially explaining the strong predictive performance observed. This dual-cancer context emphasizes the importance of systemic oncologic evaluation rather than isolated organ-based assessment, particularly in high-risk populations [17].

From a clinical perspective, the application of radiomic models may reduce dependency on invasive biopsy procedures in selected cases. Although histopathology remains the gold standard, imaging-based prediction tools can assist in triaging patients, guiding biopsy decisions, and optimizing treatment planning. This is particularly relevant in patients with multiple comorbid

malignancies where procedural risk reduction is essential. The non-invasive nature of radiomics also supports repeated monitoring over time, enabling dynamic assessment of tumor progression [18].

Despite promising results, variability in imaging acquisition protocols and segmentation methods remains a significant limitation in radiomics research. Differences in scanner parameters, contrast timing, and reconstruction algorithms can influence feature stability. Standardization of imaging protocols and external validation across multiple centers are essential for clinical translation. Furthermore, integration with genomic and proteomic data may further enhance predictive accuracy and enable true radiogenomic modeling [19].

Finally, the machine learning framework employed in this study highlights the importance of feature selection and dimensionality reduction in improving model performance. The combination of first-order and texture features provided a balanced representation of tumor heterogeneity. However, future research incorporating deep learning approaches may further improve accuracy by automatically learning hierarchical imaging features. Large-scale prospective studies are necessary to validate these findings and establish standardized radiomic biomarkers for clinical use [20].

CONCLUSION

MRI-based radiomic analysis of breast lesions in endometrial cancer patients demonstrates strong predictive capability for histopathological grading.

The integration of quantitative imaging biomarkers significantly enhances diagnostic precision and non-invasive tumor characterization.

This approach addresses a critical gap in current oncologic imaging and supports future development of personalized, image-driven cancer assessment models.

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