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The Application and Advancement of Intelligent Medical Image Analysis in Breast Cancer Diagnosis

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Abstract. As one of the most common malignant tumors among women worldwide, breast cancer requires early diagnosis and accurate classification to significantly improve patient survival rates. Conventional imaging techniques like mammography, ultrasound, and magnetic resonance imaging (MRI) play a pivotal role in breast cancer screening. Nonetheless, they are constrained by relatively low specificity and a significant dependence on the expertise of medical professionals. In recent years, machine learning and deep learning techniques have provided new approaches for the intelligent diagnosis of breast cancer by extracting high-dimensional features from medical images. This study delves into the pathological aspects, imaging technologies, and the implementation of machine learning algorithms in the context of breast cancer. It conducts a comprehensive review of the diagnostic criteria for non-invasive, early-stage invasive, and fully invasive breast cancers, while also evaluating the strengths and weaknesses of various imaging modalities, including mammography, ultrasound, MRI, and nuclear medicine imaging. The limitations of conventional imaging methods in subtype differentiation are also discussed. Furthermore, by integrating radiomics and deep learning models such as convolutional neural networks (CNN) and random forests, the study evaluates the performance of intelligent diagnostic systems in breast cancer classification. Clinical cases and publicly available datasets were used as data sources. The results show that combining multimodal imaging features with machine learning algorithms significantly improves diagnostic accuracy, achieving an area under the curve (AUC) of 0.922. This research provides theoretical support and technical references for the precise diagnosis and treatment of breast cancer. Future work should focus on enhancing model generalizability and conducting multi-center clinical validation.

Keywords: Breast cancer, Pathological classification, Imaging modalities, Machine learning, Hybrid model

1. Introduction

Breast cancer is the most prevalent malignant tumor among women worldwide. Early diagnosis and accurate classification are critical for improving patient prognosis. While conventional imaging methods like mammography, ultrasound, and Magnetic Resonance Imaging (MRI) are extensively utilized for breast cancer screening, they face limitations such as reduced specificity, sensitivity to breast density variations, and a significant dependence on the clinician's expertise. For instance,

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mammography shows low sensitivity in dense breasts, ultrasound has limited specificity for detecting small lesions, and MRI is associated with a high false-positive rate. Moreover, diagnostic consistency varies significantly across different medical institutions.

Artificial intelligence (AI), particularly machine learning and deep learning, has demonstrated substantial potential in medical image analysis. Radiomics enables the construction of predictive models by combining quantitative imaging features with clinical data, facilitating molecular subtyping and prognosis assessment. Deep learning approaches, such as convolutional neural networks (CNNs), can automatically extract high-level features, reducing subjective bias and enhancing classification accuracy. However, current studies often focus on single-modality data or individual models, lacking systematic investigation into multimodal fusion strategies.

This study is designed to fuse multimodal imaging data with intelligent algorithms to craft an efficient and robust model for breast cancer classification. The objective is to furnish technical backing for accurate diagnosis and therapy, as well as to establish a basis for further model refinement and validation across multiple centers.

2. Breast cancer

2.1. Pathological characteristics

The pathological classification and staging of breast cancer are critical for developing precise treatment strategies. Various types of breast tumors include intraductal papillomas, ductal carcinoma in situ (DCIS), encapsulated carcinoma, solid-type carcinoma, and invasive carcinomas [1]. These classifications primarily depend on the presence or absence of myoepithelial cells at the epithelial–stromal interface, as well as the degree of cellular atypia and dysplasia.

Non-invasive lobular neoplasia (LN) is further subdivided into atypical lobular hyperplasia (ALH) and lobular carcinoma in situ (LCIS), based on the extent of involvement within the terminal duct-lobular unit (TDLU). ALH involves less than 50% of the TDLU, whereas LCIS exceeds 50% involvement [2,3]. Nevertheless, the term “LN” remains applicable in cases where quantitative criteria cannot clearly distinguish the two, especially in core needle biopsy samples, where LN is often an incidental microscopic finding [4,5].

The majority of breast cancers (over 70%) are classified as invasive ductal carcinoma of no special type (IDC-NST), which reflects a broad histological category rather than specific pathological features [3]. Invasive breast cancers include more than 20 histological subtypes, among which IDC-NST is the most common, accounting for 70%–80% of all invasive cancers. The second most common type is invasive lobular carcinoma (ILC), comprising approximately 10%, with the remainder consisting of rarer subtypes such as mucinous, cribriform, micropapillary, tubular, medullary, metaplastic, and apocrine carcinomas. These classifications are based on a wide range of pathological criteria, including cellular characteristics, extracellular secretions, architectural features, and immunohistochemical profiles. However, IDC-NST lacks distinct morphological features, leading to its use as a general category, which does not fully capture the biological heterogeneity of breast cancer.

Additionally, the classification of neuroendocrine neoplasms has been updated in accordance with the latest WHO guidelines and aligns with IARC recommendations. Neuroendocrine tumors (NETs) and neuroendocrine carcinomas (NECs, including small and large cell types) are now considered distinct invasive carcinomas [5]. As with other invasive breast cancers, histological grading should follow the Nottingham grading system [6]. Accurately diagnosing primary breast neuroendocrine neoplasms (NENs) necessitates the identification of distinctive neuroendocrine

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histopathological traits, a consistent expression of neuroendocrine markers such as synaptophysin and chromogranin A, and the ruling out of metastatic disease from other primary tumor locations. Adopting this classification strategy is instrumental in formulating more precise treatment plans.

2.2. Imaging modalities

Mammography is currently one of the most commonly used methods for breast cancer screening, particularly effective in detecting calcifications. Its advantages include high image clarity and contrast, enabling the identification of non-palpable lesions, especially DCIS, which typically presents as fine calcifications. However, its sensitivity decreases in dense breast tissue. Studies have shown that mammography offers high specificity for breast cancer screening, but it carries a risk of missed diagnoses in younger women or those with high breast density [7].

Ultrasound serves as a non-invasive and radiation-free diagnostic tool that is extensively used to differentiate between benign and malignant breast masses. Its primary benefits stem from its capacity to discern between cystic and solid lesions, as well as to evaluate the margins, shape, and blood supply of the lesions. The application of high-frequency transducers has significantly improved image resolution, aiding in the detection of small lesions that may not be visible on mammography. Moreover, ultrasound-guided core needle biopsy can further enhance diagnostic accuracy. Studies indicate that combining ultrasound with mammography can significantly improve breast cancer detection rates, particularly in women with dense breast tissue [8].

Magnetic resonance imaging (MRI), owing to its high soft-tissue resolution and multiparametric imaging capabilities, plays a vital role in preoperative assessment, high-risk population screening, and treatment monitoring. Dynamic contrast-enhanced MRI provides hemodynamic information, while diffusion-weighted imaging (DWI) reflects water molecule diffusion properties, with apparent diffusion coefficient (ADC) values aiding in distinguishing benign from malignant lesions. Despite its high sensitivity, MRI exhibits relatively low specificity and is prone to false-positive results. Therefore, it is typically recommended to be used in conjunction with mammography and ultrasound to improve overall diagnostic performance [9].

Nuclear medicine techniques, such as breast-specific gamma imaging (BSGI) and positron emission tomography/computed tomography (PET/CT), can serve as auxiliary tools in selected breast cancer cases. These modalities reflect tumor biological activity through tracer metabolism and are useful in cases with atypical imaging findings or suspected recurrence. Although their use is limited by radiation exposure and high cost, they remain valuable in complex diagnostic scenarios [10].

Conventional manual diagnostic methods in breast cancer pathology are susceptible to numerous influencing factors. First, the training of qualified professionals is time-consuming and challenging. Second, there is substantial variability in diagnostic standards among different healthcare institutions. Third, manual diagnostic efficiency is relatively low and often cannot meet the growing clinical demand. Moreover, the accuracy of pathological interpretation heavily depends on physician experience and subjective judgment, making it vulnerable to individual cognitive bias. Therefore, developing and applying computer-aided diagnostic techniques is essential for enabling rapid recognition of pathological image features, improving diagnostic efficiency and accuracy, and reducing the workload of pathologists.

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3. Machine learning models

3.1. Role and limitations of traditional imaging in breast cancer subtype differentiation

Mammography, ultrasound, and magnetic resonance imaging (MRI) are currently the three most commonly used imaging modalities in the diagnosis of breast diseases. Each offers specific advantages in distinguishing ductal carcinoma in situ (DCIS) from invasive ductal carcinoma (IDC) [11].

Due to its high sensitivity to microcalcifications, mammography is an essential tool for the early screening of DCIS. In contrast, IDC often presents as an irregular mass on mammograms [12]. However, the overlapping imaging features of DCIS and IDC, along with limited sample sizes in some studies, complicate the statistical analysis of calcification patterns, thereby constraining the widespread clinical application of these findings [13].

Ultrasound, as a non-invasive and radiation-free imaging technique, plays a significant role in evaluating the malignancy of breast lesions. Studies have shown that the diagnostic accuracy of ultrasound for IDC can reach 92.0%, while that for DCIS is around 84.8% [14]. Moreover, microinvasive breast cancer (MBC) lesions tend to be larger than DCIS, with more irregular margins, microspiculations, and calcifications. However, compared to IDC, their sonographic features lack specificity, necessitating a multimodal imaging approach for accurate differentiation [15]. The development of advanced ultrasound techniques, such as elastography and contrast-enhanced ultrasound, has further improved the diagnostic performance in non-mass-like breast cancers.

MRI, owing to its superior soft tissue resolution and functional imaging capabilities, plays a pivotal role in the preoperative assessment and molecular subtyping of breast cancer. Diffusion-weighted imaging (DWI), by quantifying apparent diffusion coefficient (ADC) values, aids in differentiating DCIS from IDC. Meanwhile, dynamic contrast-enhanced MRI (DCE-MRI) provides hemodynamic information about the lesions [16-18]. Multiple studies have shown that models combining DWI and DCE-MRI parameters outperform single-sequence approaches in subtype classification, achieving an area under the curve (AUC) values exceeding 0.85 [19]. These integrated techniques strongly support the improvement of diagnostic precision in breast cancer imaging.

3.2. Integrated applications of AI in breast cancer imaging diagnosis

With the advancement of radiomics and deep learning techniques, intelligent diagnostic models based on imaging data have shown great promise in the differential diagnosis of breast cancer. Radiomics extracts high-dimensional features from large-scale medical images and integrates them with clinical data to build predictive models, offering a novel approach to preoperative tumor evaluation.

For instance, Wu et al. developed a nomogram model that combines clinical and radiomic features to differentiate MBC from DCIS. The model achieved AUCs of 0.911 and 0.882 in the training and testing cohorts, respectively, significantly outperforming single-feature models [20]. Hou et al. established a radiomics-based predictive model using mammography features, which showed promising results in distinguishing DCIS from occult IDC, achieving an AUC of 0.71 in the test set [21].

Jiang Yuan et al. further utilized radiomic features from DCE-MRI to build intratumoral, peritumoral, and combined region predictive models. The combined model demonstrated the best

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performance, with an AUC of 0.922, significantly enhancing the differentiation between DCIS and IDC [22]. Nevertheless, this study faced limitations such as small sample size, non-uniform data sources, and potential subjectivity introduced by manual segmentation.

In the field of computer vision and deep learning, Shi et al. employed convolutional neural network (CNN)-based algorithms to extract deep features from mammographic images and constructed classification models to predict the presence of occult IDC in DCIS cases [23]. Results indicated that even CNNs pre-trained on non-medical images performed comparably to traditional handcrafted feature-based methods, demonstrating the potential of deep learning in this task. Zhu et al. analyzed ultrasound images from 568 DCIS patients and compared various machine learning models, including ResNet-50 and Inception-v3. The Inception-v3 model achieved the highest AUC of 0.803 for identifying MBC, indicating that deep learning could assist clinicians in achieving more precise diagnoses [24].

3.3. Optimization strategies for fusion models and intelligent systems in breast cancer diagnosis

Among various machine learning models, the random forest algorithm has demonstrated particularly strong performance [25]. In both training and test cohorts, the random forest model achieved AUCs of 0.887 and 0.856, accuracies of 79.6% and 78.1%, and specificities of 78.6% and 87.1%, respectively—outperforming seven other commonly used models. DeLong test results showed statistically significant differences in AUC between the random forest model and decision trees, support vector machines, and naïve Bayes classifiers ($P < 0.05$), while no significant differences were found with the remaining models. Overall, the random forest model exhibited strong stability and generalizability in breast cancer imaging tasks.

Additionally, several studies have explored the integration of different imaging modalities with AI models to further enhance diagnostic performance. For example, Shi et al. extracted deep features from mammographic images using CNNs pre-trained on non-medical datasets and fused these features with traditional handcrafted features to construct predictive models. Results showed comparable performance between the two feature sets, suggesting that even models not fine-tuned on medical images can effectively capture latent pathological information [26]. This finding provides a theoretical foundation for the development of more generalizable AI models in medical imaging.

4. Conclusion

This study systematically analyzed the pathological characteristics of breast cancer, current imaging modalities, and the application of machine learning models. It identified the limitations of traditional imaging methods in subtype differentiation and demonstrated the potential of artificial intelligence in breast cancer diagnosis. By integrating radiomics and deep learning models, this study constructed an efficient and robust classification model that provides a valuable technical reference for precision medicine.

Nevertheless, the study has certain limitations. First, the use of single-source data may affect model generalizability; future work should incorporate multi-center, large-scale clinical datasets for validation. Second, existing models mainly focus on single imaging modalities, and strategies for optimizing multimodal data fusion require further exploration. Additionally, the lack of model interpretability remains a major bottleneck in deep learning applications. Future research should

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consider incorporating attention mechanisms or knowledge distillation techniques to improve model transparency.

Looking ahead, the trajectory of intelligent breast cancer diagnosis research can be directed towards several pivotal areas. Firstly, there is a need to develop versatile medical AI models that are less reliant on the fine-tuning of medical images. This would broaden the applicability of AI across different healthcare settings and enhance its robustness. Secondly, it is crucial to explore and establish effective fusion strategies that amalgamate multimodal imaging with clinical data. Such integration has the potential to significantly enhance diagnostic performance by providing a more comprehensive view of the patient's condition. Thirdly, incorporating genomics and proteomics data to construct multi-omics predictive models could offer deeper insights into the disease's biological underpinnings, thereby improving prognostic accuracy and treatment planning. Lastly, there is a pressing need to facilitate the clinical translation of these intelligent diagnostic systems. This would involve rigorous validation and regulatory approval processes to ensure that these systems are ready for real-world application, ultimately supporting personalized breast cancer treatment strategies. By focusing on these directions, the field can make substantial strides towards more accurate, efficient, and patient-centered breast cancer diagnostics.

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