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Advances in Artificial Intelligence for Predicting Breast Cancer Using Chest CT Scans

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Abstract: Breast cancer is the most common malignant tumor among women worldwide, with its incidence and mortality ranking first among all cancers. Early diagnosis and treatment significantly improve prognosis and reduce disease-related mortality. Chest computed tomography (CT), a routine examination for physical assessments and hospitalized patients, can screen for the presence of breast nodules and provide an initial assessment of malignancy risk. In recent years, artificial intelligence (AI) has advanced rapidly in the medical field. Studies have demonstrated that the sensitivity and accuracy of chest CT in diagnosing breast cancer are enhanced through the application of AI methods. This article explores the research progress in breast cancer diagnosis utilizing artificial intelligence based on chest CT examinations.

Keywords: Thoracic CT; Artificial intelligence; Breast cancer; Progress

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1. Introduction

Breast cancer is the most prevalent malignancy in women. According to the American Cancer Society, nearly 300,000 new cases of invasive breast cancer and more than 50,000 diagnoses of ductal carcinoma in situ are expected in 2023, with over 43,000 deaths attributed to breast cancer in the United States alone. While most breast cancers are detected through mammograms or ultrasounds, they can also be identified incidentally during other diagnostic tests. Chest computed tomography (CT) examinations, which routinely include the breast area, can detect incidental breast lesions in up to 7% of scans, with 24% to 48% of these lesions ultimately diagnosed as breast cancer [1].

Early diagnosis and treatment are widely acknowledged as critical for improving the prognosis of breast cancer patients [2]. Therefore, the potential for incidental breast cancer detection during chest CT examinations should not be overlooked [3]. With ongoing advancements, artificial intelligence is increasingly being applied to various aspects of medical diagnosis and treatment, reflecting both societal progress and technological innovation. This paper reviews the efficacy of chest CT in breast cancer diagnosis as evaluated in previous studies and examines the research progress of artificial intelligence in enhancing chest CT-based breast cancer diagnosis.

2. The value of chest CT in breast cancer diagnosis

Over the past decade, the demand for chest CT scans has grown exponentially, covering a wide range of indications. Chest CT scans include all or part of the breast, making them a potential modality for detecting new breast lesions. However, breast lesions incidentally identified on CT scans are often overlooked, inadequately described, or occasionally misdiagnosed. Critical features for accurate assessment of breast lesions on CT include margins, morphology, enhancement patterns, density, and associated findings. Notably, edge spiculation, irregular morphology, and enhancement patterns are highly predictive of malignant tumors. Additional findings may include skin thickening, lymphadenopathy, structural deformation, or invasion of the chest wall or skin [4].

Chest CT scans present an opportunity for breast cancer detection, particularly as screening mammography rates decline [5] while chest CT usage increases [6,7]. For example, the availability of low-dose chest CT for lung cancer screening has risen. Consequently, some women may undergo chest CT scans without receiving mammograms or other breast screening tests. In such cases, chest CT may be the sole imaging modality that includes the breast, offering radiologists a crucial chance to identify cancers incidentally detected through "screening." This trend is particularly relevant given recent guidelines from the American Cancer Society (ACS) [8] and the United States Preventive Services Task Force (USPSTF) [5,9]. The ACS recommends annual mammograms for women aged 45 to 54 and biennial mammograms for women aged 55 and older. Similarly, the USPSTF guidelines suggest initiating mammograms at age 50, followed by biennial screening for women aged 50 to 74. These recommendations diverge from the American College of Radiology guidelines, which advocate annual mammograms starting at age 40. Consequently, women in their 40s or older women in years without mammograms may rely on chest CT scans for incidental breast cancer detection.

Chest CT scans offer promising potential for evaluating breast parenchyma without additional radiation exposure, patient time, or direct costs. Certain breast regions, such as the distal medial side, which may be challenging to assess through mammography, can often be better visualized on CT.

Several studies have reported incidental breast cancer findings on chest CT scans. Swensen *et al.* identified three cases of breast cancer (1.4%) among 210 patients screened for lung cancer [10]. Monzawa *et al.* reported 10 breast cancers (0.34%) among 2,945 women [11], while Poyraz *et al.* identified 12 cases (0.64%) among 1,872 women [12]. Lin found 36 cases (0.26%) among 13,651 patients after excluding individuals with a history of breast cancer [13]. Parvaiz and Isgar analyzed a population of 21,127 patients undergoing chest CT and identified 40 cases (0.19%) with sporadic breast lesions, of which 20 were confirmed as cancer. Of these, only four cases were operable [14]. These findings underscore the potential of chest CT to detect unsuspected breast cancer.

Chest radiologists can evaluate and report CT BI-RADS density [15] while interpreting chest CT images, including assessing breast parenchyma. Studies have demonstrated that the BARCS assessment, similar to the BI-RADS assessment, identifies 82% of invasive breast cancers visible on mammograms. Although mammography remains the gold standard for early breast cancer detection and is proven to reduce mortality [16,17], declining utilization and increasing reliance on chest CT highlight the responsibility of chest radiologists to evaluate breast parenchyma when recent mammograms are unavailable.

Agliata *et al.* analyzed 42,864 chest CT scans performed between January 1, 2016, and April 30, 2022, on patients with unrelated diagnoses [18]. Among these, 68 patients (3 men and 65 women) underwent CT detection of breast nodules followed by mammography, breast ultrasonography, and biopsy. Histopathological confirmation of malignancy was obtained in 35 cases. Pearson's chi-squared test revealed that CT features significantly associated with BI-RADS 5 after mammography included post-contrast enhancement ($P = 0.001$), irregular margins ($P = 0.0001$), nipple retraction ($P = 0.001$), skin thickening ($P = 0.024$), and structurally atypical lymph nodes suggestive of metastatic involvement ($P = 0.0001$). Predictors of positive biopsy results included post-contrast enhancement ($P = 0.0001$), irregular margins ($P = 0.0001$), and suspicious lymph nodes ($P = 0.011$). The incidence of incidental breast nodule detection on chest CT was 0.21%. Accurate descriptions of CT features, such as post-contrast enhancement, irregular margins, nipple retraction, skin thickening, and atypical lymph nodes, can significantly aid in establishing radiological suspicion of malignancy.

3. Radiomics

3.1. Overview of radiomics

The concept of radiomics was first proposed by Dutch scholar Lambin in 2012. It refers to the high-throughput extraction of numerous quantitative image features from medical images, such as X-rays, CT scans, and MRI, and the application of data mining methods for the diagnosis and prediction of tumor diseases [19]. Radiomics technology evolved from computer-aided detection/diagnosis (CAD) technology, mining vast quantities of quantitative imaging features to characterize tumor heterogeneity and support clinical decision-making [20]. In the analysis of breast tumor images, radiomics methods have been widely utilized. Generally, the radiomics workflow includes data screening, medical imaging, feature extraction, exploratory analysis, and model construction [21].

3.2. Research progress of radiomics in the diagnosis of breast cancer

Radiomics involves transforming medical images into high-dimensional, mineable data [22,23]. In oncology, tumors are segmented, and hundreds or thousands of quantitative imaging features are extracted, including tumor shape, texture, and dynamics. These features encode simple patterns visible in medical images and complex higher-order patterns that are imperceptible to the human eye. This collection of features is collectively referred to as "radiomics features." Statistical or machine learning classifiers are then applied to these radiomics signals to categorize patients based on predictions, such as distinguishing benign from malignant breast nodules. In supervised machine learning, paired data of "radiomics features" and patient outcomes are used to train the model to identify patterns, enabling the prediction of outcomes for new inputs [23]. Machine learning methods used for this purpose include logistic regression, random forests/decision trees, and support vector machines (SVMs).

Several studies have evaluated the potential of machine learning in chest CT for breast cancer diagnosis. Feng *et al.* [24] retrospectively analyzed 300 randomly selected patients, comprising 100 patients with triple-negative breast cancer (TNBC) and 200 patients without TNBC (NTNBC). The cohort included 180 patients in the training group and 120 in the validation group. Molecular subtypes of breast cancer were determined using immunohistochemical methods. Radiomics features were extracted from 3D CT images, and the least absolute shrinkage and selection operator (LASSO) logistic regression method was used to select image features and calculate radiomics scores. Receiver operating characteristic (ROC) curve analysis was employed to assess the diagnostic value of the radiomics score for TNBC. Five image features were significantly associated with TNBC subtypes ($P < 0.001$). Radiomics features based on imaging demonstrated strong predictive value for TNBC, with the area under the ROC curve (AUC) of the discovery group and validation group being 0.881 (95% CI: 0.781–0.921) and 0.851 (95% CI: 0.761–0.961), respectively. Sensitivity and specificity were 0.767 and 0.873 for the discovery group and 0.785 and 0.915 for the validation group, respectively. These findings indicate that radiomics features derived from preoperative CT can differentiate TNBC from NTNBC, offering additional value to conventional chest contrast-enhanced CT and assisting in clinical treatment planning.

In another study, Liu *et al.* [25] retrospectively collected data from 112 patients with pathologically confirmed breast cancer. The patients were randomly divided into a training set (75 cases) and a test set (37 cases). Radiomics features were extracted from breast CT images using the LASSO algorithm. A multivariate logistic regression model was constructed by combining the selected radiomics features with relevant clinical risk factors, and the model was validated. A corresponding nomogram was developed, and a calibration curve was used to evaluate model performance. The model constructed with the training set achieved a C-index value of 0.727 (95% CI: 0.719–0.736), while the test set yielded a C-index value of 0.711 (95% CI: 0.703–0.718). The mean square error of the prediction model, calculated from predicted and actual probabilities of axillary lymph node metastasis, was 0.072. These results suggest that the prediction model based on radiomics features extracted from preoperative CT images effectively predicts the status of axillary lymph node metastasis in breast cancer patients.

4. Deep learning

4.1. Overview of deep learning

Unlike traditional radiomics methods, deep learning constructs end-to-end models using multi-layer neural networks to achieve the detection, diagnosis, and prediction of breast tumors [26]. Currently, convolutional neural networks (CNNs) are the most commonly employed deep learning models in breast cancer research. A CNN model typically consists of input layers, convolutional layers, activation functions, pooling layers, and fully connected layers. Classical models, such as AlexNet, VGG, and GoogleNet, have been applied to the detection and diagnosis of breast tumors [27].

In comparison to traditional radiomics models, deep learning models do not require predefined features. Instead, they can autonomously extract valuable deep image information from breast tumor images through iterative training, resulting in higher predictive performance. However, as data-driven algorithms, high-performance deep learning models often require extensive datasets, typically comprising tens of thousands of samples. The limited availability of large, multi-center datasets hinders the clinical translation and application of these models in current studies. Additionally, the “black box” nature of deep learning models presents challenges in terms of interpretability. Exploring methods to enhance the interpretability of deep learning models for breast tumor images remains a critical area of research.

4.2. Research progress of deep learning in the diagnosis of breast cancer

Advances in computer technology and the widespread application of big data have driven the rapid development of deep learning, particularly convolutional neural networks [28]. In recent years, deep learning technology has been widely implemented in medical imaging [29]. Its application has shown the potential to enhance the sensitivity of chest CT in diagnosing early breast cancer, as evidenced by several studies.

A retrospective study conducted by Koh *et al.* [3] collected 1,170 preoperative chest CT scans following breast cancer diagnoses for algorithm development (n = 1,070), internal testing (n = 100), and external testing (n = 100). A deep learning algorithm based on RetinaNet was developed and tested for breast cancer detection using chest CT. On an in-house test set, the algorithm detected 96.5% of breast cancers with 13.5 false positives (FPs) per case. On the external test set, it detected 96.1% of breast cancers with 15.6 FPs per case. When a candidate probability of 0.3 was used as the cut-off value, the sensitivity of the internal test set was 92.0% with 7.36 FPs per case, and the sensitivity of the external test set was 93.0% with 8.85 FPs per case. When the candidate probability was increased to 0.4, the sensitivity of the internal test set was 88.5% with 5.24 FPs per case, and the sensitivity of the external test set was 90.7% with 6.3 FPs per case. These findings indicate that the deep learning algorithm can effectively and sensitively detect breast cancer on chest CT in both internal and external test sets.

Another study by Yang *et al.* [30] retrospectively collected data from 348 breast cancer patients with pathologically confirmed sentinel lymph node (SLN) metastases. All patients underwent enhanced CT examinations before surgery, and the CT images were segmented and analyzed to extract deep features. After feature selection, key features were used to construct deep learning signatures. The discrimination, calibration, and clinical utility of these signatures were evaluated in a main cohort (184 patients from January 2016 to March 2017) and validated in an independent cohort (164 patients from April 2017 to December 2018). Ten deep-learning features were selected from the main cohort to establish a deep-learning signature for SLN metastasis. The AUC was 0.801 (95% confidence interval: 0.736–0.867) for the main cohort and 0.817 (95% confidence interval: 0.751–0.884) for the validation cohort.

To further distinguish the number of metastatic SLNs (1–2 or more than 2), an additional deep-learning signature was developed, demonstrating moderate performance (AUC = 0.770). These findings suggest that the developed deep-learning model can be used to predict SLN metastasis status and the number of metastatic SLNs preoperatively in breast cancer patients. Deep learning models offer a non-invasive approach to assist clinicians in predicting SLN metastasis in breast cancer patients.

5. Conclusion

Radiomics and deep learning are two of the most widely applied technologies in the medical imaging field. Existing research on artificial intelligence applications in chest CT examinations primarily focuses on enhanced CT and multi-function CT, with limited studies investigating the direct application of non-enhanced chest CT.

Based on chest CT examinations, radiomics and deep learning have achieved advancements in several areas, including breast cancer diagnosis, axillary lymph node metastasis prediction, molecular subtype classification, and the evaluation of treatment efficacy following neoadjuvant chemotherapy. Among these, research on predicting axillary lymph node metastasis and evaluating treatment efficacy after neoadjuvant chemotherapy has garnered significant attention due to its substantial clinical relevance.

In breast cancer diagnosis using chest CT, both radiomics and deep learning have shown promise. However, research in radiomics is more extensive and mature compared to that in deep learning. Nonetheless, deep learning remains in a stage of significant potential within this field, offering vast opportunities for further exploration and development.

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