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The role of Artificial Intelligence in detecting breast lesions using ultrasound

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Abstract:
Introduction and objective: Breast cancer is the most diagnosed cancer and the second leading cause of cancer deaths in women globally, with rising cases and mortality. Early detection via mammography, ultrasound, or MRI is vital, with ultrasound excelling in dense breast tissue due to its safety and accuracy.
Review methods: A literature review utilizing databases like Scopus, Google Scholar, and PubMed, with keywords such as "AI use in radiology" and "BI-RADS scale" underscores the need for advancements in understanding and managing graft rejection.
Brief knowledge status: AI develops systems that simulate human intelligence, excelling in breast imaging by detecting patterns and providing accurate results. Machine learning (ML) and deep learning (DL) drive advances, with DL's CNNs leading in image analysis. AI aids BI-RADS lesion classification, ultrasound lesion detection, lymph node analysis, and treatment response prediction, often surpassing radiologists. Its future relies on real-world validation, improved outcomes, and clinical integration.
Discussion: The integration of artificial intelligence (AI) into breast imaging marks a transformative leap in diagnostic radiology, enhancing precision, efficiency, and scalability. Driven by advancements in machine learning (ML) and deep learning (DL), AI excels in analyzing complex datasets. However, its clinical adoption requires addressing key considerations with a nuanced approach.
Summary: In conclusion, AI holds immense promise in breast imaging, poised to redefine the field through enhanced diagnostic capabilities and clinical utility. Continued advancements and validation efforts will ensure its broader acceptance and sustained impact in medical imaging.

Keywords:
artificial intelligence, breast imaging, computer-aided detection, breast cancer, BI-RADS scale, image analysis

I. Introduction

Breast cancer is the most frequently diagnosed cancer and the second leading cause of cancer-related deaths among women worldwide, with rising incidence and mortality rates.[1] Early detection and timely treatment are crucial for reducing mortality. Imaging techniques like mammography, breast ultrasound, and MRI play key roles in screening and diagnosis. Breast ultrasound stands out for its safety, convenience, non-invasive nature, and high diagnostic accuracy, especially in patients with dense breast tissue, where mammography sensitivity is lower[2]

Imaging plays a key role in early detection and clinical staging of breast cancer, but challenges persist. Radiologists face heavy workloads from large volumes of imaging data, while low-quality images or ambiguous features limit diagnostic accuracy. Subtle or complex disease manifestations often require combining imaging with clinical information for accurate judgment.

Computer-assisted diagnosis and treatment (CAD/CAT) leverages computer technology, often integrated with electronic health records (EHR), to support healthcare professionals in accurate diagnosis and evidence-based treatment.

The primary objectives of CAD/CAT are to minimize diagnostic errors, enhance treatment efficiency and effectiveness, and improve patient outcomes. By providing accurate, up-to-date, and evidence-based information, CAD/CAT aids healthcare teams in delivering high-quality care.[3]. Advances in AI-based CAD have enhanced its flexibility and clinical value, particularly in breast cancer. Reliable, optimized CAD method with a high-performance computing may play a significant role in assisting radiologists at their work.[4]

I. Materials and Methods

The Breast Imaging-Reporting and Data System (BI-RADS), created by the American College of Radiology (ACR), standardizes breast imaging findings from mammography, ultrasound, and MRI. It categorizes results into 0–6, reflecting the suspicion level for malignancy. These categories guide clinical decisions, determining the necessity for further diagnostics, monitoring, or treatment, ensuring systematic and effective patient care.[5]

In this review, we collected studies concerning AI- enhanced CAD of breast cancer, focusing our effort to assess the stage of knowledge of its use in ultrasonography. The literature search utilized the following keywords: “breast cancer,” “artificial intelligence,” “deep learning,” “machine learning,” “imaging,”""ultrasound,””BI-RADS”

Articles and reviews were manually excluded if they were irrelevant to the primary diagnosis of breast cancer or focused specifically on computer-aided diagnosis using pathological data. Publications in languages other than English were also excluded.

III. The BI-RADS System in Breast Cancer Diagnostics

Breast density is classified by a radiologist into four BI-RADS categories, ranging from the lowest density (predominantly fatty tissue) to the highest density (predominantly non-fatty tissue). These categories are defined based on a visual assessment of fibroglandular tissue content. High breast density may hinder the identification of calcifications and small lesions. In such cases, additional examinations, such as ultrasonography, may be considered [6].

The BI-RADS system is used to standardize breast imaging reports.

- **BI-RADS 0** indicates the need for additional imaging studies or comparison with prior examinations.
- **BI-RADS 1** informs the physician of a normal breast image and a 0% risk of cancer, meaning the patient can return to regular screening without the need for further diagnostic procedures.
- **BI-RADS 2** represents benign findings with no cancer risk, also requiring only routine follow-up. This category includes findings such as benign lymph node enlargement, dilated ducts, simple cysts, certain complex cysts, and benign tumors like lipomas or hamartomas.
- **BI-RADS 3** suggests a probably benign lesion, with a low or moderate risk of malignancy, warranting short-term follow-up.
- **BI-RADS 4** indicates a suspicious abnormality requiring prompt and comprehensive diagnostic workup. This category is further divided into three subgroups:
    - **BI-RADS 4A** (malignancy risk below 10%),
    - **BI-RADS 4B** (risk between 10-50%), and
    - **BI-RADS 4C** (risk between 51-95%).

- **BI-RADS 5** signals a very high probability of malignancy (95%), necessitating a biopsy.
- **BI-RADS 6** includes cases with a confirmed malignancy [7].

There is a proven strong correlation between mammography results presented and described using the BI-RADS system and ultrasound findings. Ultrasonography, often used to complement mammography, is increasingly applied, facilitating accurate diagnosis and enabling the timely initiation of appropriate treatment. Early intervention contributes significantly to improved survival rates and patient recovery. However, it is important to note that both examinations demonstrate a high level of agreement in differentiating between benign and malignant lesions [8,9,10,11].

Mammography is undoubtedly the primary screening method that should be performed to diagnose various breast abnormalities. However, in young patients, breast glandular tissue may be too dense for mammographic imaging, leading to false-positive or, worse, false-negative results. Ultrasonography is particularly useful in such cases. Studies have shown it to have higher sensitivity in patients with dense breast tissue. As a result, abnormalities in younger women are detected earlier, enabling quicker initiation of oncological treatment and improving survival rates [12].

Breast ultrasonography is a method that should unquestionably be further developed and improved. It has numerous advantages, such as broad accessibility and low cost of the procedure. However, there are also drawbacks to this method, primarily related to the limited experience of the examiner. Incorrect assessment of abnormalities revealed during ultrasonography can lead to an increased number of diagnostic errors, delayed treatment, and reduced chances of therapeutic success for the patient. False-positive results are more common with ultrasound; nonetheless, it plays a crucial role in cases where mammography proves insufficient [13].

IV. Artificial Intelligence (AI) in Breast Imaging Diagnostics

AI is a multidisciplinary field focused on developing computer systems capable of simulating human intelligence, including learning, decision-making, visual perception, and speech recognition [14,15]. Its application in breast imaging has rapidly transitioned from research and development to clinical practice [16]. AI algorithms are particularly effective at detecting complex patterns within data, enabling them to provide automated, quantitative solutions to problems. Consequently, their outcomes are often more accurate and consistent than those achieved by humans [15].

Artificial intelligence refers to the capability of algorithms to perform tasks that typically require intelligence. Machine learning (ML), a subset of AI, is a data-driven learning approach that uses mathematical models built on observed 'training' data [17,18]. ML allows computers to learn and improve performance through experience, leveraging available data without explicit programming [15].

In recent decades, advancements in algorithms, increased computing power, and the availability of large datasets have established machine learning as the state-of-the-art in numerous computer vision tasks, including healthcare applications [14].

Among ML-based algorithms, deep learning (DL) is the most influential in medical imaging, widely recognized as the leading AI tool for image analysis. A recent survey found that over 80% of studies on AI in medical imaging employed DL techniques [15].

DL relies on neural networks to extract high-level features from data, with convolutional neural networks (CNNs) being the most commonly used architecture for image analysis [16].
Radiologists use the Breast Imaging-Reporting and Data System (BI-RADS) to classify lesions. AI has been integrated into this process through computer-aided detection (CAD) systems, which support radiologists in selecting the appropriate BI-RADS category. While some CAD systems are based on pathological classification, others rely on radiologists' assessments. However, the latter approach has limitations, as the training data for these systems may incorporate inter-observer variability and structural misclassification of malignancy likelihood [17].
AI can also be applied to detect and segment lesions in ultrasound imaging [16]. Relevant images are processed by CAD systems, which identify the presence of lesions and document their size and extent. This analysis can utilize standard ultrasound images or 3D Automated Breast USG scans. Furthermore, detection and classification tasks can be integrated into a single network [17].
DL is also employed for classifying lymph nodes in axillary ultrasound images. Studies have shown that DL-based networks can analyze lymph nodes in breast cancer patients with greater accuracy than expert radiologists, increasing accuracy from 77.9% to 87.0% [17]. Additionally, DL-based models have been applied to ultrasound images to predict responses to neoadjuvant chemotherapy [16].
The future of AI in breast imaging appears promising, with its success hinging on validation in real-world clinical settings, proven improvements in patient outcomes and clinical efficiency, and smooth integration into existing clinical workflows [16].

V. Challenges, limitations, and development prospects

Current imaging techniques, including detection methods, lesion segmentation, qualitative diagnosis, and analysis of lesion image features, are not yet advanced enough to enable AI-assisted imaging diagnosis to function independently or fully support clinical diagnosis. [19] Main issues regarding use of AI-enhanced tools in breast imaging were: data quality, evaluation and validation, reliability, ethical and economic concerns, legal reasons.[20]

The effectiveness of AI in breast imaging is hindered by small datasets for training and validation, datasets used to train AI-algorithms may suffer from insufficient diversity in areas like population variance, leading to under/overrepresenation of certain categories, that can affect accuracy of judgments made by algorithms trained on such dataset.[21]

Performing reliable data labeling demands trained personnel, is time consuming and often needs additional budget to cover its expenses. [22]. Some authors suggest that extensive data sharing across centers dedicated to development of new- AI models may help by improving databases, and spread the cost of development across different institutions . Increase of input data, especially from independent sources will benefit diversity of data, and as result an accuracy of model[22].

Operations undertaken by AI - model are often unclear and untransparent even for its creators. This raises discussion on accountability of AI- tools, attitude towards predictions made by them, levels of confidence that are put in them, and liability for possible errors. [23][24].

There is a need to create AI - models, that predictions are explainable, to detect possible errors and biases, generated by algorithms[25]. AI is a revolutionary solution, unfortunately often leaving behind law-makers, patient-privacy regulations[26].
AI holds significant potential for improving breast imaging and cancer detection. However, addressing the identified barriers, including data challenges, trust, validation, and education, requires collaborative efforts among stakeholders. By leveraging facilitators, AI solutions can be effectively integrated into clinical practice, leading to enhanced healthcare outcomes.

VI. Discussion

The incorporation of artificial intelligence (AI) into breast imaging constitutes a transformative development in diagnostic radiology, offering novel capabilities in precision, efficiency, and scalability. This advancement is underpinned by rapid innovations in AI algorithms, particularly machine learning (ML) and deep learning (DL), which are increasingly regarded for their unparalleled proficiency in analyzing complex datasets. While the clinical applications of AI hold significant promise, several critical considerations merit a more nuanced discussion.

Advancements in AI for Breast Imaging

Deep learning approaches, particularly those employing convolutional neural networks (CNNs), have demonstrated substantial efficacy in breast imaging tasks such as lesion detection, segmentation, and classification. The integration of AI into the Breast Imaging-Reporting and Data System (BI-RADS) workflow has enhanced diagnostic consistency and accuracy by supporting radiologists in the classification of breast lesions. Similarly, AI-driven tools have demonstrated superior performance in the evaluation of axillary lymph nodes, surpassing the accuracy of expert radiologists. The application of AI in predicting responses to neoadjuvant chemotherapy further exemplifies its potential in advancing personalized medicine, enabling more informed clinical decision-making and potentially improving therapeutic outcomes.

Challenges and Limitations

Despite these advancements, the integration of AI into clinical breast imaging workflows is not without its limitations. A major concern lies in the dependence of AI algorithms on high-quality, heterogeneous training datasets. The limited diversity in training data may result in algorithmic biases, potentially compromising the generalizability and equity of AI performance across diverse patient populations. Furthermore, systems trained using radiologists' assessments may propagate interobserver variability and structural misclassification errors, undermining the reliability of AI-based outputs.
Another critical challenge pertains to the validation of AI systems within real-world clinical settings.
While many studies have demonstrated the efficacy of AI under controlled experimental conditions, the translation of these findings to clinical environments remains a key hurdle. Ensuring the robustness, adaptability, and reproducibility of AI algorithms across various healthcare settings is imperative for widespread adoption and sustained utility.

Opportunities for Enhancement

To unlock the full potential of AI in breast imaging, targeted strategies must address these limitations. The development of standardized, high-quality datasets that encompass a diverse array of patient demographics and imaging scenarios is paramount. Collaborative efforts among radiologists, computer scientists, and healthcare stakeholders can further refine the design and implementation of AI systems, ensuring that they align with clinical needs and ethical standards. The seamless integration of AI into existing clinical workflows requires prioritization of usability and efficiency, with the technology serving as an adjunct to, rather than a replacement for, radiologists' expertise. Moreover, establishing comprehensive regulatory frameworks and guidelines will be essential to safeguard the accuracy, transparency, and accountability of AI-driven tools in clinical practice.

Future Directions

The role of AI in breast imaging is poised for significant expansion as advancements continue to unfold. Emerging modalities such as 3D Automated Breast Ultrasound (ABUS) and multi-task networks capable of concurrent detection, segmentation, and classification hold particular promise for advancing diagnostic capabilities. Furthermore, the integration of AI with electronic health records and broader healthcare systems may facilitate holistic, data-driven approaches to patient care.

In conclusion, while AI has demonstrated immense potential in breast imaging, its success is contingent upon addressing existing challenges and fostering a multidisciplinary approach to development and implementation. Through rigorous validation, ethical oversight, and collaborative innovation, AI is positioned to redefine the field of breast imaging, ultimately enhancing diagnostic accuracy, clinical efficiency, and patient outcomes.

VII. Conclusions

Artificial intelligence (AI) has emerged as a transformative force in breast imaging, advancing from research to clinical practice at a remarkable pace. By leveraging machine learning (ML) and deep learning (DL) techniques, AI algorithms demonstrate exceptional capabilities in detecting complex patterns, yielding more accurate and consistent outcomes than human assessments.

Deep learning, particularly convolutional neural networks (CNNs), has become the cornerstone of AI applications in medical imaging, including breast imaging. Its ability to extract high-level features enables effective lesion detection, segmentation, and classification, significantly enhancing diagnostic accuracy. AI-integrated systems, such as computer-aided detection (CAD), support radiologists in BI-RADS classification and ultrasound-based lesion analysis, offering automated and quantitative solutions to clinical challenges.

Notably, DL-based models have outperformed expert radiologists in tasks such as lymph node classification and prediction of treatment responses, showcasing the potential to improve patient outcomes and clinical efficiency. Despite these advancements, the successful integration of AI into routine clinical workflows depends on further validation in real-world settings, consistent evidence of improved patient care, and seamless adaptability to existing systems.

In conclusion, AI holds immense promise in breast imaging, poised to redefine the field through enhanced diagnostic capabilities and clinical utility. Continued advancements and validation efforts will ensure its broader acceptance and sustained impact in medical imaging.

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