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Comparative Performance of AI-Based CAD vs Traditional CAD in Mammography

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ABSTRACT

Traditional computer-aided detection (CAD) systems have supported radiologists in mammographic interpretation for over two decades, yet their contribution to diagnostic improvement has been limited by high false-positive rates and inconsistent performance across breast densities. Recent advances in artificial intelligence (AI), particularly deep learning–based CAD systems, have redefined image interpretation by enabling automated feature learning from large datasets. This manuscript provides a technical comparison of traditional CAD and AI-based CAD in mammography, focusing on diagnostic accuracy, workflow efficiency, and robustness across diverse imaging environments. Evidence shows that AI-based CAD demonstrates superior sensitivity, specificity, false-positive reduction, and radiologist support, reflecting substantial progress toward reliable early breast cancer detection. Despite challenges involving transparency, dataset bias, and clinical implementation, AI-based CAD is positioned to become an essential component of modern screening programs.

Keywords: Artificial Intelligence; Computer-Aided Detection; Mammography;

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1. INTRODUCTION

Computer-aided detection systems were introduced to mammography primarily to improve radiologists' ability to identify early signs of breast cancer, including microcalcifications and small masses. Traditional CAD methods rely on manually engineered features and rule-based algorithms, which often fail to capture the complex heterogeneity of breast tissue. These limitations have contributed to inflated recall rates and minimal improvements in cancer detection [1]. In contrast, AI-based CAD systems use deep learning architectures capable of autonomously extracting hierarchical representations from imaging data, thereby enhancing lesion detection while reducing false positives [2]. The increasing availability of large annotated mammographic datasets and advances in computational efficiency have accelerated the adoption of AI in breast imaging. This review evaluates the comparative performance of traditional CAD and AI-based CAD in mammography, highlighting their respective diagnostic capabilities and clinical implications.

System Architecture and Technical Differences

Traditional CAD follows a predefined pipeline consisting of preprocessing, segmentation, handcrafted feature extraction, and classification. The performance of these systems is dependent on the quality of engineered features, which are sensitive to variations in exposure parameters, breast density, and imaging equipment. These systems often lack adaptability and generalizability, performing inconsistently across clinical environments [3]. AI-based CAD systems diverge fundamentally in design. Convolutional neural networks (CNNs) learn from raw pixel data, enabling them to identify intricate imaging patterns associated with malignancy without manual feature design. This automated learning process improves robustness across diverse populations and imaging conditions [4]. Additionally, AI-based CAD systems can be updated or retrained with new datasets, supporting continuous performance enhancement, unlike traditional CAD which remains static after deployment.

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2. METHODS

Comparative assessment of CAD technologies requires the use of validated clinical and technical performance metrics. Sensitivity, specificity, accuracy, positive predictive value (PPV), and the area under the receiver operating characteristic curve (AUC) remain standard diagnostic indicators [5]. Workflow-based assessments include changes in radiologist reading time, recall rates, and reduction in unnecessary biopsies. Clinical impact is measured by early cancer detection rates, interval cancer reduction, and diagnostic consistency across breast density categories. Studies comparing traditional CAD and AI-based CAD frequently employ multi-reader, multi-case (MRMC) designs, retrospective dataset analysis, and prospective clinical implementation trials [6].

Comparative Results

Across multiple large-scale international studies, AI-based CAD consistently outperforms traditional CAD. Traditional CAD typically achieves sensitivities in the range of 70–80%, while modern AI-based systems reach values between 88% and 96% [7]. Specificity similarly improves due to fewer false-positive markings, reducing radiologist fatigue and unnecessary recalls. One landmark trial involving more than one million screening examinations demonstrated that AI assistance reduced false positives by 25% while maintaining or improving cancer detection rates [8]. Another widely cited prospective study reported that radiologists supported by AI achieved significantly higher diagnostic accuracy than radiologists working independently [9]. AI-based CAD also improves performance in dense breast tissue, where traditional CAD shows marked limitations. Deep learning models provide better discrimination between overlapping structures and true lesions, enhancing early detection in this high-risk population [10].

Technical Analysis and Interpretation

The enhanced sensitivity of AI-based CAD is attributable to its ability to identify subtle radiographic cues that often precede clinically evident abnormalities. Deep learning systems interpret global and local mammographic patterns, capturing complex contextual relationships that traditional CAD cannot model. Improvements in specificity stem from AI's superior ability to distinguish benign anatomic variations from malignant features, thereby reducing false alarms. Workflow-related benefits include reductions in interpretation time and improved triaging efficiency, supporting radiologists in managing high-volume screening programs. The superior generalization of AI-based CAD reflects its exposure to millions of training images, enabling performance stability across scanners, vendors, and population cohorts. However, concerns persist regarding interpretability, dataset bias, and the need for regulatory compliance. Continuous monitoring and high-quality dataset curation remain essential to ensure safe deployment.

3. DISCUSSION

The comparison between traditional and AI-based CAD underscores a paradigm shift in mammography. AI-based CAD has transitioned from a simple highlighting tool to an advanced decision-support system capable of approaching expert-level performance. Its advantages extend beyond diagnostic accuracy, influencing workflow optimization, radiologist confidence, and potential reductions in healthcare costs. Despite these advancements, broad implementation requires addressing challenges such as algorithm transparency, ethical AI governance, and dataset heterogeneity. Ensuring fairness across demographic groups is critical, as biases may lead to unequal diagnostic quality. Additionally, radiologists must adapt to the integration of AI outputs, interpreting probability maps, heatmaps, and saliency-based explanations responsibly. Effective regulations, post-deployment validation, and interdisciplinary collaboration will play essential roles in ensuring safe integration into national screening programs.

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4. CONCLUSION

AI-based CAD systems offer clear advantages over traditional CAD in terms of diagnostic performance, false-positive reduction, workflow efficiency, and clinical adaptability. Their ability to autonomously learn informative imaging features and generalize across populations positions them as superior tools for modern breast cancer screening. As radiology continues to evolve toward data-driven precision diagnostics, AI-based CAD is expected to become a core component of mammographic assessment. Future work should focus on improving transparency, minimizing bias, and ensuring rigorous clinical evaluation to maximize patient benefit and maintain trust in AI-enabled healthcare.

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