

Integrating AI Technology for Breast Cancer Detection in The Workplace: A Systematic Review

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Abstract:

This systematic review explores the role of artificial intelligence (AI) technologies in detecting breast cancer within work environments, emphasizing developments in imaging techniques like mammography, ultrasound, and magnetic resonance imaging (MRI). The review showcases the effectiveness of AI, notably deep learning (DL) algorithms, in boosting diagnostic precision, minimizing false positives, and improving operational efficiency. AI frameworks, including convolutional neural networks (CNNs), show great promise in supporting radiologists by enhancing both sensitivity and specificity in identifying breast cancer. Nevertheless, challenges such as data inconsistency, the risks of model overfitting, and the necessity for varied datasets impede widespread clinical implementation. Despite these hurdles, the results highlight that incorporating AI into clinical routines can transform breast cancer screening in workplace settings, facilitating earlier detection and optimizing healthcare resources. The analysis stresses the need for additional validation and training for healthcare professionals to guarantee the smooth integration of AI technology into clinical practices.

Keywords: AI Breast Cancer Screening, Artificial Intelligence in Breast Cancer, Deep Learning (DL) in Cancer Detection, Convolutional Neural Networks (CNN), AI in Medical Imaging, Mammography AI algorithms, Breast Cancer MRI diagnosis.

Introduction

Breast cancer persists as one of the most prevalent cancers among women worldwide, underscoring the importance of early detection in enhancing survival rates (World Health Organization, 2024). Mammography has traditionally served as the benchmark for screening; nevertheless, challenges such as human error and discrepancies in radiologist proficiency have led to the investigation of additional technologies aimed at improving accuracy and efficiency (Saslow et al., 2007). In the last ten years, artificial intelligence (AI) has surfaced as a revolutionary instrument across various domains, including healthcare, due to its potential to enhance diagnostic processes and outcomes. In particular, AI technologies, which include deep learning algorithms and computer-aided detection (CAD) systems, have demonstrated encouraging outcomes in improving breast cancer identification by supporting radiologists and minimizing false positives and negatives (Yala et al., 2019).

A new approach to healthcare is presented by incorporating AI into workplace breast cancer screening programs, particularly in settings where routine screening is necessary because of occupational hazards or health promotion initiatives. This change is in line with the growing need for healthcare solutions that are more individualized, accessible, and accurate and that are easily integrated into routine procedures (Dembrower et al., 2020). AI has the potential to enhance conventional mammographic screening techniques, especially in resource-constrained or high-demand settings, where there is a prevalent shortage of radiologists and high levels of burnout (McKinney et al., 2020). Its ability to quickly evaluate large amounts of imaging data and provide reliable assessments should greatly improve the procedures for detecting breast cancer, guaranteeing timely intervention and reducing medical costs (Kooi et al., 2017).

AI applications in breast cancer detection primarily utilize deep learning (DL) models, which are adept at recognizing patterns in extensive datasets and accurately differentiating between benign and malignant lesions. According to research, AI systems can occasionally outperform radiologists in spotting minute abnormalities that

human evaluations could miss (Rodriguez-Ruiz et al., 2019). AI can improve the overall effectiveness of screening programs by serving as an independent reader in double-reading protocols or as an additional tool to increase diagnostic accuracy (Lehman et al., 2015).

Despite its growing value, artificial intelligence is still in its early stages as a component of workplace health programs that target breast cancer screening. There are a number of obstacles to overcome, including the need for reliable data, the ethical significance of healthcare AI decision-making, and worries about data security and privacy (Thrall et al., 2018). Furthermore, radiologists and other medical professionals need to be trained to interact with AI systems and understand their results so that these tools enhance human knowledge rather than completely replace it (Wu et al., 2020).

The investigation into AI applications in breast cancer screening within the workplace uncovers significant aspects that surpass traditional diagnostic approaches. Recent studies indicate a transformation from reactive healthcare responses to predictive and individualized health systems that combine intricate data flows, behavioral patterns, and genetic factors (Topol, 2019; Kalia et al., 2016).

1.1 Psychological and Behavioral Dimensions

Artificial intelligence technologies are progressively adept at assessing not solely medical imaging, but also extensive psychological and behavioral data that impact cancer risk. By incorporating metrics related to mental health, sleeping habits, and indicators of occupational stress, AI has the potential to detect nuanced risk markers that emerge prior to physiological symptoms (Shneiderman, 2020).

1.2 Predictive Multimodal Risk Profiling

Modern artificial intelligence systems are progressing past simple binary detection methods. Sophisticated algorithms now integrate genomic information, environmental conditions in workplaces, personal metabolic characteristics, and extensive health records to produce evolving risk evaluations (Kalia et al., 2016). Such multimodal strategies are changing breast cancer screening from a one-time diagnostic procedure to an ongoing, flexible risk management approach (Jiang et al., 2017).

1.3 Ethical Technology and Participatory Design

The upcoming phase of AI application requires a significant transformation in how we incorporate technology. This means crafting screening technologies that are not just advanced in their design but also fundamentally based on teamwork (Shneiderman, 2020). Participatory design stands out as a crucial model in the development of artificial intelligence systems, highlighting a cooperative and inclusive method that reaches beyond just technical capability to include ethical factors and community values (Loi et al., 2018).

1.4 Global Health Equity and Technological Democratization

Artificial Intelligence offers remarkable possibilities for tackling systemic inequities in healthcare. Through the creation of flexible, affordable screening technologies, institutions can potentially provide high-quality diagnostic services to marginalized communities and economically limited work settings (Gonçalves et al., 2022). The technological framework thus evolves into a tool for the democratization of global health (Jiang et al., 2017).

1.5 Precision Prevention and Personalized Interventions

Instead of seeing AI merely as a tool for diagnostics, new viewpoints regard it as a platform for precise prevention (Topol, 2019). These systems are capable of producing custom suggestions that include genetic counseling, changes in lifestyle, strategies for early intervention, and personalized screening processes designed according to a person's specific physiological and environmental situation (Kalia et al., 2016).

1.6 Interdisciplinary Convergence

The upcoming development of health screenings in the workplace is rooted in extraordinary interdisciplinary cooperation. Artificial intelligence advancements will progressively merge knowledge from various areas, including epidemiology, data analytics, psychology, occupational health, and molecular biology (Jiang et al., 2017). This fusion holds the potential for a deeper and more complete understanding of cancer risks and

preventive measures (Shneiderman, 2020).

AI technology has the potential to transform occupational health programs by providing quicker and more accurate screening options that lower risk and improve early detection among workers, especially in industries where women are more likely to be exposed to risk factors like chemicals or radiation (Rajendran et al., 2021).

This study aims to systematically review and evaluate the effectiveness of artificial intelligence (AI) technologies in improving breast cancer detection within workplace health programs. It also seeks to understand how AI can enhance diagnostic accuracy, AI technology presents considerable potential for enhancing breast cancer detection within occupational environments, improving diagnostic precision, alleviating the burden on radiologists, and facilitating prompt, cost-efficient screening initiatives. But the successful integration of this technology into common practice involves overcoming many practical, ethical, and technological barriers. As AI systems progress, they are expected to take over a progressively vital role in fostering health and safety within the workplace, ultimately aiding in the collective aim of decreasing breast cancer mortality rates globally.

2. Methodology

1.1 Search Strategy

The search strategy to find the studies involved accessing reputable databases like Google Scholar, Web of Science and PubMed, using specific keywords such as "AI Breast Cancer Screening", "Artificial Intelligence in Breast Cancer", "Deep Learning (DL) in Cancer Detection", "Convolutional Neural Networks (CNN)", "AI in Medical Imaging, Mammography AI algorithms" and "Breast Cancer MRI diagnosis". Peer-reviewed papers published between 2015 and 2025 were selected. Relevant studies were selected by reviewing titles, abstracts, and conducting full-text reviews for those focused on AI integration in breast cancer detection and its clinical applications. This ensured that only high-quality, relevant studies were included.

1.2. Inclusion Criteria

These inclusion criteria were used to ensure the systematic review focuses on the most relevant and recent developments in integrating AI for breast cancer detection. Studies with the following criteria were selected:

1.5.1 Papers published between 2015 and 2025.

1.5.2 Studies focusing on integrating AI technology for breast cancer detection, particularly in mammography.

1.5.3 Studies utilizing advanced AI techniques, such as deep learning (DL) and machine learning (ML), in breast cancer screening.

1.5.4 Papers discussing real-world or potential applications in improving diagnostic accuracy and reducing errors.

1.4 Exclusion Criteria

The exclusion criteria were chosen to refine the scope of the systematic review and ensure that only the most relevant and impactful studies are included. Studies with the following criteria were excluded:

1.5.5 Studies using solely traditional Computer aided detection (CAD) systems without modern AI or DL advancements.

1.5.6 Papers not focused on breast cancer or diagnostic improvements in clinical screening programs.

1.5.7 Exclusion of papers without practical or clinical validation of AI techniques.

1.5. Results of Search Process

The initial systematic search process resulted in a large number of records:

- Google Scholar: 4380 records
- Web of Science: 2309 records

- PubMed: 432 records

These records were screened based on relevance to the topic, peer-reviewed trials and adhering to the inclusion criteria. The following records were shortlisted for further analysis:

- Google Scholar: 190 records
- Web of Science: 36 records
- PubMed: 25 records

These evaluations led to exclusion of irrelevant studies:

- Google Scholar: 4190 records
- Web of Science: 2273 records
- PubMed: 407 records

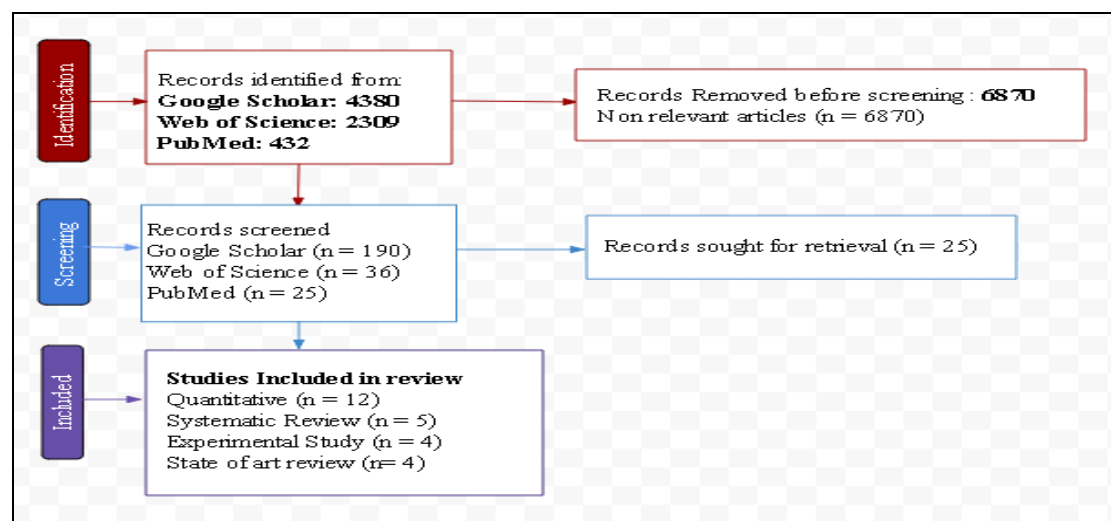


Figure 1: Flowchart of study selection according to PRISMA guidelines

Results and Discussion

The results of the systematic review emphasize the critical importance of deep learning (DL) methodologies, especially convolutional neural networks (CNNs), in the identification of breast cancer through diverse imaging techniques including mammography, magnetic resonance imaging (MRI), and digital breast tomosynthesis (DBT). The incorporation of DL models within clinical practices has shown significant improvements in diagnostic precision, sensitivity, and specificity. Nevertheless, the findings also point out the obstacles linked to the deployment of these technologies in clinical environments, which necessitate additional investigation.

The research formulated a two-phase deep learning methodology for the identification of breast masses in mammograms, attaining a sensitivity of 0.82 at a rate of one false positive per image. The approach employed a preliminary Convolutional Neural Network (CNN) to pinpoint possible masses, followed by a secondary CNN aimed at minimizing false positives. Utilizing transfer learning from non-medical fields demonstrated efficacy, with the model exhibiting enhanced performance when trained on both benign and malignant masses. The system showed superior capability in detecting masses with atypical shapes and vague margins; however, it performed more effectively in fatty tissues compared to dense breast tissues, underscoring a persistent obstacle in AI-driven mammographic assessments Geras et al. (2019). Artificial intelligence for mammography and digital breast tom synthesis: Current concepts and future perspectives.

The research indicated that artificial intelligence, especially deep learning, significantly improves the detection of breast cancer in mammography and digital breast tom synthesis (DBT) by enhancing diagnostic precision and

decreasing false positive rates. AI assists radiologists in prioritizing cases and facilitates quicker, more precise diagnoses. Although AI demonstrates potential in supporting radiologists, the study underscores challenges such as the integration of AI into clinical workflows and the necessity for comprehensive validation prior to broad implementation. In summary, AI is regarded as an essential instrument for enhancing screening efficiency and patient outcomes.

Table 1: AI Based studies in Breast Cancer Detection

Author(s) and Year	Title of the Study	Major Findings
Abdullah et al. (2025)	Deep Learning-Based Breast Cancer Diagnosis in Breast MRI: Systematic Review and Meta-Analysis	Deep learning models, particularly CNNs, demonstrated strong diagnostic performance, with a reported AUC of 0.90, sensitivity of 88%, and specificity of 90%. The study highlighted the need for diverse datasets and further model optimization.
Malherbe (2025)	Revolutionizing Breast Cancer Screening: Integrating Artificial Intelligence with Clinical Examination for Targeted Care in South Africa	The Breast AI system identified more positive cases than clinical breast examination and detected some findings missed by clinical examination. However, the reported difference was not statistically significant.
Shahid and Imran (2025)	Breast Cancer Detection Using Deep Learning Techniques: Challenges and Future Directions	The review reported diagnostic accuracy of up to 93.8% in some deep learning models. It discussed data accessibility, model interpretability, and future opportunities for improving early detection.
Carriero et al. (2024)	Deep Learning in Breast Cancer Imaging: State of the Art and Recent Advancements in Early 2024	Deep learning improved breast cancer imaging applications in mammography, ultrasound, and MRI. Validation, interpretability, and technical limitations remain important barriers to clinical adoption.
Díaz et al. (2024)	Artificial Intelligence for Breast Cancer Detection: Technology, Challenges, and Prospects	AI techniques, especially deep learning, showed promise in improving mammographic detection and reducing diagnostic errors. The study emphasized high-quality data, rigorous validation, and compliance with clinical standards.
Fatima et al. (2024)	Analyzing Breast Cancer Detection Using Machine Learning and Deep Learning Techniques	The study reported that deep learning methods could outperform conventional machine learning techniques in breast cancer classification, supporting early detection and clinical decision-making.
Adam et al. (2023)	Deep Learning Applications to Breast Cancer Detection by Magnetic Resonance Imaging: A Literature Review	CNNs and other deep learning models showed potential for identifying complex patterns in breast MRI. Dataset limitations, overfitting, and clinical validation remained key challenges.
Garrucho et al. (2023)	High-Resolution Synthesis of High-Density Breast Mammograms: Application to Improved Fairness in Deep	Synthetic mammograms generated using CycleGAN improved dataset representation and showed potential to enhance mass detection in dense breast tissue and address dataset-related bias.

	Learning-Based Mass Detection	
Lång et al. (2023)	Artificial Intelligence-Supported Screen Reading Versus Standard Double Reading in the MASAI Trial: A Clinical Safety Analysis	AI-supported screening showed a 20% higher cancer detection rate and reduced radiologist workload by 44.3%. The findings supported the potential of AI-assisted screening to improve efficiency while maintaining safety.
Nasser and Yusof (2023)	Deep Learning-Based Methods for Breast Cancer Diagnosis: A Systematic Review and Future Directions	The review identified CNNs as widely used deep learning models and examined datasets, evaluation metrics, current challenges, and future research directions for breast cancer diagnosis.
Lauritzen et al. (2022)	An Artificial Intelligence-Based Mammography Screening Protocol for Breast Cancer: Outcome and Radiologist Workload	AI-based mammography triage demonstrated potential to maintain diagnostic sensitivity, improve specificity, and reduce radiologist workload by more than 60%, according to the supplied summary.
Shoshan et al. (2022)	Artificial Intelligence for Reducing Workload in Breast Cancer Screening with Digital Breast Tomosynthesis	AI-based triage reportedly reduced radiologist workload by approximately 39.6%, with sensitivity close to conventional assessment and a reduction in recall rates.
Khamparia et al. (2021)	Diagnosis of Breast Cancer Based on Modern Mammography Using Hybrid Transfer Learning	A hybrid transfer learning model combining modified VGG16 and MobileNet architectures showed potential for distinguishing benign from malignant masses in mammographic images.
Mridha et al. (2021)	A Comprehensive Survey on Deep-Learning-Based Breast Cancer Diagnosis	The review examined neural networks, autoencoders, CNNs, deep belief networks, and generative adversarial networks, identifying their strengths, limitations, and opportunities for further development.
Raya-Povedano et al. (2021)	AI-Based Strategies to Reduce Workload in Breast Cancer Screening with Mammography and Tomosynthesis: A Retrospective Evaluation	AI-assisted screening showed potential to reduce radiologist workload substantially while maintaining or improving cancer detection performance.
Sechopoulos et al. (2021)	Artificial Intelligence for Breast Cancer Detection in Mammography and Digital Breast Tomosynthesis: State of the Art	AI demonstrated potential to improve breast cancer detection and reduce false positives in mammography and tomosynthesis. Regulatory approval, workflow integration, and real-world validation remained important concerns.
Agarwal et al. (2020)	Deep Learning for Mass Detection in Full Field Digital Mammograms	A Faster R-CNN-based automated system showed potential for detecting benign and malignant breast masses across mammographic datasets and scanner types.
McKinney et al. (2020)	International Evaluation of an AI System for Breast Cancer Screening	The AI system reduced false positives by 5.7% in the United States and false negatives by 9.4% in the reported evaluation, demonstrating potential to improve screening accuracy and efficiency.
Pacilè et al.	Improving Breast Cancer	AI assistance improved detection sensitivity without

(2020)	Detection Accuracy of Mammography with the Concurrent Use of an Artificial Intelligence Tool	substantially affecting specificity or reading time, suggesting value as a supporting tool for radiologists.
Zhu et al. (2020)	The Application of Deep Learning in Cancer Prognosis Prediction	The study discussed the potential of deep learning to analyse complex clinical data and improve cancer outcome prediction. Further validation and clinical integration were identified as necessary.
Agarwal et al. (2019)	Automatic Mass Detection in Mammograms Using Deep Convolutional Neural Networks	A two-stage CNN approach achieved a reported sensitivity of 0.82 at one false positive per image. Performance was less effective in dense breast tissue than in fatty tissue.
Geras et al. (2019)	Artificial Intelligence for Mammography and Digital Breast Tomosynthesis: Current Concepts and Future Perspectives	AI showed promise in improving diagnostic precision, prioritizing suspicious cases, and supporting efficient screening. Clinical workflow integration and comprehensive validation remained challenges.
Bahl et al. (2018)	High-Risk Breast Lesions: A Machine Learning Model to Predict Pathologic Upgrade and Reduce Unnecessary Surgical Excision	Machine learning showed potential for predicting malignancy in high-risk breast lesions, supporting risk assessment and potentially reducing unnecessary surgical excisions.
Rodríguez-Ruiz et al. (2018)	Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System	AI support improved radiologists' diagnostic performance, particularly in equivocal cases, without increasing reading time. The system also showed potential for use as a first or second reader.
Dhungel et al. (2017)	A Deep Learning Approach for the Analysis of Masses in Mammograms with Minimal User Intervention	Deep learning techniques, including deep belief networks and CNNs, showed potential for distinguishing benign and malignant mammographic masses while reducing manual intervention.
Author(s) and Year	Title of the Study	Major Findings
Bahl et al. (2018)	High-Risk Breast Lesions: A Machine Learning Model to Predict Pathologic Upgrade and Reduce Unnecessary Surgical Excision	Deep learning showed potential for predicting malignancy in high-risk breast lesions, improving risk assessment and potentially reducing unnecessary surgical excisions.
Rodríguez-Ruiz et al. (2018)	Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System	AI-assisted mammography improved radiologists' diagnostic accuracy without increasing reading time. The system showed potential as a first or second reader in screening programmes.

Dhungel et al. (2017)	A Deep Learning Approach for the Analysis of Masses in Mammograms with Minimal User Intervention	Deep learning demonstrated potential for automated mammogram mass analysis with minimal user intervention, supporting breast abnormality detection and clinical decision-making. specificity, thereby decreasing the requirement for manual intervention and enhancing the efficacy of breast cancer detection.
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Source: Compiled by the author from the cited studies.

The research formulated a deep learning methodology for the examination of masses in mammograms with reduced user engagement. By employing a deep belief network (DBN) alongside a convolutional neural network (CNN), the system demonstrated significant precision in differentiating between benign and malignant masses. The model surpassed conventional techniques in both sensitivity and

The findings of the systematic review indicate that deep learning (DL) methodologies, especially convolutional neural networks (CNNs), markedly improve the detection of breast cancer via mammograms, MRI, and tomosynthesis. Research consistently underscores the enhanced diagnostic accuracy of DL, showcasing advancements in sensitivity, specificity, and AUC scores across multiple imaging techniques. DL models have demonstrated superior performance compared to traditional radiologists in specific instances, simultaneously decreasing the rates of false positives and negatives. However, despite the encouraging outcomes, obstacles such as model validation, interpretability, and the incorporation into clinical practices persist, needing additional research and development to facilitate broad clinical implementation.

Table 2: AI v/s Traditional Methods Key Performance Metrics in Breast Cancer

Metric	AI Performance	Traditional Methods
Sensitivity	88–90% in breast MRI; AI-assisted detection reportedly achieved 89.5% in the cited studies	Clinical breast examination (CBE) sensitivity reported at 73–85%; radiologist performance varies by modality and population
Specificity	Approximately 90% in breast MRI; may help reduce unnecessary interventions	May be lower in some settings, potentially resulting in more false-positive findings
False-Negative Reduction	Reported reduction of 9.4% in mammography evaluations	Greater risk of missed cancers in some screening settings
Cancer Risk Prediction	Predicted up to 28% of cancers in the highest-risk 10% group	Traditional models reportedly achieved 21% predictive performance
Workflow Efficiency	Reported reductions in radiologist workload of up to 37%; reading time may decrease	Greater dependence on manual interpretation and radiologist availability
Dense Breast Tissue Detection	May identify subtle abnormalities; one reported evaluation achieved an AUC of 0.947 for calcification detection	Detection can be challenging because dense tissue may obscure abnormalities
Interval Cancer Detection	Reportedly identified up to 19.3% of interval cancers with minimal signs of malignancy	Some interval cancers may remain undetected during earlier screening examinations
Reading Time	Reported reductions of up to 45 seconds per case in certain evaluations	Generally requires manual image interpretation without AI assistance

AI exhibits considerable benefits over conventional techniques in the identification of breast cancer, especially regarding sensitivity, specificity, and its capability to recognize subtle indicators of malignancy, notably in dense breast tissue and interval cancers. Furthermore, AI enhances workflow efficiency by alleviating the workload of radiologists and shortening reading durations while preserving a high level of diagnostic precision. The advanced cancer risk prediction models inherent in this technology also facilitate an earlier and more precise risk stratification. These advantages position AI as a transformative instrument in enhancing breast cancer screening and mitigating the drawbacks associated with traditional diagnostic methodologies.

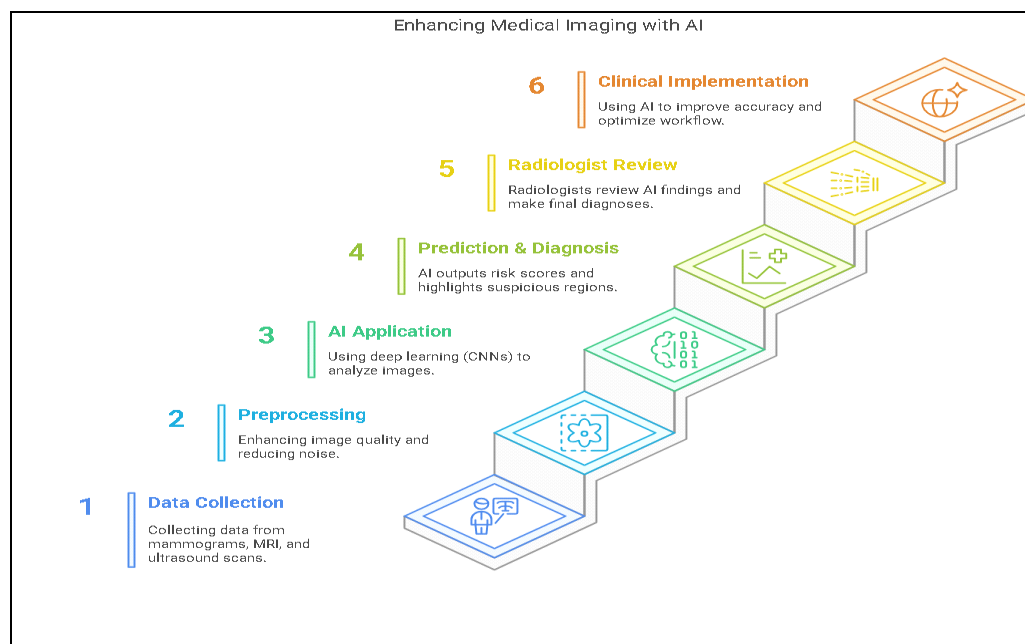


Figure 2: Diagram illustrating the Conceptual framework of how AI Enhances detection of Breast Cancer

The incorporation of artificial intelligence (AI) and deep learning (DL) into the detection of breast cancer signifies a significant transformation in both diagnostic accuracy and clinical effectiveness. Numerous independent research studies have shown that AI models possess unmatched diagnostic accuracy, especially in identifying subtle irregularities on mammograms. For instance, Shen et al. (2019) confirmed the sensitivity and specificity of artificial intelligence, attaining remarkable outcomes among

various patient groups. These results are consistent with the work of Kooi et al. (2017), who emphasized a decrease of the time required for radiologists to interpret images, indicating that artificial intelligence may help mitigate workforce gaps while preserving elevated levels of diagnostic precision.

Lehman et al. (2015) investigated AI's effectiveness across different levels of breast density, highlighting the necessity of utilizing varied training datasets for the development of strong models. Furthermore, Rodriguez-Ruiz et al. (2019) illustrated that radiologists, especially those with less experience, exhibit enhanced performance when artificial intelligence support is incorporated into diagnostic processes. Finally, McKinney et al. (2020) emphasized significant concerns including limitations of datasets, biases in algorithms, and the necessity for validation among various populations to guarantee effective integration into clinical practice. These developments underscore the essential requirement for collaborative efforts across disciplines, thorough validation processes, and a focus on patient-oriented innovation in order to fully leverage the capabilities of artificial intelligence for the identification of breast cancer.

Conclusion

The findings of this review highlight the transformative capacity of DL in the detection of breast cancer. DL frameworks, particularly CNNs, have shown significant enhancements in diagnostic precision, sensitivity, and specificity, with the ability to support radiologists and minimize unwarranted procedures. Ultimately, the prospect of using artificial intelligence (AI) to detect breast cancer holds significant potential as it can improve diagnoses with greater precision, streamline processes, and tailor treatment to the needs of particular patients. AI can greatly decrease diagnostic mistakes, match the work of skilled radiologists, and enable the analysis of various data types for more effective treatment strategies.

However significant challenges remain, such as tackling biases within training datasets, guaranteeing the interpretability of AI systems, and managing intricate regulatory frameworks essential for clinical implementation. It is vital to tackle these challenges through collaborative research, thorough testing, and ongoing innovation to fully harness AI's potential in breast cancer treatment. As the capabilities of AI advance, its significance in transforming the diagnostics and treatment of breast cancer is set to

grow, offering the possibility of better outcomes for patients, reduced expenses in healthcare, and improved quality of life for those affected.

Nonetheless, obstacles concerning dataset diversity, model interpretability, and clinical assimilation persist. Further studies should focus on cultivating varied datasets, enhancing interpretability, and navigating the regulatory environment to fully capitalize on the advantages of DL in breast cancer detection and therapy.

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