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Artificial Intelligence in Breast Cancer Diagnosis, Prognosis, and Personalized Treatment: Current Applications and Future Directions

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Abstract

Breast cancer is the most frequently diagnosed malignancy among women worldwide and remains a leading cause of cancer-related mortality despite significant advances in screening and therapeutic strategies. Conventional diagnostic and treatment approaches rely heavily on expert interpretation and population-based guidelines, which may lead to inter-observer variability, delayed diagnosis, and suboptimal personalization of care. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools capable of transforming breast cancer management by enabling automated image analysis, predictive modeling, and data-driven clinical decision support. AI-based methods have demonstrated strong performance across multiple stages of the clinical workflow, including screening, diagnosis, risk stratification, prognosis prediction, and treatment response assessment. This comprehensive review systematically examines the current landscape of AI applications in breast cancer diagnosis, prognosis, and personalized treatment. We discuss key machine learning and deep learning techniques, multimodal data integration strategies involving medical imaging, histopathology, and genomic information, and the clinical deployment of AI systems. Additionally, we address challenges related to explainability, bias, data quality, regulatory approval, and ethical considerations. By synthesizing recent advances and identifying existing gaps, this review aims to provide clinicians and researchers with a clear understanding of the role of AI in advancing precision oncology for breast cancer.

Keywords: Breast Cancer, Artificial Intelligence, Machine Learning, Deep Learning, Medical Imaging, Digital Pathology, Precision Oncology, Prognosis Prediction.

Introduction

Breast cancer is a complex and heterogeneous disease that represents a major public health challenge worldwide. According to global cancer statistics, breast cancer has become the most commonly diagnosed cancer among women, accounting for a substantial proportion of cancer-related morbidity and mortality [1]. Despite continuous improvements in screening programs, diagnostic imaging, surgical techniques, and systemic therapies, breast cancer outcomes remain highly variable due to differences in tumor biology, disease stage at diagnosis, and patient-specific factors [2]. Early detection and accurate characterization of breast lesions are critical for improving survival rates; however, conventional diagnostic pathways continue to face significant limitations.

Traditional breast cancer screening and diagnostic workflows rely primarily on mammography, ultrasound, magnetic resonance imaging (MRI), and histopathological examination. While these modalities have proven clinical value, their interpretation is largely dependent on expert judgment, making them susceptible to inter- and intra-observer variability, diagnostic fatigue, and subjective bias [3].

Furthermore, increasing screening volumes have placed a growing burden on radiologists and pathologists, raising concerns about workflow efficiency and diagnostic consistency [4]. These challenges highlight the need for more robust, reproducible, and scalable diagnostic solutions.In parallel, advances in molecular biology have revealed that breast cancer is not a single disease entity but rather a collection of biologically distinct subtypes with different prognostic and therapeutic implications [5]. Molecular classifications such as hormone receptor status and human epidermal growth factor receptor 2 (HER2) expression have become essential for treatment planning; however, integrating molecular, imaging, and clinical data into cohesive decision-making frameworks remains difficult in routine clinical practice [6]. Conventional statistical models often struggle to capture the nonlinear and high-dimensional relationships inherent in such complex datasets.

AI encompassing ML and deep learning (DL) techniques has emerged as a promising approach to address these challenges. AI systems can learn complex patterns from large-scale data and have demonstrated strong performance across tasks such as image recognition, natural language processing, and predictive analytics [7]. In the context of breast cancer, AI has shown potential in automating lesion detection on medical images, improving diagnostic accuracy, predicting disease prognosis, and supporting personalized treatment decisions [8]. The rapid growth of digital medical data, combined with increased computational power and improved algorithms, has accelerated the adoption of AI-based methods in oncology research. Recent studies have reported that AI models can achieve diagnostic performance comparable to, and in some cases exceeding, that of experienced clinicians in breast cancer screening and classification tasks [9]. Beyond diagnosis, AI has also been applied to predict treatment response, recurrence risk, and patient survival using multimodal data sources such as imaging, histopathology, genomics, and electronic health records [10]. These developments align with the broader shift toward precision oncology, which aims to tailor treatment strategies based on individual patient characteristics rather than population-level averages.

Despite these promising advances, the clinical integration of AI in breast cancer care remains at an early stage. Challenges related to data quality, model generalizability, explainability, regulatory approval, and ethical considerations must be addressed before widespread adoption can be achieved [11]. A comprehensive understanding of the current state of AI applications, their clinical impact, and their limitations is therefore essential for guiding future research and implementation efforts. The objective of this review is to provide a structured and critical overview of AI applications in breast cancer diagnosis, prognosis, and personalized treatment. We synthesize recent developments across imaging, pathology, and data-driven decision support systems, discuss the clinical readiness of AI tools, and highlight key challenges and future research directions. By doing so, this review aims to serve as a reference for clinicians, researchers, and policymakers interested in the role of AI in advancing breast cancer management.

Figure 1 provides a conceptual overview of AI applications in breast cancer diagnosis, prognosis, and personalized treatment.

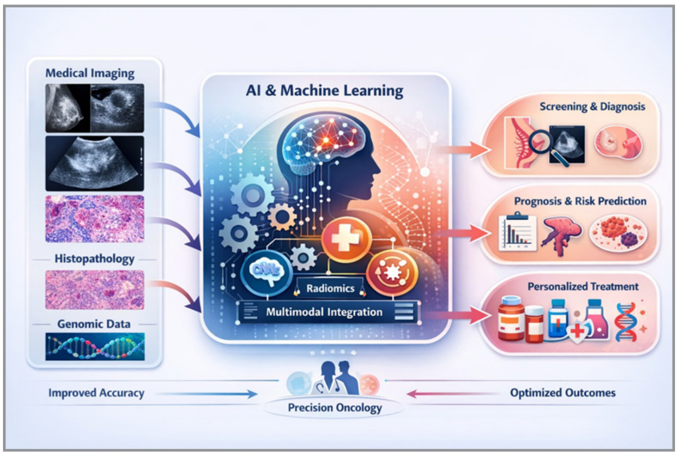

Figure 1: Conceptual framework illustrating the role of artificial intelligence in breast cancer diagnosis, prognosis, and personalized treatment through multimodal data integration

Methods of Literature Review

This review was conducted as a comprehensive narrative review to summarize and critically analyze recent advances in AI applications for breast cancer diagnosis, prognosis, and personalized treatment. A systematic search of the scientific literature was performed using major biomedical and engineering databases, including PubMed, Scopus, Web of Science, and IEEE Xplore. The literature search covered studies published between January 2010 and March 2024, reflecting the period during which machine learning and DL techniques have seen substantial development and application in medical imaging and oncology. The search strategy combined controlled vocabulary terms and free-text keywords related to breast cancer and AI. Representative search terms included "breast cancer," "artificial intelligence," "machine learning," "deep learning," "radiomics," "medical imaging," "digital pathology," and "precision oncology." Boolean operators (AND/OR) were used to refine and combine search queries across databases. Studies were included if they met the following criteria: (i) peer-reviewed journal articles published in English; (ii) studies focusing on the application of AI, machine learning, or DL in breast cancer screening, diagnosis, prognosis, or treatment planning; and (iii) articles reporting methodological development, validation, or clinical evaluation of AI-based approaches. Review articles, original research studies, and clinically relevant validation studies were considered to ensure a comprehensive overview of the field. Studies were excluded if they were unrelated to breast cancer, focused solely on non-oncological diseases, lacked methodological detail, or were limited to non-peer-reviewed sources such as editorials, commentaries, or unpublished manuscripts. Conference papers and preprints were considered only when they provided substantial methodological contributions and were clearly identified as preliminary work. The selected articles were qualitatively synthesized and organized thematically according to clinical application areas, including screening and diagnosis, prognostic and risk prediction, radiomics and multimodal data integration, and translational considerations. This approach enabled a structured and critical discussion of current trends, limitations, and future research directions in the application of AI for breast cancer management.

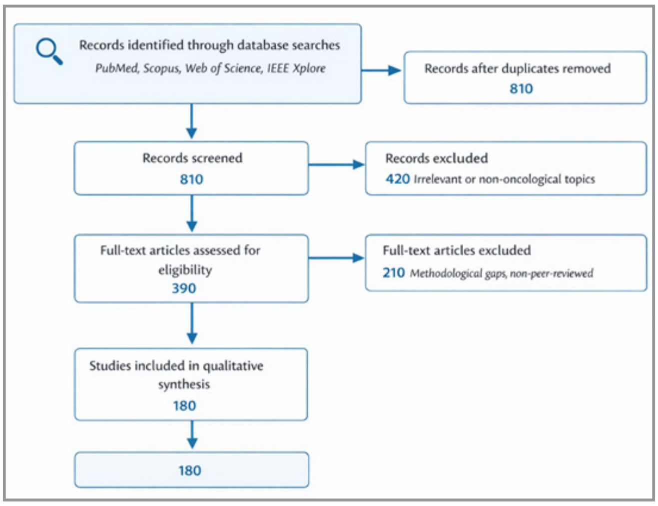

Figure 2: Literature identification and selection process

Global Burden and Clinical Challenges of Breast Cancer

Breast cancer represents a significant and growing global health burden. Recent epidemiological data indicate that breast cancer is the most commonly diagnosed cancer worldwide, with incidence rates continuing to rise in both developed and developing countries [12]. While higher-income regions such as North America and Western Europe report greater incidence due to widespread screening programs, low- and middle-income countries experience disproportionately higher mortality rates, largely due to late-stage diagnosis and limited access to effective treatment [13]. The global variation in breast cancer outcomes underscores the importance of early detection, accurate diagnosis, and timely therapeutic intervention. Improvements in survival rates over recent decades have been attributed to advances in screening, systemic therapies, and multidisciplinary care. However, these gains are unevenly distributed, and disparities persist across geographic regions, ethnic groups, and socioeconomic strata [14]. Addressing these disparities requires innovative approaches that can enhance diagnostic accuracy and clinical decision-making at scale, particularly in resource-limited settings.

Molecular and Clinical Heterogeneity of Breast Cancer: Breast cancer is a biologically heterogeneous disease characterized by distinct molecular subtypes with varying clinical behaviors and prognoses. Gene expression profiling has identified intrinsic subtypes, including luminal A, luminal B, HER2-enriched, and triple-negative breast cancer, each associated with different therapeutic responses and survival outcomes [15]. This heterogeneity complicates disease management and highlights the limitations of one-size-fits-all treatment strategies. Clinically, patients with similar histopathological features may experience markedly different disease trajectories, suggesting that conventional prognostic markers are insufficient for precise risk stratification [16]. The integration of molecular, imaging, and clinical data is therefore essential for capturing the complexity of breast cancer biology and enabling personalized care.

Challenges in Breast Cancer Screening and Diagnosis: Population-based screening programs, particularly mammography, have played a critical role in reducing breast cancer mortality by facilitating early detection. However, screening is not without limitations. False-positive findings can lead to unnecessary biopsies, patient anxiety, and increased healthcare costs, while false-negative results may delay diagnosis and treatment [17]. Dense breast tissue further complicates image interpretation, reducing the sensitivity of mammography and increasing the risk of missed lesions [18]. Histopathological examination remains the gold standard for definitive diagnosis, yet it is also subject to variability in interpretation, especially for borderline lesions and tumor grading [19]. As screening volumes continue to increase, the workload placed on radiologists and pathologists raises concerns regarding diagnostic consistency and efficiency. These challenges provide a strong rationale for the adoption of AI-based tools to assist clinicians in screening and diagnostic tasks.

Limitations in Prognosis and Treatment Decision-Making: Accurate prognosis and optimal treatment selection are central to improving breast cancer outcomes. Traditional prognostic models rely on clinicopathological factors such as tumor size, nodal status, and receptor expression, which may not fully capture individual risk profiles [20]. As a result, some patients may receive overtreatment, exposing them to unnecessary toxicity, while others may be undertreated, increasing the risk of recurrence. The increasing availability of genomic assays has improved risk stratification; however, these tests are costly and not universally accessible [21]. Moreover, integrating genomic results with imaging and clinical data remains challenging in routine practice. AI-driven predictive models offer the potential to synthesize diverse data sources and provide individualized prognostic and therapeutic insights, thereby addressing key limitations of current decision-making frameworks.

Need for Advanced Computational Approaches: The complexity of breast cancer biology, coupled with the growing volume of clinical and biomedical data, exceeds the analytical capacity of traditional methods. Advanced computational approaches, particularly AI and ML, are uniquely suited to handle high-dimensional data and uncover latent patterns that may not be apparent to human observers [22]. By leveraging large datasets and learning from real-world clinical outcomes, AI systems have the potential to improve diagnostic accuracy, prognostic precision, and treatment personalization across the breast cancer care continuum.

Table 1: Summary of artificial intelligence and machine learning methodologies commonly used in breast cancer research

AI Category	Representative Algorithms	Typical Data Type	Key Strengths	Main Limitations	References
Traditional Machine Learning	Logistic Regression, SVM, Random Forest, k-NN	Structured clinical data, engineered imaging features	Interpretability, low computational cost, robustness on small datasets	Requires manual feature engineering, limited scalability	[26–29]
Deep Learning	Convolutional Neural Networks (CNNs)	Medical imaging (mammography, ultrasound, MRI, pathology)	Automated feature extraction, high accuracy in image analysis	Limited interpretability, requires large labeled datasets	[30]
Sequence Models	RNN, LSTM	Longitudinal clinical data, time-series patient records	Captures temporal dependencies, suitable for sequential data	Training instability, limited adoption in imaging tasks	[31]
Transformer-Based Models	Vision Transformer, attention-based architectures	High-dimensional imaging and multimodal data	Attention mechanisms, global feature modeling	High computational cost, emerging clinical validation	[32]

Fundamentals of Artificial Intelligence and Machine Learning in Healthcare

AI refers to the development of computational systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, perception, and decision-making. In healthcare, AI aims to augment clinical expertise by extracting meaningful patterns from complex biomedical data and translating them into actionable insights [23]. ML, a subset of AI, focuses on algorithms that learn from data without being explicitly programmed, while DL, a further subset of ML, employs multilayer neural networks to model high-level abstractions in large datasets [24]. The relevance of AI in oncology arises from its ability to handle high-dimensional, heterogeneous data sources, including medical images, genomic profiles, and electronic health records. These data characteristics often exceed the analytical capacity of traditional statistical methods, making AI a powerful alternative for modeling disease complexity [25].

Traditional Machine Learning Algorithms in Medical Applications

Before the widespread adoption of DL, traditional ML algorithms were commonly used in medical research and clinical prediction tasks. These methods typically rely on handcrafted features derived from clinical or imaging data and include logistic regression, support vector machines (SVMs), decision trees, random forests, and k-nearest neighbors (k-NN) [26]. In breast cancer research, traditional ML models have been applied to tasks such as tumor classification, recurrence prediction, and risk assessment using structured datasets. Logistic regression remains widely used due to its interpretability and statistical grounding, particularly in clinical risk modeling [27]. SVMs are effective for high-dimensional classification problems and have been employed in breast cancer diagnosis using imaging and gene expression data [28]. Ensemble methods such as random forests improve predictive performance by combining multiple decision trees, offering robustness against overfitting and noise [29]. Despite their utility, these models often require extensive feature engineering and may struggle to generalize across diverse datasets. DL has revolutionized medical AI by enabling end-to-end learning directly from raw data. Convolutional neural networks (CNNs) are the most widely used DL architecture in medical imaging due to their ability to learn spatial hierarchies and local patterns [30]. CNNs have been successfully applied to mammography, ultrasound, MRI, and histopathology images for breast cancer detection and classification. Recurrent neural networks (RNNs), including long short-term memory (LSTM) networks, are designed to model sequential data and have been used for time-series analysis and longitudinal patient monitoring [31]. More recently, transformer-based architectures, originally developed for natural language processing, have been adapted for medical imaging and multimodal data integration, demonstrating strong performance in complex prediction tasks [32]. These architectures enable attention-based learning, allowing models to focus on the most informative features within large datasets. The performance of AI models is heavily influenced by the quality and quantity of training data. Supervised learning, which relies on labeled datasets, is the most common paradigm in medical AI applications; however, obtaining high-quality annotations is often labor-intensive and costly [33]. Semi-supervised and self-supervised learning approaches have therefore gained attention as means to leverage unlabeled data and improve model generalizability [34]. Data imbalance is a frequent challenge in medical datasets, particularly in cancer screening where disease prevalence is low. Techniques such as data augmentation, resampling, and cost-sensitive learning are commonly employed to mitigate this issue [35]. Ensuring external validation across multiple institutions and populations is also critical for assessing the robustness and clinical applicability of AI models. Evaluating AI models in healthcare requires careful consideration of clinically meaningful performance metrics. Common classification metrics include accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve (AUC) [36]. In breast cancer screening, sensitivity and specificity are particularly important due to their direct impact on missed diagnoses and false-positive rates. For prognostic and survival models, metrics such as the concordance index (C-index), hazard ratios, and calibration plots are widely used [37]. Beyond statistical performance, clinical utility, interpretability, and integration into workflow are increasingly recognized as essential criteria for successful AI deployment in real-world settings.

Artificial Intelligence in Breast Cancer Screening and Diagnosis
Early and accurate detection of breast cancer is a cornerstone of effective disease management and improved survival outcomes. Screening and diagnostic imaging generate large volumes of complex data, making them well-suited for AI-driven analysis. Over the past decade, AI—particularly DL—has demonstrated substantial potential in enhancing the accuracy, efficiency, and consistency of breast cancer screening and diagnostic workflows.

AI-Assisted Mammography: Mammography remains the primary screening modality for breast cancer worldwide. However, its interpretation is challenging due to factors such as breast density, subtle lesion appearance, and reader fatigue. AI-based systems, predominantly using convolutional neural networks (CNNs), have been developed to assist radiologists by detecting suspicious lesions, classifying abnormalities, and prioritizing high-risk cases [38]. Large-scale studies have shown that AI systems can achieve diagnostic performance comparable to expert radiologists. Notably, AI-assisted mammography has been associated with improved cancer detection rates and reduced false-positive recalls in screening populations [39]. AI algorithms can also quantify breast density automatically, which is an important risk factor for breast cancer and a known limitation of conventional mammography interpretation [40]. By acting as a second reader or triage tool, AI has the potential to reduce radiologist workload while maintaining or improving diagnostic accuracy.

AI Applications in Breast Ultrasound Imaging: Breast ultrasound is commonly used as an adjunct to mammography, particularly in women with dense breast tissue. Ultrasound interpretation is highly operator-dependent, leading to variability in diagnostic performance. AI-based models have been developed to classify breast masses as benign or malignant using grayscale ultrasound images and Doppler data [41]. DL approaches have demonstrated promising results in mass detection, segmentation, and classification, often outperforming traditional machine learning methods that rely on handcrafted features [42]. AI-assisted ultrasound systems may help standardize image interpretation, reduce unnecessary biopsies, and improve diagnostic confidence, especially in settings with limited access to specialized radiologists.

AI in Breast Magnetic Resonance Imaging: Magnetic resonance imaging (MRI) is the most sensitive imaging modality for breast cancer detection, particularly in high-risk populations. However, MRI interpretation is time-consuming and prone to inter-reader variability. AI models have been applied to automate lesion detection, segmentation, and characterization in breast MRI, leveraging multiparametric imaging sequences [43]. Radiomics-based AI approaches extract quantitative features from MRI scans to distinguish between benign and malignant lesions and to assess tumor aggressiveness [44]. DL models have further improved performance by learning hierarchical image representations directly from raw MRI data. These advances suggest that AI-assisted MRI analysis could enhance diagnostic accuracy while reducing interpretation time in clinical practice.

Digital Pathology and Histopathological Image Analysis: Histopathological examination of biopsy specimens is the gold standard for breast cancer diagnosis. The digitization of whole-slide images has enabled the application of AI to digital pathology. DL models have been developed to identify malignant regions, classify tumor subtypes, and grade tumors with high accuracy [45]. AI systems have demonstrated the ability to detect mitotic figures, quantify tumor-infiltrating lymphocytes, and assess histological features associated with prognosis [46]. Importantly, AI-assisted pathology has shown potential in reducing diagnostic variability among pathologists and improving reproducibility. These tools may serve as decision support systems, particularly in high-volume pathology laboratories.

Comparison of AI Performance with Human Experts: Several studies have directly compared the performance of AI systems with that of experienced clinicians in breast cancer screening and diagnosis. In mammography, AI models have achieved sensitivity and specificity comparable to expert radiologists and have demonstrated additive value when used as an adjunct rather than a replacement [47]. Similar findings have been reported in ultrasound and pathology applications, where AI-assisted interpretation improved diagnostic consistency and reduced error rates [48]. Despite these promising results, it is widely recognized that AI systems should complement, rather than replace, human expertise. The optimal role of AI lies in augmenting clinical decision-making, enhancing efficiency, and reducing variability while preserving clinician oversight and accountability.

Radiomics and Multimodal Data Integration
The increasing availability of high-resolution medical imaging and diverse clinical data has enabled the development of radiomics and multimodal AI approaches in breast cancer research. Radiomics refers to the extraction of large numbers of quantitative features from medical images, capturing tumor shape, texture, intensity, and spatial relationships that may not be discernible through visual assessment alone. When combined with machine learning, radiomics has shown promise in enhancing diagnosis, prognosis, and treatment prediction in breast cancer.
Radiomics pipelines typically involve image acquisition, segmentation of regions of interest (ROIs), feature extraction, feature selection, and predictive modeling. Extracted features may include first-order statistics, shape-based features, texture features, and higher-order features derived from wavelet transformations [49]. These quantitative descriptors provide a comprehensive representation of tumor heterogeneity, which is a key determinant of breast cancer behavior. Given the high dimensionality of radiomic features, feature selection is a critical step to reduce redundancy, prevent overfitting, and improve model interpretability. Techniques such as least absolute shrinkage and selection operator (LASSO), recursive feature elimination, and principal component analysis are commonly employed to identify the most informative features for predictive modeling [50].

Machine learning algorithms, including support vector machines, random forests, and gradient boosting methods, have been widely used to develop radiomics-based predictive models. These models have demonstrated utility in distinguishing benign from malignant lesions, predicting molecular subtypes, and assessing tumor aggressiveness using mammography, ultrasound, and MRI data [51]. More recently, DL–based radiomics approaches have emerged, enabling automated feature learning directly from imaging data without the need for handcrafted features [52]. Studies have shown that radiomics models can outperform traditional clinical models in certain tasks, such as predicting lymph node metastasis and response to neoadjuvant chemotherapy [53]. However, variability in imaging protocols and segmentation methods remains a challenge for reproducibility and generalizability. While radiomics provides valuable insights from imaging data, breast cancer management increasingly requires the integration of multiple data modalities. Multimodal AI models combine radiomic features with clinical variables, pathological findings, and genomic information to improve predictive performance and enable precision oncology [54]. For example, integrating imaging features with gene expression profiles has been shown to enhance the prediction of tumor subtypes and patient outcomes [55]. DL architectures, such as multimodal neural networks and attention-based models, facilitate the fusion of heterogeneous data sources. These approaches allow models to learn complex interactions between imaging, molecular, and clinical features, providing a more holistic representation of disease biology [56]. Multimodal integration is particularly relevant for personalized treatment planning, where decisions depend on multiple patient-specific factors.

Challenges in Radiomics and Multimodal Modeling

Despite promising results, several challenges hinder the clinical translation of radiomics and multimodal AI models. Variability in imaging acquisition protocols, lack of standardized feature definitions, and differences in segmentation practices can significantly impact model performance [57]. Additionally, many studies rely on retrospective, single-institution datasets, limiting external validity. Data harmonization techniques, standardized reporting guidelines, and large-scale multicenter studies are essential to address these issues. Furthermore, interpretability and transparency remain critical concerns, particularly when integrating complex multimodal data into clinical decision-making workflows [58].

Discussion

The rapid integration of AI into breast cancer research and clinical practice reflects the growing recognition of its potential to address long-standing challenges in diagnosis, prognosis, and personalized treatment. As reviewed in the preceding sections, AI-based methods have demonstrated strong performance across multiple stages of the breast cancer care continuum, particularly in screening, imaging interpretation, digital pathology, and radiomics-based risk assessment. One of the most significant strengths of AI in breast cancer management lies in its ability to analyze large-scale, high-dimensional data that exceed the capacity of traditional analytical approaches. DL models, especially convolutional neural networks, have shown robust performance in mammography, ultrasound, MRI, and histopathological image analysis, often achieving diagnostic accuracy comparable to expert clinicians. Importantly, studies indicate that AI systems perform best when used as decision-support tools rather than autonomous systems, reinforcing the complementary role of AI in clinical workflows rather than replacement of human expertise. Radiomics and multimodal data integration further highlight the value of AI in capturing tumor heterogeneity and complex biological interactions. By combining imaging-derived features with clinical and genomic data, AI models can improve prognostic accuracy and treatment response prediction. These capabilities align closely with the goals of precision oncology, where individualized risk stratification and therapy selection are essential for optimizing outcomes and minimizing overtreatment. Despite these advances, several limitations remain. Many AI models are developed using retrospective, single-center datasets, raising concerns regarding generalizability and robustness across diverse patient populations. Variability in imaging protocols, annotation standards, and data quality can significantly affect model performance. Moreover, the “black-box” nature of many DL models continues to pose challenges for clinical trust, regulatory approval, and medico-legal accountability. Addressing issues of explainability, bias, and transparency is therefore critical for broader clinical acceptance.

Future Directions

Future research in AI-driven breast cancer management should focus on improving model generalizability, interpretability, and real-world clinical impact. Large-scale, multicenter, and multiethnic datasets are essential to ensure that AI systems perform reliably across diverse healthcare settings. The adoption of standardized imaging protocols, data harmonization strategies, and reporting guidelines will further enhance reproducibility and comparability across studies. Explainable artificial intelligence (XAI) is expected to play a central role in future developments. Techniques such as saliency mapping, attention mechanisms, and feature attribution methods can help clinicians understand model predictions and build trust in AI-assisted decision-making. Regulatory agencies increasingly emphasize transparency and validation, making explainability a prerequisite for clinical deployment. Another promising direction is the integration of AI with emerging technologies such as federated learning, which enables collaborative model training across institutions while preserving patient privacy. This approach may be particularly valuable in breast cancer research, where ethical and legal considerations often constrain data sharing. Additionally, the development of multimodal foundation models capable of learning from imaging, pathology, genomics, and longitudinal clinical data may further advance personalized breast cancer care. Ultimately, prospective clinical trials and real-world impact studies are needed to evaluate whether AI-assisted systems translate into improved patient outcomes, reduced diagnostic errors, and more efficient healthcare delivery.

Conclusion

Artificial intelligence has emerged as a transformative force in breast cancer diagnosis, prognosis, and personalized treatment. The evidence reviewed in this article demonstrates that AI-based approaches can enhance diagnostic accuracy, reduce variability in image and pathology interpretation, and support data-driven risk stratification and treatment planning. Radiomics and multimodal AI models further expand the potential of AI to capture tumor heterogeneity and enable precision oncology. However, despite promising results, the widespread clinical adoption of AI in breast cancer care remains limited by challenges related to data quality, generalizability, explainability, and regulatory oversight. Addressing these issues through standardized methodologies, transparent model design, and rigorous clinical validation is essential for realizing the full potential of AI in routine practice. In conclusion, AI is poised to play an increasingly important role in advancing breast cancer management. With continued interdisciplinary collaboration between clinicians, data scientists, and policymakers, AI-driven systems have the potential to improve patient outcomes and contribute meaningfully to the future of precision oncology.

References

1. Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: A Cancer Journal for Clinicians, 71(3), 209-249.
2. DeSantis, C. E., Ma, J., Gaudet, M. M., Newman, L. A., Miller, K. D., Goding Sauer, A., Jemal, A. (2019). Breast cancer statistics, 2019. CA: A Cancer Journal for Clinicians, 69(6), 438-451.
3. Elmore, J. G., Wells, C. K., Lee, C. H., Howard, D. H., Feinstein, A. R. (1994). Variability in radiologists' interpretations of mammograms. The New England Journal of Medicine, 331(22), 1493-1499.
4. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., … Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410.
5. Perou, C. M., Sørlie, T., Eisen, M. B., van de Rijn, M., Jeffrey, S. S., Rees, C. A., … Botstein, D. (2000). Molecular portraits of human breast tumours. Nature, 406(6797), 747-752.
6. Curigliano, G., Burstein, H. J., Winer, E. P., Gnant, M., Dubsky, P., Loibl, S., … Goldhirsch, A. (2017). De-escalating and escalating treatments for early-stage breast cancer: The St. Gallen International Expert Consensus Conference on the Primary Therapy of Early Breast Cancer 2017. Annals of Oncology, 28(8), 1700-1712.
7. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56.
8. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.
9. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., … Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. Nature, 577(7788), 89-94.
10. Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., Fotiadis, D. I. (2015). Machine learning applications in cancer prognosis and prediction. Computational and Structural Biotechnology Journal, 13, 8-17.
11. Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G.,King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine, 17(1), Article 195.
12. Bray, F., Laversanne, M., Weiderpass, E., Soerjomataram, I. (2021). The ever-increasing importance of cancer as a leading cause of premature death worldwide. Cancer, 127(16), 3029-3030.
13. Unger-Saldaña, K. (2014). Challenges to the early diagnosis and treatment of breast cancer in developing countries. World Journal of Clinical Oncology, 5(3), 465-477.
14. Daly, B.,Olopade, O. I. (2015). A perfect storm: How tumor biology, genomics, and health care delivery patterns collide to create a racial survival disparity in breast cancer and proposed interventions. CA: A Cancer Journal for Clinicians, 65(3), 221-238.
15. Sørlie, T., Perou, C. M., Tibshirani, R., Aas, T., Geisler, S., Johnsen, H., … Børresen-Dale, A. L. (2001). Gene expression patterns of breast carcinomas distinguish tumor subclasses with clinical implications. Proceedings of the National Academy of Sciences of the United States of America, 98(19), 10869-10874.
16. Weigelt, B., Reis-Filho, J. S. (2009). Histological and molecular types of breast cancer: Is there a unifying taxonomy? Nature Reviews Clinical Oncology, 6(12), 718-730.
17. Nelson, H. D., Fu, R., Cantor, A., Pappas, M., Daeges, M., Humphrey, L. (2016). Effectiveness of breast cancer screening: Systematic review and meta-analysis. Annals of Internal Medicine, 164(4), 244-255.
18. Boyd, N. F., Guo, H., Martin, L. J., Sun, L., Stone, J., Fishell, E., … Yaffe, M. J. (2007). Mammographic density and the risk and detection of breast cancer. The New England Journal of Medicine, 356(3), 227-236.
19. Elmore, J. G., Longton, G. M., Carney, P. A., Geller, B. M., Onega, T., Tosteson, A. N. A., … Weaver, D. L. (2015). Diagnostic concordance among pathologists interpreting breast biopsy specimens. JAMA, 313(11), 1122-1132.
20. Ravdin, P. M., Siminoff, L. A., Davis, G. J., Mercer, M. B., Hewlett, J., Gerson, N., Parker, H. L. (2001). Computer program to assist in making decisions about adjuvant therapy for women with early breast cancer. Journal of Clinical Oncology, 19(4), 980–991.
21. Sparano, J. A., Gray, R. J., Makower, D. F., Pritchard, K. I., Albain, K. S., Hayes, D. F., … Sledge, G. W. (2018). Adjuvant chemotherapy guided by a 21-gene expression assay in breast cancer. The New England Journal of Medicine, 379(2), 111-121.
22. Beam, A. L., Kohane, I. S. (2018). Big data and machine learning in health care. JAMA, 319(13), 1317–1318.
23. Russell, S. J., Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.
24. Goodfellow, I., Bengio, Y., Courville, A. (2016). Deep learning. MIT Press.
25. Obermeyer, Z., Emanuel, E. J. (2016). Predicting the future-Big data, machine learning, and clinical medicine. The New England Journal of Medicine, 375(13), 1216-1219.
26. Bishop, C. M. (2006). Pattern recognition and machine learning. Springer.
27. Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., … Kattan, M. W. (2010). Assessing the performance of prediction models. Epidemiology, 21(1), 128-138.
28. Osareh, A., Shadgar, B. (2010). Machine learning techniques to diagnose breast cancer. Computer Methods and Programs in Biomedicine, 96(1), 1-9.
29. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.
30. LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
31. Hochreiter, S., Schmidhuber, J. (1997). Long short-term

memory. Neural Computation, 9(8), 1735–1780.
32. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., … Houlsby, N. (2021). An image is worth 16×16 words: Transformers for image recognition at scale. Proceedings of the International Conference on Learning Representations. https://openreview.net/forum?id=YicbFdNTTy
33. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., … Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60-88.
34. Jing, L., Tian, Y. (2021). Self-supervised visual feature learning with deep neural networks: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(11), 4037-4058.
35. Chawla, N. V., Bowyer, K. W., Hall, L. O., Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. Journal of Artificial Intelligence Research, 16, 321-357.
36. Pepe, M. S. (2003). The statistical evaluation of medical tests for classification and prediction. Oxford University Press.
37. Harrell, F. E., Jr., Califf, R. M., Pryor, D. B., Lee, K. L., Rosati, R. A. (1982). Evaluating the yield of medical tests. JAMA, 247(18), 2543-2546.
38. Kooi, T., Litjens, G., van Ginneken, B., Gubern-Mérida, A., Sánchez, C. I., Mann, R., … Karssemeijer, N. (2017). Large scale deep learning for computer aided detection of mammographic lesions. Medical Image Analysis, 35, 303-312.
39. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., … Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. Nature, 577(7788), 89-94.
40. Yala, A., Lehman, C., Schuster, T., Portnoi, T., Barzilay, R. (2019). A deep learning mammography-based model for improved breast cancer risk prediction. Radiology, 292(1), 60-66.
41. Yap, M. H., Pons, G., Martí, J., Ganau, S., Sentís, M., Zwiggelaar, R., … Martí, R. (2018). Automated breast ultrasound lesion detection using convolutional neural networks. IEEE Journal of Biomedical and Health Informatics, 22(4), 1218–1226.
42. Byra, M., Galperin, M., Ojeda-Fournier, H., Olson, L., O'Boyle, M., Comstock, C., Andre, M. P. (2019). Breast mass classification in sonography with transfer learning using a deep convolutional neural network and color conversion. Medical Physics, 46(2), 746-755.
43. Truhn, D., Schrading, S., Haarburger, C., Schneider, H., Merhof, D., Kuhl, C. K. (2019). Radiomic versus convolutional neural networks analysis for classification of contrast-enhancing lesions at breast MRI. Radiology, 290(2), 290-297.
44. Pinker, K., Chin, J., Melsaether, A. N., Morris, E. A., Moy, L. (2018). Precision medicine and radiogenomics in breast cancer: New approaches toward diagnosis and treatment. Radiology, 287(3), 732-747.
45. Bejnordi, B. E., Veta, M., van Diest, P. J., van Ginneken, B., Karssemeijer, N., Litjens, G., … van der Laak, J. A. W. M. (2017). Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA, 318(22), 2199–2210.
46. Coudray, N., Ocampo, P. S., Sakellaropoulos, T., Narula, N., Snuderl, M., Fenyö, D., … Tsirigos, A. (2018). Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning. Nature Medicine, 24(10), 1559-1567.
47. Rodriguez-Ruiz, A., Lång, K., Gubern-Mérida, A., Broeders, M., Gennaro, G., Clauser, P., … Mann, R. M. (2019). Stand-alone artificial intelligence for breast cancer detection in mammography: Comparison with 101 radiologists. Journal of the National Cancer Institute, 111(9), 916-922.
48. Steiner, D. F., MacDonald, R., Liu, Y., Truszkowski, P., Hipp, J. D., Gammage, C., … Chen, P. H. C. (2018). Impact of deep learning assistance on the histopathologic review of lymph nodes for metastatic breast cancer. The American Journal of Surgical Pathology, 42(12), 1636-1646.
49. Lambin, P., Rios-Velazquez, E., Leijenaar, R., Carvalho, S., van Stiphout, R. G., Granton, P., … Aerts, H. J. W. L. (2012). Radiomics: Extracting more information from medical images using advanced feature analysis. European Journal of Cancer, 48(4), 441–446.
50. Parmar, C., Grossmann, P., Bussink, J., Lambin, P., & Aerts, H. J. W. L. (2015). Machine learning methods for quantitative radiomic biomarkers. Scientific Reports, 5, Article 13087. https://doi.org/10.1038/srep13087
51. Li, H., Zhu, Y., Burnside, E. S., Huang, E., Drukker, K., Hoadley, K. A., … Ji, Y. (2016). MR imaging radiomics signatures for predicting the risk of breast cancer recurrence as given by recurrence score. Radiology, 281(2), 382-391.
52. Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. Nature Reviews Cancer, 18(8), 500-510.
53. Liu, Z., Li, Z., Qu, J., Zhang, R., Zhou, X., Li, L., … Tian, J. (2019). Radiomics of multiparametric MRI for predicting pathological complete response to neoadjuvant chemotherapy in breast cancer. Radiology, 290(2), 388-397.
54. Aerts, H. J. W. L. (2016). The potential of radiomic-based phenotyping in precision medicine. The Lancet Oncology, 17(6), e248-e257.
55. Mazurowski, M. A., Zhang, J., Grimm, L. J., Yoon, S. C., Silber, J. I. (2014). Radiogenomic analysis of breast cancer: Luminal B molecular subtype is associated with enhancement dynamics at MR imaging. Radiology, 273(2), 365-372.
56. Huang, S., Yang, J., Fong, S., Zhao, Q. (2020). Artificial intelligence in cancer diagnosis and prognosis: Opportunities and challenges. Cancer Letters, 471, 61-71.
57. Zwanenburg, A., Vallières, M., Abdalah, M. A., Aerts, H. J. W. L., Andrearczyk, V., Apte, A., … Löck, S. (2020). The image biomarker standardization initiative: Standardized quantitative radiomics for high-throughput image-based phenotyping. Radiology, 295(2), 328-338.
58. Holzinger, A., Langs, G., Denk, H., Zatloukal, K., Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9(4), e1312. https://doi.org/10.1002/widm.1312