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The role of artificial intelligence in enhancing breast cancer screening and diagnosis: A review of current advances

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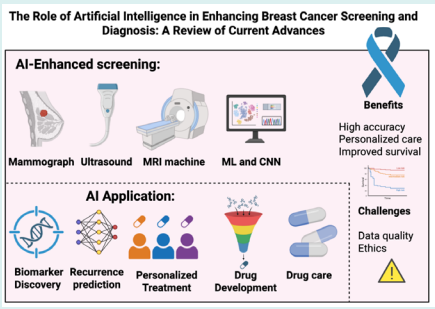
Abstract



Breast cancer (BCA) remains the most prevalent cancer globally and the leading cause of cancer-related mortality among women, with rising incidence rates driven by genetic, lifestyle, and environmental factors. Early detection through precise screening is essential to improve prognosis and survival; yet, challenges persist, especially in resource-limited areas. Recent advances in Artificial Intelligence (AI), particularly machine learning and deep learning algorithms, have illustrated significant potential to enhance breast cancer screening, diagnosis, and treatment personalization. This review highlights the multifaceted role of AI in BCA management, encompassing its applications in image-based screening modalities, genomic and immunologic profiling, and drug discovery. AI-driven approaches offer diagnostic accuracy, cost-effectiveness, time-saving, and individualized treatment regimens. Despite promising developments, further research is crucial to overcome current challenges and regulatory hurdles in clinical settings. This article highlights the positive aspects of AI technologies in advancing BCA care and the importance of continued interdisciplinary research to optimize their implementations in breast cancer workflows.

Introduction

Breast cancer (BCA) remains the most commonly diagnosed cancer globally and is a leading cause of cancer-related mortality among women. According to the most recent global data published by the World Health Organization (WHO) in 2024, BCA caused approximately 670,000 deaths worldwide in 2022 and was the most prevalent cancer among women in 157 out of 185 countries.[1] In the United States, based on the latest projections by the American Cancer Society for 2025, an estimated 316,950 new cases of invasive breast cancer and 42,170 related deaths are expected.[2] A comprehensive study by Giaquinto et al. reported a 1% annual increase in BCA incidence from 2012 to 2021, with a steeper rise among women under 50, particularly within Asian American and Pacific Islander populations.[3] These updated figures emphasize the ongoing global burden of BCA and underscore the necessity for continues advancements in prevention, early detection, and access to care. Despite medical advancements, BCA is still frequently diagnosed at advanced stages, particularly in developing countries where adequate screening, diagnosis, and treatment options are lacking. The survival rate is approximately 73% in developed countries compared to just 57% in developing countries, which emphasizes the importance of early screening.[4,5]

Artificial intelligence (AI) is defined as the use of techniques that enable computers to mimic human behavior and develop intelligent machines capable of performing tasks at or above the level of human intelligence.[6] In the field of medicine, there are two main branches of AI: virtual and physical. The virtual branch utilizes informatics approaches, employing deep learning and information management to oversee

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health management systems, including electronic health records. It also provides active guidance to physicians in their treatment decisions. The physical branch primarily involves robots that assist surgeons or elderly patients, as well as targeted nanorobots that offer a unique drug delivery system.[7] When it comes to drug design in pharmaceutical companies, the most common obstacles are time constraints and production costs.[8] Other challenges include low efficacy, inaccurate target delivery, and inappropriate dosing.[9]

AI, including deep learning (DL) and machine learning (ML) algorithms, has become integral to the drug development process. Machine learning is widely used in medicine for developing automated clinical decision systems, discovering unknown associations, and generating novel hypotheses to drive research.[10] These machine learning approaches are classified into supervised and unsupervised methods. Supervised methods are employed for risk assessment in anticoagulant therapy,[11] arrhythmia detection in electrocardiograms,[12] and the detection of lung micronodules from chest X-rays.[13] In contrast, unsupervised learning is used to identify hidden patterns in data and is often applied for data exploration and generating novel hypotheses. It can analyze treatment effectiveness compared to placebos without human involvement, thereby reducing ethical concerns about drug side effects for participants. Moreover, deep learning a branch of machine learning that utilizes artificial neural networks with multiple layers, simulate the workings of the human brain. This enables technology to generate automated predictions based on training datasets with remarkable accuracy and precision.[10]

Machine learning and deep learning algorithms are increasingly being applied across various stages of drug discovery. These applications include peptide synthesis, molecular design, virtual screening, molecular docking, quantitative structure-activity relationship (QSAR) analysis, drug repurposing, protein misfolding analysis, protein-protein interaction studies, molecular pathway identification, and pharmacology research.[14] The AI technology has made significant contributions to the diagnosis and treatment of various types of cancer, including breast cancer. With advancements in cancer screening, diagnosis, and treatment, it is evident that AI-guided care can play a crucial role in clinical practice.[15,16]

Immunology of breast cancer

Immunology

Breast cancer, an early-stage malignancy, has seen improved patient survival rates due to targeted therapies that counteract tumors driven by tyrosine kinase activation, with FDA-approved HER2-targeted treatments playing a pivotal role.[17] The importance of the interactions between tumor cells and the immune system in influencing BCA prognosis and treatment responses is becoming more evident. BCA, a diverse disease, is categorized into three primary subtypes based on hormone receptor (HR) status (estrogen receptor [ER] and progesterone receptor [PR]) and the presence of human epidermal growth factor receptor 2 (HER2): HR-positive/HER2-negative (luminal type, accounting for over 70%), HER2-positive (15–20%), and HR- and HER2-negative, also known as triple-negative breast cancer (TNBC, approximately 15%). Hormone therapy is appropriate for patients with ER- and PR-positive hormone receptors, whereas targeted therapy is ideal for those with HER2-positive status in clinical practice.[18] Genomic-level approaches have improved breast cancer treatment. Increased expression of human epidermal growth factor receptor 2 (Her-2/neu) occurs in 15-30% of BCA cases, leading to a more aggressive tumor phenotype and reduced survival. The use of monoclonal antibodies (mAbs), such as pertuzumab and trastuzumab, targeting Her-2/neu, effectively treats BCA and improves prognosis (Fig. 1).[19]

Rimawi et al found that HER2 (ErbB2), a member of tyrosine kinase receptors (HER1-4), plays a major role in 20% of BCA development. Recent years have seen the introduction of anti-HER2 monoclonal antibody trastuzumab as a means to tackle these aggressive BCA subtypes.[20] Vaccine production can activate the host's innate immune system to overcome resistance and tumor recurrence. Consequently, scientists have been studying anti-HER2 targeted therapies with complementary or synergistic mechanisms to treat patients with HER2-positive metastatic BCA.[21] To improve treatment outcomes, next-generation sequencing has allowed for the analysis of cancer genomes and transcripts, resulting in the establishment of several databases such as The Cancer Genome Atlas (TCGA), the National Institutes of Health (NIH), and the International Cancer Genome Consortium (ICGC), which are widely used to expand treatment options for BCA patients.[22] These databases encompass data on single-gene mutations, genomic structural abnormalities, and mRNA and protein expression levels, facilitating the identification of new anticancer drugs. Yoshimaru et al highlighted three molecular targets, such as MELK, TOPK, and BIG3, that are highly overexpressed in various cancers, especially in BCA. Their research showed that dominant-negative peptides exhibit selective inhibitory effects. Furthermore, leveraging this molecular mechanism to restore the innate tumor-suppressive activity of PHB2 could offer a treatment option for resistant BCA without reducing the patient's lifespan.[22] BCA consists of various histological and molecular subtypes, each showing different levels of immunogenicity and responsiveness to immune therapies. This can limit immunologic-based treatment as patients may not respond to a single immunotherapy.[23]

Immunotherapy in BCA treatment incorporates different types of vaccines, including protein-based,

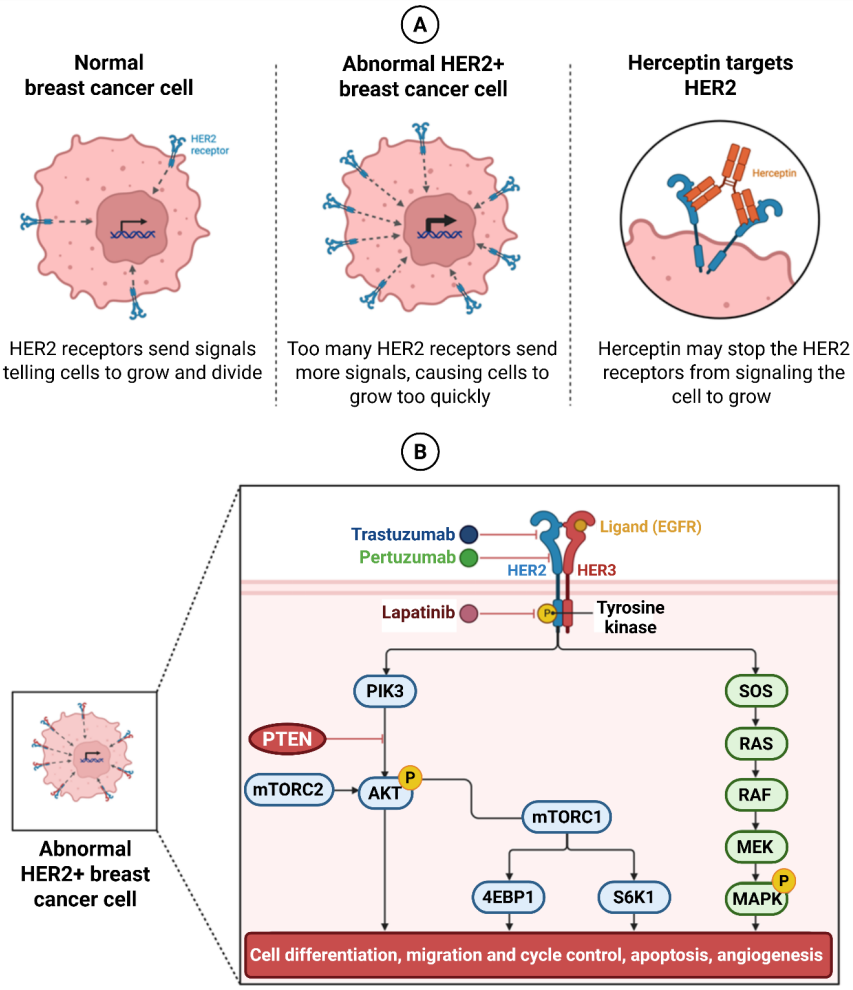


Fig. 1. HER2/EGFR Signaling Pathway in Breast Cancer and anti-HER2 treatment. (A) The role of HER2 in BCA and differences between the normal and abnormal BCA, so that the immunotherapy can stop cancer cells. (B) The intricate signaling cascade involving the Human Epidermal Growth Factor Receptor 2 (HER2) is significantly influenced by the application of monoclonal antibodies, which possess the remarkable ability to not only suppress the proliferation of cells that express HER2 but also to actively promote apoptotic cell death through a variety of mechanisms that can be classified as either intracellular or extracellular; this is primarily achieved by the specific targeting of HER2-positive cellular entities, leading to the subsequent processes of receptor internalization and degradation, ultimately contributing to the therapeutic efficacy observed in the treatment of certain malignancies characterized by HER2 overexpression. Created with BioRender.com (Used with permission).

peptide-based, bacterial or viral-based, DNA/RNA-based nucleic acid vaccines, and immune cell-based vaccines. These approaches are classified as active immunotherapies.[24] However, there are limitations in the immunotherapeutic methods for BCA, such as the efficient delivery of drugs to the cancer site. This challenge can potentially be addressed by using nanostructures designed to enhance antigen stability, promote antigen presentation, and stimulate the immune response.[25]

AI into cancer immunotherapy

AI has emerged as a transformative force in modern oncology, with particular promise in the field of cancer immunotherapy. While immunotherapy has revolutionized cancer treatment by leveraging the host's immune system to target and eliminate tumor cells, its clinical application is often limited by patient heterogeneity, variable responses, immune escape mechanisms, and challenges in selecting optimal therapeutic strategies. Integrating AI into immunotherapy workflows offers solutions to many of these challenges through advanced data analysis, predictive modeling, and real-time clinical decision support. This section explores the multifaceted applications of AI in cancer immunotherapy.[26]

Enhancing biomarker discovery

One of the critical areas where AI has significantly impacted cancer immunotherapy is in biomarker discovery. Traditional biomarker identification is labor-intensive and often constrained by the limitations of human interpretation and statistical tools. AI, particularly through ML and DL algorithms, enables high-throughput analysis of multi-omics data such as genomic, transcriptomic, and proteomic datasets to uncover novel biomarkers predictive of immunotherapy response. AI models have demonstrated high accuracy in identifying clinically relevant biomarkers such as PD-L1 expression, tumor

mutational burden (TMB), and microsatellite instability (MSI), all of which are instrumental in stratifying patients for immune checkpoint inhibitor (ICI) therapy.[27-29]

According to Olawade et al, supervised ML algorithms such as random forest and support vector machines (SVM), as well as DL methods like convolutional neural networks (CNNs), have been effectively applied to analyze complex biological data. These tools can detect subtle patterns and correlations that might be overlooked using traditional bioinformatics approaches. For instance, AI has facilitated the identification of gene signatures associated with favorable responses to PD-1 and CTLA-4 blockade therapy, thereby supporting the development of personalized immunotherapy regimens.[30]

Predicting patient response and adverse events

Another major application of AI in cancer immunotherapy lies in the prediction of patient responses and the assessment of potential adverse effects. Not all patients benefit from immunotherapy, and some may experience immune-related adverse events (irAEs), which can be severe and life-threatening. AI-based predictive models integrate diverse patient data including genomic alterations, immune signatures, imaging data, and electronic health records (EHRs) to forecast treatment responses and identify those at higher risk of toxicity.[31] For example, gradient boosting machines, logistic regression models, and multi-layer perceptrons (MLPs) have been employed to predict the effectiveness of ICIs in cancers such as melanoma, breast, and non-small cell lung cancer.[32] AI-driven analysis of pre-treatment histopathological slides has also shown promise in predicting PD-1 therapy responsiveness, offering a non-invasive and scalable method to guide treatment decisions. Moreover, AI tools can forecast the onset of irAEs using baseline immunological and clinical parameters, thereby enabling early intervention and improving patient safety.

Optimizing combination therapies

Immunotherapy is increasingly being used in combination with chemotherapy, radiotherapy, or targeted therapies to enhance efficacy and overcome resistance. However, identifying the optimal combination regimen and sequencing strategy is highly complex. AI can address this challenge by analyzing real-world clinical data and simulating treatment outcomes to identify synergistic combinations tailored to individual patients.

Reinforcement learning models and Bayesian networks have been applied to evaluate clinical trial data and real-world evidence to predict the most effective combination protocols.[33] These AI systems can model how immune responses change in the presence of different therapeutic agents and help clinicians fine-tune dosages and schedules. Olawade et al emphasize that AI not only accelerates the discovery of effective treatment combinations but also reduces reliance on traditional trial-and-error approaches, thereby improving therapeutic outcomes and patient quality of life.

Accelerating drug discovery and target identification

Drug development in immuno-oncology is a time-consuming and expensive process. AI accelerates this process by enabling the rapid identification of novel therapeutic targets and potential drug candidates. Through techniques like unsupervised ML (e.g., clustering and principal component analysis) and DL models including generative adversarial networks (GANs), AI can analyze massive datasets to identify actionable targets such as neoantigens tumor-specific mutated proteins that are ideal candidates for vaccine development.[34,35]

Additionally, AI models have been successfully deployed in virtual screening and molecular docking to simulate drug–target interactions. This allows researchers to predict the binding affinity and pharmacological properties of new compounds with unprecedented speed and accuracy. Graph neural networks (GNNs), for example, have been used to model the 3D structure of immune checkpoints and screen for novel inhibitors, dramatically shortening the drug development timeline and lowering associated costs.[36]

ML has brought transformative progress to molecular docking studies, particularly within the realm of immunotherapy drug discovery.[37] These studies aim to simulate and predict how small molecules, such as drugs, interact with biological targets like proteins a process essential for designing potent immunotherapeutic compounds.[37] Conventional docking techniques often struggle with accurately modeling three-dimensional molecular interactions due to their inherent complexity. However, the integration of ML technologies, such as deep learning architectures and reinforcement learning frameworks, has markedly enhanced the precision and robustness of these predictions.[33] By leveraging large-scale datasets of protein–ligand interactions, ML algorithms are now capable of generating highly accurate binding conformations, even for challenging targets like neoantigens and immune checkpoint molecules. This technological advancement not only increases the fidelity of molecular interaction predictions but also accelerates the screening and identification of promising therapeutic candidates. As a result, it significantly reduces the time and financial resources required by conventional drug development pipelines. For an in-depth discussion of computational approaches including target identification, molecular docking, and molecular dynamics simulations readers are referred to our recent study, where we evaluated commonly used tools, their algorithms, and practical applications.[38]

Ultimately, the application of ML in molecular docking is proving instrumental in the efficient design of next-generation immunotherapies, including checkpoint inhibitors and personalized cancer vaccines, thereby reshaping the future of immunotherapy research and development. [37]

Real-time monitoring and adaptive therapy

Beyond diagnostics and drug development, AI is also being integrated into patient monitoring systems to enable real-time assessment of treatment response and adaptive therapy. Using time-series analysis and DL algorithms such as long short-term memory (LSTM) networks, AI can interpret data from wearable biosensors, imaging modalities, and EHRs to detect early signs of treatment response or adverse reactions. This continuous feedback allows clinicians to adjust treatment protocols dynamically, personalizing therapy based on evolving patient needs.[39,40]

For instance, changes in physiological markers such as heart rate, oxygen saturation, or inflammatory cytokine levels can be flagged by AI systems as potential indicators of immune-related toxicity, prompting timely intervention. This not only improves clinical outcomes but also enhances patient safety and adherence to treatment.[41]

Improving clinical trial design

AI is revolutionizing clinical trial design by improving patient recruitment, stratification, and protocol optimization. Traditional clinical trials often face challenges in enrolling appropriate participants, particularly for rare cancer subtypes or precision immunotherapies. AI addresses this gap by analyzing clinical and molecular data to match patients with suitable trials based on predicted treatment responses.[42]

Natural language processing (NLP) and ML algorithms can process unstructured EHR data to identify eligibility criteria and generate trial cohorts more efficiently.[43] AI-driven simulation models also enable adaptive trial designs, allowing real-time modification of protocols based on interim results. This not only improves the probability of trial success but also reduces time and resource expenditures in the development pipeline.[44]

Role of AI in studying tumor–immune interactions

AI has emerged as a transformative tool in oncology, particularly in deciphering the complex interactions between tumors and the immune system. In BCA, AI-driven approaches are enhancing our understanding of the tumor immune microenvironment (TIME), predicting responses to immunotherapy, and guiding the development of personalized treatment strategies.[45]

One significant application of AI is in analyzing histopathological images to assess immune cell infiltration within tumors. For instance, researchers at Karolinska Institute utilized AI models to evaluate tumor-infiltrating lymphocytes (TILs) in triple-negative breast cancer (TNBC), demonstrating that AI can effectively predict patient prognosis by quantifying immune cell presence. Similarly, deep learning algorithms have been employed to predict tumor and immune phenotypes from histopathology slides, achieving high accuracy in classifying gene expression pathways and offering insights into the spatial distribution of immune cells.[46]

Beyond image analysis, AI is instrumental in interpreting multi-omics data to unravel the complexities of tumor–immune interactions. Explainable AI (XAI) models have been applied to RNA sequencing data from BCA patients to identify critical immune components associated with improved survival. For example, a study revealed that higher fractions of CD4+T cells and B cells within the tumor microenvironment correlate with better 5-year survival rates in both TNBC and non-TNBC patients.[47]

Furthermore, AI facilitates the prediction of immunotherapy efficacy by integrating diverse datasets, including genomic, transcriptomic, and proteomic information. By modeling the intricate dynamics of the TIME, AI algorithms can identify biomarkers indicative of positive responses to treatments like immune checkpoint inhibitors, thereby aiding in patient stratification and personalized therapy planning. In summary, AI serves as a powerful ally in cancer immunotherapy research, offering advanced analytical capabilities to decode tumor–immune interactions. Its applications in image analysis, multi-omics integration, and predictive modeling are paving the way for more precise and effective immunotherapeutic interventions in breast cancer.

Breast cancer screening

As BCA, along with lung and colorectal cancers, are the most common cancers worldwide,[48] BCA screening guidelines have been developed to improve decision-making for physicians and increase awareness of its importance globally.[49,50] Screening for BCA is highly effective in detecting early-stage disease, improving patient survival rates, enhancing women's healthcare, and enabling timely diagnosis and treatment. The American Cancer Society recommends annual screenings for women aged 45-54 and biennial screenings for those aged 55 and older.[51] Diagnostic approaches for BCA include clinical examination, mammography, ultrasound, core-needle biopsy, and molecular genetic analysis.[52] The treatment plan is based on the tumor profile, biomarker assessment, and potential risk factors associated with tumor recurrence. The standard mortality rate (SMR) index algorithm, known as PSI, is utilized to assess BCA prognosis and predict treatment benefits.[53] The cancer screening via AI application showed in Table 1.

Sonography

Screening modalities for BCA include automatic breast ultrasound, contrast-enhanced ultrasound, three-dimensional ultrasound, and computer-aided detection of breast ultrasound.[78] Ultrasonography is widely used, particularly for women with dense breasts, due to its accessibility and convenience and a high negative predictive value of 99.5% in classifying benign solid lesions. The Breast Imaging Report and Data System (BI-

Table 1. Overview of AI applications in breast cancer screening and clinical care

Category	AI Application	Details	Benefits	Limitations/Challenges	References
Early Detection	AI-driven imaging analysis	Automated analysis of mammograms, MRIs, and ultrasounds to identify subtle patterns for early-stage breast cancer detection.	Improves diagnostic accuracy, reduces human error, and enables earlier diagnosis.	Issues with data quality, model generalization, and ethical considerations.	54-56
	Risk assessment models	CNNs distinguish high-risk individuals from low-risk groups by analyzing genetic and clinical data.	Facilitates personalized screening and prevention strategies.	Limited interpretability and reliance on high-quality datasets.	57
Diagnosis	Deep learning	Identifies imaging-genomic correlations (e.g., BRCA mutations) and facilitates radio-genomic analysis for biomarker discovery.	Enables non-invasive diagnostics and biomarker-based therapies.	Requires large datasets and robust computational infrastructure.	58,59
	Natural language processing	Extracts key details from clinical notes and reports to support diagnosis and treatment.	Streamlines data organization and reduces workload.	Accuracy depends on data input quality.	60-62
	Case-based reasoning	Matches new patient cases with historical cases to support diagnostic decisions.	Particularly useful in complex cases with inconclusive traditional diagnostics.	Limited database size can affect accuracy.	63,64
Treatment	Arianna solution	Tracks patient progress, monitors adherence, and provides reminders for follow-ups.	Enhances diagnostic accuracy, patient satisfaction, and cost-effectiveness.	Limited scalability in resource-constrained settings.	65
Recurrence Prediction	DNA methylation analysis	Encodes DNA methylation patterns to model recurrence risk using machine learning algorithms (e.g., SVMs, neural networks).	Enhances prediction accuracy.	Requires robust data annotation and high-quality datasets.	66-68
	Gene weight analysis	Assesses genes' contributions to recurrence risk using techniques like SHAP values.	Identifies novel biomarkers for tailored interventions.	Computationally intensive and resource-dependent.	69-71
Risk Models	Gail model	Calculates lifetime risk using patient history (e.g., age, family history, reproductive history).	Simple and widely used.	Lacks integration with mammographic density data and underestimates risk in some cases.	72
	Tyrer-Cuzick model	Incorporates genetic, hormonal, and familial factors for risk prediction.	Provides more accurate risk predictions, especially for individuals with family history.	Data complexity can hinder widespread use. Additionally, it was first developed in non-Hispanic White women	72-74
	BCSC model	Integrates mammographic density as a key risk factor along with demographic and clinical data.	Enhances accuracy by leveraging imaging data.	Requires mammographic data integration.	75,76
	AI Mammographic Phenotyping	Analysis mammograms for texture patterns, density variations, and subtle features.	Supports individualized risk assessment and prevention strategies.	Requires advanced DL models and high-quality imaging datasets.	77

RADS) established by the American College of Radiology (ACR), standardizes reporting across mammography, ultrasonography, and MRI, reducing variability and enabling seamless integration with digital mammography and CAD systems.[79-81] Given the higher cost of mammography, sonography is often employed as a first line screening tool, especially in developing countries as it is available and better tolerated by patients.[82]

Mammography

Mammography remains the preferred method for early breast cancer detection due to its accuracy, wide availability, and cost-effectiveness in saving years of life.[83] Most national guidelines recommend mammographic screening for women aged 40 and older.[49,84,85] Studies show mammography reduces BCA mortality by about 40% in average-risk women aged 40-74.[86,87] Annual screening for women aged 40-49 is also supported to reduce mortality, with particularly strong evidence for women aged 50 and above.[88] Screening decreases the incidence of advanced cancer and is currently the only proven test to lower BCA death rates.[89,90] Guidelines typically advise annual or biennial mammography for average-risk women aged 40-74. High risk individuals may benefit from earlier and more frequent screening, including annual MRI.[91] There might be some challenges in screening patients with

mammograms including a false positive result- recalls for additional testing that ultimately reveal cancer- and overdiagnosis, where detected cancers would not have caused clinical symptoms.[92] Reported overdiagnosis rates vary widely from (0%-57%), raising concerns about their accuracy.[93-95] False-negative occur in about 20% of cases especially in lobular carcinomas and dense breast tissue.[96] AI algorithms can automatically analyze mammograms, reducing radiologists' workload and improving detection rates by highlighting suspicious areas.[97,98] A 2023 study demonstrated that a deep learning model improved BCA risk prediction in Asian women compared to traditional models.[99]

Advanced deep learning techniques enhance mammogram analysis through Dual Models and U-Net segmentation. Dual Models, combine one model that detects macro-level features such as breast density with another focusing on micro-level features such as microcalcifications for comprehensive analysis.[100] The U-Net, is a CNN architecture designed for biomedical image segmentation.[101] It captures spatial and contextual details to accurately outline suspicious regions, aiding precise localization and diagnosis.[102,103]

Thermography

Infrared thermography (IRT) has emerged as a promising adjunctive modality for BCA screening. Unlike traditional imaging techniques such as mammography, which rely on structural visualization, IRT detects subtle temperature differences on the surface of the skin that may reflect underlying pathological processes. These thermal patterns are influenced by changes in vascularization, metabolism, and inflammation, which are often present in malignant tissue even before a structural abnormality becomes apparent. IRT is completely non-invasive, radiation-free, and painless, making it particularly appealing for use in younger women or individuals with dense breast tissue, where mammographic sensitivity may be limited. Recent studies have explored the integration of thermographic imaging with AI to enhance diagnostic accuracy.[104,105] For instance, a study by Jalloul et al evaluated multiple deep learning and machine learning algorithms using thermographic datasets, and reported that the combination of ResNet152 and SVM achieved an impressive classification accuracy of over 97%, along with high sensitivity and specificity.[106] Similarly, Chi et al proposed a lightweight, high-accuracy framework by integrating pre-trained CNNs with statistical feature selection methods, such as the chi-square filter, followed by SVM-based classification. Their model not only reached a peak accuracy of 99.62% on benchmark datasets but also maintained low computational complexity, making it a practical choice for real-time, computer-aided diagnosis.[107] These findings highlight the potential of AI-powered thermography in distinguishing between healthy, benign, and malignant breast tissue.

Notably, clinical validation of AI-assisted thermography has also begun to emerge. A multicenter prospective study by Singh et al evaluated Thermalytix, an automated thermographic screening algorithm, in 258 symptomatic women. When compared to standard diagnostic modalities, Thermalytix showed non-inferior sensitivity (82.5%) and significantly higher specificity (80.5%) relative to mammography (45.9%) under BI-RADS 3 criteria. Interestingly, the method maintained strong diagnostic performance across age groups, achieving an AUC of 0.845 overall. These findings support the clinical utility of AI-enhanced thermography as a supplemental tool for early BCA detection, particularly in settings where conventional imaging may be inaccessible or suboptimal.[108] In a recent systematic review and meta-analysis, the researchers evaluated 22 clinical studies published since 2001 that investigated the diagnostic performance of digital infrared thermography for BCA. The meta-analysis reported a pooled sensitivity of 88.5% and specificity of 71.8%, indicating that while thermography is generally effective in identifying malignant cases, its ability to rule out non-cancerous findings has been more variable. Importantly, the review highlighted substantial heterogeneity across studies, attributed to differences in imaging protocols, patient selection, device quality, and interpretive criteria. Despite these limitations, the authors concluded that recent studies show performance levels approaching those of standard diagnostic tools, particularly in populations with dense breast tissue or limited access to conventional screening.[109]

Despite its promise, thermography still faces limitations, including variability in imaging protocols, environmental dependencies, and the need for standardized interpretation frameworks. Nonetheless, when used alongside conventional methods, it may serve as a valuable tool in early detection strategies, particularly in resource-limited settings or for individuals seeking radiation-free alternatives.[110]

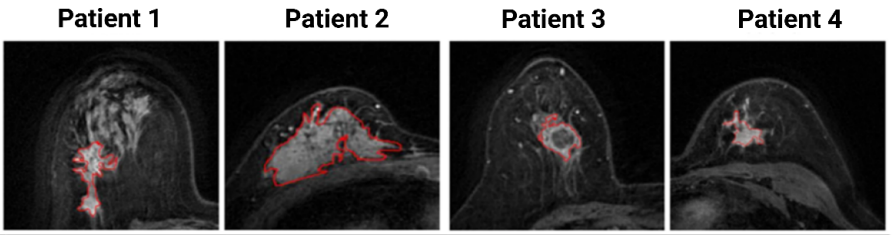
Magnetic resonance imaging (MRI)

Among breast cancer screening methods, MRI is highly sensitive (over 90%) in detecting breast masses and is notable for its high negative predictive value.[111-115] It is especially valuable for women with BRCA1 and BRCA2 mutations and those with a life-time risk of 20-25% or higher, as determined by factors such as family history, prior radiation therapy, or genetic predisposition.[116-120] Current guidelines recommend annual MRI screening alongside annual mammography for those high-risk groups, as this combination increases detection sensitivity, particularly in women aged 40-49 and even more so in the 50-69 age group.[121,122] MRI is also clinically useful for local staging before breast cancer surgery and for evaluating patients

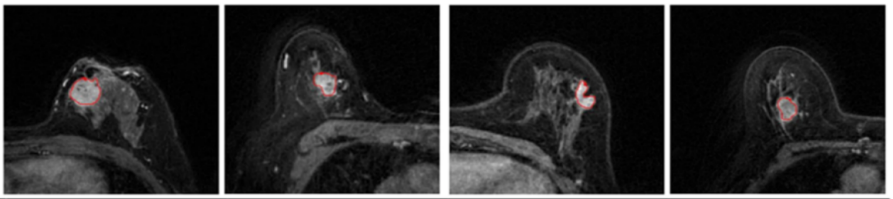
with chronic kidney disorders, since the use of gadolinium contrast can impair renal function and may lead to nephrogenic systemic fibrosis.[115,123,124] Recent advances in AI have enabled the use of radiomics, where quantitative features extracted from MRI scans can help predict the likelihood of breast cancer of recurrence.[125] Radiomics can assist clinicians in distinguishing between low-grade and high-grade cancers prior to surgery, providing valuable insights into tumor characteristics and supporting preoperative assessment of cancer aggressiveness, thereby guiding treatment decisions (Fig. 2).[126]

Digital breast tomosynthesis (DBT)

DBT is a technique that uses multiple low-dose mammographic images of the compressed breast, which are then reconstructed into synthesized 2D projection images.[128,129] DBT creates a three-dimensional reconstruction of the breast, providing clearer and more detailed images compared to traditional 2D mammography, which helps in identifying abnormalities that may be missed in standard mammograms due to tissue overlap. It is proven that the combination of DBT with digital mammography can increase the screening and diagnosis rate, with a sensitivity of 33%-53% and a specificity of 30%-40 %.[130-134] DBT has several advantages, including reducing tissue overlap, detecting more findings in dense breast tissue, decreasing false negatives, and improving mass characterization.[135,136] One study found a significant



	Patient 1	Patient 2	Patient 3	Patient 4
Individual information	59-year-old female	31-year-old female	64-year-old female	54-year-old female
Clinical subtype	HR+HER2-	HR+HER2+	HR-HER2+	TNBC
Randiomic risk level	RS = 10.53 Randiomic high risk of recurrence	RS = 90.64 Randiomic high risk of recurrence	RS = 1.77 Randiomic high risk of recurrence	RS = 7.82 Randiomic high risk of recurrence
Clinical outcome	Recurrence at 42 months Death at 70 months	Recurrence at 11 months Death at 23 months	Recurrence at 15 months Death at 24 months	Recurrence at 19 months Death at 26 months



	Patient 5	Patient 6	Patient 7	Patient 8
Individual information	48-year-old female	58-year-old female	49-year-old female	64-year-old female
Clinical Subtype	HR+HER2-	HR+HER2+	HR-HER2+	TNBC
Randiomic risk level	RS = 0.01 Randiomic low risk of recurrence	RS = 0.09 Randiomic low risk of recurrence	RS = 0.05 Randiomic low risk of recurrence	RS = 0.01 Randiomic low risk of recurrence
Clinical outcome	Recurrence at 74 months Alive at 74 months	Recurrence at 96 months Alive at 96 months	Recurrence at 92 months Alive at 92 months	Recurrence at 86 months Alive at 86 months

Fig. 2. Classification of breast cancer patients based on radiomic features and clinical variables. This figure illustrates the classification of breast cancer patients into high-risk and low-risk categories using a radiomic risk model. The model integrates radiomic features from Dynamic Contrast-Enhanced MRI (DCE-MRI), such as texture, shape, and intensity, alongside clinical variables including HER2 status, hormone receptor (HR) status, and tumor size. Patients in the high-risk group show irregular tumor shapes and high heterogeneity, while those in the low-risk group exhibit more homogeneous features. The model enables improved prediction of tumor recurrence, highlighting the potential for personalized treatment strategies.[127] Reprinted from You et al,[127] under the terms of the Creative Commons Attribution-Noncommercial-No Derivatives 4.0 International License.

increase in cancer detection in patients who underwent screening with DBT after three years of follow-up.[137] Deep Learning models on large datasets of DBT images would recognize patterns to indicate BCA. Models such as CNNs are particularly effective in analyzing the complex structures in DBT images. Using AI to extract relevant features from DBT images, such as the shape, texture, and density of lesions can help in distinguishing between benign and malignant tissues. AI algorithms can analyze the 3D images generated by DBT to detect tumors with greater accuracy than traditional 2D mammography. This leads to improved detection rates and fewer false positives.[138] AI can also enhance the visualization of DBT images by focusing on the suspicious lesions and providing clearer views of dense breast tissue, which is often challenging to interpret with conventional imaging techniques.[139] In addition, it is noted that AI can integrate DBT images with other patient data, including the genetic information and clinical history, to provide a comprehensive assessment of BCA risk and perform a personalized treatment decision.[140]

AI in breast cancer screening

Late-stage diagnosis remains a major obstacle to improving survival rates, especially in developing countries with limited access to screening and diagnostic resources, despite advancements in medical research and technology. This article delves into the role of AI technologies in addressing crucial challenges in the healthcare and pharmaceutical industries.[141-143] By automating imaging analysis and employing predictive algorithms, AI has the potential to transform BCA detection, leading to timely diagnosis and treatment and ultimately enhancing patient outcomes and survival rates. Fig. 3 presents a comprehensive flowchart illustrating the functions of AI in BCA.

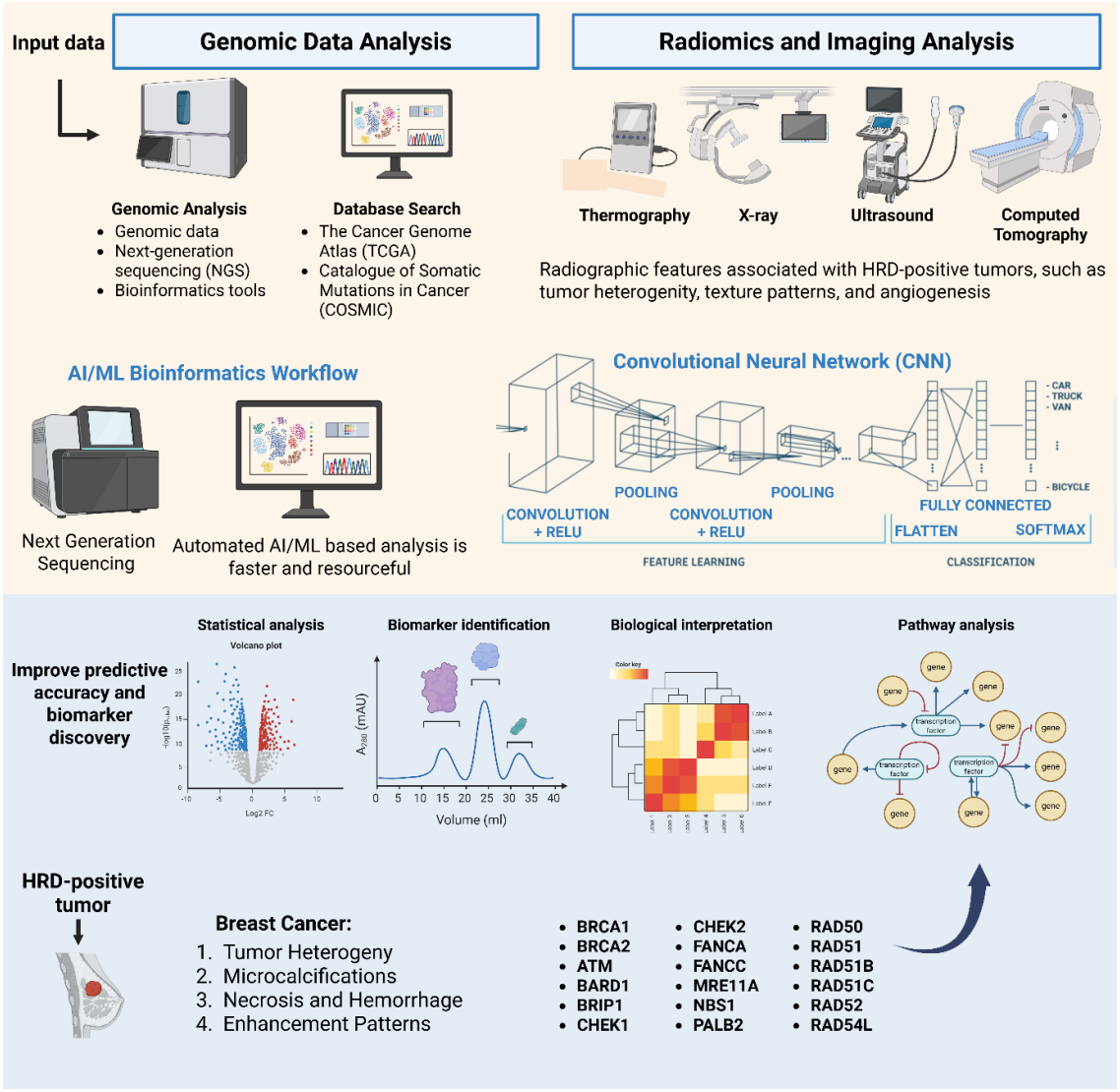


Fig. 3. The intricate flowchart detailing the procedures for diagnosing and treating breast cancer, which is continuously enhanced by the advancements in AI, plays a crucial role in facilitating the identification of novel therapeutic targets, innovative drug candidates, potential biomarkers, and other related aspects in the field. Created with BioRender.com (Used with permission).

AI-driven solutions for early detection, diagnosis, and treatment

Early detection and accurate diagnosis of BCA are paramount in improving patient outcomes and survival rates. When identified at an early stage, BCA is more likely to be treated successfully, with a broader range of therapeutic options and a lower likelihood of metastasis. The capacity of AI to incorporate and refine its understanding from data over time imbues it with significant potential as a tool for personalized medicine.[98] Specifically, AI-driven systems can support radiologists in the interpretation of mammograms, mitigating human error and augmenting diagnostic precision. These systems can determine slight patterns that might evade human observation, ultimately facilitating earlier and more accurate detection of BCA. Moreover, AI is instrumental in developing predictive models that assess an individual's risk of developing BCA based on their genetic profile, lifestyle, and other factors. These models can guide personalized screening strategies and preventive measures, ultimately improving patient outcomes.[144] AI also plays a critical role in the treatment of BCA (Table 2). It helps to devise personalized treatment plans by analyzing data from previous cases to predict how a patient might respond to different treatment plans. This ensures that patients receive the most effective treatments with the least side effects, enhancing their quality of life and their prognosis. Table 3 will summarize recent AI-based models specifically designed for predicting breast cancer prognosis (e.g., recurrence risk, survival rates) and optimizing personalized treatment strategies.

1. ML: A subset of AI that enables computers to learn from data and improve their performance over time without being explicitly programmed. ML algorithms can classify images, detect tumors, and predict patient outcomes based on historical data.

1.1. SVMs: SVMs are among ML techniques for classification tasks that find the optimal hyperplane for different classes in the feature space. SVMs have been used to classify BCA subtypes and predict consequences based on histopathological features.[166]

2. Deep learning algorithms: A more advanced subset of ML that uses neural networks with many layers (hence "deep") to analyze data. AI algorithms, particularly deep learning models, can analyze mammograms, MRIs, and ultrasound images with high precision. These models are trained on large datasets to identify subtle patterns and abnormalities that may be indicative of early-stage BCA.

2.1. DL in radio-genomics: Radio-genomics integrates radiological imaging with genomic data to improve the diagnosis and treatment plan. Deep learning models can analyze radiological images to extract features that correlate with specific genetic mutations. For example, specific imaging characteristics may contribute to mutations in BRCA1 and BRCA2.[167] The impact of radio-genomics in predictive modeling and biomarker discovery can lead to the development of non-invasive diagnostic tests and targeted therapies.[168,169]

2.2. DL in risk assessment: The advantages of CNNs are studied and compared with traditional radiographic texture analysis (RTA) in distinguishing between high-risk and low-risk subjects. The consequences demonstrate that CNNs performed similarly to RTA in distinguishing BRCA1/2 carriers and low-risk women, while noticeably better in distinguishing unilateral cancer patients and low-risk women.[170] Although the opportunities of DL outweigh the limitations, there are some challenges worth mentioning, including data quality, model interpretability, generalization, and ethical considerations that are necessary to integrate deep learning into clinical practice successfully.

3. Computer-aided detection (CAD): A type of deep learning model specifically designed for analyzing visual data. CNNs are highly effective in detecting features in images, such as tumors in mammograms, by automatically learning to identify patterns and structures associated with BCA. These systems can reduce the likelihood of human error and increase diagnostic accuracy. Some positive aspects of CNN include:

3.1. Tumor detection: CNNs can be trained to detect tumors in mammograms and other breast imaging modalities with high sensitivity and specificity. They can identify subtle patterns that may be missed by radiologists, leading to earlier and more accurate diagnoses.[144]

3.2. Image segmentation: CNNs can segment medical images to delineate the boundaries of tumors and other structures within the breast. This is crucial for accurate measurement and assessment of tumor size and local spread.[102]

3.3. Risk prediction: By analyzing imaging data alongside other clinical information, deep learning models can predict a patient's risk of developing BCA, aiding in personalized screening and prevention strategies.[171]

4. NLP: A branch of AI that focuses on the interaction between computers and human language. In the context of BCA detection, NLP can be used to analyze clinical notes and reports to extract relevant information for diagnosis and treatment planning.

5. Case-based reasoning (CBR): CBR is a method used by AI systems to solve new problems by drawing on the experiences of past cases. This approach involves four key steps: first, retrieving relevant past cases; second, reusing the knowledge gained from those cases to solve the current problem; third, revising the solution based on any new information; and finally, retaining the knowledge gained for future use.[172]

5.1. Diagnostic support: CBR systems provide diagnostic support by comparing new patient cases with a database of historical cases. Radiologists and oncologists can utilize these systems to identify patterns and similarities with past cases, helping to confirm or refine diagnoses.

Table 2. Evaluation of AI-based models for breast cancer risk, prognosis, diagnosis, and treatment

Study	Objective	Data source/ population	AI model/ methodology	Performance metrics	Strengths, limitations, and application notes	References
Lo Gullo et al, 2024	Develop a model to predict TNBC using radiomic features of contralateral breast fibroglandular tissues.	541 patients (250 training, 291 validation).	SVM (polynomial kernel, order 2); CERR platform; 132 radiomic features extracted.	F1 score: 0.66 AUC: 0.71 Sensitivity: 0.54 (0.47-0.60) Specificity: 0.74 (0.65-0.84) PPV: 0.84 (0.78-0.90) NPV: 0.39 (0.31-0.47)	Strengths: Uses contralateral breast, an innovative feature. Limitations: Low sensitivity and NPV; limited clinical utility as a stand-alone predictor.	145
Mo et al, 2024	Develop a radiomics model using photoacoustic/ ultrasound imaging to differentiate between Luminal and non-Luminal breast cancer, and identify the optimal peritumoral region for better classification.	322 patients (262 training, 60 validation).	LASSO model; feature extraction from intra- and peri-tumoral regions; RF classifier.	Combined intra-tumoral and peri-tumoral model at a 4 mm region: Accuracy: 0.90 AUC: 0.90 (0.78-1.00) Sensitivity: 0.94 Specificity: 0.75	Strengths: High accuracy with peritumoral imaging integration. Limitations: Needs high-quality multimodal imaging; less validated externally.	146
Yang et al, 2024	Develop an AI-driven framework for cancer biomarker discovery (Ki-67 gene) using radiomics and multi-omics data integration.	233 patients (70% training, 30% validation).	CNN for image feature extraction, GNNs for multi-omics integration, LASSO for feature selection and dimensionality reduction, XAI for model interpretability, cross-validation for performance evaluation.	Combined radiomics model for Ki-67 (20% cut-off): F1 score: 0.84 Accuracy: 0.82 AUC: 0.86 (0.76-0.94) Sensitivity: 0.92 Specificity: 0.73	Strengths: Integrates omics + imaging with explainability. Limitations: High computational demands; needs multi-modal data.	147
Zhang et al, 2024	Combine machine learning models (RF, SVM, CNN) with Raman spectroscopy to distinguish between normal and cancerous breast tissue, aiming to create a rapid, non-invasive diagnostic tool for breast cancer.	20 mice, 959 tumor spectra, 1075 normal tissue spectra.	RF, SVM (RBF kernel), CNN; data pre-processing (background removal, smoothing, normalization); CNN with 50 epochs, binary cross-entropy loss, SGD optimizer.	CNN: Accuracy: 0.98 Sensitivity: 0.96 Specificity: 0.99	Strengths: Rapid, non-invasive diagnostic potential. Limitations: Preclinical; only tested in mice, requires translation to human data.	148
Zuo et al, 2023	Evaluate and compare the performance of various machine learning models for predicting breast cancer recurrence risk and identify the best model for prediction.	342 patients (70% training, 30% validation).	Eleven models were used: AdaBoost showed the best performance.	AdaBoost: F1 score: 0.92 AUC: 0.99 Sensitivity: 0.95 Specificity: 0.98 PPV: 0.90 NPV: 0.99	Strengths: Very high predictive performance. Limitations: Moderate sample size; model interpretability is limited in AdaBoost.	149
Zhong et al, 2023	Develop accurate machine learning models to predict the diagnosis and prognosis of bone metastasis in breast cancer patients, helping clinicians with decision-making.	Surveillance, Epidemiology, and End Results (SEER) database; 283,373 patients (198,364 training, 85,009 validation).	Six machine learning models were used, with XGB performing best. Feature selection was done via logistic and Cox regression, and models were optimized using five-fold CV, grid search, and SHAP for feature importance.	XGB: F1 score: 0.95 AUC: 0.94 Accuracy: 0.94 Precision: 0.98 Recall: 0.94	Strengths: Large SEER dataset; interpretable with SHAP. Limitations: Based on retrospective registry; lacks imaging data.	150

Table 2. Continued.

Study	Objective	Data source/ population	AI model/ methodology	Performance metrics	Strengths, limitations, and application notes	References
C. Manikis et al, 2023	Develop machine learning models to predict poor mental health or quality of life decline in breast cancer patients, enabling personalized psychological interventions.	706 patients (80% training, 20% validation)	The study used 12 models, primarily BRF, with nested cross-validation and feature selection on clinical, psychological, and lifestyle data.	BRF: model A (mental health) and B (quality of life), respectively. F1 score: 0.60, 0.57 AUC: 0.81, 0.78 Accuracy: 0.80, 0.78 Sensitivity: 0.82, 0.79 Specificity: 0.79, 0.77	Strengths: Targets underrepresented outcomes (QoL). Limitations: Moderate performance; subject to subjective bias in inputs.	[151]
Rabiei et al, 2022	Predict breast cancer using machine learning models with mammographic, demographic, and laboratory data.	5178 records (25% breast cancer patients).	RF, GBT, MLP; SMOTE, k-fold validation, hyperparameter tuning; trained with demographic, mammography, laboratory features.	RF: Accuracy: 0.80 AUC: 0.56 Sensitivity: 0.95 Specificity: 0.80	Strengths: Combines clinical and imaging data. Limitations: AUC is low despite high sensitivity—false positives likely.	[152]
Mortazavi et al, 2022	Develop machine learning models predicting breast cancer risk based on exposure to ionizing and non-ionizing radiation (blue light, screen time).	603 women (309 breast cancer cases, 294 controls).	RF, SVM, and MLPNN, with 10-fold cross-validation and hyperparameter tuning.	RF (best performance): Accuracy: 0.99 Sensitivity: 0.99 Specificity: 0.98	Strengths: Explores novel risk factors (light exposure). Limitations: High performance may be due to overfitting in small sample.	[153]
Zhang et al, 2022	Develop a machine learning model that uses ultrasound features of breast cancer lesions to predict sentinel lymph node metastasis, improving preoperative diagnostic accuracy.	952 patients (902 training, 50 validation)	The study used 10 machine learning models (SVM, XGBoost, RF, MLP, CNN etc.,), with XGBoost performing the best. SHAP was applied for model interpretation and feature importance.	XGBoost: F1 score: 0.83 Accuracy: 0.85 AUC: 0.92 Sensitivity: 0.87 Specificity: 0.86	Strengths: High diagnostic accuracy using ultrasound features. Limitations: External validation on small cohort (n = 50).	[154]
Zhang et al, 2021	Classify breast cancer subtypes (HR + /HER2-, HER2 + , TN) using deep learning (CNN, CLSTM) on DCE-MRI, with transfer learning for improved performance across different datasets.	244 patients (99 training, 145 validation); molecular subtypes: HR + /HER2-, HER2 + , TN.	CNN, CLSTM models; 10-fold cross-validation, Adam optimizer; tumour segmentation with FCM; transfer learning for fine-tuning.	CNN: HR + /HER2- vs. others, TN vs. non-TN, HER2 + vs. HER2- Accuracy: 0.81, 0.76, 0.80 AUC: 0.86, 0.84, 0.90 Sensitivity: 0.79, 0.71, 0.73 Specificity: 0.82, 0.79, 0.83 CLSTM: HR + /HER2- vs. others, TN vs. non-TN, HER2 + vs. HER2- Accuracy: 0.90, 0.89, 0.92 AUC: 0.92, 0.89, 0.93 Sensitivity: 0.89, 0.82, 0.90 Specificity: 0.91, 0.92, 0.93	Strengths: Strong performance using deep learning and transfer learning. Limitations: Complex architecture; limited generalizability to other imaging modalities.	[155]
Naji et al, 2021	Apply machine learning algorithms to predict and diagnose breast cancer, evaluating the performance of different models to identify the most accurate and effective algorithm for cancer detection.	Breast Cancer Wisconsin Diagnostic dataset; 569 instances (357 benign, 212 malignant).	SVM, RF, K-NN, decision tree, and logistic regression.	SVM (best performance): F-measure: 0.96 (benign), 0.98 (malignant) AUC: 0.966	Strengths: Excellent performance on classic dataset. Limitations: Dataset is old, small, and not clinically representative.	[156]

Table 2. Continued.

Study	Objective	Data source/ population	AI model/ methodology	Performance metrics	Strengths, limitations, and application notes	References
Jalloul et al, 2024	Compare deep learning and machine learning models for early breast cancer detection using infrared thermography, highlighting the superior performance of CNN-based architectures in thermal image classification.	Used DRM-IR and Mendeley thermography datasets containing annotated infrared breast images from diverse diagnostic categories.	SVM, naive bayes, decision trees, K-NN, DNNs	ResNet152 + SVM (best performance): Accuracy: 0.97 AUC: 0.99 Precision: 0.98 Recall (Sensitivity): 0.94 F1-score: 0.96 Specificity: 0.97	Strengths: Excellent performance metrics; integration of deep learning and classical ML; multi-dataset training improves generalizability. Limitations: Potential overfitting; no clinical validation reported.	106
Chi T et al, 2024	To design a lightweight, high-performance thermography-based model for early breast cancer detection using optimized CNN features and efficient classification.	56 patients (47 training, 9 testing); image labels: 380 normal, 740 abnormal (cancerous); classes: normal vs. abnormal.	SVM, RF, K-NN, Adaboost, XGBoost	ResNet34 + SVM (best performance): Accuracy: 0.99 AUC: 0.99 Precision: 0.99 Recall (Sensitivity): 0.99 F1-score: 0.99	Strengths: Lightweight architecture; very high accuracy; suitable for low-power or embedded systems. Limitations: Small sample size; minimal external validation; possible overfitting on limited data.	107
Singh et al, 2021	To evaluate the diagnostic performance and non-inferiority of Thermalytix, an AI-based automated thermographic screening tool, compared with standard breast cancer screening modalities (mammography and/ or ultrasound) in symptomatic women suspected of having breast cancer.	Pre-trained model, clinical testing only (258 total; age-stratified analysis: < 45 years and ≥ 45 years)	Screenin tool (Thermalytix)	≥ 45 years AUC: 0.88 Sensitivity: 0.81 Specificity: 0.87 < 45 years AUC: 0.85 Sensitivity: 0.87 Specificity:0.81	Strengths: Real-world clinical validation; performance analyzed across age groups. Limitations: No F1-score or precision reported; focused only on symptomatic women.	108

Abbreviations: TNBC, triple-negative breast cancer; SVM, support vector machine; AUC, area under the curve; PPV, positive predictive value; NPV, negative predictive value; LASSO, least absolute shrinkage and selection operator; CNN, convolutional neural network; GNN, graph neural network; XAI, explainable artificial intelligence; RF, random forest; RBF, radial basis function; SGD, stochastic gradient descent; XGB, extreme gradient boosting; SHAP, SHapley Additive exPlanation; GBT, gradient boosted trees; MLP, multilayer perceptron; SMOTE, synthetic minority oversampling technique; CLSTM, convolutional long short-term memory; DCE-MRI, dynamic contrast-enhanced magnetic resonance imaging; FCM, fuzzy C-means clustering; K-NN, K-nearest neighbours.

This process is particularly useful in complex cases where traditional diagnostic methods may be inconclusive.[173]

5.2. Treatment plan: CBR can assist in treatment planning by suggesting therapeutic approaches based on similar past cases. For instance, if a newly diagnosed patient shows a specific type of BCA, the system can retrieve cases with similar features and recommend treatment regimens that were effective in those cases enabling personalized treatment plans tailored to the patient's unique characteristics.[174]

5.3. Prognosis prediction: By analysing the outcomes of similar past cases, CBR systems can help predict the prognosis for new patients, for example estimating survival rates, potential complications, and the likelihood of recurrence. Such predictions are invaluable for setting realistic expectations and planning follow-up care.[175]

6. Stand-alone AI: Stand-alone AI systems for cancer detection utilize advanced machine learning techniques, including deep learning, to analyse medical images for the identification of patterns and anomalies that might indicate the presence of cancer, including the detection of calcifications, masses, and architectural distortions that are typical indicators of BCA. [98] Moreover, as the AI systems improve, the Machine learning algorithms can adapt to novel patterns and investigations, enhancing their diagnostic capabilities over time. [176]

7. Transformers in breast cancer information extraction: Transformers, particularly models such as BERT (bidirectional encoder representations from transformers), GPT (generative pre-trained transformer), and their derivatives, have shown noticeable proficiency in understanding human language. These models are especially accomplished in extracting relevant information from unstructured clinical text to manage

Table 3. Comparative analysis of AI models in breast cancer research[157-165]

Model	Type	Strengths	Weaknesses	Best use cases	Performance metrics
Vision Transformer (ViT)	Transformer-based	High accuracy; effective in multi-class classification; captures global context	Requires large datasets; computationally intensive	Histopathology image classification; complex pattern recognition	Accuracy: 93%–98.17%
ResNet-50	CNN	Robust feature extraction; good generalization; efficient training	May underperform in multi-class tasks compared to newer models	Image classification; feature extraction	Accuracy: 84.5%–90%; Sensitivity: 93%
Xception	CNN	High sensitivity; effective in binary and multi-class classification	Slightly lower accuracy than ViT	Histopathology classification; carcinoma detection	Accuracy: 88%; Sensitivity: 95%
DenseNet-121	CNN	Efficient feature reuse; good performance in classification tasks	Potential overfitting; high memory usage	Image classification; feature extraction	Accuracy: ~96%
EfficientNet	CNN	High accuracy with fewer parameters; scalable	May require careful tuning	Image classification; resource-constrained environments	Not specified in provided sources
MobileNet	CNN	Lightweight; suitable for mobile and embedded applications	Lower accuracy compared to larger models	On-device image classification	Not specified in provided sources
SqueezeNet	CNN	Small model size; fast inference	Lower accuracy compared to larger models	Resource-limited scenarios	Not specified in provided sources
Support Vector Machine (SVM)	Traditional ML	High accuracy; effective in high-dimensional spaces	Sensitive to parameter selection; less effective with large datasets	Binary classification; small to medium datasets	Accuracy: 95.83%–97.66%
Random Forest (RF)	Ensemble Learning	Robust to overfitting; handles high-dimensional data	Less interpretable; may require large number of trees	Feature selection; classification tasks	Accuracy: 95.24%–95.32%
k-Nearest Neighbors (k-NN)	Instance-based Learning	Simple implementation; effective with well-separated classes	Computationally intensive with large datasets; sensitive to noise	Classification with small datasets	Accuracy: 97.62%
Logistic Regression (LR)	Traditional ML	Interpretable; performs well with linearly separable data	Limited to linear relationships; less effective with complex patterns	Risk prediction; binary classification	Accuracy: 83%–97%
Artificial Neural Network (ANN)	Neural Network	Captures complex patterns; adaptable to various tasks	Requires large datasets; prone to overfitting	Prediction; classification	Accuracy: 71%–97.07%
Decision Tree (DT)	Tree-based Model	Easy to interpret; handles both numerical and categorical data	Prone to overfitting; less stable with small changes in data	Initial modeling; feature importance analysis	Accuracy: 93.15%–94.15%
Gradient Boosting (e.g., XGBoost)	Ensemble Learning	High accuracy; handles missing data well	Computationally intensive; complex tuning	Classification; prediction	Accuracy: 95.91%
Multilayer Perceptron (MLP)	Neural Network	Captures nonlinear relationships; flexible architecture	Requires significant training time; sensitive to hyperparameters	Classification; regression tasks	Accuracy: ~99.04%

and analyse BCA data.[177-179] The advantages compared to the traditional methods are noteworthy including automated coding of clinical data,[180] information retrieval and data mining,[181] which can extract specific details such as genetic mutations, tumor characteristics, and treatment responses for research and personalized medicine.

8. AI solutions in breast cancer care pathways; the Arianna solution: The Arianna solution is an advanced AI-driven platform designed to improve BCA care. Arianna tracks patient progress, monitors treatment adherence, and provides reminders for follow-up appointments. The usage of AI is to improve diagnostic accuracy, enhanced patient satisfaction, and cost effectiveness. As AI technology continues to advance, the role of Arianna Solution in BCA care is set to expand, offering even greater benefits in the future [182]

9. Autoencoded DNA methylation data for recurrence prediction: After encoding DNA methylation data, various supervised learning methods can be employed to forecast recurrence. These models are trained on datasets with known outcomes (recurrence or non-recurrence) to identify the correlation between methylation patterns and recurrence risk. This approach leverages the predictive capabilities of SVMs, random forests, and neural networks to make accurate predictions [183]

10. Gene-Weight Significance for Recurrence Prediction:

In machine learning models, particularly those utilizing neural networks, the significance or weight of individual genes can be analyzed to comprehend their contribution to the model's predictions. Techniques like SHapley Additive exPlanations (SHAP) values can be employed to assign a relevance score to each gene based on its influence on the model's output.[184] Additionally, by analyzing the weights of genes, researchers can identify the genes that are associated with cancer recurrence, providing valuable biological insights and potentially highlighting new biomarkers for recurrence risk [185]

Breast cancer risk assessment

BCA risk assessment typically involves combining multiple risk factors, including genetic, lifestyle, and reproductive factors. Commonly used models include the Gail model, the Tyrer-Cuzick model, and the Breast Cancer Surveillance Consortium (BCSC) model, which collectively provide a comprehensive framework for assessing BCA risk.

Gail model

The Gail model estimates a woman's risk of developing BCA based on factors such as age, family history, reproductive history, and history of breast biopsies. Some limitations include the underestimation of risk in women with a strong family history of BCA and the lack of integration with mammographic density data.[186]

Tyrer-Cuzick model

The Tyrer-Cuzick model or the IBIS model, performs a more comprehensive set of risk factors, including detailed familial history, genetic factors, and hormonal factors. This model provides more accurate risk predictions, especially for women with a positive family history of BCA.[187]

BCSC Model

The BCSC model incorporates mammographic density as a significant risk factor, along with age, race, family history, and breast procedure history. Mammographic density is a significant independent risk factor for BCA, and its inclusion enhances the accuracy of risk prediction. [188]

AI in mammographic phenotyping of breast cancer risk

AI algorithms analyze the texture patterns in mammographic images to identify features associated with high BCA risk, for example variations in tissue density, microcalcifications, and distortions.[171] Furthermore, AI techniques determine volumetric breast density, providing a more accurate measure of breast tissue. In addition, CNNs show high accuracy in identifying mammographic phenotypes that correlate with BCA risk, learning to detect subtle patterns that may not be visible to the human eye.[98] This holistic approach maintains early detection and prevention strategies, ultimately improving patient outcomes due to the individualized risk assessment.[189]

Ethical consideration in AI application in medicine

The widespread use of AI in the medical field necessitates considering measures to evaluate such technological developments to protect human rights. Our decisive responsibility is to ensure researchers that the advantages of AI tools outweigh their drawbacks. In the medical setting, the importance of powerful algorithms to safeguard people's lives cannot be overstated.[190] These ethical measures must ensure both patients and physicians the accuracy and safety of the diagnostic approaches and treatment plans recommended by AI. Patient should have the right to decide independently whether an AI algorithm involved in their medical care. Moreover, the specific gaps that are filled by AI must be clarified to patients, as this information can significantly influence their decision-making. In high-risk areas of healthcare such as BCA, the capabilities of AI systems have to be explained to patients to ensure the positive impacts of AI on this crucial issue. Although achieving explainability in some complex cases of machine learning and deep learning can be challenging, it is beneficial for the patients to be aware of the potential for improved outcomes when combining AI models with traditional methods. Finally, it is worth noting that the widespread utilization of AI models in the medical setting requires many scientists and researchers to address any conflict of interest in future endeavors.[191]

The implementation of Al in clinical wards faces difficulties that impact its practical susceptibility. To handle real-world issues, important challenges include regulatory hurdles, training sessions for healthcare professionals, and infrastructure facilities. Given the direct impact of AI on patient care, the European Commission has emphasized important regulatory requirements such as ensuring accuracy, clearly outlining intended uses, and validating training information. While these regulations may slow the adaptation of AI in clinical settings, they ultimately lead to a more standardized and qualified implementation of AI. Training healthcare professionals in integrative AI aims to improve their understandings of deep learning algorithms among physicians. It is essential to equip them with technical skills related to AI applications, data-driven learning, validation and liability, which must be passed on to future scientists. Structured educational strategies are needed to help professionals build trust in AI tools. Additionally, hospitals and clinics require infrastructure to support AI including data security measures in clinical domains and monitoring AI's role in patient treatment plans. A lack of collaborative efforts, regulatory policies, and clear strategies contribute to the limited implementation of AI in hospitals. Multidisciplinary plans for standardized AI tools can help bridge the gap between AI's potential benefits and its practical use by clinical staff.[192,193]

Limitations and future horizons

To maximize the benefits of AI in BCA screening, some

future recommendations should be adopted:

- Standardization and interoperability: Developing standardized protocols for AI algorithms and ensuring interoperability with existing healthcare systems is crucial. This will facilitate the seamless integration of AI tools into clinical workflows and enhance data sharing across institutions.[194,195]
- Continuous learning and adaptation: AI algorithms should be designed to continually learn and adapt from new data. The incorporation of feedback loops that enable AI systems to update their models based on real-world performance will enhance their accuracy and robustness over time.[144]
- Ethical considerations and bias mitigation: It is crucial to address ethical concerns related to data privacy, informed consent, and algorithmic bias. The development of guidelines and best practices for the ethical deployment of AI will play a significant role in ensuring that these technologies are used responsibly and equitably.[196]
- Collaboration and multidisciplinary research: Practical collaboration between AI developers, radiologists, oncologists, and other healthcare professionals is crucial for improving AI in BCA screening. Multidisciplinary research projects can stimulate innovation and accelerate the creation of effective AI solutions.[197]
- Education: Providing efficient training for healthcare professionals on the use of AI equipment is essential, which includes understanding how AI algorithms work, interpreting AI-generated results, and integrating AI insights into clinical decision-making.[198]
- Regulatory guidelines: To guarantee the safe and efficient use of AI-based screening tools, regulatory bodies must establish clear guidelines and frameworks. This can be achieved by collaborating with industry stakeholders to set standards for AI development, evaluation, and post-market monitoring.[199]

Challenges of AI in breast cancer

AI has emerged as a transformative tool in breast cancer care, offering advancements in detection, diagnosis, and treatment planning. However, its integration into clinical practice presents several multifaceted challenges that must be addressed to ensure effective and equitable utilization. A primary concern is the scarcity of high-quality, annotated datasets necessary for training robust AI models. The process of annotating medical images is labor-intensive and requires expert input, leading to limited availability of comprehensive datasets. This limitation hampers the generalizability of AI algorithms across diverse populations and clinical settings.[200,201] Moreover, the heterogeneity of data sources poses significant obstacles. Variations in imaging equipment, acquisition protocols, and patient demographics can introduce inconsistencies that affect AI performance. Standardizing data across institutions is challenging but essential for developing universally applicable AI solutions.[200] The "black box" nature of many AI systems raises issues of interpretability and trust among clinicians. Without transparent reasoning pathways or explainable outputs, physicians may hesitate to rely on AI-generated recommendations, particularly in high-stakes scenarios like cancer diagnosis or treatment selection. This lack of explainability also complicates the validation and regulatory approval processes, as medical devices and diagnostic tools must meet rigorous standards for safety, efficacy, and accountability.[202] Integrating AI into existing clinical workflows is another significant challenge. Healthcare systems vary widely in terms of infrastructure, electronic health record systems, and clinical practices. Adapting AI tools to fit seamlessly into these diverse environments requires substantial effort and resources.[203,204]

Ethical and legal considerations also present formidable challenges. Concerns about data privacy, informed consent, and the potential misuse of patient information are amplified in AI applications that rely heavily on sensitive medical data. Furthermore, questions about liability in cases of AI error whether due to flawed algorithms or inaccurate data inputs, remain largely unresolved, creating uncertainty for both clinicians and developers. The financial implications of implementing AI technologies cannot be overlooked. Developing, deploying, and maintaining AI systems require significant investment in hardware, software, and personnel training.[205-207] These costs can be prohibitive, particularly for resource-limited healthcare settings, potentially exacerbating existing disparities in BCA care.[200]

Lastly, the rapid pace of AI development often outstrips the speed at which regulatory frameworks evolve, leading to a mismatch between innovation and oversight. Ensuring that AI tools are not only effective but also safe, equitable, and ethically designed requires sustained collaboration among clinicians, data scientists, regulatory bodies, and policymakers. In conclusion, while AI offers transformative potential in the field of BCA care, addressing these multifaceted challenges is essential to ensure its responsible, equitable, and effective integration into routine clinical practice.

Conclusion

The integration of AI in BCA holds immense promise for revolutionizing disease screening, diagnosis, biomarker evaluation, and personalized treatment strategies. Techniques such as machine learning, deep learning, and radiomics have shown potential in enhancing the detection and classification of breast lesions, reducing the risk of false positive and false negative reports. Studies indicate that AI can significantly decrease the workload

Review Highlights

- Emphasizing AI's role in improving the accuracy of breast cancer screening and diagnosis.
- Review the contribution of AI-driven data analysis and precision oncology for more personalized breast cancer care.
- Demonstrate the AI potential to address limitations in drug delivery and immunotherapy in breast cancer.

for radiologists while maintaining or even improving the sensitivity and specificity of cancer detection in early stages. Additionally, AI has proven useful in gene expression assessment in patients with a positive familial history, reducing the incidence of missed cancers. By addressing potential challenges and embracing AI in BCA care, we can greatly improve patient outcomes, reduce health disparities, and usher in a new era of precision medicine. The integration of AI in BCA care has the potential to redefine our approach to screening, diagnosis, and treatment, ultimately leading to higher survival rates for patients.

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The authors declare that there are no conflicts of interest related to this publication process.

Ethical Approval

The authors' institution granted ethical approval for this case study. IRB review and approval was waived for this review study. The ethics committee at Babol University of Medical Sciences, Babol, Iran, granted an exemption for this study protocol as review articles are not subject to ethical approval by the ethical review board.

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