

Exploring AI Approaches for Breast Cancer Detection and Diagnosis: A Review Article

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Abstract: Artificial intelligence (AI), particularly deep learning, is reshaping breast cancer diagnostics in the radiology and pathology fields. This review synthesizes recent advances in mammography, digital breast tomosynthesis (DBT), ultrasound, MRI, and whole-slide imaging, with an emphasis on convolutional neural networks (CNNs), Vision Transformers (ViTs), and generative adversarial networks (GANs). When embedded within established screening and diagnostic workflows, AI systems can enhance lesion detection and triage, as well as reduce interpretive variability. However, performance and generalizability depend on dataset quality, population and vendor heterogeneity, acquisition protocols, and calibrated probability outputs; diminished performance on external datasets and miscalibration remain recurrent risks that require explicit mitigation during development and deployment of these models. Beyond detection and classification, segmentation and risk prediction models increasingly integrate imaging with clinicopathological and, where available, genomic variables to enable individualized risk stratification and follow-up planning. Data generation strategies, including GAN-based augmentation, can partially address data scarcity and class imbalance but require rigorous quality control and bias monitoring. Persistent barriers to clinical adoption include uneven external validation, domain shifts across institutions, variability in reporting standards, limited interpretability, and ethical, privacy, and regulatory constraints. Overall, AI should augment, rather than replace, the role of clinicians. Priorities for responsible integration include multi-site prospective evaluations, transparent and standardized reporting, bias mitigation, robust calibration, and lifecycle monitoring to ensure sustained safety and equity.

Keywords: breast cancer, mammography/DBT, digital pathology, deep learning, CNNs, ViTs, GANs, risk prediction, external validation

Introduction

Breast cancer remains a global health challenge, with over 2.3 million new cases diagnosed annually, underscoring the need for effective early detection and accurate diagnosis methods.^{1,2} Traditional screening methods, such as mammography, are widely used but have limited sensitivity, particularly for dense breast tissue, often leading to false negatives and delayed diagnosis.³ Magnetic Resonance Imaging (MRI) offers a higher sensitivity (94.6%) than mammography (54.5%) and ultrasound (67.2%), but at the cost of specificity, which results in false positives that complicate patient management.³ To address these limitations, combining multiple imaging modalities has shown promise in improving the diagnostic accuracy and providing a more comprehensive evaluation.⁴

Mammography (X-ray) is the cornerstone of population screening, and digital breast tomosynthesis (DBT) is increasingly being adopted to enhance lesion conspicuity, reduce recall rates, and lower the incidence of interval cancers.⁵ Studies show that DBT increases the detection of invasive cancers without a surge in overdiagnosis (in situ lesions) and significantly lowers recall rates for normal findings.⁵ Ultrasound serves as a complementary test, especially in dense breasts, for the targeted evaluation of palpable or mammography-occult findings, while also supporting cyst/

solid differentiation and biopsy guidance, with greater operator dependence and modestly lower specificity when used for screening purposes.^{6–8} Breast MRI is reserved for high-risk screening and diagnostic problem-solving due to its high sensitivity; however, its lower specificity, cost, and availability limit its use in average-risk populations. Abbreviated MRI protocols are under evaluation to mitigate these constraints. Nuclear medicine techniques (eg, FDG PET/CT and MBI) and CT are not used for routine screening, but they contribute to staging, assessment of therapy response, and selected preoperative decisions. In contemporary practice, multimodal pathways strike a balance between sensitivity and specificity, linking imaging to BI-RADS assessment and triaging patients to image-guided biopsy and management algorithms.⁹ In practice, breast imaging follows a multimodal, stepwise approach to balance sensitivity and specificity. Mammography/DBT is the first-line approach for most, with ultrasound or MRI added based on individual risk or imaging findings, thereby minimizing unnecessary biopsies while catching cancers.⁵

Disease biology is heterogeneous, comprising hormone receptor–positive/HER2-negative, HER2+, and triple-negative subtypes, with distinct patterns of growth, metastasis, and therapeutic responsiveness.^{10,11} Prognosis and therapeutic choices are further modulated by grade, stage, and biomarkers from histopathology and genomics. Risk reflects multiple interacting determinants: age, family history, pathogenic germline variants (eg, BRCA1/2), breast density, reproductive factors (early menarche, late menopause, nulliparity, late first birth), and modifiable exposures such as obesity and alcohol use. The global burden remains high and unevenly distributed, with a later stage at diagnosis and limited access to high-quality imaging and systemic therapy, driving excess mortality in many settings.^{10,12} Contemporary surveillance and guideline reports, therefore, emphasize risk-adapted screening, standardized reporting and quality assurance, and integration of imaging with clinicopathologic data to support timely diagnosis and equitable care. These clinical fundamentals frame the role of AI and deep learning in augmenting detection, characterization, and treatment planning.

Recent advances in AI, particularly in deep learning models, have introduced transformative potential for breast cancer diagnosis. These models excel in processing complex imaging data, enhancing diagnostic precision across modalities such as mammography, ultrasound, and MRI.^{13,14} AI-driven techniques are effective not only for image analysis but also for risk assessment, tumor characterization, and treatment monitoring. For example, AI-based mammography has demonstrated superior diagnostic accuracy in dense breast tissue compared with traditional radiological assessments.¹⁵ AI models trained on extensive datasets also exhibit reduced false-positive and false-negative rates, thereby minimizing diagnostic inconsistencies and missed diagnoses.¹⁶ In addition to imaging, AI is used for predictive modeling and personalized diagnosis. By integrating multimodal data, including genetic, histological, and clinical information, AI models enable individualized risk assessment and outcome prediction based on patient-specific factors.^{17,18} Such comprehensive insights support tailored treatment strategies and advance precision oncology in breast cancer.¹⁹

Despite these advancements, challenges remain in clinical implementation. Ensuring extensive validation, enhancing model interpretability, and addressing biases, particularly those stemming from underrepresented demographics in the training data, are critical for widespread adoption.²⁰ Additionally, ethical and regulatory considerations such as patient data privacy and model transparency are essential for the integration of AI into clinical practice.²⁰ Sechopoulos and Mann (2021) advocated continuous validation across diverse populations to mitigate bias and foster equitable diagnostic capabilities.²¹ This review synthesizes the recent advancements in AI and deep learning applications for breast cancer diagnosis, covering foundational models, data integration strategies, and the ethical landscape. As the field evolves, addressing these challenges will likely establish new standards for early detection, diagnostic accuracy, and personalized care in breast cancer treatment.

Advanced Deep Learning Models in Breast Cancer Detection

Deep learning has revolutionized breast cancer diagnosis by offering unparalleled accuracy, sensitivity, and specificity across various imaging modalities. This section discusses advanced architectures such as CNNs, residual networks (ResNet), DenseNet, Vits, and Generative Adversarial Networks (GANs), and explores their contributions to the field. In addition, we discuss integrative approaches, challenges, and future research directions to leverage the potential of these models in clinical practice fully.

CNNs Residual Networks (ResNet) and DenseNet

Convolutional Neural Networks (CNNs) have fundamentally transformed medical image analyses, thereby offering significant advances in breast cancer detection. Key architectures such as AlexNet, VGGNet, InceptionNet, DenseNet, and ResNet have been pivotal in addressing challenges such as computational inefficiency and vanishing gradients.^{22,23} AlexNet and VGGNet have laid the foundation for deep feature extraction, enabling early breakthroughs in image classification research. InceptionNet expands these capabilities through multi-scale feature extraction, whereas DenseNet introduces dense layer connections, promoting efficient gradient flow and feature reuse to improve detection in complex cases, such as dense breast tissue.^{23,24}

ResNet, through its innovative use of skip connections, has proven particularly effective for analyzing high-dimensional and complex imaging datasets such as Digital Breast Tomosynthesis (DBT).²⁵ These connections mitigate the vanishing gradient problem, allowing for the training of deeper networks and facilitating the detection of subtle abnormalities, which are crucial for early diagnosis.²⁴ Transfer learning has further enhanced the utility of CNNs, enabling pre-trained models on large datasets, such as ImageNet, to be fine-tuned for specific tasks, such as breast lesion detection, risk stratification, and image classification. This approach significantly alleviates the challenge of limited annotated medical datasets, which are often costly and time-consuming to curate.^{26,27}

Despite their transformative impact, CNNs continue to face several challenges. These include optimizing architectures for specific medical imaging tasks, addressing class imbalances inherent in medical datasets, and improving interpretability for clinical adoption.²⁸ Future research must focus on refining the CNN frameworks to adapt to these unique challenges and ensure their robust and reliable application in breast cancer diagnosis.^{29,30}

Vision Transformers (ViTs) in Breast Cancer Imaging: A Transformative Approach

Vision Transformers (ViTs) represent a groundbreaking shift in image analysis by replacing traditional convolutional operations with self-attention mechanisms, thereby enabling simultaneous capture of local and global contextual information. Unlike CNNs, which excel at detecting localized patterns, ViTs divide images into patches and treat them as sequences, rendering them particularly effective for breast cancer imaging. Breast tissue tumors often exhibit complex morphological and spatial relationships that span multiple regions, and ViTs are uniquely equipped for analysis.³¹ The integration of self-supervised learning has further enhanced the utility of ViTs, allowing them to be pre-trained on vast unlabeled medical image datasets.³² This pre-training enables the models to learn generalized features that can be fine-tuned on smaller annotated datasets, which is a critical advantage in breast cancer diagnostics, where labeled data are often scarce and costly to produce. Hybrid models that combine CNNs for local feature extraction with ViTs for capturing long-range dependencies have demonstrated superior performance, particularly in challenging cases such as dense breast tissue and multifocal tumors.³³ Recent studies underscored the versatility of ViTs across various breast cancer imaging modalities. For instance, ViTs have achieved remarkable accuracy rates of up to 99.92% in mammography image classification.³⁴

Recent studies have demonstrated the effectiveness of Vision Transformers (ViTs) in breast cancer imaging. In breast ultrasound classification, ViTs have shown performance comparable to or surpassing that of state-of-the-art CNNs.³⁵ The BU ViTNet model, which utilizes multistage transfer learning, achieved superior results in breast ultrasound detection compared to conventional methods.³⁶ For histopathological image classification, ViT-based models have exhibited significant improvements through pre-training on ImageNet and the employment of advanced data augmentation techniques.³⁷ The self-attention mechanism in ViTs excels in capturing intricate morphological and spatial features crucial for breast cancer diagnosis, offering a compelling alternative to traditional CNN-based approaches.³⁸ These findings highlight the potential of ViTs to enhance diagnostic precision across various breast imaging modalities, potentially revolutionizing breast cancer diagnostics and supporting improved clinical decision-making (Table 1).

Generative Adversarial Networks (GANs) for Data Augmentation

GANs have emerged as robust solutions for data scarcity and class imbalance issues in breast cancer research. By generating synthetic mammograms and histopathological images, GANs enrich the training datasets, ensuring that the

Table 1 Vision-Transformer-Based Approaches for Breast Cancer Imaging (2023–2024). Representative Studies Summarizing Key Findings, Headline Performance Metrics, Imaging Modalities, and Reference Numbers

Key Insight	Accuracy	Modality	Ref.
Fine-tuned ViT on BreakHis achieved 99.99% accuracy, showcasing potential in histopathology analysis	99.99%	Histopathology	[39]
Proposed ViT-based hashing method, achieving MAP scores of 98.9% on BreakHis	98.9% (MAP)	Medical Image Retrieval	[40]
Wavelet-based ViT achieved an AUC of 0.984, excelling in dense breast tissue classification	AUC: 0.984	Ultrasound	[41]
ViT with majority voting mechanism achieved 98.2% accuracy in MRI classification	98.20%	MRI	[42]
ViT model achieved 99.42% accuracy with multi-resolution ROI and post-processing	99.42%	Histopathology	[43]
Compared ViT, CCT, and TVIT, with CCT achieving 99.92% accuracy	99.92%	Mammography	[34]
Explored pretraining and augmentation techniques, achieving 91% accuracy on BACH dataset	91%	Histopathology	[44]
Introduced SupCon-ViT, achieving F1-score of 0.8188 and specificity of 0.8971	81.88% (F1-score)	Histopathology	[45]
Combined ViTs and LSTM, achieving 99.2% accuracy in histopathology	99.20%	Histopathology	[46]
Proposed Dual-CapsViT for 3D ABUS, improving accuracy and AUC metrics	High AUC	Ultrasound (3D ABUS)	[47]

Notes: Metrics were reproduced from the original studies. Percentage-based measures (accuracy, F1-score, MAP) are shown to two decimal places; AUC is reported on a 0–1 scale to three decimals unless otherwise specified. Specificity was presented on a 0–1 scale, as previously reported. Reference numbers correspond to the primary bibliography.

Abbreviations: ViT, Vision Transformer; ROI, region of interest; AUC, area under the ROC curve; MAP, mean average precision; MRI, magnetic resonance imaging; ABUS, automated breast ultrasound; LSTM, long short-term memory; SupCon-ViT, supervised contrastive ViT; CCT, TViT, model variants as defined in the cited studies; BreakHis, BACH, public histopathology datasets.

models generalize better across diverse patient populations.^{48,49} This is particularly important for rare breast cancer subtypes for which real-world data are often insufficient.⁵⁰ GANs have shown significant potential in various medical imaging applications. They have been utilized for data augmentation to address the scarcity of training data in medical imaging applications. GANs have demonstrated efficacy in super-resolution imaging by enhancing low-quality images to improve the visibility of critical diagnostic markers.⁵¹ They have also been applied in cross-modality synthesis, converting images between different modalities such as MRI and CT.⁵¹ GANs have proven helpful in image reconstruction, denoising, and reducing the radiation dose and scan time.⁵² In mammography, GANs have been used to generate high-resolution mammograms for radiology education⁵³ and to synthesize images with architectural distortions.⁵⁴ These applications not only improve model training but also support radiologists in making informed decisions regarding patient care.

Integrative Approaches

The integration of these advanced architectures has led to significant improvements in breast cancer detection. Multi-task learning (MTL), which enables models to perform multiple related tasks, such as classification, segmentation, and tumor grading concurrently, has demonstrated enhanced diagnostic performance.^{55,56} This integrated approach reduces the need for separate analyses, and provides a holistic assessment of breast abnormalities.⁵⁷ Explainable AI (XAI) techniques are becoming increasingly important in healthcare as they address the “black-box nature of traditional AI models and foster trust among clinicians.^{58,59} Various XAI methods, including LIME, SHAP, and Grad-CAM, have been applied to make deep learning models more interpretable for disease diagnosis and medical imaging.^{59,60} These techniques provide visual explanations for model predictions, thereby enhancing the transparency and understanding of AI-assisted diagnosis.⁶⁰ Federated learning is emerging as a solution to address data-sharing barriers while maintaining patient privacy in distributed healthcare environments such as the Internet of Medical Things (IoMT). The integration of XAI and federated learning contributes to the development of more privacy-preserving, trustworthy, and explainable AI systems, which are essential for ethically sound healthcare applications.⁶⁰

Research is increasingly focusing on personalized AI models that incorporate patient-specific factors such as genetic predisposition, hormonal status, and breast density. These models aim to deliver tailored diagnostic and

Table 2 Generative Adversarial Networks (GANs) Related Studies. Representative Works Using GAN-Family Models for Data Synthesis, Augmentation, and Enhancement with Headline Performance Outcomes and Reference Numbers

Key Contribution	Performance Metrics	Ref.
DCGAN synthesizes mammograms, enhancing dataset diversity and clustering consistency.	Clustering consistency enhanced	[62]
Proposed cGAN improves classification by addressing class imbalance.	3.9% improvement in classification accuracy	[63]
Integrated segmentation and GAN for high-quality mammograms, improving diagnostic accuracy.	Higher diagnostic accuracy	[64]
Combines VAEs and GANs to improve cancer survival prediction on missing data.	Significant ($p < 0.001$) improvement	[65]
TVAE and CTGAN improve diagnostic accuracy to 96.66%.	96.66% accuracy	[66]
Pix2Pix GANs augment mammography data, enhancing VGG-16 and ResNet-50 accuracy.	Improved accuracy for VGG-16, ResNet-50	[67]
Synthetic ultrasound images improve CNN classification accuracy by 15.3%.	15.3% improvement in CNN classification	[68]
WA-SRGAN enhances histopathology images; achieves AUC of 0.826.	AUC: 0.826	[69]
SRGAN improves radiomic feature extraction for tumor grading with AUC of 0.826.	AUC: 0.826	[69]

Notes: Metrics were taken from the original studies. Accuracy is shown as two decimals; AUC is on the 0–1 scale (three decimals when available). “+x%” indicates absolute gain versus baseline unless stated otherwise. “Improved” denotes a qualitative/non-single-number gain; p -values are reported as in the sources. Reference numbers correspond to the primary bibliography.

Abbreviations: GAN, generative adversarial network; DCGAN = Deep Convolutional GAN; cGAN, conditional GAN; VAE, variational autoencoder; TVAE, tabular variational autoencoder; CTGAN, conditional tabular GAN; Pix2Pix, paired image-to-image GAN; CNN, convolutional neural network; VGG-16, ResNet-50 = CNN backbone.

prognostic insights, thereby enhancing the precision of breast cancer management.^{18,61} In addition, advancements in self-supervised learning are expected to reduce reliance on large annotated datasets further, thereby paving the way for scalable and efficient AI solutions for breast cancer diagnostics. The seamless integration of these models into clinical decision support systems (CDSS) is critical for optimizing diagnostic workflows and improving patient outcomes (Table 2 and Figure 1).

In-Depth Exploration of AI Applications in Breast Cancer Diagnostics Mammography and Digital Breast Tomosynthesis (DBT)

Recent studies have demonstrated the significant potential of AI in enhancing mammography interpretation, particularly digital breast tomosynthesis (DBT). AI algorithms have shown improved diagnostic performance, surpassing radiologists in terms of sensitivity and area under the curve (AUC) values.⁷⁰ In DBT, AI reduced recall rates by 2–27% and reading times by up to 53%.⁷¹ AI has also been applied to assess parenchymal density, detect cancer, and predict breast cancer risk.⁷² Although AI has shown promise in retrospective studies, further prospective validation is necessary, especially in large-scale screening programs with low breast cancer prevalence.⁷¹ The integration of AI into breast cancer screening workflows could help reduce radiologists’ workload and improve interpretation efficiency, although further research is required to determine the most effective clinical implementation.⁷³

Mammography is widely used for breast cancer screening and is particularly effective in women with fatty breast tissues. However, its diagnostic accuracy diminishes in patients with dense breast tissue, where overlapping structures can obscure malignancies.⁷⁴ AI-enhanced mammography addresses these limitations by identifying subtle markers with greater sensitivity, such as microcalcifications and architectural distortions. In DBT, AI plays a transformative role by decomposing the 3D structure of the breast into thin slices, thereby significantly improving the visibility of lesions that may be hidden in traditional 2D mammography.^{75,76} Additionally, AI algorithms help prioritize images with a higher likelihood of abnormalities, thereby reducing the cognitive load on radiologists. Incorporating AI into DBT has resulted in increased diagnostic accuracy, with sensitivity improvements of up to 15%, while reducing recall and false-positive rates.⁷⁷

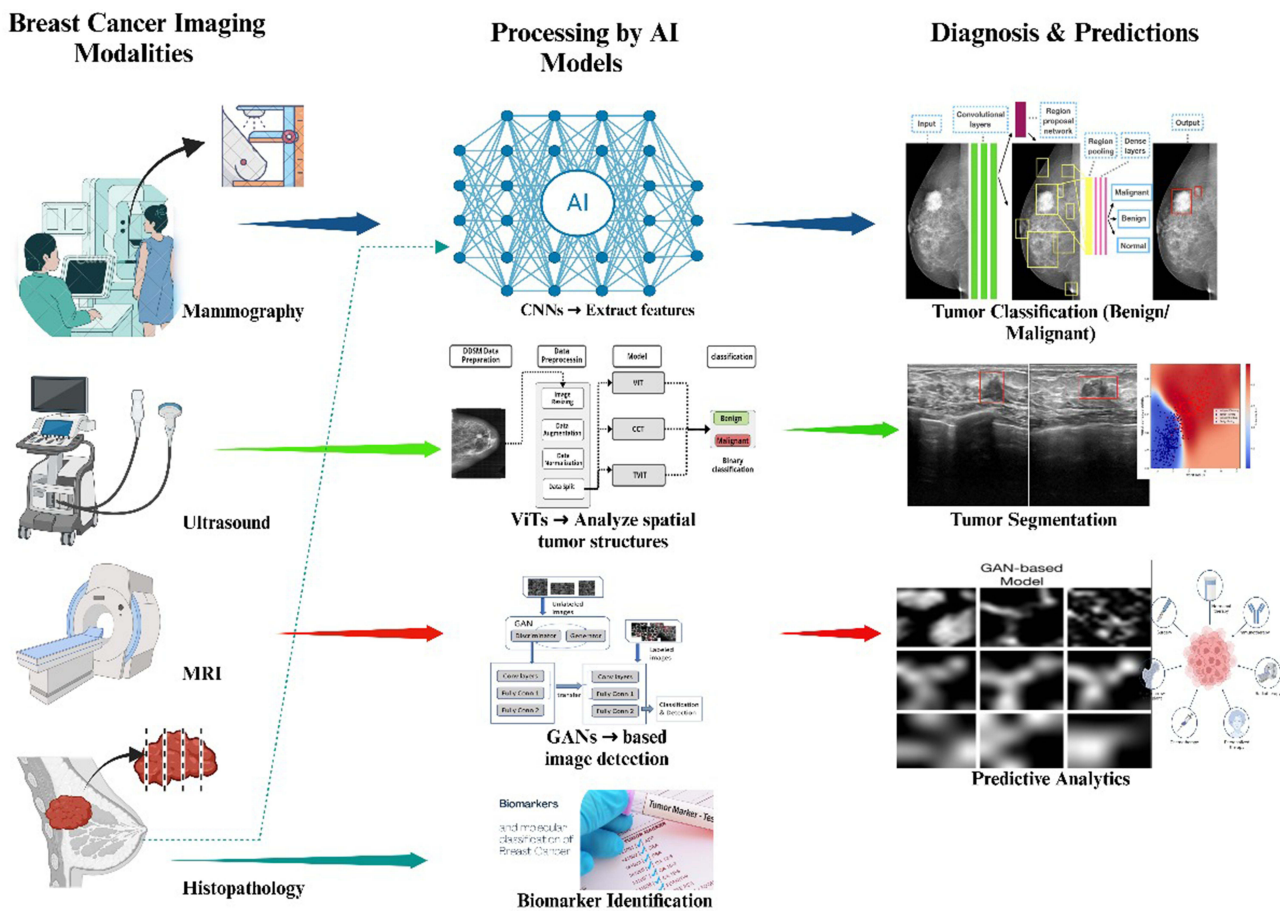


Figure 1 Imaging-to-AI pipeline for breast cancer diagnosis and prediction. Left: Clinical imaging modalities (mammography, ultrasound, MRI, and histopathology). Center—representative AI families (CNNs, ViTs, GAN-based methods) and biomarker identification. Right—downstream tasks: tumor classification, tumor segmentation, and predictive analytics. Indicators: yellow square boxes = candidate regions of interest (ROIs) from the attention/region-proposal stage (screening cues, not diagnostic); red square boxes = final AI-flagged suspicious ROIs used for the reported output—classification in the mammography panel (top right) and segmentation guidance in the ultrasound panel (middle right).

Ultrasound and Elastography

AI is revolutionizing breast ultrasound imaging by addressing key limitations, such as operator dependence and false-positive results.⁷⁸ AI, particularly deep learning models, enhances the detection, diagnosis, and prognosis of breast cancer by using ultrasonography.⁷⁹ These technologies improve lesion segmentation, malignancy classification, and the prediction of molecular subtypes and treatment responses.^{77,80} AI-assisted ultrasound complements mammography and is especially valuable for women with dense breasts, complementing mammography.⁷⁹ Recent advancements have also included AI applications in axillary lymph node assessment and the prediction of neoadjuvant chemotherapy outcomes.⁸⁰ Although AI shows promise in improving diagnostic accuracy and workflow efficiency, challenges remain in data curation, model interpretability, and clinical implementation.⁷⁷ Overall, the integration of AI with breast ultrasound has the potential to enhance breast cancer detection, diagnosis, and management significantly. Ultrasound is efficient in evaluating breast tissue in women with dense breasts and serves as a complementary imaging modality to mammography. However, traditional ultrasound interpretation is operator-dependent, leading to variability in diagnostic outcomes. AI technologies, intense learning models such as U-Net and fully convolutional networks (FCNs), address this issue by automating and precisely segmenting the breast lesions. These algorithms accurately delineate lesion boundaries, assess their internal characteristics, and classify them according to the likelihood of malignancy.⁸¹

Recent advances in AI have significantly enhanced the use of ultrasound elastography in breast cancer screening. AI-based techniques improve diagnostic accuracy by reducing operator dependence and variability in visual observations.⁸² Machine learning models, including deep learning approaches such as convolutional neural networks (CNNs), have been

applied to both shear-wave elastography and strain elastography for automated lesion detection, segmentation, and classification.⁸³ These AI tools have demonstrated high sensitivity ($\geq 80\%$) in distinguishing benign from malignant lesions, potentially reducing unnecessary biopsies.⁸³ A novel mobile AI solution for real-time breast ultrasound analysis has shown promising results, with 100% sensitivity for malignancy detection and an area under the ROC curve of 0.835–0.850.⁸⁴ Despite these advancements, challenges remain in standardizing reporting methods and avoiding over-fitting AI models.⁸³

MRI and Dynamic Contrast-Enhanced MRI (DCE-MRI)

AI has revolutionized breast cancer imaging, diagnosis, and treatment. AI-enhanced techniques, particularly radiomics, are being applied to various imaging modalities, including mammography, ultrasound, and magnetic resonance imaging (MRI).⁸⁵ Dynamic contrast-enhanced MRI (DCE-MRI) has shown promise in predicting the molecular subtypes of invasive ductal breast cancer using machine learning models, with high accuracy in distinguishing triple-negative and HER2-overexpressed subtypes.⁸⁶ AI technologies are advancing image quality, lesion detection and segmentation, cancer characterization, and outcome prediction by integrating multi-omics data.⁷⁷ Radiomics, a quantitative approach using AI for the advanced mathematical analysis of medical images, has demonstrated potential for enhancing clinical decision-making in breast cancer care. However, challenges regarding data curation, model interpretability, and clinical implementation.⁸⁷ The integration of radiomics with clinical, histopathological, and genomic information is expected to enable the more personalized management of patients with breast cancer.

Histopathology and Digital Pathology

AI has revolutionized breast cancer histopathology by enhancing diagnostic accuracy, efficiency, and standardization. AI-powered systems can be used to analyze whole-slide images to identify invasive tumors, detect lymph node metastases, and evaluate hormonal status with a high precision.⁸⁸ Convolutional neural networks are widely used to process complex visual data and achieve expert-level performance in some applications.⁸⁹ AI tools have demonstrated remarkable ability to predict genetic alterations, identify prognostic biomarkers, and assess tumor-infiltrating lymphocytes.⁸⁹ These advancements have contributed to improved patient stratification and treatment planning, potentially reducing delays between diagnosis and prognosis determination.⁹⁰ Despite challenges such as preanalytical variables and annotation demands, the integration of AI in breast cancer pathology shows great promise for enhancing clinical outcomes. Continued research and innovation are crucial for overcoming the existing limitations and fully harnessing AI's potential of AI in precision oncology.⁹⁰

Challenges

Despite these promising advancements, several challenges remain in the clinical implementation of AI in breast cancer diagnosis. One major hurdle is variability in imaging protocols and data quality across institutions, which can affect the performance and generalizability of AI models. Additionally, the “black box” nature of many AI algorithms raises concerns regarding interpretability and clinical trust. Efforts are underway to develop explainable AI (XAI) models that provide insights into decision-making processes and enhance their acceptance among clinicians. Regulatory and ethical considerations also play a critical role as AI systems must comply with stringent guidelines to ensure patient safety and data privacy. Future research should focus on integrating AI with other emerging technologies, such as liquid biopsies and multi-omics data, to create a comprehensive diagnostic ecosystem. The goal is to enable seamless, accurate, and personalized breast cancer care and improve the outcomes and quality of life of patients (Table 3 and Figure 2).

Predictive Diagnostics and Early Intervention for Breast Cancer

Recent advances in artificial intelligence (AI) have significantly transformed breast cancer screening and diagnosis. Deep learning algorithms, particularly convolutional neural networks, have demonstrated remarkable success in analyzing complex medical images, including mammography, ultrasound, and MRI.^{13,29} AI-driven imaging techniques enhance diagnostic precision, enabling early detection of malignancies and improving patient outcomes. These systems identify subtle tumor features and often surpass human radiologists in their detection and classification

Table 3 AI Applications in Breast Cancer Diagnostics (2018–2024). Representative Studies Across Imaging and Biosensing, Summarizing Datasets, Model Families, Headline Performance, and Key Findings

Ref.	Year	Modality	Dataset	AI Model/Technique	Overall Accuracy/ (AUC-ROC)	Key Findings
[16]	2020	Mammography & Digital Breast Tomosynthesis (DBT)	Large representative dataset (UK), large enriched dataset (USA)	DeepMind AI	11.5% AUC	Improved sensitivity and specificity over radiologists (+11.5%, +5.7%)
[91]	2020	Screening Mammography	240 women (100 cancers, 40 false positives, 100 normal; 2013–2017)	AI support with decision support and lesion markers	0.89% AUC	AI support improved AUC from 0.87 to 0.89; increased sensitivity (86% vs 83%); specificity
[92]	2018	Ultrasound Imaging	Dataset A: 306 images (60 malignant, 246 benign) - Dataset B: 163 images (53 malignant, 110 benign)	Patch-based LeNet - U-Net - Transfer learning (pretrained FCN-AlexNet)	Not specified	Deep learning outperforms state-of-the-art, with improved metrics and Dataset B available.
[93]	2021	Ultrasound Imaging	Breast Ultrasound Images (BUSI) - Mendeley Breast Ultrasound Dataset - Dataset A: 306 images - Dataset B: 163 images	Transfer Learning (various CNNs)	99% accuracy	Achieved accuracies: 97.8% (BUSI), 99% (Mendeley), 98.7% (MT-Small).
[94]	2022	Multiparametric MRI	93 women, 104 histopathologically verified lesions	Radiomics + Machine Learning (10 predictive models)	AUC = 0.93–0.96	Radiomics with DWI and ADC boosts accuracy (88.5%) over radiologists (85.6%), aiding less experienced readers.
[95]	2023	Breast MRI	Multiple datasets	CNN, RNN, RCNN, AE, Ensemble models	AUC-ROC: up to 0.98	Deep learning aided in breast cancer diagnosis, molecular classification, chemotherapy response, and lymph node prediction.
[96]	2023	Pathology Imaging	H&E and fluorescent-stained datasets	Color Normalization, Nucleus Extraction, Segmentation AI Model	H&E: 89.6%, Fluorescent: 80.5%	Cross-staining inference achieved high accuracy, demonstrating potential for expanding current pathology AI models to different staining technologies.
[97]	2023	Histopathological Imaging	95 TNBC and HER2+ BC H&E-stained WSI (1037 regions of interest)	Pathomic feature extraction, Random-Forest, other ML models	AUC-ROC: 0.86	Enhanced consistency in tumor grading
[98]	2024	Electrochemical Biosensors	-	Signal Processing AI	90.0	Improved biomarker detection for early diagnosis

Notes: Values are reported in the original studies. Accuracy is given in % and AUC-ROC on a 0–1 scale. “NR” = not reported; “pp” = percentage-point difference versus the comparator. Where both baseline and post-AI AUC are available, the change is shown (eg, 0.87 → 0.89).

Abbreviations: AE, autoencoder; ADC, apparent diffusion coefficient; AUC-ROC, area under the receiver operating characteristic curve; B, benign; BUSI, Breast Ultrasound Images dataset; DBT, digital breast tomosynthesis; DL, deep learning; DWI, diffusion-weighted imaging; FP, false positive; H&E, hematoxylin and eosin; M, malignant; ML, machine learning; RCNN, region-based convolutional neural network; RNN, recurrent neural network; SOTA, state of the art; TL, transfer learning; TNBC, triple-negative breast cancer; HER2+, human epidermal growth factor receptor 2–positive; WSI, whole-slide image; pp, percentage points.

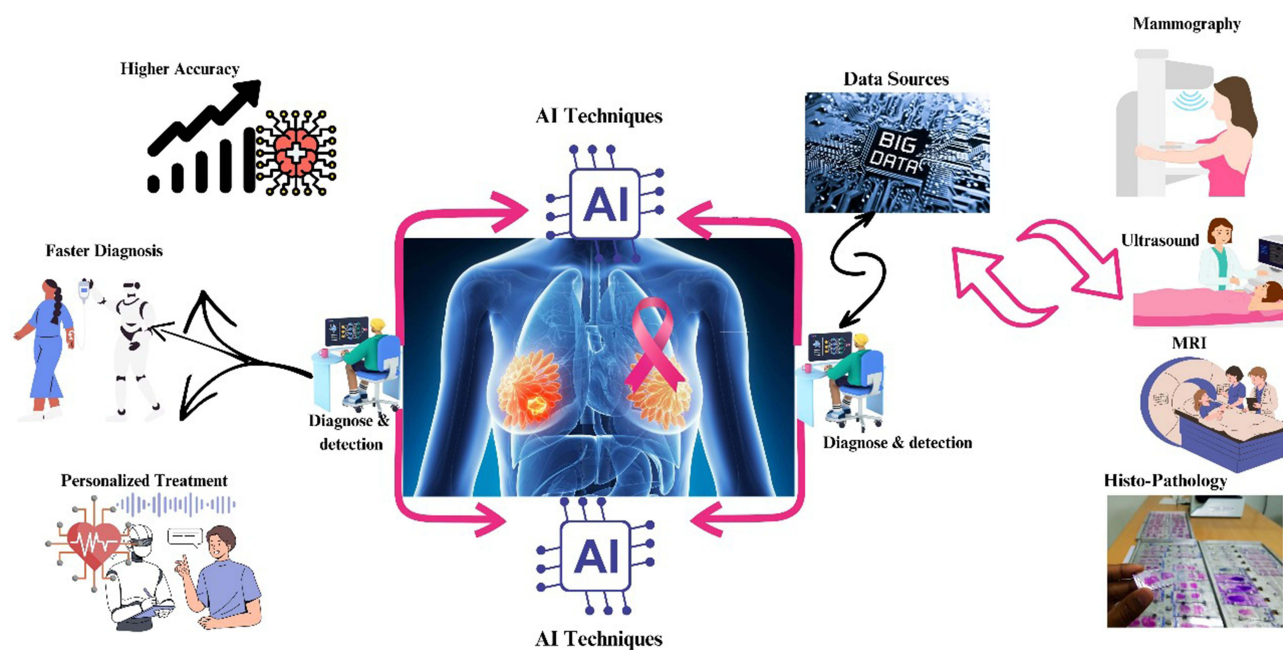


Figure 2 Multimodal AI framework for breast cancer detection and diagnosis. Imaging from mammography, ultrasound, magnetic resonance imaging (MRI), and histopathology is aggregated as data sources and processed by AI modules. The fused outputs support AI-assisted detection and diagnosis, enabling higher accuracy, faster diagnosis, and personalized treatment. Indicators: pink curved arrows = cross-modality fusion/feedback; black arrows = forward data flow (sources → AI → outputs); monitor icons = AI decision support endpoints.

tasks.²⁹ AI technologies also show promise in breast cancer segmentation, biological characterization, and prognosis prediction by integrating multi-omics data.⁸² However, challenges remain, including the need for rigorous validation, interpretability, and addressing technical considerations for widespread clinical adoption.¹³ Despite these hurdles, AI-assisted imaging is an ideal strategy for improving the efficiency and accuracy of breast cancer screening and diagnosis.⁷⁷

Recent advancements in AI have shown significant potential in the management of breast cancer. AI-based tools integrate multi-omics data, imaging biomarkers, and clinical information to develop comprehensive patient risk profiles, thereby enabling personalized screening and treatment strategies.⁹⁹ These models assist with various aspects of breast cancer care, including risk stratification, lesion detection and classification, treatment planning, and prognosis prediction.⁷⁷ AI algorithms have demonstrated promising results in automating diagnosis, segmenting relevant data, and predicting tumor responses to neoadjuvant chemotherapy.⁹⁹ The integration of AI with radiomics, pathomics, and multi-omics data (genomics, transcriptomics, epigenomics, and proteomics) has led to significant advancements in cancer diagnosis and prognosis.¹⁰⁰ However, challenges remain in data curation, model interpretability, and clinical implementation, necessitating ongoing research to ensure the safe and effective integration of AI in breast cancer management.^{77,100}

Although AI shows promise in breast cancer management, it faces challenges in terms of clinical integration. Key issues include the “black-box” nature of AI algorithms, data privacy concerns, and need for transparency.⁷⁶ Explainable AI (XAI) has emerged as a solution for making AI models more interpretable and building trust among healthcare professionals.¹⁰¹ XAI techniques, such as SHAP, are increasingly used to explain model predictions in breast cancer detection and risk assessment.¹⁰² Federated learning enables AI models to be trained on decentralized datasets while protecting patient privacy and enhancing model performance and generalizability across diverse populations.¹⁰³ Despite these advancements, the successful implementation of AI in clinical practice requires addressing challenges related to data quality, extensive validation, and regulation.¹⁰¹ Continued research and development in XAI and federated learning are crucial for improving AI’s adoption and effectiveness of AI in breast cancer management.

Real-Time Patient Monitoring

Recent advances in AI have significantly affected breast cancer management, particularly in the fields of imaging and pathology. AI has enhanced the accuracy of mammographic imaging, tomosynthesis, and other diagnostic modalities.⁷⁷ In pathology, AI has improved the identification of invasive tumors, lymph node metastasis, and hormonal status evaluation.⁸⁸ AI-based frameworks have shown promise in breast carcinoma classification and mitotic figure quantification, contributing to improved prognosis.⁸⁸ AI-driven risk prediction models that integrate multiple data streams can aid in planning individualized screening protocols.¹⁰⁴ However, challenges remain, including the need for large high-quality datasets, external validation, and improved code and data availability to enhance the reliability and clinical translation. Furthermore, AI has demonstrated considerable potential for predicting treatment responses and clinical outcomes through the analysis of patient data, imaging, and pathology.¹⁰⁵

AI has revolutionized the management of breast cancer across multiple domains. AI enhances the detection accuracy of mammography, MRI, and ultrasound, rivaling that of expert radiologists.¹⁰⁶ AI applications in pathology have improved biomarker detection and assessment, particularly for HER2 and Ki67.¹⁰⁶ AI models also show promise in personalizing treatment strategies and predicting outcomes, although methodological weaknesses and biases remain concern.¹⁰⁴ The integration of AI into clinical practice faces several challenges, including the need for extensive validation, model generalizability, and practical implementation.¹⁰⁷ Beyond AI, circulating tumor DNA (ctDNA) analysis is emerging as a complementary tool to imaging for monitoring breast cancer, offering potential advantages in the early detection of recurrence or progression.¹⁰⁸ However, technical, strategic, and economic hurdles currently impede the widespread clinical adoption of ctDNA analysis for breast cancer monitoring.¹⁰⁸

Recent advancements in AI have revolutionized breast cancer care across the clinical spectrum. AI applications in imaging and pathology enhance detection accuracy, rivaling expert radiologists in mammography, MRI, and ultrasound interpretation.¹⁰⁶ These technologies also improve biomarker assessments and personalize treatment strategies.¹⁰⁶ AI-powered decision support systems streamline clinical workflows and enable more precise diagnostics.¹⁰⁶ However, the integration of AI into health care faces significant ethical, legal, and regulatory challenges, necessitating the establishment of robust governance frameworks.¹⁰⁶ Current research has focused on addressing these challenges, including data variability and real-world validation.¹⁰⁶ Despite these hurdles, AI shows immense potential for improving breast cancer diagnosis, prognosis, and treatment outcomes^{109,110} with ongoing efforts aimed at fully realizing its capabilities in clinical practice. Ongoing research efforts are focused on addressing these challenges, with the goal of fully realizing AI's potential to enhance breast cancer care and ultimately improve patient outcomes and survival rates.

Federated Learning and Decentralized Data Sharing

Federated learning (FL) has emerged as a promising approach in healthcare, facilitating collaborative machine learning model development while ensuring patient data privacy and security.^{111,112} This decentralized method enables multiple institutions to collaboratively train algorithms while maintaining the sensitive data localized within each institution.¹¹³ FL has been successfully applied in diverse healthcare areas including medical imaging, COVID-19 research, and smart healthcare systems, thereby demonstrating its versatility.¹¹⁴ By sharing only model updates instead of raw data, FL mitigates privacy concerns and reduces the risk of data breach.¹¹⁵ Despite challenges, such as potential privacy leakage due to adversarial attacks, emerging privacy-preserving techniques have been developed to address these issues. Overall, FL offers substantial potential for improving the generalizability and external validity of AI models in healthcare, particularly when working with heterogeneous data from multiple centers.¹¹⁶

Decentralized Clinical Trials

Decentralized clinical trials (DCTs) are transforming clinical research by leveraging digital technologies to overcome the traditional limitations. DCTs utilize remote data capture, wearables, and digital biomarkers to enable continuous monitoring and data collection outside clinical setting.¹¹⁷ This approach addresses challenges, such as limited participant diversity, geographical constraints, and logistical barriers. The COVID-19 pandemic has accelerated the adoption of DCTs, promoting the use of digital health technologies, while maintaining privacy and security.¹¹⁸ Despite these benefits,

challenges such as data security, remote patient monitoring, and regulatory variations remain. Future research should focus on developing standardized protocols, exploring long-term effects, and addressing challenges through multi-disciplinary collaboration. As digital technologies evolve, DCTs are poised to become an increasingly essential component of clinical research, offering new opportunities to improve healthcare outcomes.¹¹⁹

AI-Driven Personalized Monitoring and Adaptive AI Treatment Plans

AI-Driven Personalized Monitoring

AI has revolutionized personalized monitoring in breast cancer care, offering unparalleled precision and efficiency. By leveraging advanced machine-learning algorithms, AI enables the analysis of diverse data streams, including genomic, proteomic, and radiomic data. These systems are capable of real-time, individualized patient monitoring, and detecting subtle changes that may indicate disease progression or treatment resistance. AI has revolutionized breast cancer care through advanced imaging analysis, personalized treatment planning, and remote monitoring.¹²⁰ AI algorithms can detect subtle patterns in mammograms and other imaging modalities with high accuracy, potentially leading to earlier diagnosis.¹⁰⁶ Machine learning and deep learning methods have shown promising results in predicting treatment response, prognosis, and patient survival, with average accuracy rates of 90–96%.¹⁰⁶

AI has shown promising results in detecting tumor metastasis and in improving cancer diagnosis using medical imaging. A meta-analysis of AI algorithms for tumor metastasis detection reported a pooled sensitivity of 82% and specificity of 84%, with an AUC of 0.90.¹²¹ Deep learning models have demonstrated high diagnostic accuracy across various medical specialties, with AUCs ranging from 0.864 to 1.0, for conditions such as diabetic retinopathy, lung cancer, and breast cancer.¹²² In abdominopelvic malignancies, AI-based radiomics models outperformed radiologists in lymph node metastasis detection, with AUCs of 0.895 for radiomics and 0.912 for deep learning compared with 0.774 for radiologists.¹²³ Applications of AI in oncology extend beyond diagnosis to molecular tumor characterization, drug discovery, and treatment outcome prediction, potentially revolutionizing personalized cancer.¹²³ Wearable devices integrated with AI can further enhance the monitoring capability. These devices continuously collect data on vital signs, activity levels, and other physiological metrics, which are analyzed to predict potential complications. This approach fosters a proactive healthcare environment, in which interventions can be deployed well before the manifestation of clinical symptoms. AI-driven monitoring not only enhances patient care, but also reduces the burden on healthcare systems by prioritizing high-risk patients for more intensive surveillance.

Adaptive AI Treatment Plans

Adaptive AI treatment plans redefine cancer care by tailoring therapies to meet each patient's unique and evolving needs. By integrating pharmacogenomic, proteomic, and tumor evolution data, these systems can identify the most effective interventions for AI, revolutionizing cancer research and precision medicine by offering improved methods for predicting treatment response and optimizing drug selection.¹²⁴ AI algorithms, including support vector machines (SVM), random forests (RF), and neural networks, have demonstrated high accuracy in predicting treatment outcomes, drug interactions, and resistance.¹²⁵ These techniques analyze complex datasets by integrating patient-specific information with drug characteristics to enhance treatment.¹²⁵ AI models have shown promise in predicting treatment duration, adverse reactions, and drug resistance.¹²⁶ AI applications extend to various stages of drug discovery including virtual screening, lead identification, and ADMET analysis.¹²⁷ The integration of AI in oncology research spans cancer detection and classification to molecular tumor characterization and drug repurposing, potentially transforming cancer care paradigms.¹²⁸ One of the key applications of adaptive AI is in drug resistance management. Tumor heterogeneity and genetic mutations often lead to resistance, which complicates the treatment outcomes. AI-driven models anticipate these changes by analyzing longitudinal genetic and proteomic data, thereby allowing oncologists to modify treatment regimens proactively. For example, reinforcement learning algorithms can simulate various therapeutic scenarios, thereby helping clinicians to choose strategies that maximize efficacy while minimizing toxicity.

Recent advancements in artificial intelligence (AI) have revolutionized personalized oncology by integrating various data streams to develop adaptive treatment plans. Circulating tumor DNA (ctDNA) kinetics has emerged as a promising

biomarker for monitoring treatment efficacy and guiding therapy adjustments.¹²⁹ AI algorithms can analyze complex transcriptomic profiles to predict drug responses and identify optimal treatment combinations for individual patients.¹³⁰ These AI-driven approaches have enabled the development of dynamic and personalized treatment strategies that can adapt to the evolving nature of cancer progression.¹³¹ In lung cancer, AI models integrate molecular information, radiomics, and patient characteristics to optimize diagnosis and treatment.¹³²

Transforming the Landscape of Oncology

AI is revolutionizing oncology, particularly breast cancer management, by enabling personalized monitoring and adaptive treatment planning. AI applications in oncology range from cancer detection and classification to predicting treatment outcomes and drug discovery.¹²⁸ These technologies analyze patient-specific data, including genetic and molecular information, to tailor interventions and improve cancer care.¹³³ Deep learning and machine learning methods have shown promising results in predicting treatment responses, prognosis, and patient survival, with average model accuracies of 90–96%.¹⁸ However, challenges remain, such as ensuring data quality, mitigating algorithmic biases, and addressing disparities in access to AI-driven care.¹³⁴ Overcoming these hurdles requires collaborative efforts among policymakers, healthcare providers, and technology developers to ensure the equitable and effective implementation of AI in clinical oncology.¹³⁴ Therefore, the fusion of AI-driven personalized monitoring and adaptive treatment planning is reshaping oncology into a field that is defined by precision and adaptability. By continuously analyzing patient-specific data and making real-time adjustments, AI systems enable care to evolve along with the disease. These technologies ensure that the interventions are timely, effective, and tailored to the unique molecular and clinical characteristics of each patient.

Despite these advancements, this document underscores challenges, such as ensuring data quality, mitigating algorithmic biases, and addressing disparities in access to AI-driven care. Collaborative efforts between policymakers, healthcare providers, and technology developers are critical for overcoming these hurdles and paving the way for equitable and effective breast cancer management. Therefore, AI-driven personalized monitoring and adaptive treatment plans represent the future of oncology and offer a transformative approach to breast cancer management. These innovations hold the promise of revolutionizing cancer care by enhancing precision, reducing toxicity, and improving patient outcomes (Figure 3).

Ethical and Regulatory Innovations for AI in Breast Cancer

Ethical Implications of AI in Breast Cancer Diagnosis

AI use in breast cancer care has significant ethical, legal, and social implications. Key concerns include algorithmic bias, data ownership, consent, and professional responsibility.^{135,136} The “black box” nature of AI systems raises issues of transparency and accountability, particularly in clinical decision making.¹³⁷ While AI has shown the potential to outperform human experts in breast cancer screening, reducing false positives and negatives,¹⁶ its implementation requires careful consideration of patient trust and healthcare equity.^{136,138} Addressing these challenges requires broad stakeholder engagement, robust oversight systems, and proactive roles for regulators and professional groups.¹³⁵ Integrating social science perspectives into AI development is crucial for exploring under-examined ethical implications and potential discriminatory effects.^{137,139} Overall, the ethical use of AI in breast cancer care requires a balanced approach that maximizes benefits, while mitigating risks.

Regulatory and Legal Considerations in AI Implementation

The integration of AI into health care presents significant legal and ethical challenges. Key issues include privacy, data security, accountability, and liability,^{140,141} and there is a pressing need for tailored regulatory frameworks to address these concerns while fostering innovation.^{140,142} The lack of clear regulations raises questions about responsibility in cases of AI-related errors or harm.¹⁴² Data protection, informed consent, and algorithmic transparency are crucial considerations.¹⁴³ The rapid advancement of AI technology has outpaced legal and regulatory development, creating a gap that must be addressed. Stakeholders must collaborate to develop comprehensive governance frameworks that balance innovation with ethical

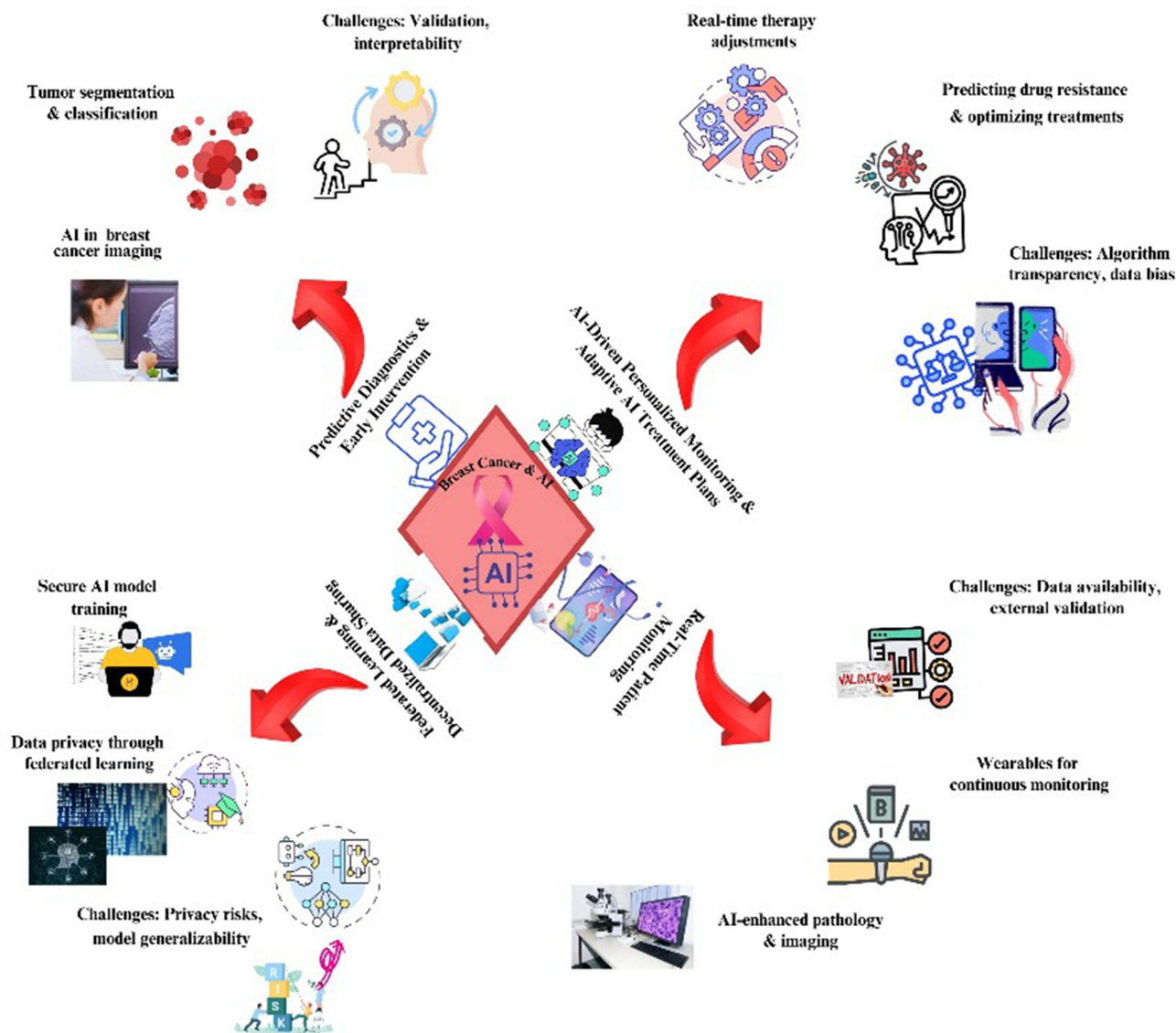


Figure 3 Predictive diagnostics and early intervention for breast cancer. Concept map linking the central hub ("Breast Cancer & AI") to application areas—tumor segmentation/classification, real-time therapy adjustment, prediction of drug resistance, AI-enhanced pathology, and wearables for continuous monitoring—and to cross-cutting issues (secure model training, federated learning for data privacy, external validation/data availability, interpretability, algorithmic bias). Indicators: Red curved arrows = iterative, closed-loop flow (data → modeling → deployment → evaluation → back to data); dashed callout bubbles = challenges/constraints; solid icon panels = application areas.

considerations and patient protection.¹⁴³ This includes addressing issues related to data ownership, consent, and the role of technology-giants in handling sensitive health information.¹⁴¹ Furthermore, AI's reliance of AI on large and diverse datasets raises concerns about data ownership, patient consent, and privacy. The use of sensitive health data by technology companies, often without explicit patient consent, raises ethical questions regarding who controls this data and how it is utilized. With the introduction of AI in medical decision making, a tailored regulatory framework that addresses these unique challenges is urgently required. Such a framework must not only safeguard patient rights and privacy, but also foster innovation, ensuring that AI is integrated into healthcare systems ethically and effectively.

Patient Autonomy and Consent in AI-Driven Healthcare

Patient Autonomy in AI-Driven Health Care

The integration of AI in healthcare raises concerns regarding patient autonomy and decision-making. Studies have shown that patients, physicians, and dieticians have varying levels of trust in AI-driven healthcare, with privacy and ethical issues significantly impacting patient autonomy.^{144,145} The use of unexplainable machine learning algorithms may undermine the trusted doctor-patient relationship and patient autonomy, necessitating improved explainability in healthcare AI.¹⁴⁶ However, some argue that fears about AI threatening patient autonomy may be misplaced, as machine learning has the potential to enhance personalized medicine through big data analysis.¹⁴⁷ Research indicates that patients' preferences for AI autonomy in healthcare decision-making vary by individual and context, suggesting a need for patient involvement in defining appropriate levels of AI assistance.^{148,149} These findings highlight the complex interplay between AI, patient autonomy, and healthcare decision making. AI also has the potential to enhance patient autonomy by providing precise, personalized, and accessible information. Predictive models and data-driven tools can empower patients to make informed decisions regarding their condition and treatment options. For example, AI can offer predictive insights that help patients to understand the course of their illness, treatment choices, and potential outcomes. This information can enable individuals to make better decisions that align with their personal values and preferences, thereby strengthening their autonomy.

Informed Consent in AI-Driven Healthcare

The integration of AI into healthcare presents significant challenges for the informed consent process. Patients may struggle to understand AI-driven decision making, potentially compromising their ability to provide informed consent.^{150,151} This issue is exacerbated by the complexity and opacity of AI systems, which can make it difficult for healthcare providers to adequately explain their use to patients adequately.¹⁵² While the current legal doctrine may not generally require disclosure of AI involvement in treatment recommendations, there are situations in which such disclosure might be necessary, such as when patients inquire or when AI plays a significant role in decision-making.¹⁵² To address these challenges, suggestions include adopting patient-centric information disclosure standards, restructuring medical liability rules, enhancing professional training, and improving public education on the use of AI in healthcare.^{151,153} These efforts aim to build an AI-driven healthcare system that promotes trust and ensures equitable access to health care. Furthermore, AI tools may generate recommendations that patients feel pressured to follow, especially if they perceive these recommendations as “scientifically” grounded and therefore more reliable than human expertise. This creates a potential conflict in which patients may consent to treatment based on AI recommendations without fully understanding or agreeing with the underlying decision-making process. For health care professionals, ensuring that consent remains informed and voluntary, even in an AI-driven environment, is a key challenge that must be addressed.

Challenges to Patient Autonomy and Informed Consent in AI Healthcare

One of the major challenges in AI-driven healthcare is the opacity of the AI models. Many machine-learning algorithms, particularly deep-learning models, function as “black boxes” that are difficult to interpret. This lack of transparency can make it difficult for patients to understand the reasoning behind AI recommendations, and therefore, to make informed decisions. For healthcare professionals, this raises concerns about the ethics of providing treatment recommendations based on systems that cannot fully explain their rationale for doing so. Another challenge is the potential for bias in the algorithms. AI systems learn from large datasets that may contain biases that could affect their treatment recommendations. For example, an AI system trained on data that underrepresents certain demographic groups might generate biased recommendations that do not adequately address the needs of these populations. This creates ethical dilemmas in maintaining equitable and personalized care, while respecting the autonomy of diverse patient populations.

Additionally, there are concerns regarding data privacy and security. The use of AI in healthcare requires collection and analysis of large amounts of sensitive patient data. Patients must be assured that their data are handled securely, and

that they have control over how they are used. Ensuring transparency and providing patients with clear and understandable options for consenting to data usage are crucial components for respecting their autonomy.

Ethical Frameworks for Ensuring Autonomy and Consent in AI-Driven Healthcare

To address the ethical challenges associated with AI in healthcare, new frameworks are needed to ensure that patient autonomy and informed consent remain central to medical practice (Figure 4). One potential framework is the development of explainable AI (XAI), which aims to make AI systems more transparent by providing clear explanation of how decisions are made. XAI can help bridge the gap between complex AI models and patient understanding, ensuring that they are better informed when making decisions. Furthermore, the informed consent process must evolve to accommodate the use of AI technology. Instead of relying solely on traditional methods of explaining treatment options, consent processes must be adopted to ensure that patients understand the role of AI in their care, how it functions, and its potential benefits and risks. This could involve simplified explanations, visual aids, and interactive tools to make AI-driven healthcare more accessible and comprehensible. Collaborative decision making is an important consideration. AI

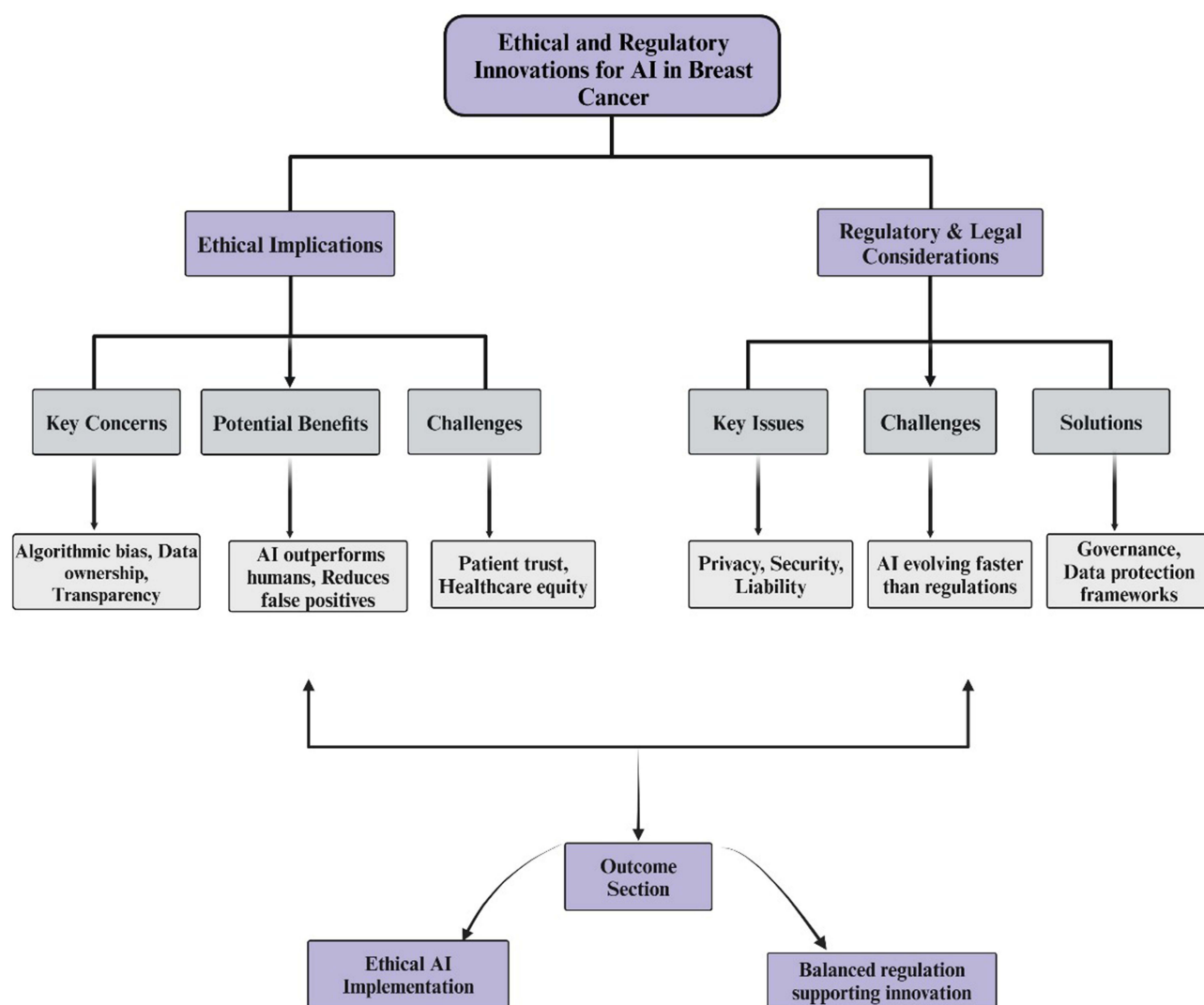


Figure 4 Ethical and regulatory innovations for AI in breast cancer. Parallel domains—ethical implications (left) and regulatory and legal considerations (right)—with downstream outcomes. Ethical: Key concerns (algorithmic bias, data ownership, transparency), potential benefits (AI may outperform humans and reduce false positives), and challenges (patient trust and healthcare equity). Regulatory: key issues (privacy, security, liability), challenges (AI evolving faster than regulation), solutions (governance and data protection frameworks). The paths converge on the ethical implementation of AI and balanced regulations that support innovation. Indicators: purple rounded boxes = section headers; gray rectangles = subtopics; connectors/arrows = information flow towards outcomes.

should not replace human judgment or patient involvement in decision-making but rather act as a tool to support these processes. Healthcare professionals should engage patients in open discussions about AI use in their care to ensure that their values, preferences, and goals are prioritized.

Conclusion

Artificial intelligence (AI), particularly deep learning, has advanced breast cancer diagnostics across mammography/digital breast tomosynthesis (DBT), ultrasound, magnetic resonance imaging (MRI), and digital pathology, particularly when embedded in clinician-centered workflows. Evidence is most mature in screening mammography; applications in other modalities and in multimodal fusion—combining imaging with clinicopathologic and, where available, genomic data—are promising, but heterogeneous. Real-world performance remains sensitive to the quality of the dataset, population and vendor differences, acquisition protocols, probability calibration, and workflow design. Responsible clinical deployment requires multi-site external validation, bias mitigation with representative datasets, interpretable outputs that support decision-making, and post-deployment monitoring for drift, safety, and equity, along with compliance with privacy, data governance, and evolving regulatory standards. Near-term priorities include second-reader and triage use cases, integrating routinely available clinical and pathological data to refine individualized risk and reliability measures, such as robust training, cross-site harmonization, and predefined escalation pathways for uncertain cases. Overall, AI should augment, not replace, clinicians. When deployed within well-validated and transparently governed systems, it can enable earlier detection, more consistent diagnosis, and personalized care.

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Disclosure

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