

Recent Advancements in Artificial Intelligence for Breast Cancer: Image Augmentation, Segmentation, Diagnosis and Prognosis Approaches

Nitish Verma¹, Ayush Sharma², Kelvin Luntsi³, Anshika Varshney⁴

¹Assistant Professor, School of Health Sciences, Chhatrapati Shahu Ji Maharaj University, Kanpur, Uttar Pradesh, India

²Master's Student, Department of Medical Radiology and Imaging Technology, Shri Ram Murti Smarak Institute of Allied and Healthcare Sciences, Bhojipura, Bareilly, Uttar Pradesh, India

^{3,4} Master's Student, Department of Radiology, Faculty of Allied Healthcare Science, Vivekananda Global University, Jaipur, Rajasthan, India

Abstract

Breast cancer remains the most frequently diagnosed malignancy and a leading cause of cancer death among women worldwide, with GLOBOCAN 2022 estimating 2.30 million new cases and 666,103 deaths globally (Bray et al., 2024; Gu et al., 2026). Artificial intelligence (AI), and deep learning (DL) in particular, has become central to efforts to improve early detection, diagnostic accuracy, and outcome prediction across the breast-imaging pipeline. This review synthesizes recent, peer-reviewed literature across four interconnected stages of the AI pipeline for breast cancer: (a) image augmentation, principally through generative adversarial networks (GANs) that mitigate small and imbalanced datasets; (b) semantic segmentation of tumor regions in ultrasound, mammographic, and magnetic resonance images using U-Net-based architectures; (c) diagnosis and classification of lesions as benign or malignant using convolutional neural networks (CNNs), transfer learning, and AI-assisted computer-aided diagnosis (CAD) systems applied to mammography, ultrasound, and histopathology; and (d) prognosis and survival prediction using multimodal and multi-omics deep learning. Reported performance metrics are summarized, including Dice similarity coefficients above 0.87 for state-of-the-art segmentation networks, classification accuracies exceeding 99% on benchmark histopathology datasets, and improvements in radiologist area-under-the-curve (AUC) from 0.84 to 0.91 with AI assistance (Abu Abeerh & Abuabeileh, 2025). The review also discusses persistent challenges — dataset scarcity, generalizability, interpretability, and clinical validation — and highlights emerging directions such as multimodal fusion and explainable AI. Findings indicate that while AI systems increasingly match or exceed human-level performance on narrow imaging tasks, translation into routine clinical workflows requires larger prospective trials, standardized reporting, and attention to fairness across breast densities and populations.

Keywords: artificial intelligence, deep learning, breast cancer, image augmentation, generative adversarial networks, segmentation, diagnosis, prognosis, mammography, ultrasound, histopathology

Introduction

Breast cancer is the most commonly diagnosed cancer among women and a leading cause of cancer-related mortality worldwide. According to the GLOBOCAN 2022 estimates, breast cancer accounted for approximately 2.30 million new cases and 666,103 deaths globally, representing 11.5% of all new cancer diagnoses and 6.8% of cancer deaths across both sexes, and it remains the most frequently diagnosed malignancy in 158 countries when considering women alone (1-4). Regional analyses show that Asia accounted for the highest absolute incidence (985,817 cases), followed by Europe (557,532) and Northern America (306,307), while age-standardized incidence rates were highest in Northern America (95.12 per 100,000) and lowest in Africa (40.5 per 100,000), even though Africa recorded the highest mortality-to-incidence ratio, reflecting disparities in early detection and access to treatment (5-7). Figure 1 summarizes this regional distribution.

Against this backdrop, artificial intelligence has emerged as a transformative tool across the breast-imaging and diagnostic pipeline. Deep learning models, inspired by hierarchical processing in the human visual cortex, have demonstrated strong performance in analyzing complex medical images, and are increasingly applied to mammography, ultrasonography, magnetic resonance imaging (MRI), and histopathology, as well as to radiomic and multi-omic data for risk assessment, prognosis, and treatment-response monitoring (8,9). However, clinical translation is constrained by the limited size and imbalance of annotated datasets, inter-institutional variability in image acquisition, and the need for rigorous external validation and interpretability (10-13).

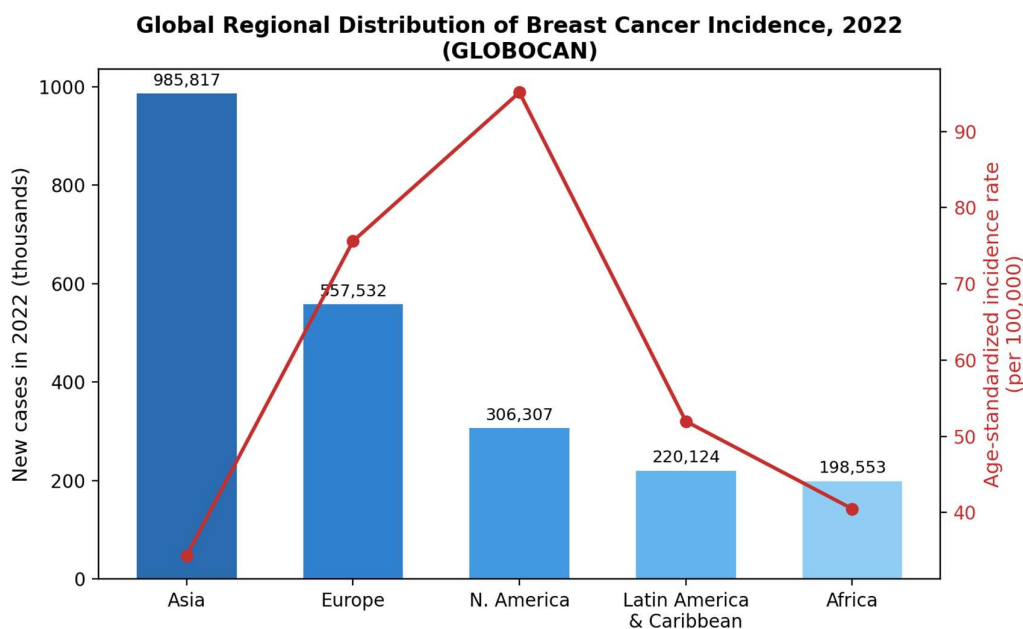


Figure 1. Global regional distribution of new breast cancer cases and age-standardized incidence rates, 2022 (data from Gu et al., 2026, based on GLOBOCAN).

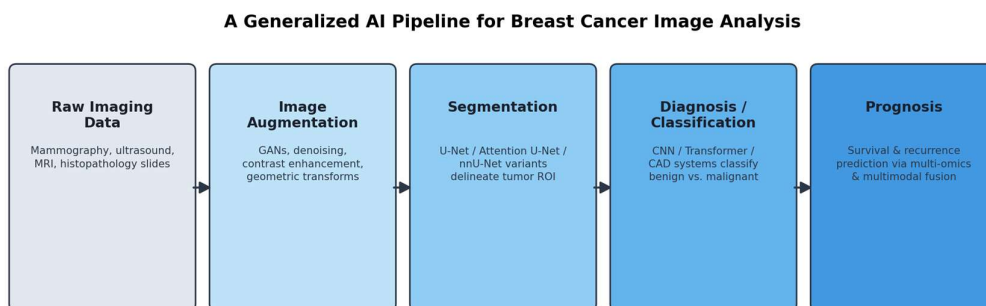


Figure 2. A generalized four-stage AI pipeline for breast cancer image analysis, from raw imaging data through augmentation, segmentation, diagnosis, and prognosis.

This review organizes recent advances around four stages that mirror a typical AI-based breast cancer image-analysis workflow, illustrated schematically in Figure 2: (1) image augmentation, which addresses data scarcity and class imbalance; (2) segmentation, which localizes tumors within an image; (3) diagnosis, which classifies findings as benign or malignant (and increasingly predicts molecular subtype); and (4) prognosis, which estimates survival, recurrence risk, and treatment response. For each stage, representative peer-reviewed studies and their quantitative outcomes are summarized to give an evidence-based picture of the current state of the art.

Review Approach

This narrative review draws on peer-reviewed articles indexed in Scopus-covered databases (including PubMed/MEDLINE, Web of Science, ScienceDirect, Nature Portfolio journals, PLOS ONE, SAGE, Springer, and MDPI outlets, many of which are also indexed in Scopus) published predominantly between 2020 and 2025, supplemented by foundational earlier studies where relevant to methodological context. Search terms combined "artificial intelligence," "deep learning," "breast cancer," and stage-specific terms ("data augmentation," "generative adversarial network," "segmentation," "diagnosis," "classification," "prognosis," "survival prediction"). Priority was given to systematic reviews, meta-analyses, and primary studies reporting quantitative performance metrics (e.g., accuracy, sensitivity, specificity, area under the curve [AUC], Dice similarity coefficient [DSC]) on recognized public datasets such as BreaKHis, BUSI, UDIAT, DDSM, and CBIS-DDSM, or on institutional cohorts with defined validation protocols.

Image Augmentation Approaches

A central obstacle to training robust deep learning models for breast cancer imaging is the limited size of publicly available, expertly annotated datasets, compounded by substantial class imbalance because malignant findings are rare relative to normal screening images (14-19). To address this, generative adversarial networks (GANs) have become the dominant augmentation strategy, alongside classical techniques such as denoising, contrast enhancement, rotation, and flipping.

Wu et al. (2018) introduced a class-conditional infilling GAN (ciGAN) that synthesizes lesions directly onto healthy screening mammograms, producing high-resolution (256×256 pixel) synthetic patches; augmenting training data with these samples improved the AUROC of a ResNet-50 classifier relative to traditional augmentation alone. Building on this line of work, Jiménez-Gaona et al. (2024) systematically compared four GAN architectures — Wasserstein GAN with gradient penalty (WGAN-GP), CycleGAN,

conditional GAN (cGAN), and spectral-normalization GAN (SNGAN) — for augmenting mammography and ultrasound regions of interest. Using Fréchet Inception Distance (FID) and related image-quality metrics, they found that SNGAN produced the most realistic synthetic mammography patches (FID = 52.89) while cGAN performed best for ultrasound (FID = 116.03), and that a ResNet18 classifier trained on the augmented data maintained strong benign/malignant discrimination in both modalities.

More recent work has combined GAN-based synthesis with additional preprocessing. Alawee et al. (2024) proposed a multi-stage pipeline combining denoising, contrast enhancement, and GAN-based augmentation prior to classification with a two-hidden-layer artificial neural network, reporting a 22.5–42.5 percentage-point improvement in classification accuracy over unaugmented scans. Collectively, these studies indicate that GAN-based augmentation is most beneficial when tailored to the target modality (e.g., SNGAN for mammography vs. cGAN for ultrasound) and when combined with conventional image-quality preprocessing rather than used in isolation.

Study	Modality	Augmentation method	Key reported outcome
Wu et al. (2018)	Mammography	Class-conditional infilling GAN (ciGAN)	Higher AUROC vs. traditional augmentation (ResNet-50)
Jiménez-Gaona et al. (2024)	Mammography & ultrasound	WGAN-GP, CycleGAN, cGAN, SNGAN	SNGAN best for mammography (FID = 52.89); cGAN best for ultrasound (FID = 116.03)
Alawee et al. (2024)	Mammography	Denoising + contrast enhancement + GAN	+22.5–42.5 percentage points in classification accuracy

Table 1. Representative studies on AI-based image augmentation for breast cancer imaging.

Segmentation Approaches

Accurate tumor segmentation is a prerequisite for quantitative lesion characterization and for downstream computer-aided diagnosis. U-Net and its variants remain the dominant architecture for breast tumor segmentation in ultrasound, mammography, and MRI, owing to their encoder–decoder structure with skip connections that preserves fine spatial detail (20).

Zhang et al. (2023) proposed a dual-branch network — one branch classifying images as normal or containing a mass, and a second branch performing segmentation — trained on a large, pixel-wise annotated dataset of 1,600 breast ultrasound (BUS) images from 625 patients. The model achieved a Dice similarity coefficient (DSC) of 0.898 for mass segmentation and an AUC of 0.991 for normal/abnormal classification, with good transferability to an external test set and low false-positive rates on video-recorded scans. Pramanik, Pramanik, Schwenker, and Sarkar (2023) introduced DBU-Net, a dual-branch U-Net enhanced with attention gates, achieving DSC values of 0.7423 and 0.7858 on the BUSI and UDIAT datasets, respectively. Their subsequent DAU-Net model, integrating a Positional Convolutional Block Attention Module and Shifted Window Attention within a residual U-Net, reported similar or improved dice scores on the same benchmark datasets (21–23).

Other attention-augmented U-Net variants have pushed reported DSC values higher still: a densely connected U-Net with channel, spatial, and scale attention modules (ACL-DUNet) achieved DSC of 0.8764 and 0.8313 on the Mendeley and BUSI datasets, respectively, outperforming several prior architectures on the same benchmarks. In parallel, comparative evaluations of U-Net, Attention U-Net, Residual U-Net, and multi-input attention U-Net on asynchronous volume-sweep-imaging ultrasound data identified the multi-input attention U-Net as the best performer, with a leave-one-out cross-validated Dice

coefficient of 72.45%. Figure 3 compares reported Dice scores across these representative segmentation studies, illustrating the substantial variability driven by dataset composition, image quality, and annotation protocol as much as by architectural choice(24-28).

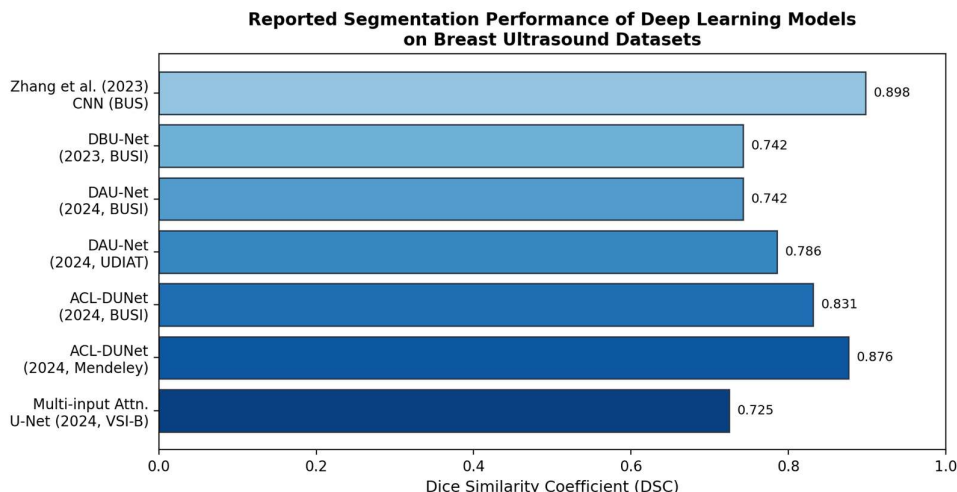


Figure 3. Reported Dice similarity coefficients for representative deep learning segmentation models on breast ultrasound datasets (see Table 2 for full citations).

Study	Architecture	Dataset	Reported DSC
Zhang et al. (2023)	Dual-branch classification–segmentation CNN	In-house BUS (n = 1,730)	0.898
Pramanik et al. (2023) — DBU-Net	Dual-branch attention U-Net	BUSI / UDIAT	0.742 / 0.786
Pramanik et al. (2024) — DAU-Net	PCBAM + Shifted-Window Attention Residual U-Net	BUSI / UDIAT	0.742 / 0.786
ACL-DUNet (2024)	Densely connected attention-gated U-Net	BUSI / Mendeley	0.831 / 0.876
Ochoa et al. (2024)	Multi-input attention U-Net	VSI-B ultrasound (n = 53 patients)	0.7245

Table 2. Representative deep-learning segmentation studies in breast ultrasound imaging and their reported Dice similarity coefficients.

Diagnosis and Classification Approaches

AI-based diagnostic and classification systems for breast cancer span three principal imaging modalities: screening mammography, ultrasound, and histopathology, each supported by a growing evidence base of systematic reviews and primary studies.

Mammography

A systematic review of AI in screening mammography spanning studies from 2013–2024 found that AI-assisted readings were comparable or superior to traditional double reading by radiologists, reducing unnecessary recalls and improving specificity while, in some cases, increasing cancer detection rates (29-31). Within the included evidence, radiologist performance measured by AUC improved from 0.84 without AI support to 0.91 with AI support in a randomized comparison of 643 mammograms (32). A

related systematic review and meta-analysis of AI-based receptor typing from mammograms, covering 25 studies, reported pooled AUC/sensitivity/specificity of 0.86/84%/80% for luminal subtype, 0.80/70%/78% for HER2-enriched tumors, and 0.76/75%/83% for triple-negative breast cancer, suggesting that mammography-based AI can non-invasively inform molecular subtyping in addition to binary malignancy detection. Retrospective evaluations of commercial AI-based computer-aided diagnosis (CAD) systems have reported sensitivity, specificity, and overall diagnostic accuracy of 84.7%, 91.5%, and 86.3%, respectively, on diagnostic mammograms, with the ability to retrospectively localize a majority of previously missed cancers on prior mammograms. However, head-to-head comparisons across breast densities show trade-offs: radiologists have demonstrated higher sensitivity (98% vs. 87% for AI) but lower specificity (17% vs. 44.4% for AI) in some cohorts, underscoring that AI and human readers may have complementary error profiles rather than one uniformly dominating the other.

Histopathology

Histopathological image classification, typically performed on the BreaKHis benchmark dataset of hematoxylin-and-eosin–stained tissue sections, has seen some of the highest reported accuracies in the field. Liu, Juhas, and Zhang (2020) proposed a Bilinear Convolutional Neural Network (BCNN) that aggregates orderless deep features and achieved 99.24% accuracy for binary (benign/malignant) classification and 95.95% accuracy for fine-grained subtype classification on BreaKHis. Hameed, Garcia-Zapirain, Aguirre, and Isaza-Ruget (2022) used multilevel features extracted from an Xception network to classify hematoxylin-eosin–stained images into normal tissue, benign lesion, in situ carcinoma, and invasive carcinoma, reporting strong multiclass performance and outperforming several prior single-network and ensemble baselines. Ensemble approaches combining multiple CNN backbones with channel and spatial attention have pushed BreaKHis classification accuracy above 99% across multiple magnification levels (40×, 100×, 200×, 400×), though such gains partly reflect the well-curated nature of BreaKHis relative to more heterogeneous clinical whole-slide-image datasets(33,34).

Ultrasound and Multimodal Diagnosis

Hybrid pipelines that combine segmentation and classification stages have also been proposed for ultrasound-based diagnosis, using U-Net-derived masks as region-of-interest inputs to downstream classifiers evaluated by accuracy, precision, recall, F1-score, and AUC; such joint segmentation–classification frameworks are reported to outperform single-task classification alone, particularly for lesions with low contrast or irregular margins. Figure 4 summarizes representative reported performance figures across the histopathology and mammography classification studies discussed above; note that these values are not directly comparable across studies because they rely on different datasets, class definitions, and validation protocols(35).

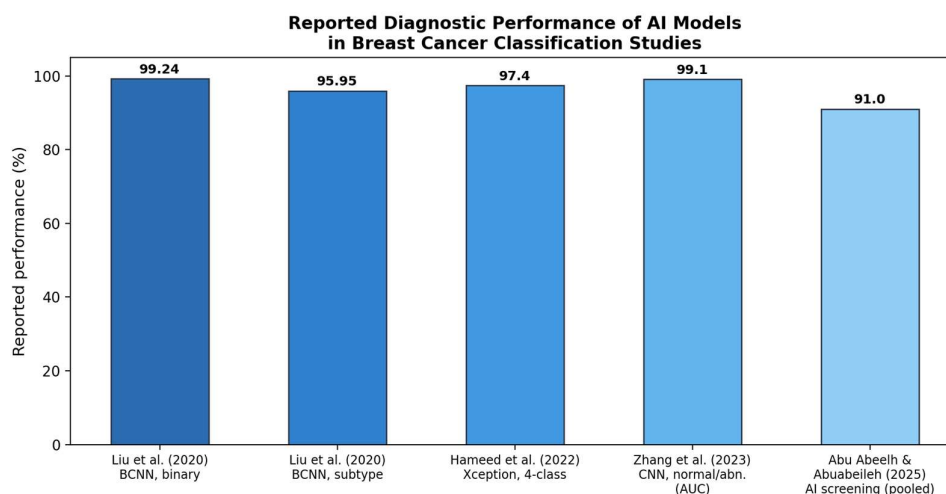


Figure 4. Reported diagnostic performance (accuracy or AUC, ×100) across representative AI classification studies in breast histopathology and mammography.

Study	Modality / Task	Model	Key reported metric
Liu et al. (2020)	Histopathology, binary & 8-class	Bilinear CNN (BCNN)	99.24% (binary); 95.95% (fine-grained)
Hameed et al. (2022)	Histopathology, 4-class	Multilevel Xception features	High multiclass accuracy vs. baselines
Abu Abeeel & Abuabeileh (2025)	Screening mammography (13 studies)	Mixed commercial AI-CAD	AUC 0.84 → 0.91 with AI support
Non-invasive receptor typing review	Mammography, molecular subtype	Mixed DL models (25 studies)	AUC 0.86 (luminal); 0.80 (HER2+); 0.76 (TNBC)
Retrospective AI-CAD review	Diagnostic mammography	Commercial AI-CAD	Sensitivity 84.7%; specificity 91.5%; accuracy 86.3%

Table 3. Representative AI diagnosis and classification studies across mammography and histopathology.

Prognosis and Survival Prediction Approaches

Beyond detection and diagnosis, AI is increasingly applied to breast cancer prognosis — predicting overall survival, recurrence, and treatment response — often by fusing imaging, clinical, genomic, and histopathological data. Mooghal et al. (2024) provide a narrative review of AI-driven breast cancer survival prediction, describing a shift from classical machine learning toward deep neural networks capable of refining prognostic accuracy and supporting individualized treatment planning, while cautioning that model generalizability, clinician integration, and ethical considerations remain open challenges.

Multimodal and multi-omics fusion architectures represent an especially active area. Wang, Li, Wang, and Li (2021), for example, proposed a deep bilinear network (GPDBN) integrating genomic and pathological image data for breast cancer prognosis prediction, while other groups have developed stacked ensemble learners combining deep neural networks, gradient boosting machines, and distributed random forests over multi-omics inputs, reporting strong area-under-the-curve performance across diverse cohorts. Multi-input

CNN architectures that fuse multiple data modalities for breast cancer prognosis have reported cross-validated AUC values around 0.89–0.90, exceeding single-input CNN baselines and several prior multimodal comparators.

Collectively, these studies suggest that (a) multimodal fusion — combining histopathological imaging with genomic, transcriptomic, or clinical variables — consistently outperforms single-modality models for survival and recurrence prediction, and (b) attention- and graph-based architectures (e.g., graph convolutional networks with fuzzy integral fusion) are increasingly used to model relationships between heterogeneous data types. However, reviewers consistently note the need for larger, prospectively validated cohorts, dynamic models that capture tumor heterogeneity over time, and interpretable outputs that clinicians can act upon (36).

Discussion: Challenges and Future Directions

Across all four stages of the pipeline, several recurring challenges limit clinical translation. First, dataset scarcity and imbalance remain fundamental constraints: public benchmarks such as BreakHis, BUSI, and DDSM are useful for methodological comparison but are considerably smaller and less heterogeneous than real-world clinical populations, which motivates continued investment in GAN-based and other synthetic augmentation strategies (37,38).

Second, reported performance metrics are frequently not comparable across studies because of differences in dataset composition, preprocessing, cross-validation strategy, and outcome definitions; a Dice coefficient of 0.90 on one curated dataset does not guarantee equivalent performance on an external, more heterogeneous population, as demonstrated by the meaningful spread of DSC values in Figure 3 even among similarly structured U-Net variants.

Third, external validation and prospective clinical evaluation remain comparatively rare; most of the studies reviewed here report internal cross-validation or retrospective test-set performance rather than prospective, multi-site trials. Where prospective or comparative clinical data exist — such as the AUC improvement from 0.84 to 0.91 with AI-assisted mammography reading — the results are encouraging but still limited in number (39,40).

Fourth, interpretability and fairness remain open concerns. Differences in AI sensitivity and specificity across breast densities, and the complementary rather than uniformly superior error profiles of AI versus radiologists, suggest that AI is best positioned as a decision-support tool rather than a stand-alone replacement for expert readers in the near term. Future work is likely to emphasize explainable AI methods, multimodal and multi-omics fusion for prognosis, federated learning to expand training data across institutions without compromising privacy, and larger prospective trials that directly measure patient-relevant outcomes rather than proxy imaging metrics alone(41).

Conclusion

Artificial intelligence has produced measurable advances at every stage of the breast cancer imaging and diagnostic pipeline: GAN-based augmentation mitigates data scarcity, attention-augmented U-Net variants achieve Dice coefficients approaching or exceeding 0.90 in tumor segmentation, CNN- and transformer-based classifiers exceed 99% accuracy on curated histopathology benchmarks and meaningfully improve radiologist AUC in mammography screening, and multimodal deep learning models are beginning to demonstrate improved survival and recurrence prediction. Nonetheless, the evidence base remains dominated by retrospective, single-institution, or benchmark-dataset studies.

Realizing the full clinical potential of these approaches will require larger and more diverse annotated datasets, standardized and transparent reporting of performance metrics, prospective multi-site validation, and continued attention to interpretability and equity across patient populations.

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