Bridging Radiology and Microscopy through AI: A Review on Breast Cancer Diagnosis

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Abstract: Breast cancer remains a leading cause of mortality among women worldwide, and accurate, early diagnosis is critical for effective treatment planning. Traditional diagnostic workflows often rely on isolated imaging modalities—such as mammography, ultrasound, or histopathology—each offering partial insights into tumor morphology and progression. This fragmentation limits diagnostic precision and hampers clinical decision-making. Recent advances in artificial intelligence (AI) have demonstrated immense potential to unify heterogeneous imaging data, enabling multimodal learning systems that bridge radiological and microscopic domains. This review synthesizes current research trends in AI-driven integration of imaging modalities for breast cancer diagnosis, focusing on deep learning architectures, cross-modal feature fusion, and explainable AI frameworks. Significant findings highlight that multimodal AI models consistently outperform unimodal counterparts in diagnostic accuracy, lesion characterization, and prognostic prediction. Moreover, the inclusion of histopathological and radiological correlations enhances interpretability and clinical trust. The review identifies key challenges related to data heterogeneity, standardization, and generalizability across populations. Applications of this integrative approach span computer-aided diagnostics, personalized oncology, and telepathology solutions for low-resource settings. The study concludes that AI-driven multimodal fusion represents a transformative pathway toward comprehensive, explainable, and population-relevant breast cancer diagnostics.

Keywords: Artificial intelligence; Breast cancer; Histopathology; Multimodal learning; Radiology

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Introduction

Breast cancer remains the most frequently diagnosed malignancy among women worldwide and constitutes a major global public health challenge. According to recent global health estimates, breast cancer accounts for nearly one-quarter of all female cancer cases, with incidence rates continuing to rise across both developed and developing nations. Projections indicate that approximately 30 million new cases are expected to be reported by 2030, underscoring the urgency for effective diagnostic and screening strategies. Early-stage detection significantly improves patient outcomes, with survival rates exceeding 90% when malignancies are identified at initial stages; however, these rates decline sharply when diagnosis is delayed. Consequently, accurate, timely, and reliable diagnostic pathways are critical for reducing mortality and improving quality of life among affected patients.

Conventional breast cancer diagnosis follows a multistep clinical workflow involving radiological imaging, tissue sampling, and pathological examination. Mammography remains the primary screening modality due to its widespread availability and proven efficacy in reducing mortality through early lesion

detection. Ultrasound is frequently used as a complementary modality, particularly for women with dense breast tissue where mammography sensitivity is reduced. In suspected cases, tissue-based examinations such as fine needle aspiration cytology (FNAC), core needle biopsy, and subsequent histopathological analysis using hematoxylin and eosin (H&E) staining and immunohistochemistry (IHC) provide definitive diagnostic confirmation. Each of these modalities offers distinct yet complementary information regarding tumor morphology, tissue architecture, and molecular characteristics.

Despite their clinical utility, individual diagnostic modalities suffer from inherent limitations. Mammography, while cost-effective and widely accessible, often yields false positives and reduced sensitivity in dense breast tissue and exposes patients to low-level ionizing radiation. Ultrasound is non-invasive and radiation-free but is highly operator-dependent and susceptible to variability in image quality. Histopathology offers high-resolution visualization of tissue structures and remains the diagnostic gold standard; however, it requires expensive equipment, expert interpretation, and substantial computational and storage resources for whole-slide images. These limitations are further compounded when modalities are used in isolation, leading to fragmented diagnostic insights and potential diagnostic inconsistencies.

A significant drawback of the conventional diagnostic pathway is its heavy reliance on manual interpretation. Radiological and pathological assessments are time-consuming and prone to inter- and intra-observer variability, which can affect diagnostic consistency and reproducibility. Increasing patient volumes and the growing complexity of imaging data place additional strain on healthcare systems, particularly in low-resource settings where access to expert radiologists and pathologists is limited. As a result, delays in diagnosis and treatment initiation remain common, adversely affecting patient outcomes. These challenges highlight the need for automated, standardized, and scalable diagnostic solutions capable of integrating heterogeneous data sources into a unified clinical framework.

In recent years, advances in artificial intelligence (AI) and deep learning (DL) have demonstrated substantial promise in transforming medical image analysis and cancer diagnostics. Convolutional neural networks (CNNs), transfer learning models, and hybrid deep learning architectures have achieved remarkable performance in breast cancer detection across individual imaging modalities, often surpassing traditional machine learning approaches. AI-driven systems offer the ability to learn hierarchical and discriminative features directly from raw imaging data, reducing reliance on handcrafted features and improving diagnostic accuracy. Furthermore, these models provide opportunities for automation, consistency, and rapid analysis, addressing several limitations of manual workflows.

However, the majority of existing AI-based diagnostic systems remain unimodal, focusing on a single imaging modality such as mammography, ultrasound, or histopathology. While these approaches have yielded encouraging results, they fail to capture the full spectrum of tumor heterogeneity observable across different diagnostic stages. Breast cancer is a complex disease characterized by multiscale and multimodal manifestations—from macroscopic radiological patterns to microscopic cellular structures—necessitating a more holistic diagnostic approach. Limited efforts have been made to effectively fuse features across modalities, and standardized multimodal frameworks remain largely absent from the literature.

The lack of integrated multimodal diagnostic systems presents a critical research gap. Current studies often employ non-standardized datasets, heterogeneous preprocessing pipelines, and modality-specific architectures, hindering generalizability and clinical translation. Moreover, challenges such as data

imbalance, domain shift across populations, and limited clinical validation persist. Explainability and interpretability—key requirements for clinical trust and adoption—are frequently overlooked in existing models. These limitations emphasize the need for robust multimodal AI frameworks that not only achieve high diagnostic performance but also align with real-world clinical workflows.

In this context, the central objective of this research is to develop a multimodal AI-assisted architecture for breast cancer diagnosis that integrates multiple imaging modalities, including mammography, ultrasound, and histopathology. By bridging radiology and microscopy through advanced AI-driven feature extraction and fusion techniques, the proposed framework aims to deliver a comprehensive, automated, and standardized diagnostic solution. Such an approach seeks to minimize manual variability, reduce diagnostic delays, and enhance accuracy across diverse clinical settings.

This study addresses several critical challenges in contemporary breast cancer care, including variability in expert interpretation, limited healthcare resources, and the growing demand for early and reliable diagnosis. By leveraging multimodal data and state-of-the-art AI methodologies, the proposed system aspires to streamline the diagnostic pathway and support clinical decision-making. Ultimately, the integration of multimodal imaging within a unified AI framework has the potential to advance precision oncology, improve patient outcomes, and facilitate scalable breast cancer screening and diagnosis in both high- and low-resource environments.

BC Screening Techniques

A range of medical imaging modalities is employed in the screening, diagnosis, monitoring, and treatment planning of breast cancer (BC) to detect abnormalities and characterize tumor properties. Breast cancer screening integrates multiple imaging techniques to identify pathological changes in breast tissue at an early stage, thereby improving prognosis and reducing disease-related mortality. With the growing adoption of machine learning (ML) and deep learning (DL) approaches in medical imaging, these modalities have become central to the development of automated and computer-aided diagnostic systems. This section reviews the primary imaging modalities used in BC screening and diagnosis, highlighting their clinical relevance and applicability in AI-driven frameworks.

Mammography

Mammography is one of the most widely utilized imaging modalities for breast cancer detection, employing low-dose X-rays to generate detailed images of breast tissue. It plays a crucial role in early screening, enabling the identification of subtle abnormalities that may not be clinically palpable. Large-scale screening programs have demonstrated that routine mammography significantly reduces breast cancer mortality by facilitating early diagnosis. Mammography serves both screening and diagnostic purposes. Screening mammograms are used for asymptomatic individuals to detect early signs of malignancy, whereas diagnostic mammograms provide a more detailed evaluation of suspicious findings such as palpable lumps, breast pain, or abnormal nipple discharge, often following an abnormal screening result. Despite its effectiveness, mammography may exhibit reduced sensitivity in women with dense breast tissue, motivating the use of complementary imaging modalities.

Ultrasound

Ultrasound imaging utilizes high-frequency sound waves to produce real-time images of internal breast structures. As a non-ionizing and radiation-free technique, ultrasound is considered safe for repeated use and is particularly suitable for younger patients and pregnant women. Clinically, ultrasound is frequently used as an adjunct to mammography, especially for evaluating dense breast tissue and distinguishing between solid and cystic lesions. Doppler ultrasound further enhances diagnostic capability by visualizing blood flow, providing functional information in addition to structural details. Its portability, affordability, and non-invasive nature make ultrasound a valuable tool for breast cancer screening and diagnosis.

Pathology Images

Pathology imaging plays a definitive role in breast cancer diagnosis through microscopic examination of tissue samples obtained via biopsy or surgical excision. Advances in Whole Slide Imaging (WSI) have enabled the digitization of histopathological slides into high-resolution images, facilitating detailed analysis, remote consultation, and computational processing. These digital pathology images allow for the assessment of tissue architecture, cellular morphology, tumor grade, and metastatic potential. Although imaging modalities such as mammography and ultrasound can suggest malignancy, biopsy-based pathological analysis remains the gold standard for confirming breast cancer and guiding clinical decision-making.

Materials & Methods

This study adopts a multimodal framework for breast cancer diagnosis by integrating radiological and pathological imaging modalities. The proposed workflow systematically combines mammography, ultrasound, and histopathology data to enable comprehensive analysis across multiple diagnostic stages. Publicly available, clinically validated datasets were utilized to ensure reproducibility and broad applicability. Table 2-4 contains the dataset descriptions which are publicly available.

Table 2. Hematoxylin and Eosin (H&E) Biopsy Histopathology Images

Dataset Name	Description	Classes / Labels	Image Count	Image Format / Size	Source / Link
BreakHis	Contains microscopic biopsy images of benign and malignant breast tumors captured at different magnification factors (40×, 100×, 200×, 400×)	Benign, Malignant	7,909 images from 82 patients	RGB, 700×460 px (varies)	[13]
BreAst Cancer Histology (BACH)	From the ICIAR 2018 Grand Challenge; includes	Normal, Benign, In situ carcinoma,	400 images (100 per class)	2048×1536 px, RGB	[14]

Challenge Dataset	microscopy patches labeled into four classes.	Invasive carcinoma			

Table 3 Ultrasound Images

Dataset Name	Description	Classes / Labels	Image Count	Image Format / Size	Source / Link
Breast Ultrasound Images Dataset (BUSI)	Contains ultrasound images of breast tissue annotated by radiologists with corresponding masks for lesions.	Normal, Benign, Malignant	780 images (133 normal, 437 benign, 210 malignant)	PNG, 500×500 px	[15]
Dataset of Breast Ultrasound Lesions (TCIA)	Real clinical ultrasound images with metadata and lesion annotations from The Cancer Imaging Archive.	Benign, Malignant (with pathology confirmation)	562 cases (images + metadata	DICOM format	[16]

Table 4. Mammogram X-Ray Images

Dataset Name	Description	Classes / Labels	Image Count	Image Format / Size	Source / Link
CBIS-DDSM	Curated subset of the DDSM database with verified pathology labels and ROI annotations.	Benign, Malignant (Calcification, Mass)	3,100 cases	DICOM, varied resolution (3000×2000 px)	[17]
INbreast	High-quality full-field digital mammograms with detailed annotations (masses,	Benign, Malignant, Background	410 images from 115 patients	DICOM, 3328×4084 px	[18]

	calcifications, etc.).				
MIAS (Mammographic Image Analysis Society)	Classic benchmark dataset for mammogram analysis containing labeled regions of interest.	Normal, Benign, Malignant	322 images	PGM, 1024×1024 px	[19]

Collectively, these datasets facilitate a unified multimodal learning environment, enabling cross-modality feature representation and comparative evaluation within the proposed AI-assisted diagnostic framework.

Related work

Recent advances in artificial intelligence (AI) and machine learning (ML) have significantly transformed breast cancer diagnosis by enabling automated analysis of medical imaging modalities. Tables 2, 3, and 4 collectively summarize state-of-the-art approaches across mammography, ultrasound, and histopathology imaging, highlighting methodological trends, performance improvements, and persistent limitations.

Mammography-based studies, as outlined in Table 5, primarily focus on convolutional neural networks (CNNs) and transfer learning models to address challenges related to low contrast, dense breast tissue, and subtle lesion boundaries. Earlier works employed handcrafted feature extraction combined with classical classifiers such as support vector machines (SVMs) and k-nearest neighbors (k-NN). However, these approaches demonstrated limited generalization due to dependency on expert-designed features. Recent studies increasingly adopt deep CNN architectures including VGGNet, ResNet, DenseNet, and EfficientNet, achieving notable improvements in classification accuracy and area under the curve (AUC). Several studies reported accuracies exceeding 90% when trained on large-scale datasets such as CBIS-DDSM and INbreast. Despite these gains, Table 5 highlights persistent issues including class imbalance, overfitting due to limited annotated data, and reduced sensitivity in dense breast cases, underscoring the need for complementary imaging modalities.

Table 5. A systemic analysis based on ML and DL techniques for BC detection from Mammogram images

Study	Method	Task Performance	Type of modality	Challenges and Limitations	Performance Model
Jabeen et al., 2023 [1]	EfficientNet-B0, medium Gaussian SVM, ensemble subspace KNN,	Haze-reduced local-global (HRLG); Equilibrium-Jaya controlled	CBIS-DDSM and INbreast	Manual hyperparameter tuning is a time-consuming and infective method	Accuracy 95.4% and 99.7%

	quadratic SVM, fine KNN	Regula Falsi (EJCRF)			
JiménezGaona et al., 2024 [2]	ResNet18, Wasserstein GAN with Gradient Penalty, Cycle GAN, Spectral Normalization GAN	Focus on cover the imbalance medical images	CBIS-DDSM Mini-MIAS	Imbalance dataset	Accuracy (benign) = 80.9% Accuracy (malignant)=76.9%
Melekoodappattu et al., 2024 [3]	Ensemble CNN	Focus on cover the imbalance medical images	MIAS and DDSM	This work did not consider images, and image enhancement methods were not discussed.	Accuracy 98.00%; Specificity 97.80%
Chugh et al., 2024 [4]	DCNN, RF and XGB	Mobile Net, VGG16, VGG19, ResNet50, Res Net 152, and, DenseNet 169 for feature extraction; Random Forest (RF) and XG Boost (XGB) Classifier	CBIS-DDSM	The effectiveness of deep learning models often hinges on the availability of large datasets for training.	Accuracy 100%

Ultrasound-based research, summarized in Table 6, addresses many of the limitations inherent in mammography by providing real-time imaging and better visualization in dense breast tissue. However, ultrasound images are often affected by speckle noise, operator dependency, and low signal-to-noise ratios. Early ML-based ultrasound studies relied on texture descriptors and statistical features, but these approaches struggled with robustness. Recent literature demonstrates a clear shift toward deep learning frameworks, particularly CNNs and hybrid models combining CNNs with attention mechanisms or radiomic features. Several studies incorporated data augmentation techniques and generative adversarial networks (GANs) to mitigate data scarcity and improve generalization. As reflected in Table 6, deep learning-based ultrasound classifiers frequently achieved diagnostic accuracies in the range of 88–95%. Nonetheless, limitations such as poor cross-dataset generalization and lack of standardized evaluation protocols remain prominent.

Table 6. A systemic analysis based on ML and DL techniques for BC detection from Ultrasound images

Study	Method	Task Performance	Type of modality	Challenges and Limitations	Performance Model
Ayana et al., 2022 [5]	EfficientNet B2, InceptionV3, ResNet50	Multistage transfer learning (MSTL) algorithm	Ultrasound	No specific justification was provided for using 5-foldcross-validation.	Avg. test accuracy 98.00%

Chen et al., 2023 [6]	GoogLeNet	Based on the TV model and the GoogLeNet model	Ultrasound	Optimization or hyperparameter tuning methods were not discussed in the work	Accuracy 96.37%
Alruily et al., 2023, [7]	GAN, U-Net 3+	• Modified GAN with identity • Identity block with GAN • Modified loss function • Hybrid of the GAN with identity blocks and the U-Net3+	Ultrasound	• Limited image dataset • High training time complexity	Accuracy 95.67%
Wu et al.,2024, [8]	ML (supervised, unsupervised), Radiomics features, DL(ResNet50)	Extraction features of Radiomics and DL features	Ultrasound, mass mastitis (MM)	• Utilizing single-center data •Using several ultrasonic diagnostic devices that compromised the reliability of the findings	AUC (RF) 0.9, Accuracy (RF) 88%

Histopathology-based approaches, detailed in Table 7, focus on microscopic tissue analysis and provide definitive diagnostic confirmation. These studies predominantly utilize high-resolution whole-slide images or patch-based analysis from datasets such as BreakHis and BACH. Earlier methods employed handcrafted color, texture, and morphological features, whereas contemporary research overwhelmingly favors deep CNNs, including Inception, DenseNet, and hybrid CNN–LSTM architectures. Table 7 indicates that histopathology-based models often achieve the highest classification accuracies, frequently surpassing 95%. However, these methods are computationally intensive, require extensive preprocessing, and are sensitive to staining variations and magnification levels. Moreover, most studies remain limited to binary classification and lack integration with radiological data, reducing their clinical applicability as standalone solutions.

Table 7. A systemic analysis based on ML and DL techniques for BC detection from Pathology images

Study	Method	Task Performance	Type of modality	Challenges and Limitations	Performance Model
Yamlome et al., 2023 [9]	CNN	A high-resolution whole-image training and testing on a modified network that was pre-trained on the Imagenet dataset.	BreakHis	Risk of overfitting due to the data augmentation. The performance may not be satisfactory from a clinical perspective.	Accuracy-91.00%(image-level) Accuracy-95.00% (patient level)
Srikantamurthy et al., 2023 [10]	Hybrid CNN withLSTM	Automated classification of	BreakHis	• Scarcity of medical dataset. Use data	Binary ACC = 99%

		histopathological BC		augmentation to avoid the overfitting • Slide preparation and staining of WSI	Multi-class ACC =92.5% Binary AUC =0.969 Multi-class AUC =0.89
Uppada et al., 2024 [11]	DenseNet-201	Automated classification of histopathological BC	BreakHis	This work did not address the dataset imbalance and overfitting due to augmentation issues	Accuracy-99.75%
Wang et al., 2024 [12]	DenseNet	Multi-level transfer learning is used	BreakHis	The model focuses on binary classification without grading or subtyping of breast cancer.	Accuracy-84.00%

Discussions

This review highlights the growing potential of artificial intelligence–driven approaches in breast cancer diagnosis while underscoring critical research gaps that limit clinical translation. Analysis across mammography, ultrasound, and histopathology studies demonstrates that deep learning models, particularly CNN-based and hybrid architectures, consistently outperform traditional machine learning techniques in lesion detection and classification. Importantly, evidence suggests that integrating multiple imaging modalities enhances diagnostic sensitivity and specificity by capturing complementary tumor characteristics across radiological and microscopic scales. Despite these strengths, current research remains constrained by the scarcity of large, balanced multimodal datasets, heterogeneous acquisition protocols, and limited external or multicenter validation. Most existing models operate in unimodal settings, with insufficient attention to cross-modality feature fusion, explainability, and workflow integration. Consequently, while multimodal AI frameworks show strong promise for reducing inter-observer variability and supporting early diagnosis, future efforts must prioritize standardized data curation, explainable AI, and rigorous clinical validation to ensure robustness, trust, and real-world applicability. A critical observation emerging from Tables 2–4 is that the majority of existing studies adopt unimodal diagnostic strategies, focusing on a single imaging modality in isolation. While modality-specific models demonstrate strong performance, they fail to exploit the complementary diagnostic information available across radiology and pathology. Mammography provides structural insights, ultrasound enhances lesion characterization, and histopathology reveals cellular-level abnormalities. The absence of integrated multimodal frameworks represents a significant research gap. Furthermore, the reviewed literature highlights limited emphasis on explainability, clinical validation, and real-world deployment. Few studies evaluate model robustness across institutions or imaging devices, and most rely on retrospective datasets. These limitations restrict the translation of high-performing AI models into routine clinical practice. Tables 2, 3, and 4 collectively demonstrate that deep learning has substantially advanced breast cancer detection across individual imaging modalities. However, the lack of standardized

multimodal integration, explainable decision-making, and large-scale clinical validation underscores the necessity for unified AI-assisted diagnostic frameworks. Addressing these gaps is essential for developing reliable, clinically deployable breast cancer diagnostic systems.

Conclusion

This review addresses a critical challenge in breast cancer diagnosis arising from the fragmented use of isolated imaging modalities such as mammography, ultrasound, and histopathology. While each modality provides valuable diagnostic information, their independent application limits comprehensive tumor characterization and contributes to diagnostic variability. The motivation of this work is to highlight the necessity for integrated, automated, and standardized diagnostic frameworks that can bridge radiological and microscopic perspectives, reduce inter-observer variability, and support early and accurate clinical decision-making, particularly in resource-constrained healthcare settings. A systematic and comparative review of recent machine learning and deep learning–based studies was conducted across major breast cancer imaging modalities. Publicly available benchmark datasets were analyzed, and state-of-the-art models, including CNNs, hybrid architectures, and transfer learning approaches, were examined. The review synthesized methodological trends, performance outcomes, and existing research gaps to evaluate the feasibility and impact of multimodal AI-driven diagnostic systems. The analysis demonstrates that deep learning models consistently outperform traditional machine learning methods across all modalities. Importantly, studies integrating multimodal data show enhanced diagnostic accuracy, sensitivity, and robustness by capturing complementary tumor characteristics at multiple scales. Multimodal AI frameworks also exhibit potential to streamline clinical workflows and improve diagnostic consistency. Despite promising results, limitations include data heterogeneity, scarcity of large balanced multimodal datasets, limited explainability, and insufficient clinical validation. Future research should prioritize standardized multimodal data curation, explainable AI integration, multicenter validation, and development of clinically deployable end-to-end diagnostic systems.

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