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Use of Artificial Intelligence in Breast Ultrasound Imaging: Diagnosis and Clinical Decision Support

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ABSTRACT

Breast ultrasound (US) is a critical non-invasive imaging modality for evaluating breast lesions, particularly in women with dense breast tissue. However, conventional interpretation suffers from inter-observer variability and high false-positive rates due to operator dependence and subjectivity. **Objectives:** To evaluate the role of Artificial Intelligence (AI), specifically deep learning models, in enhancing diagnostic accuracy, reducing unnecessary interventions, and supporting clinical decision-making in breast ultrasound imaging. **Methods:** A comprehensive review of recent literature (2000-2025) was conducted, focusing on AI applications in breast ultrasound for lesion detection, classification, segmentation, and clinical workflow integration. **Results:** AI systems, particularly convolutional neural networks, demonstrate diagnostic accuracy with area under the curve (AUC) values ranging from 0.92 to 0.98, often matching or exceeding expert radiologist performance. These systems achieve sensitivities and specificities typically exceeding 85%, with some studies reporting up to 98% sensitivity. AI integration reduces false-positive rates by up to 37% and unnecessary biopsies by approximately 28%. Beyond diagnosis, AI assists in lesion segmentation, BI-RADS classification consistency, and risk stratification. Portable AI-powered devices have shown promise in resource-limited settings, achieving 96-98% sensitivity. Integration of quantitative ultrasound parameters with AI enhances lesion differentiation and treatment planning. **Conclusions:** AI in breast ultrasound significantly improves diagnostic precision, workflow efficiency, and accessibility. Despite challenges, including dataset diversity, model interpretability, and clinical integration, ongoing developments support AI as a valuable adjunct tool for enhancing breast cancer detection and supporting personalized patient management.

INTRODUCTION

Breast cancer remains one of the most prevalent malignancies affecting women globally, accounting for approximately 2.3 million new cases and over 680,000 deaths in 2020 alone [1]. Early and accurate diagnosis is critical to improving patient outcomes and facilitating appropriate treatment planning. Among diagnostic imaging modalities, breast ultrasound (US) has become increasingly significant, particularly for women with dense breast tissue where mammography's sensitivity is compromised [2, 3]. Breast ultrasound is a non-invasive, radiation-free, and cost-effective imaging technique providing real-time visualization of breast tissue [4]. However, conventional US interpretation is highly operator-dependent and susceptible to inter-observer variability, leading to increased false-positive findings, unnecessary biopsies, and inconsistent clinical decisions [5]. Artificial Intelligence (AI), encompassing machine learning (ML) and deep learning (DL), has emerged as a transformative approach to address these challenges [6]. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated high performance in identifying complex image patterns, often equating or exceeding expert-level diagnostic accuracy [7]. In breast ultrasound, AI applications have shown potential in improving diagnostic precision, reducing false positives, and assisting with early cancer detection [8, 9]. Despite

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significant advances, challenges persist. Many AI models are trained on limited datasets, restricting their applicability in diverse clinical settings. Additionally, integration into routine workflows remains nascent, with unresolved issues regarding model interpretability, regulatory oversight, and clinician trust [10]. While numerous studies have demonstrated AI's technical capabilities in breast ultrasound, there remains a need for a comprehensive synthesis of its clinical applications, performance across diverse settings, and practical implementation challenges. This systematic narrative review aims to: (1) evaluate the diagnostic performance of AI techniques in breast ultrasound imaging, (2) assess their impact on clinical decision-making and workflow efficiency, (3) identify persistent research gaps and implementation barriers, and (4) propose evidence-based directions for clinically integrated AI solutions in breast cancer diagnosis and management.

The Role of Ultrasound in Breast Cancer Diagnosis

Breast ultrasound, also known as sonography, is a non-invasive imaging technique using high-frequency sound waves (typically 5-14 MHz) to produce detailed images of internal breast structures. Ultrasound (US) plays an essential role in breast cancer imaging and diagnosis, particularly in women with dense breast tissue [11]. While mammography remains the standard for screening, its sensitivity significantly decreases in dense breast composition. In such cases, breast US becomes more effective, detecting lesions that mammography may miss [12]. The US is also used to evaluate palpable lumps, guide needle biopsies, and assess abnormal findings from other imaging tests. The versatility of breast US includes grayscale B-mode imaging and Doppler modalities, allowing clinicians to observe lesion vascularity [13]. However, breast US has limitations. It is highly dependent on operator skill, patient anatomy, and equipment quality, resulting in interpretation variability and both false-negative and false-positive findings [14]. US diagnostic utility is further challenged by its subjective nature. Radiologists assess lesion features such as shape, margin, echogenicity, orientation, and posterior acoustic behavior. The Breast Imaging Reporting and Data System (BI-RADS) helps standardize interpretations but still relies on human input [15]. This has driven demand for computer-aided diagnosis (CAD) systems and AI applications that can support or augment human interpretation [16].

Limitations of Traditional Ultrasound Interpretation

Traditional interpretation of breast US involves manual evaluation by radiologists examining features such as lesion morphology, acoustic patterns, and margins. While experienced radiologists achieve high diagnostic accuracy, studies highlight significant inter-reader variability [17]. The subjective nature of feature assessment, along with variability in training and experience, leads to inconsistent conclusions. Interpretation of BI-RADS categories 3 and 4 remains particularly challenging [18]. Another limitation is the high false-positive rate. Studies show that adding US to mammography can increase recall rates by 5-15% and biopsy rates by 4-8%, but only 7-8% of these biopsies yield malignant results [4]. This means many patients undergo unnecessary invasive procedures, leading to anxiety, discomfort, and increased healthcare costs. Furthermore, the increasing volume of breast US exams places pressure on radiologists, raising the risk of fatigue-related errors [19]. Inconsistent interpretation due to cognitive load or lack of standardized reporting protocols further reduces reliability. These challenges create opportunities for AI and deep learning algorithms that can provide standardized, reproducible, and accurate interpretations [20].

Emergence of Artificial Intelligence in Medical Imaging

Artificial Intelligence (AI) has significantly transformed medical imaging. AI refers to the simulation of human intelligence by machines and encompasses subfields such as machine learning (ML) and deep learning (DL) [6]. In imaging applications, AI algorithms are trained on large datasets to detect patterns, classify anomalies, and provide diagnostic suggestions. Deep learning, particularly through convolutional neural networks (CNNs), has been especially impactful in medical image analysis [7]. CNNs can learn spatial hierarchies from image data, extracting increasingly complex features as the network deepens. Unlike traditional ML, which relies on handcrafted features, CNNs learn directly from raw image inputs, improving accuracy and reducing bias. These characteristics make CNNs particularly suited for the US, which is known for variability in image quality [21]. In breast imaging, AI is applied for classification (benign vs. malignant), lesion detection, segmentation, and disease prognosis prediction [22]. AI systems can analyze millions of images faster than humans and can be deployed to flag suspicious cases, aid in triage, or serve as second readers. Importantly, these systems are now being designed with explainability features like saliency maps, allowing clinicians to understand AI-generated decisions, fostering trust in clinical environments [17].

This review article evaluates the role of Artificial Intelligence (AI), specifically deep learning models, in enhancing diagnostic accuracy, reducing unnecessary interventions, and supporting clinical decision-making in breast ultrasound imaging.

RESULTS

The aggregated data comprises 123 cases from women (95% female) with a mean age of 52 ± 15 years, all evaluated for breast masses. Of the total lesions, 27 were malignant, primarily invasive ductal carcinoma (IDC) and ductal

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carcinoma in situ (DCIS), while 96 were benign. Lesion size distribution varied, with 7% measuring ≤10 mm and 28% falling within the 10-20 mm range. Most patients (85%) exhibited low breast density. Ultrasound features observed included non-circumscribed margins (44.7%), irregular lesion shapes (34.1%), and spiculation (25.2%). Additional findings included calcifications in 14.6% of cases and evidence of surrounding tissue alterations or increased vascularity in 19.5%. These varied morphological and textural characteristics provide representative examples of the diverse datasets used for training, validating, and optimizing AI-based diagnostic models in breast US imaging (Table 1).

Table 1: Representative Demographics and Imaging Features from AI-Assisted Ultrasound Studies (Illustrative Case Series, N=123)

Characteristics	Values
Number of patients	123
Female (%)	95.1%
Mean age (years)	52.0 ± 14.7
Lesions	123 breast masses
Malignant / Benign	27 malignant (22 IDC, 4 DCIS,1 mucinous) 96 benign
Tumor size ≤10 mm	9 (7.3%)
Tumor size 10-20 mm	34 (27.6%)
Breast density (low/med/high)	105/17/1
Non-circumscribed margins	55 (44.7%)
Irregular shape	42 (34.1%)
Spiculation	31 (25.2%)
Calcification	18 (14.6%)
Moderate-high blood flow	7 (5.7%)
Surrounding tissue changes	24 (19.5%)

Several high-quality studies have demonstrated the effectiveness of AI in interpreting breast US images. One of the most robust efforts involved an AI model trained on over 5.4 million US images from 288,767 breast exams [23]. This model achieved an area under the receiver operating characteristic curve (AUROC) of 0.976 on a test dataset of 44,755 exams. When compared to 10 board-certified radiologists, the AI system not only matched but outperformed them in diagnostic accuracy, reducing false-positive rates by 37.3% and unnecessary biopsy recommendations by 27.8%. Transfer learning, which allows models pre-trained on general image datasets to be fine-tuned for specific tasks, has been used with great success [8, 23]. Byra *et al.* employed a VGG19 model pre-trained on ImageNet and adapted it for breast US classification, achieving a high AUC of 0.936 for classifying malignant vs. benign lesions [12]. Another study by Xiao et al. compared different CNN architectures and found that transfer learning-based models achieved superior diagnostic accuracy over traditional ML and standard CNNs [13]. AI has also been shown to improve diagnostic consistency across diverse patient populations. The AI system developed by Shen *et al.* maintained high accuracy across all age groups, breast densities, and US machine types [8]. The model was further validated on an external dataset (BUSI) from Egypt, achieving a strong AUROC of 0.927, which suggests good generalizability [3]. Automated Breast Ultrasound; CAD = Computer-Aided Diagnosis; AUC = Area Under the Curve. Across numerous studies, AI systems consistently demonstrate high diagnostic performance, with mean sensitivities and specificities often ranging between 80% and 100% for breast cancer detection and classification. AI is also increasingly utilized to predict molecular subtypes, axillary lymph node involvement, and response to neoadjuvant chemotherapy, enabling more personalized treatment strategies. Some models, such as recurrent neural networks (RNNs), have achieved over 98% accuracy in experimental settings [23-26]. The integration of AI with automated breast US (ABUS) and radiomics has further improved diagnostic precision and enabled quantitative assessment for therapy monitoring. Additionally, smartphone-based AI applications have shown promise in delivering rapid and accurate diagnoses, particularly in resource-constrained settings [20, 24] (Table 2).

Table 2: Comparison of AI Model Efficacy in Breast Ultrasound Imaging (2000-2025)

References	AI Approach	Dataset Size/ Type	Diagnostic Task (s)	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC	Key Applications
[20]	ABUS radiomics + AI	Not specified	Diagnosis, therapeutic evaluation	Not stated	Not stated	Not stated	Not stated	Personalized treatment, therapy monitoring
[22]	ML/DL (77.6% DL)	58 studies (2017-2022)	Diagnosis, prognosis, subtyping, axillary status, response to therapy	Mean: 85-95	Mean: 80-95	Mean: 85-95	0.85-0.95	Treatment planning, response prediction
[24]	YOLOv3 (DL)	316 images (benign/ malignant)	Lesion detection/ classification	100 (smart phone)	75 (AI server) 97.5 (smart phone)	Not stated	Not stated	Point-of-care diagnosis
[25]	Various AI	Not specified	Detection, diagnosis, axillary status, response to therapy	Not stated	Not stated	Not stated	Not stated	Treatment response, molecular subtyping

[26]	RNN, GP, TL, ANN, CNN	30 datasets, 310 articles	Early diagnosis, precision treatment	>98 (RNN)	>96 (GP, TL, ANN)	>96 (DL)	Not stated	Precision treatment, automated triage
[27]	ML, DL	Not specified	Benign/malignant differentiation	Not stated	Not stated	Not stated	Not stated	Early screening, workflow improvement
[28]	ML, CAD	Not specified	Early diagnosis, detection	Improved vs. traditional ML	Improved	Improved	Not stated	Reducing misdiagnosis, workflow efficiency

ML = Machine Learning; DL = Deep Learning; RNN = Recurrent Neural Network; GP = Gaussian Process; TL = Transfer Learning; ANN = Artificial Neural Network; CNN = Convolutional Neural Network

The study summarizes the distribution of breast US cases across multiple AI research studies conducted between 2002 and 2025, reflecting variations in dataset composition, imaging platforms, and study designs (Table 3).

Table 3: Case Overview of AI Applications in Breast Ultrasound Imaging

Scanner Model	Malignant Cases	Benign Cases (Biopsy / Follow-up)	Total Cases
Canon Aplio 500 & GE LOGIQ E10	79	92 (77 via follow-up)	171
Siemens ACUSON Sequoia & Canon Aplio 500 (portable)	95	107 (unspecified method)	202
Samsung S Detect (multi-mode clinical analysis)	70 (27%)	190 (44 biopsy, 100 follow-up)	260
Handheld B-mode ultrasound (not specified)	450	601	1,051
Koios DS with US-guided biopsy	45	155	200

Accurate lesion segmentation is critical for measuring tumor size, planning treatment, and monitoring progression or response to therapy [13]. Traditionally, segmentation requires manual annotation, which is time-consuming and prone to variability. AI-powered segmentation tools can automate this process with high accuracy, designed to delineate lesion boundaries from surrounding tissue, even in cases of poor contrast or irregular shapes, which are common in US imaging [9]. Gu *et al.* developed a 3D segmentation method for breast US using morphological reconstruction and edge-detection techniques [14]. This approach achieved high accuracy in differentiating tissues and structures within 3D US volumes. Beyond segmentation, AI has been applied to assess tumor heterogeneity and predict biological behavior. Deep learning models have been trained to classify lesion stiffness, vascularity, and posterior acoustic features, attributes that help determine malignancy risk. In some cases, AI has outperformed radiologists in distinguishing between BI-RADS 3 and 4 lesions, aiding in biopsy decision-making and potentially reducing overtreatment [15, 18]. One of the most critical applications of AI in breast US is the reduction of false positives and unnecessary biopsies [3]. False positives not only burden healthcare systems but also cause significant psychological stress to patients. AI can mitigate this by accurately identifying lesions that do not require biopsy and flagging those that do with greater precision [29] (Table 4).

Table 4: AI in Breast Ultrasound for Low-Resource Settings: Key Studies (2000-2025)

References	Setting and Sample	AI Task	Key Performance
[30]	Rural Mexico, portable handheld US by minimally trained users (758 masses in 300 women)	CADx classification using Koios DS	Sensitivity 96-98%, specificity 38-67%, AUC ≥ 0.95
[31]	Mexico, low-cost handheld US by non-physicians (subset of Berg cohort)	CAD-assisted triage	Accuracy comparable to radiologists (100% sensitivity/specificity in small subset)
[32]	Brazil, 83 biopsy-proven breast masses	CAD system on elastography +BI-RADS lexicon	AUC improved from ~0.80 to 0.90-0.93 across readers; κ_i.c.c. improved
[33]	Dataset from clinical breast US images	Semi-supervised DL integrating BI-RADS features (BIRADS-SDL)	Classification accuracy ~83.9-92.0% on two datasets
[34]	Automation via 3D ABUS, 418 patients	3D detection + classification network	Sensitivity 97.7%, AUC ≈ 0.872
[35]	BUS images (multiple datasets)	ROI-free Transformer (HoVer-Trans)	Outperformed CNNs/sonographers; state-of-the-art accuracy

Several quantitative ultrasound (QUS) parameters significantly differ between malignant and benign breast lesions, offering valuable diagnostic insights. Malignant lesions generally exhibited higher attenuation coefficients and speed of sound values, likely reflecting increased tissue density and stiffness [36]. In contrast, benign lesions showed greater effective scatterer diameter (ESD), indicating a more uniform internal microstructure [37]. Parameters such as mid-band fit, spectral slope, and spectral intercept also trended higher in malignant lesions, corresponding to increased tissue heterogeneity [38]. Although some features, like effective scatterer concentration, did not show significant variation, the overall combination of spectral and textural QUS features enabled high diagnostic accuracy, with reported AUCs nearing 0.97 [39]. These findings

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support the integration of QUS metrics into AI systems for more accurate lesion classification and early breast cancer detection(Table 5).

Table 5: Quantitative Ultrasound Parameters by Final Diagnosis and Pathology Outcome

QUS Parameter	Malignant (mean ± SD)	Benign (mean ± SD)	Significance
Attenuation co-efficient (AC)	Higher	Lower	$p < 0.05$
Speed of sound (SoS)	Higher	Lower	$p < 0.05$
Effective scatterer diameter (ESD)	Lower	Higher	$p < 0.05$
Effective scatterer concentration (ESC)	No significant difference	–	–
Mid-band fit (MBF)	↑	↓	–
Spectral slope (SS)	↑	↓	–
Spectral intercept (SI)	↑	↓	–
Textural QUS features	More heterogeneous	Less heterogeneous	AUC 0.97

BI-RADS 4 lesions displayed markedly higher elasticity values (e.g., Emean and Emax), indicative of increased tissue stiffness commonly associated with malignancy [40]. Quantitative differences were also noted in attenuation, speed of sound, and velocity indices, with BI-RADS 4 lesions deviating significantly from the more benign BI-RADS 3 profiles [35]. Doppler assessments revealed more frequent abnormal vascular features in BI-RADS 4 lesions, supporting their use in enhancing diagnostic confidence [27]. Texture-based QUS features showed greater heterogeneity in suspicious lesions, further contributing to lesion stratification. These quantitative differences highlight the potential of combining QUS with AI to refine BI-RADS classification, particularly by identifying low-risk BI-RADS 4A lesions that may not require biopsy, thereby improved clinical decision-making and reducing unnecessary interventions [36](Table 6).

Table 6: Quantitative Ultrasound Parameters within (QUS) BI-RADS Categories 3 and 4

Parameter	BI-RADS 3 (Probably Benign)	BI-RADS 4 (Suspicious)	Clinical Insight
Attenuation and SoS	Similar to benign profiles	Shift toward malignant values	May aid in resolving indeterminate cases (BI-RADS 4A)
Strain elastography (mean elasticity, Emean)	Lower (<4.5 kPa)	Higher (>30 kPa), Emax > 36 kPa	Improves downgrading from BI-RADS 4A to 3, reducing unnecessary biopsies
Velocity index (VI)	Lower (~3%)	Higher (~5%)	Supports differentiation between benign and malignant lesions
Doppler flow (including bidirectional flow)	Absent or minimal	>3 abnormal features detected ~100% sensitivity, ~76% specificity	Enhances vascular assessment
QUS texture/heterogeneity	Homogeneous	Heterogeneous	Supports lesion characterization in indeterminate BI-RADS categories

A DL system trained on B-mode and Doppler US images significantly improved diagnostic performance, achieving an internal AUC of 0.94 and an external AUC of 0.96, reducing false-positive rates by 7.6% and improving interobserver agreement. Google's AI model trained on over 288,000 US exams and 5.44 million images achieved AUROC values of 0.976 (internal) and 0.927(external), while reducing false-positive diagnoses by 37.3% and unnecessary biopsies by 27.8% [34-36](Table 7).

Table 7: Use of Artificial Intelligence in Breast Ultrasound Imaging for Diagnosis and Clinical Decision Support

References	Setting and Sample	AI Task	Key Performance
[34]	Multivendor, multicenter; 45,909 B-mode + Doppler images	Deep learning classification; model-assisted radiologist support	AUC 0.94 internal, 0.96 external; reduced false positives by 7.6%; improved interobserver agreement
[35]	288,767 exams, 5.44 M images; B-mode and Doppler	AI vs radiologists; reader aid	AUROC 0.976 internal, 0.927 external; reduced false positives 37.3%, reduced biopsies 27.8%
[36]	4,998 patients: comparison of CNN architectures and resolutions	CNN model vs senior sonographers	Best AUC 0.924 (MobileNet_224), accuracy 87.3%; outperformed senior US readers

DISCUSSION

The integration of artificial intelligence (AI) into breast ultrasound (US) imaging marks a major advancement in diagnostic radiology, consistently improving accuracy, efficiency, and clinical decision-making [1–3]. AI systems employing deep learning (DL) and convolutional neural networks (CNNs) now demonstrate diagnostic performance comparable to, or exceeding, that of expert radiologists [26, 34–36]. Large-scale validation studies provide the most compelling evidence. The Google AI model, trained on 288,767 exams comprising 5.44 million images, achieved AUROC values of 0.976 (internal) and 0.927(external), showing robust generalizability. It reduced

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false-positive interpretations by 37.3% and unnecessary biopsies by 27.8%, addressing one of the main drawbacks of conventional US high false-positive rates leading to patient anxiety and increased healthcare costs [4-5]. This underscores AI's role as both an educational aid and a quality assurance tool. Recent developments have extended AI capabilities beyond binary classification. Transfer learning using pre-trained models such as ImageNet and fine-tuning them for breast US enables high accuracy even with smaller datasets [12-13]. Transformer-based architectures, such as HoVer-Trans, outperform traditional CNNs and expert sonographers by capturing long-range dependencies critical for interpreting complex breast tissue patterns [33]. Explainability features such as saliency maps and attention mechanisms help mitigate the "black box" criticism of AI systems [17]. The integration of quantitative ultrasound (QUS) parameters with AI represents another promising direction [34–38]. QUS provides measurable tissue characteristics—such as attenuation, speed of sound, and spectral features that distinguish benign from malignant lesions. When combined with AI, diagnostic accuracy improves markedly, with reported AUC values up to 0.97 [34–37]. Incorporating elastography further refines BI-RADS classification: lesions with Emean >30 kPa or Emax >36 kPa correlate strongly with malignancy in BI-RADS 4 cases [37-38]. AI-assisted reclassification of low-risk BI-RADS 4A lesions could reduce unnecessary biopsies by 15–18% while maintaining sensitivity. AI has also expanded access to quality breast imaging in resource-limited settings. AI-assisted portable US devices operated by minimally trained personnel achieved 96–98% sensitivity in rural populations, approaching expert performance. However, specificity varied (38–67%) due to differences in device quality and operator skill [29, 36]. AI-assisted interpretation benefits radiologists of all experience levels, with the greatest impact seen among less experienced readers. Benign biopsy rates decreased from 52% to 33% for junior and from 46% to 34% for senior radiologists when using AI support [39]. Successful deployment requires robust algorithms, standardized imaging protocols, quality assurance, and local training programs [36, 37]. Smartphone-based AI tools further enhance accessibility. Deep learning models deployed on mobile devices achieved 100% sensitivity and 97.5% specificity for lesion detection [24], enabling rapid triage in primary care and reducing specialist workload. Despite encouraging progress, challenges persist. Dataset diversity and generalizability remain major concerns, as most models are trained on data from single institutions or homogeneous populations [17–20]. Although some studies demonstrated external validation with an AUROC of 0.927 on diverse populations [3], comprehensive cross-population evaluation remains limited. Model interpretability, while improving, is still insufficient for full clinical adoption. Since radiologists bear ultimate diagnostic responsibility, AI predictions must be transparent and explainable [17-18]. Regulatory approval, workflow integration, and interoperability with radiology information systems (RIS) and picture archiving and communication systems (PACS) also pose barriers [10,19]. Most current models remain focused on binary classification (benign vs. malignant) [19–21], whereas comprehensive breast cancer management requires AI tools capable of risk stratification, molecular subtype prediction, lymph node assessment, and treatment response monitoring [21–25]. However, significant challenges remain. Dataset diversity and external validation across heterogeneous populations require attention to ensure generalizability. Model interpretability must improve to foster clinical trust and meet regulatory requirements. Clinical workflow integration, cost-effectiveness evaluation, and prospective validation through randomized controlled trials are necessary before widespread implementation. Additionally, expanding AI capabilities beyond binary classification to address multi-task clinical needs, including molecular subtyping, treatment response prediction, and surgical planning, represents an important frontier. The evidence supports AI as a valuable adjunct tool that augments rather than replaces radiologist expertise. Optimal implementation likely involves human-AI collaboration, where AI serves as a consistent "second reader," quality assurance mechanism, and decision support tool. Continued research addressing technical limitations, validation in diverse settings, and practical implementation strategies will determine whether AI's promise translates into improved breast cancer outcomes globally. With thoughtful development emphasizing clinical utility, interpretability, and equitable access, AI has substantial potential to transform breast US imaging and enhance patient care.

CONCLUSION

This review demonstrates that AI, particularly deep learning-based approaches, significantly enhances breast US imaging for cancer diagnosis and clinical decision support. AI systems consistently achieve high diagnostic accuracy with AUC values ranging from 0.92 to 0.98, often matching or exceeding expert radiologist performance. Critically, AI integration reduces false-positive rates by up to 37% and unnecessary biopsies by approximately 28%, addressing major limitations of conventional US interpretation. Beyond diagnostic accuracy, AI provides several clinical benefits: (1) improved inter-reader and intra-reader consistency, reducing interpretation variability; (2) enhanced performance across reader experience levels, with particularly pronounced benefits

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for less experienced radiologists; (3) automated lesion segmentation and BI-RADS classification support; (4) integration with quantitative US parameters for refined risk stratification; and (5) potential for expanding access to quality breast imaging in resource-limited settings through portable, AI-assisted devices.

Authors Contribution

Conceptualization: MIUH
Methodology: MIUH, SMYF, MM
Formal analysis: SMYF
Writing review and editing: MIUH, SMYF, MM

All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

All the authors declare no conflict of interest.

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