Review Article

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Clinical Application of Artificial Intelligence in Breast Ultrasound

유방초음파에서 인공지능의 임상적 활용

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Breast cancer is the most common cancer in women worldwide, and its early detection is critical for improving survival outcomes. As a diagnostic and screening tool, mammography can be less effective owing to the masking effect of fibroglandular tissue, but breast US has good sensitivity even in dense breasts. However, breast US is highly operator dependent, highlighting the need for artificial intelligence (AI)-driven solutions. Unlike other modalities, US is performed using a handheld device that produces a continuous real-time video stream, yielding 12000–48000 frames per examination. This can be significantly challenging for AI development and requires real-time AI inference capabilities. In this review, we classified AI solutions as computer-aided diagnosis and computer-aided detection to facilitate a functional understanding and review commercial software supported by clinical evidence. In addition, to bridge healthcare gaps and enhance patient outcomes in geographically under resourced areas, we propose a novel framework by reviewing the existing AI-based triage workflows including mobile ultrasound.

Index terms Artificial Intelligence; Breast Neoplasm; Ultrasonography; Breast Diseases

INTRODUCTION

Breast cancer is the most common cancer in women worldwide. According to a World Health Organization report, approximately 2.3 million new cases of breast cancer were globally diagnosed in 2020, accounting for 24.5% of all cancers in women and had the highest incidence rate (1). Breast cancer ranks first in terms of cancer-related mortality among women. In 2020, approximately 685000 women died of breast cancer, accounting for 15.5% of all cancer deaths in women (1). Mortality rates vary across countries and tend to be higher in low-resource countries and regions with limited geographical accessibility. This disparity is multifactorial but is presumed to arise substantially from differences in accessibility to screening, particularly the availability of breast imaging and treatment-related resources. If breast cancer is detected earlier, the survival rate increases (2). Moreover, early diagnosis enables treatment options such as breast-conserving surgery, thereby helping maintain patients' quality of life, reduce recurrence rates, and prevent the spread of cancer.

Mammography is considered the standard of care imaging modality for breast cancer screening, but the cancer detection can be affected by mammographic density. Dense breasts are characterized by a higher proportion of fibroglandular tissue relative to fatty tissue, a condition that not only increases the risk of developing breast cancer but is also challenging for breast cancer detection. It is estimated that 40%–50% of women have dense breast tissue, although its prevalence varies with age, ethnicity, and other factors (3). In women with dense breasts, supplemental imaging such as breast ultrasound is required for better cancer detection. Breast US is essential as a supplemental screening tool. Unlike mammography, which can be less effective in dense breasts owing to the masking effect of fibroglandular tissue, US is a more sensitive tool and offers real-time imaging that aids in detecting small invasive cancers (4). The Japan Strategic Anticancer Randomized Trial (J-START) showed that using US along with mammography increased sensitivity from 77.0% to 91.1% and increased the cancer detection rate from 0.32% to 0.50% in asymptomatic women aged between 40–49 years (5). Similarly, the ACRIN 6666 trial found that in high-risk women with dense breasts, supplemental US improved cancer detection by 4.2 per 1000 women, and the combined sensitivity of both modalities was 76% compared with 52% sensitivity for mammography alone. Notably, almost all cancers detected by US are invasive, small (with a mean size of 10 mm), and node-negative, highlighting the advantages of early diagnosis (6).

AI APPLICATIONS IN BREAST US DIAGNOSTICS: CLINICAL AND TECHNICAL CHALLENGES

Even though breast imaging modalities, such as mammography or US, are widely available for early diagnosis, the potential benefits of these modalities in clinical settings that lack trained professionals to acquire and interpret images are limited. Consequently, there is a growing need for AI-driven solutions that can assist in image acquisition, improve diagnostic accuracy, and ultimately make breast cancer screening and diagnosis more accessible, efficient, and equitable.

However, unlike X-ray, CT, or MRI, US imaging presents unique challenges in AI development and deployment. US is typically performed using a handheld device that captures tis-

sue images in real time. Unlike other modalities, US generates a continuous video stream that is constantly reviewed for detection and interpretation of abnormalities simultaneously. Given that US devices typically produce 20–40 frames per second, 10–20 minutes examination can yield 12000–48000 frames for review. If a clinician examines 10–20 patients per day, this could amount to 120000–960000 frames per day. Missing even a few critical moments in this massive volume of frames can have serious implications. This represents substantial clinical and technical hurdles in the creation of effective AI systems.

AI-computer-aided diagnosis (CAD) systems are generally divided into two categories (Fig. 1): computer-aided detection (CADe) and computer-aided diagnosis (CADx). In US imaging, CADe and CADx address the unique demands of this modality such as operator dependence and real-time data acquisition. The typical workflow of US is as follows: lesion detection, image capture, image analysis, and lesion diagnosis. CADe systems assist in lesion detection. In particular, for real-time CADe, on-device AI and rapid inference speeds are crucial so that suspicious lesions can be identified quickly and highlighted during the examination, enabling clinicians to focus on critical areas without disrupting workflow. Building on these detection results, CADx systems assist readers in image analysis and lesion diagnosis by further analyzing the identified regions and evaluating factors such as shape, texture, and echogenicity to distinguish between benign and malignant lesions. By integrating advanced machine learning/deep learning techniques and real-time processing technologies, AI-CAD solutions for US can reduce intra- and inter-observer variability, deliver consistent measurements, and provide immediate feedback.

To ensure the value of AI-CAD systems in clinical practice, it is essential that they address two key aspects, i.e., robustness in diagnostic performance and workflow enhancement. Robustness in diagnostic performance requires a large-scale dataset that includes the variations found in US imaging, and can be difficult to standardize. Ensuring that this dataset is appropriately labeled using reference standards supports the reliability of the system. Workflow enhancement in AI-CAD systems underscores the need for swift AI inference to enable real-time lesion detection. Seamless integration into the existing clinical infrastructure is also essential. This includes Digital Imaging and Communications in Medicine (DICOM) support to maintain compatibility with standard Picture Archiving and Communication System (PACS),

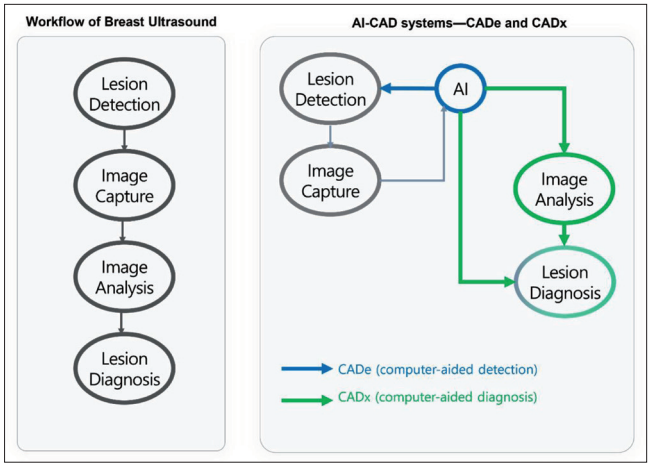

Fig. 1. AI-CAD systems are generally divided into two categories—CADe and CADx based on the primary function. CADe focuses on identifying potential lesions or abnormalities within medical images, and CADx makes a differential diagnosis for the detected lesions (benign vs. malignant).
AI = artificial intelligence, CADe = computer-aided detection, CADx = computer-aided diagnosis

automated lesion segmentation to reduce scanning time, and the generation of structured preliminary reports based on AI results. By streamlining these processes, AI-CAD systems can be integrated smoothly into current healthcare workflows, allowing clinicians to save time and focus on delivering better patient care.

EXISTING AI APPLICATIONS

Currently, several commercial AI-CAD systems are available for handheld breast US (Table 1). Several commercial tools have been designed to assist in the characterization of breast lesions (CADx) by generating a probability of malignancy, assigning BI-RADS scores, or binary classification to user-defined regions of interest or images.

The Koios Decision Support (DS) (Koios Medical, Inc., Chicago, IL, USA) by Koios Medical is an Food and Drug Administration/Comformite Europeenne (FDA/CE)-cleared AI-CADx designed to classify breast lesions based on user-selected regions in up to two orthogonal US views. The system provides a quantitative malignancy score (0–1) and a qualitative BI-RADS

Table 1. Commercial AI-CAD Software for Breast Ultrasound

	Koios DS Breast	S-Detect for Breast	Live BreastAssist	BU-CAD	CadAI-B for Breast
Manufacturer	Koios	Samsung Medison	Samsung Medison	Taihao	BeamWorks
Type	Standalone	Embedded	Embedded	Standalone	Standalone
AI function	CADx	CADx	CADe	CADe/x	CADe/x
CADe display	N/A	N/A	Rectangle, Color Overlay, Edge Enhance	Box	Heatmap
CADx output	4 categories (Benign, Probably benign, Suspicious, Probably malignant)	2 categories (Possibly benign, Possibly malignant)	N/A	6 categories (BI-RADS 2: Benign, BI-RADS 3: Probably benign, BI-RADS 4A: Low suspicion for malignancy, BI-RADS 4B: Moderate suspicion for malignancy, BI-RADS 4C: High suspicion for malignancy, BI-RADS 5: Highly suggestive of malignancy)	6 categories (BI-RADS 1/2: Negative/Benign, BI-RADS 3: Probably benign, BI-RADS 4A: Low suspicion for malignancy, BI-RADS 4B: Moderate suspicion for malignancy, BI-RADS 4C: High suspicion for malignancy, BI-RADS 5: Highly suggestive of malignancy)
Real-time capability	No	No	Yes	No	Yes
Compatible devices	Vendor-neutral	Samsung Medison ultrasound devices	Samsung Medison ultrasound devices	Vendor-neutral	Vendor-neutral
Implementation requirements	Cloud/Server	Samsung Medison ultrasound devices	Samsung Medison ultrasound devices	Cloud/Server	Tablet PC, MiniPC

AI = artificial intelligence, CADe = computer-aided detection, CADx = computer-aided diagnosis, Mini PC = small-sized, inexpensive, low-power, legacy-free desktop computer designed for basic tasks, N/A = not applicable, PACS = Picture Archiving and Communication System

based four classifications (e.g., benign as BI-RADS 2, probably benign as BI-RADS 3, suspicious as BI-RADS 4A or 4B, and probably malignant as BI-RADS 4C or 5). In a multicenter study involving 15 physicians, 11 radiologists, 2 breast surgeons, and 2 obstetrician-gynecologists with approximately 0–39 years of experience in US interpretation, reviewed 900 breast lesions. Of these, 52.2% (470/900) were benign and 47.8% (430/900) were malignant, and 77% of the lesions measuring less than 2 cm. Of the 470 benign lesions, 249 (53.0%) had a biopsy. The use of Koios DS improved mean reader area under the curve (AUC) from 0.83 to 0.87 ($p < 0.0001$). The study demonstrated a reduction in inter-observer variability, with the mean Kendall τ-b among readers increasing from 0.54 with US alone to 0.68 with US plus Koios DS, indicating a significant improvement ($p = 0.05$). Intra-reader variability resulted in less class-switching with US plus Koios DS than with US alone. In 13.6% of the cases, there was an upgrade to the higher-risk category with US alone compared with 10.8% with Koios DS support, demonstrating a statistically significant improvement. This study suggested that Koios DS systems can facilitate a more consistent diagnostic approach while minimizing the influence of subjective factors, such as physician experience or individual image interpretation. In another validation study, 9 breast imaging radiologists reviewed 319 orthogonally paired US lesions detected during screening including 88 cancers (27.6%) with a median size of 7 mm (7). In this study, although Koios DS did not substantially impact the overall AUC measured by radiologists (0.82 vs. 0.82; $p = 0.92$); however, that the AUC measured by the radiologists improved and were more responsive to malignant cues with Koios DS in high-specificity mode (0.82 vs. 0.89; $p < 0.001$). In another study, compared evaluations of 200 lesions using Koios DS (155 benign, 45 malignant) and US-guided biopsies by two radiologists (8). That study showed that although there was no significant difference in diagnostic metrics (accuracy [73.0% vs. 69.8%], positive predictive value (PPV) [45.5% vs. 42.4%], negative predictive value (NPV) [100% vs. 98.5%], sensitivity [100% vs. 96.7%], and specificity [65.2% vs. 61.9%]) between Koios DS and the pooled reader assessment, Koios DS improved US diagnostic accuracy, particularly in cases where reader confidence was low, thereby reducing false positives (PPV [24.7% vs. 19.3%; $p = 0.004$], specificity [57.8% vs. 44.6%; $p = 0.008$]). Recent studies have specifically evaluated Koios DS in triple-negative breast cancer (9) and invasive lobular carcinoma (10). These studies suggest that Koios DS is useful for standardizing diagnostic approaches and mitigating inter-observer variability. Additionally, Koios DS might support diagnostic decision-making in challenging cases in which the confidence of radiologists is low.

S-Detect for Breast (Samsung Medison Co., Ltd., Seoul, Republic of Korea) is an AI-CADx system used for selecting Samsung Medison US devices. After the operator marks the center of the lesion, S-Detect for Breast automatically outlines the lesion, allowing manual adjustments if required. It then generates a report with BI-RADS descriptors, and the operator can input additional details such as associated features, calcifications, and special cases. Using a deep learning algorithm based on convolutional neural networks, S-Detect for Breast provides a dichotomized assessment, classifying lesions as possibly benign vs. possibly malignant. A retrospective study compared results obtained from S-Detect for Breast with that of an experienced breast radiologist who analyzed 192 breast masses (mean size, 14.7 mm), of which 72 (37.5%) were malignant (11). The AUC was significantly higher for S-Detect for Breast than for the radiologist when the cutoff was set at category 4A (0.725–0.653, $p = 0.038$),

but was not significantly different when the cutoff was set at category 4B ($p = 0.775$). Another study in which 119 breast masses (54 [45.4%] malignant and 65 [54.6%] benign; 88.2% biopsied) were evaluated by two expert readers showed that the sensitivity and NPV were significantly higher for both radiologists than for S-Detect for Breast, whereas the specificity, PPV, and accuracy were higher for S-Detect for Breast (all $p < 0.05$) (12). Although the AUCs reported for the radiologists' reports were significantly higher than that of S-Detect for Breast (0.887 and 0.901 vs. 0.815; $p = 0.023$ and 0.004, respectively), integrating S-Detect for Breast led to a significant increase in specificity, PPV, and accuracy compared with the individual performances of the radiologists (all $p < 0.05$). However, the AUCs of the reports by the radiologists integrated with S-Detect for Breast did not show significant differences compared with the AUCs of the radiologists report only (0.895 compared to 0.887 and 0.901 compared to 0.901; all $p > 0.05$). A nine-center prospective study in China including 757 patients found that S-Detect for Breast demonstrated a significantly higher AUC and specificity than assessments by radiologist (AUC: 0.83 vs. 0.74, $p < 0.0001$; specificity: 74.0% vs. 54.0%, $p < 0.0001$), with no significant difference in sensitivity (13). These findings suggest that the impact of performance improvements on S-Detect for Breast may vary depending on the clinical environment. In a study of 73 consecutive women with 73 breast lesions (mean size: 15.9 mm) detected on US, S-Detect for Breast was improved inter-reader reproducibility (14). Five reviewers assessed each lesion according to the BI-RADS US lexicon with and without S-Detect for Breast. According to the kappa statistics, S-Detect for Breast significantly improved inter-reader agreement ($p < 0.0001$) for most lexicon variables, except for the isoechoic pattern. These results indicate that S-Detect for Breast might be particularly beneficial for improving specificity, which may reduce unnecessary biopsies. In addition, S-Detect for Breast enhances inter-reader agreement, which may be helpful in standardizing interpretation. However, its overall diagnostic value can vary depending on the clinical environment and the level of experience of the radiologist.

Beyond its role as a CADx system, AI-driven CADe is gaining traction in US to ensure that small, invasive breast cancers are not overlooked, ultimately improving patient outcomes. Because only a few commercial solutions currently exist, there is a growing need for AI-CAD systems that operate in real time during scans. The FDA approved AI-CADe/x BU-CAD (TaiHao Medical Inc., Taipei, Taiwan) supports lesion detection by providing bounding box outlines and generates a lesion characteristic score for lesions identified by either the user or software. The lesion characteristic score, which ranges from 0–100, corresponded to BI-RADS categories as follows: 0–25 for BI-RADS 2, 26–50 for BI-RADS 3, 51–97 for BI-RADS 4A-C, and 98–100 for BI-RADS 5 with BI-RADS descriptors (shape, orientation, margin, echo pattern, and posterior features) were also provided for each lesion. In a reader study involving 16 physicians who retrospectively reviewed 172 cases (65 biopsy-proven malignant, 71 biopsy-proven benign, and 36 benign with a 2-year follow-up) BU-CAD use led to a significant increase in the mean location specific area under the curve from 0.76 to 0.83 ($p < 0.001$) (15). The sensitivity increased from 95.8% to 98.2%, and the specificity increased significantly from 24.1% to 30.67% ($p = 0.04$). Beyond accuracy gains, BU-CAD also demonstrated clinical utility by significantly reducing interpretation time. The mean interpretation time dropped by 40.0% (from 30.2 seconds [median 30.0] to 18.1 seconds [median 16.1] per case) with each case consisting of at least two

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orthogonal projections of the lesion. This result indicates an enhancement in the workflow efficiency. Although BU-CAD is the first product to integrate CADe/x capabilities, its PACS-based workflow imposes limitations on real-time assistance, highlighting the need for a more seamlessly integrated real-time AI system for breast US practice.

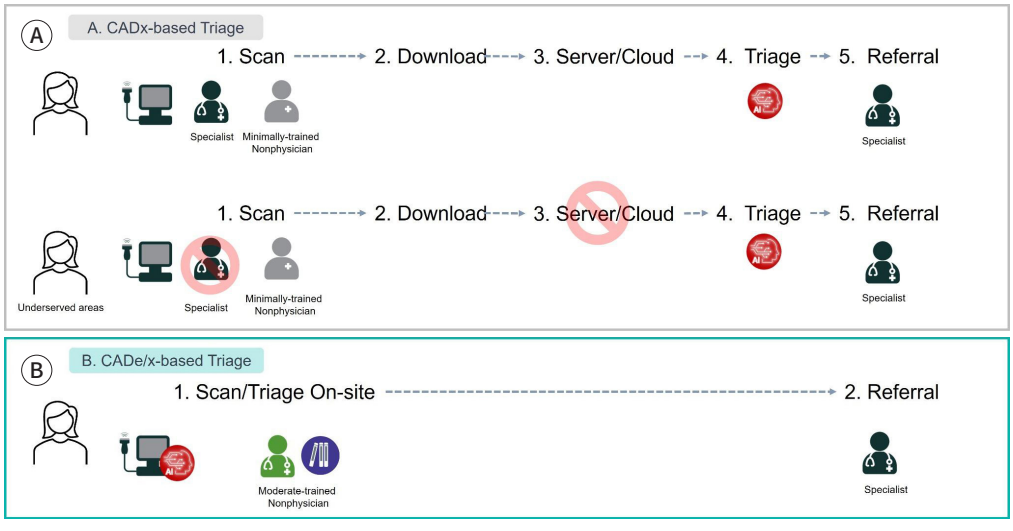
Live BreastAssist (Samsung Medison Co., Ltd., Seoul, Republic of Korea) is an integrated feature that highlights breast lesions using a bounding box and works in conjunction with S-Detect for Breast to provide real-time detection during US scans. Although it has been approved by the Ministry of Food and Drug Safety (MFDS) in Korea, its usefulness is limited by a two-stage approach to differential diagnosis. To date, there have been no studies investigating the clinical validation of Live BreastAssis.

The MFDS Korea-approved AI-CADe/x solution, CadAI-B for Breast (BeamWorks Inc., Daegu, Republic of Korea), was recently commercialized to assist healthcare providers who conducted breast US by offering real-time detection of suspicious lesions (CADe) and differential diagnosis (CADx), with its AI algorithms based on a convolutional neural network architecture trained through weakly supervised learning (16). CadAI-B for Breast employs a synchronous, one-stage approach for detection (CADe) and differential diagnosis (CADx) that closely mirrors human-like intuitive and simultaneous cognition. It uses heatmap to highlight suspicious areas in real time and after freezing the image, it provides a malignancy probability score and calibrated BI-RADS categories aligned with the American College of Radiology (ACR)'s recommended likelihood of malignancy. However, large-scale multi-reader multi-case studies are needed to comprehensively assess and validate its diagnostic accuracy and clinical utility across diverse clinical settings. A prospective study using CadAI-B for Breast evaluated the feasibility and early clinical efficacy in a real-world clinical setting, 33 patients (14 malignancies, 17 benign lesions, and 2 normal cases) were enrolled at a tertiary medical center in Taiwan (17). In this real-world application, CadAI-B for Breast successfully identified all malignancies in real time. The standalone performances, as indicated by the AUCs for the malignancy score and BI-RADS, were 0.835 and 0.850, respectively, with a sensitivity of 100% and a specificity of 52.6%. Additionally, the BI-RADS categorization of malignant cases was consistent between CadAI-B for Breast and expert radiologists. Among the benign cases, CadAI-B for Breast classified 50.0% as BI-RADS 4A or 4 B compared with 72.2% classified by experts suggesting a possible reduction in unnecessary biopsies. Owing to the intuitive nature of one-stage CADe/x, CadAI-B for Breast seems to offer educational benefits. A study of 42 non-specialist medical professionals assessed the impact of CadAI-B for Breast on breast US interpretation over three sessions: baseline (S1), post-education (S2), and AI-assisted (S3). The CadAI-B for Breast significantly increased the mean sensitivity from 66.5% (S1) to 88.7% (S2), although the increase in AUC from 0.664 (S1) to 0.684 (S2) was not statistically significant (18). Notably, AI alone achieved an AUC of 0.75 which was comparable to expert performance. These findings indicate that AI-assistance enhances diagnostic accuracy and narrows the performance gap between inexperienced readers and experts, highlighting AI to be an effective educational tool for breast imaging.

FUTURE PERSPECTIVES

Beyond AI applications that can be integrated into the current standard workflow, AI applications can also be used as triage tools in geographically underserved areas. In these areas, mammographic breast cancer screening poses challenges owing to limited resources, inadequate infrastructure, and the need for specialized equipment and personnel. As a result, US, which is relatively affordable and easily transportable, is promising as a screening and a diagnostic tool. In a pilot study (19), researchers developed an AI-CADx tool as a low-cost portable US system to triage patients, evaluating the feasibility of minimally trained healthcare workers performing US examinations in resource-limited settings. In another study, researchers evaluated whether combining handheld US devices and AI could improve early detection and assist in triaging palpable breast lumps in resource-limited settings (20). Women presenting with at least one palpable breast lump at two Mexican hospitals underwent imaging with both a low-cost portable US (operated by either a minimally trained coordinator or a board-certified radiologist) and a standard-of-care (SOC) US performed by a radiologist. The results showed that AI correctly identified 96%–98% of cancer cases with AUCs of 0.91 for portable US and 0.95 for SOC US. Among 251 women with benign masses, AI classified 67% of SOC US cases versus 38% of portable US cases as benign or probably benign ($p <$ 0.001). However, there are limitations to scaling the current workflow because it requires a

Fig. 2.Illustration of AI-based triage for breast cancer diagnosis using ultrasound in geographically underserved areas.
A. In CADx-based triage, the patient is first scanned by either a specialist or a minimally trained operator, acquired images are then downloaded and uploaded to a server or cloud for AI analysis, patients are triaged and referred, if necessary. However, specialist or server/cloud are generally limited in geographically underserved areas which limits the scalability of this workflow.
B. Compared to this, in CADe/x-based triage, on-site AI-based scanning and triage are performed using AI-CADe/x-equipped devices. This may enhance image acquisition and interpretation by personnel with minimal training. By eliminating the need to upload images to an external server, this approach reduces infrastructure demands and enables immediate referral decisions, potentially improving access to timely breast care in remote or underserved areas.
AI = artificial intelligence, CADe = computer-aided detection, CADx = computer-aided diagnosis



server or cloud for AI analysis, which makes it time-consuming and resource dependent. Additionally, scan quality could be compromised when performed by minimally trained personnel because support for CADe support is limited. In this study, portable US scans performed by radiologists achieved an AI AUC of 0.98 (with a sensitivity of 97%–100% and specificity of 52%–80%), whereas AI performance was significantly lower for images obtained by minimally trained research coordinators and had an AUC of 0.78 (sensitivity of 86%, and specificity of 33%). Herein, we suggest that AI-CADe/x-based triage model illustrated in Fig. 2, in which onsite AI-based scanning and triage are performed using portable US devices equipped with AI-CADe/x, may enhance image acquisition and interpretation by minimally trained personnel. By eliminating the need to upload images to an external server, this approach reduces infrastructure demand and enables immediate referral decisions, potentially improving access to timely breast care in remote or underserved areas. For example, a study showed that this approach led to 9 total weeks of in-person training and 20 months of remote mentorship and could provide a more efficient and accessible solution compared to traditional, training-intensive methods (21).

Despite the expansion of AI applicability and its value, there are several challenges for AI interpretability and real-world implementation. A key area for future development is improving AI interpretability, which is essential for gaining the trust of clinicians and ensuring effective integration into clinical workflow. Implementing explainable AI techniques such as visual heat maps and feature attribution methods, can help radiologists understand the decisions made by AI-CAD systems. Additionally, providing case-specific reasoning and confidence scores may enhance user acceptance and facilitate better clinical decision making. Beyond interpretability, real-world implementation can be challenging owing to variability in US equipment, operator dependency, and differences in patient populations. Large-scale multicenter validation studies are required to assess AI-CAD performance across diverse clinical settings. Furthermore, ethical considerations such as data privacy, algorithmic biases, and accountability for AI-driven decision must be carefully addressed to ensure equitable and responsible deployment. Overcoming these challenges is crucial for optimizing the clinical impact and widespread adoption of AI-CAD systems in breast US diagnostics.

Supplementary Materials

Korean translation of this article is available with the Online-only Data Supplement at https://doi.org/10.3348/jksr.2025.0019.

Author Contributions

Conceptualization, K.W.H., P.H.Y.; data curation, A.Z.I., S.K.A.; resources, K.W.H.; supervision, K.W.H.; writing—original draft, B.J., K.W.H.; and writing—review & editing, B.J., K.J., K.H.J., L.J., K.B., A.Z.I., S.K.A., K.W.H.

Conflicts of Interest

Won Hwa Kim and Jaeil Kim are the CEOs of BeamWorks., John Baek is an employee of BeamWorks.

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유방초음파에서 인공지능의 임상적 활용

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유방암은 전 세계에서 가장 흔한 여성암으로, 조기 발견이 생존율 향상에 중요한 역할을 한다. 선별 및 진단 검사로서, 유방촬영술은 섬유유선 조직의 가림 효과로 인해 효과가 감소할 수 있지만, 유방초음파는 치밀유방에서도 우수한 민감도를 보인다. 하지만, 유방초음파는 검사자 의존성이 높아, 인공지능(artificial intelligence; 이하 AI) 기반의 솔루션 개발이 요구된다. 초음파는 다른 영상기법과 달리 검사당 약 12000–48000 프레임의 실시간 비디오 스트림을 생성하고 검사자가 프로브(probe)를 잡고 직접 시행하는(hand-held) 장비를 사용한다. 이는 AI 개발에 있어 큰 도전 요소이며, 실시간 AI 추론 기능이 요구된다. 이 종설에서는 AI 기반 유방초음파 솔루션을 진단보조와 검출보조로 분류하여 기능적 이해를 돕고, 임상 근거를 바탕으로 상용화된 소프트웨어를 알아본다. 또한, 의료 자원이 부족한 지역에서의 보건의료 격차를 해소하고 환자 예후를 향상시키기 위해, 모바일 초음파를 포함한 기존 AI 기반 병변 분류(triage) 워크플로우를 살펴봄으로써 새로운 프레임워크를 제안한다.

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