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Clinical Application of Artificial Intelligence in Breast MRI

유방 MRI에서 인공지능의 임상적 활용

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Breast MRI is the most sensitive imaging modality for detecting breast cancer. However, its widespread use is limited by factors such as extended examination times, need for contrast agents, and susceptibility to motion artifacts. Artificial intelligence (AI) has emerged as a promising solution for these challenges by enhancing the efficiency and accuracy of breast MRI in multiple domains. AI-driven image reconstruction techniques have significantly reduced scan times while preserving image quality. This method outperforms traditional parallel imaging and compressed sensing. AI has also shown great promise for lesion classification and segmentation, with convolutional neural networks and U-Net architectures improving the differentiation between benign and malignant lesions. AI-based segmentation methods enable accurate tumor detection and characterization, thereby aiding personalized treatment planning. An AI triaging system has demonstrated the potential to streamline workflow efficiency by identifying low-suspicion cases and reducing the workload of radiologists. Another promising application is synthetic breast MR image generation, which aims to generate contrast enhanced images from non-contrast sequences, thereby improving accessibility and patient safety. Further research is required to validate AI models across diverse populations and imaging protocols. As AI continues to evolve, it is expected to play an important role in the optimization of breast MRI.

Index terms MRI; Artificial Intelligence; Recontruction; Segmentation; Breast; Screening

INTRODUCTION

Breast MRI is the most effective imaging modality for detecting breast cancer. It can identify more breast cancers than mammography, detect cancers at an earlier stage, and reduce interval cancer rates (1, 2). Breast MRI commonly utilizes pulse sequences, such as those used in T1-weighted, T2-weighted, dynamic contrast-enhanced (DCE), and diffusion-weighted (DW) imaging. DCE-MRI allows the analysis of dynamic changes in contrast agent distribution over time and facilitates the evaluation of tumor vascular characteristics. DW imaging helps to differentiate between benign and malignant breast lesions, without the need for contrast agents, by exploiting the diffusion associated with the higher cellular density of breast cancers. Despite the high sensitivity of breast MRI, its low specificity is a limitation. To address this issue, multi-parametric techniques that combine non-contrast and DW images are utilized in clinical practice, to improve diagnostic accuracy (3). However, the inherent features of breast MRI, such as a wide field of view (FOV), use of contrast agents, and extended examination times, limit its widespread usage. In addition, breast tissue is particularly susceptible to motion artifacts caused by respiration, cardiac motion, and patient movement. These artifacts can degrade image quality, especially in DCE-MRI, where temporal signal changes are important for diagnosis. Furthermore, a wide FOV may compromise magnetic field inhomogeneity, resulting in failed fat suppression, which can affect diagnostic accuracy. DW imaging, often performed using rapid techniques such as echo planar imaging (EPI), is also prone to artifacts, such as ghost artifacts, which can degrade image quality. In recent years, artificial intelligence (AI) has emerged as a key solution for addressing the challenges of breast MRI. Since the mid-2010s, advancements in AI have been applied in various medical imaging fields, including breast MRI (4, 5). These advancements aim to overcome the inherent limitations of breast MRI, particularly by improving imaging acquisition speed and minimizing artifacts through reconstruction techniques. AI-based diagnostic tools have also significantly enhanced diagnostic accuracy, enabling automated analysis of lesion location, size, and characteristics to help in clinical decision-making. Moreover, there is growing interest in synthetic generation techniques to provide diagnostic information comparable to contrast-enhanced images without the need for contrast agent injection, thereby improving patient safety. This review aims to introduce AI applications in breast MRI, focusing on areas where these AI techniques enhance efficiency and address the challenges inherent to breast MRI.

AI FOR BREAST MR IMAGE RECONSTRUCTION

MRI scanners acquire data in the k-space, which are then reconstructed into images. The acquisition time can be reduced by undersampling in the frequency domain, although this leads to reduced image quality. Parallel imaging is a widely used reconstruction technique that accelerates image acquisition by utilizing multiple receiver coils to acquire signals during a single spatial encoding step. However, its performance is hardware dependent. In breast MRI, the structural characteristics of breast limit the placement of multiple coils (6, 7). Both traditional compressed sensing and deep learning have proven to be effective in reconstructing high-quality images from undersampled k-space data. Compressed sensing, introduced in the 2000s, further reduces the number of encoding steps by exploiting signal redundancy in the spatial, temporal, and frequency domains (8). Although effective, compressed sensing requires computationally intensive regularization processes, which can lead to prolonged reconstruction times. Since the 2010s, AI has been used to overcome the limitations of parallel imaging and compressed sensing. Traditionally, reconstruction techniques that combine the strengths of well-established mathematical models and deep-learning-based data training processes have contributed to overcoming the limitations of imaging acquisition speed and acceleration while addressing the issue of hallucinations in AI (9, 10). For example, generative adversarial networks (GANs) have halved the scan time while improving the signal-to-noise ratio, structural similarity, and error metrics (11). AI-accelerated DW imaging has achieved a 50% reduction in scan time without compromising image quality (12). Three-dimensional (3D) high-resolution T2-weighted imaging using deep learning-based compressed sensing has demonstrated significantly superior performance in image quality, tissue depiction, and breast tissue boundary delineation, compared with conventional two-dimensional sequences and traditional compressed sensing methods (13). In a prospective study by Lee et al. (14), the AI network approach resulted in a 47.2% reduction in acquisition time. The reconstructed images outperformed the standard images from single-shot EPI for DW imaging in both quantitative and subjective evaluations by radiologists. Such innovations in AI-based image reconstruction technology not only enhance image quality but also improve diagnostic efficiency and accuracy. These advancements that simultaneously enhance both image quality and efficiency in breast MRI highlight the growing role of AI in breast MRI.

AI FOR BREAST MRI LESION CLASSIFICATION AND SEGMENTATION

One of the primary applications of AI in breast imaging is the differentiation between benign and malignant lesions (15). Jiang et al. (16) reported that after using AI software, the diagnostic ability of 19 breast radiologists, in distinguishing between benign and malignant lesions, improved. Several studies have reported on the use of convolutional neural network (CNN) to detect and diagnose breast lesions. In 2021, Hu et al. (17) reported a CNN classifier that incorporated four-dimensional information (volumetric and temporal) from DCE-MRI to distinguish between benign and malignant breast lesions. In 2022, Zhu et al. (18) reported the impact of multiparametric MRI sequences in ResNet-based models to differentiate benign and malignant lesions and achieved high sensitivity, specificity, and accuracy, compared with individual DW and DCE MRI models. In 2024, Cong et al. (19) demonstrated that the best performance in lesion classification was achieved with inputs from T2-weighted imaging, T1-weighted imaging, DW with b-values of 50 and 850, and an apparent coefficient map (Table 1). AI has also been important in tumor segmentation as it provides detailed information, such as shape, morphological structure, texture, and enhancement dynamics, which can improve the diagnosis and prognosis of patients with breast cancer (20). Deep-learning methods such as U-Net have been widely used for breast tumor segmentation. Tumor segmentation can be

Table 1. Breast MRI and Lesion Classification

Author	Year	Method	Patient No.	AUC Results
Hu et al. (17)	2021	CNN	1979	0.93
Zhu et al. (18)	2022	CNN	2823	0.88
Cong et al. (19)	2024	CNN	569	0.91

AUC = area under the curve, CNN = convolutional neural network classified into three levels of detection: image level (presence or absence of lesions), object level (bounding boxes indicating lesion location and size), and pixel level (detailed lesion boundaries). Pixel-level detection provides critical information for treatment planning and precise quantification of size and shape. Park et al. (21) used a 3D U-Net model on contrast-enhanced T1-weighted images to achieve a Dice coefficient of 0.89, enabling precise detection of tumor boundary and volume. Similarly, Guo et al. (22) applied CNNs to T2-weighted and short tau inversion recovery sequences, achieving a Dice coefficient of 0.93 and demonstrating exceptional segmentation performance. AI-based techniques are used not only for segmentation but also for characterizing breast cancer, proving effective in detecting invasive cancer and distinguishing molecular subtypes (23-25). Liang et al. (26) evaluated the diagnostic accuracy of MRI-based machine learning models in predicting the pathological response to neoadjuvant chemotherapy in patients with breast cancer and showed that deep learning outperformed machine learning and radiomics in terms of predictive accuracy. Zhang et al. (25) compared CNNs with convolutional long short-term memory networks in differentiating hormone receptor-positive and -negative breast cancer subtypes. In 2019, Saha et al. (27) reported the results of a retrospective study in which they assessed whether AI could predict breast cancer in the 2 years following breast MRI screening. In this study, a machine-learning model was developed based on the extraction of tissue characteristics from non-fat-suppressed sequences during breast MRI screening, focusing on background parenchymal enhancement. By applying segmentation techniques, the model achieved an area under the curve value of 0.70 for predicting breast cancer risk. This advancement in AI-based segmentation technology not only enhances diagnostic accuracy but also aids in breast cancer risk prediction, enabling personalized patient care.

AI FOR TRIAGING OF BREAST MRI

Most breast MRI screening examinations yield negative results; thus, radiologists invest a significant portion of their time reviewing scans that do not show any suspicious findings (28, 29). AI can serve as an automated method for enhancing the clinical workflow by triaging low-suspicion cases from highly suspicious ones. AI is a promising tool for handling high-volume repetitive tasks and triaging as part of breast cancer screening. AI-based triaging can be implemented in the daily workflow so that low-suspicion cases can be assigned to specific radiologists. Jing et al. (30) reported the results of their retrospective study, in which they investigated a deep-learning model for automatically detecting negative scans to improve workflow efficiency. A more recent study utilized 16535 contrast-enhanced MRI scans from 8354 women (31). In this study, cases classified as breast imaging reporting and data system (BI-RADS) category 1 or 2 were labelled with "extremely low suspicion for cancer," whereas those classified as BI-RADS category 3–6 were labelled with "suspicious for cancer." The model demonstrated the potential to achieve 100% sensitivity while reducing the workload by 11%.

AI FOR SYNTHETIC BREAST MR IMAGE GENERATION

Breast MRI is routinely performed with an intravenous injection of gadolinium-based con-

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trast agents. However, contrast agent administration limits the accessibility of MRI, particularly in screening settings. Furthermore, gadolinium deposition in the human body is a barrier to annual screening (Fig. 1). Recently, GAN has been employed to generate contrast-enhanced images from non-contrast MRI data (Table 2). Chung et al. (32) trained a 3D CNN to simulate contrast-enhanced T1 weighted imaging using five non-contrast sequences as inputs. Almost all the simulated images were of diagnostic quality, and quantitative analysis showed a strong similarity between the simulated and real images. There still exists variability based on which sequences are used as an input to train and synthesize virtual contrast-enhanced imaging: T1-weighted sequence, T1-weighted with T2-weighted imaging, or T1- and T2-weighted and DW imaging. The most recent study revealed the highest overall performance for generating virtual images when the inputs were obtained by combining ultrahigh b-values with high-resolution morphologic T1-weighted image acquisition (33). In contrast, the study reported that there is limited capability of virtual image generation using morphological sequences alone and that it requires at least low-contrast dose images (34). In this study, synthetic images were generated using simulated low-contrast images as inputs, and it was suggested

Fig. 1. Example of an artificial intelligence-generated synthetic breast MR image in a patient with invasive ductal carcinoma.
A. Pre-contrast fat-suppressed T1-weighted axial breast MR image shows invasive ductal carcinoma in the left breast (arrow).
B. Real contrast-enhanced T1-weighted axial breast MR image shows an enhancing invasive ductal carcinoma in the left breast (arrow).
C. Synthetic contrast-enhanced T1-weighted axial breast MR image shows invasive ductal carcinoma in the left breast (arrow). The inputs used for reconstruction were obtained using non-contrast sequences, including T2-weighted imaging and diffusion weighted imaging (b values of 0, 800, 1200 s/mm^2).

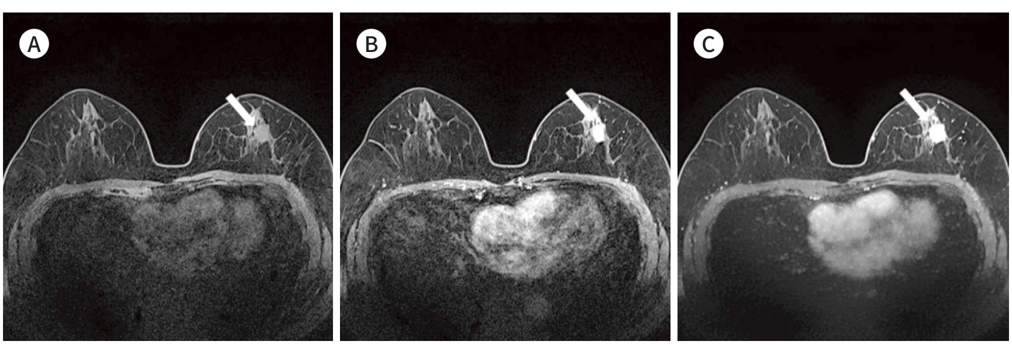

Table 2. Artificial Intelligence for Synthetic Breast MR Image Generation

Study	Neural Network Architecture	Input Sequence	Quantitative Evaluation
Müller-Franzes et al. (34)	GAN-Pix2PixHD	T1w, T2w, simulated low dose	SSIM, PSNR, MSE, MAE
Chung et al. (32)	Encoder-Decoder architecture-GadNET	T1w, T1w fat-saturated, T2w, DW (b values of 0 and 600), ADC	SSSIM, neighborhood cross correlation, HMRI, NRMSE, MEDSYMAC and log accuracy ratio, Dice coefficient, lesion size
Wang et al. (35)	GAN-enhanced border lifelike synthesize model	T1w	SSIM, PSNR, MSE, MAE

ADC = apparent diffusion coefficient, DW = diffusion weighted, GAN = generative adversarial network, HMI = histogram mutual information, MAE = mean absolute error, MEDSYMAC = median symmetrical accuracy, MSE = mean square error, NRMSE = normalized root mean square error, PSNR = peak signal to noise ratio, SSIM = structural similarity index that a GAN could improve the accuracy of contrast-enhanced images by incorporating simulated low-contrast images with non-contrast images to reduce false-negative diagnoses (34). However, there are many challenges that need to be addressed regarding synthetic breast MR image generation. First, further research is required to ensure its generalizability, robustness, and clinical applicability. Most studies included invasive cancers or mass lesions, indicating a selection bias. Further studies on diagnostic accuracy should be conducted.

CONCLUSION

Standardization of breast MRI is challenging and encompasses many aspects, including hardware, imaging protocols, imaging parameters, and post-processing and image analysis methods. However, solutions to overcome standardization issues have been proposed, and there has been a shift toward deep-learning models, which have shown greater robustness across various MRI scanners. This review summarizes several clinically relevant issues related to AI in breast MRI. Although barriers to the adoption of AI in clinical practice exist, several solutions have been proposed to overcome them. With the active participation and support of not only the radiology and AI research communities but also clinicians, patients, and other stakeholders, AI-based models have the potential to generate real-world value across various settings.

Supplementary Materials

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Author Contributions

Writing—original draft, all authors; and writing—review & editing, all authors.

Conflicts of Interest

The authors have no potential conflicts of interest to disclose.

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유방 MRI에서 인공지능의 임상적 활용

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유방 MRI는 유방암을 조기에 발견하는 가장 효과적인 영상 검사법으로 높은 민감도를 제공하지만, 긴 촬영 시간, 움직임으로 인한 인공물, 낮은 특이도로 인해 널리 활용되기에는 몇 가지 제한 점이 있다. 최근 인공지능의 발전은 이러한 문제를 해결하며 유방 MRI의 효율성과 진단 정확도를 향상시키고 있다. 인공지능 기반 영상 재구성 기술은 촬영 시간을 단축하면서도 영상 품질을 유지하는 데 기여하고 있다. 또한, 인공지능 기반 병변 분류 및 분할 기술은 유방암의 정밀한 분석과 특성화를 가능하게 한다. 인공지능을 활용한 자동 선별(triaging) 시스템은 고위험 사례를 우선적으로 평가하도록 하여 영상의학과 의사의 업무 부담을 줄이고 효율적인 진료 흐름을 구축하는 데 도움을 준다. 나아가, 인공지능 기반 합성 영상 기법은 조영제를 사용하지 않고도 조영증강 영상을 생성할 수 있어 유방 MRI의 접근성을 높이고 환자의 안전성을 향상시킬 가능성을 보이고 있다. 이러한 인공지능의 임상적 적용을 위해서는 다양한 환자 군과 영상 프로토콜에서의 추가적인 검증 연구가 필요하다. 유방 MRI에서의 인공지능의 지속적인 발전은 유방 MRI 최적화 및 개인 맞춤형 진단 및 치료에 중요한 역할을 할 것으로 기대된다.

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