Review Article

J Korean Soc Radiol 2025;86(2):205-215
https://doi.org/10.3348/jksr.2025.0011
eISSN 2951-0805

JOURNAL of THE KOREAN SOCIETY of RADIOLOGY

Clinical Application of Artificial Intelligence in Digital Breast Tomosynthesis

디지털 유방 토모신테시스에서 인공지능의 임상 적용

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Received February 7, 2025
Revised February 24, 2025
Accepted March 4, 2025

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Digital breast tomosynthesis (DBT) provides improved cancer detection and lower recall rates when compared with full-field digital mammography (DM) and has been widely adopted for breast cancer screening. However, adopting DBT presents new challenges such as an increased number of acquired images resulting in longer interpretation times. Artificial intelligence (AI) offers numerous opportunities to enhance the advantages of DBT and mitigate its shortcomings. Research in the DBT AI domain has grown significantly and AI algorithms play a key role in the screening and diagnostic phases of breast cancer detection and characterization. The application of AI may streamline the workflow and reduce the time required for radiologists to interpret images. In addition, AI can minimize radiation exposure and enhance lesion visibility in synthetic two-dimensional DM images. This review provides an overview of AI technology in DBT, its clinical applications, and future considerations.

Index terms Digital Breast Tomosynthesis; Mammography; Artificial Intelligence

INTRODUCTION

Digital breast tomosynthesis (DBT) was developed and approved by the Food and Drug Administration (FDA) in 2011 to improve cancer detection and reduce the rate of false-positives (1). DBT enables quasi-three-dimensional breast reconstruction, allowing better visualization of lesions and removal of the overlying tissue. Consequently, key mammographic findings, such as masses, areas of architectural distortion, and asymmetries are better discerned and characterized with greater confidence in DBT images than in conventional two-dimensional (2D) mammographic images (2, 3). A recent meta-analysis reported a pooled incremental cancer detection rate (CDR) of 1.6 per 1000 screening examinations with DBT after a negative as-

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sessment using digital mammography (DM) (4). DBT combined with DM or synthesized mammography (SM) is rapidly becoming a routine screening tool for breast cancer. As of 2024, 92% of all accredited mammography units in the United States are DBT units (5). According to the American College of Radiology Appropriateness Criteria, mammography and DBT are the first options for breast cancer screening (6). In addition, reports showed that women with clinical symptoms or abnormal screening findings could be more effectively evaluated for breast cancer using DBT, which exhibited superior diagnostic performance in comparison to DM alone (2).

Although DBT combined with DM or SM provides enhanced breast cancer detection and characterization when compared with DM alone, it has also introduced challenges, such as an increase in acquired images and doubled reading time. Furthermore, cognitive (an abnormality is prospectively identified at the initial image interpretation, but its significance is incorrectly understood, resulting in an incorrect diagnosis) and perception errors (an abnormality is determined to have been present in retrospect but not detected prospectively) still occur (7-9). Consequently, to reduce the DBT workload and improve diagnostic accuracy, assistance is needed. Several studies have suggested the application of artificial intelligence (AI) for these tasks. AI can be applied to DBT in various ways, including breast cancer detection, case prioritization, breast density assessment, and cancer risk evaluation (10, 11).

TECHNICAL CONSIDERATIONS OF AI FOR DBT

As the clinical use of DBT for breast cancer screening increases, application of AI models for DBT is highly anticipated. Current FDA-cleared AI products utilizing DBT and/or SM are listed in Table 1 (12, 13). Interpretation times for DBT images are longer than those for DM images (14), thus, AI models are crucial for improving efficiency. However, developing AI algorithms for DBT, as opposed to DM, poses increased and significant technical challenges.

One of the primary challenges is the nature of DBT imaging, which involves the use of multiple high-resolution slices. This inherently leads to the requirement of significantly more computational resources to develop AI models for DBT than for DM. DM and DBT both produce high-resolution images that require significant computational power but in the case of DBT, the presence of multiple images per study further amplifies the resource demands for training and inference processes. Consequently, the development of AI for DBT is subject to stricter cost-sensitivity constraints than that for DM. For instance, AI methodologies that combine craniocaudal and mediolateral oblique view images, or leverage both prior and current examinations, are technically more challenging to develop for DBT (15, 16).

Another challenge is that the number of examinations available for DBT model training is limited in comparison to DM. Acquiring a large dataset of DBT examinations is challenging for several reasons. The publicly available datasets available for DBT are fewer than those for DM. This may be due to larger DBT image sizes that increase the labor-intensity of collection, processing, and sharing. Some studies attempted to overcome this limitation by using an annotation-efficient deep-learning approach that effectively leveraged both strongly and weakly labeled data, progressive training in stages while maintaining localization-based interpretability, ultimately achieving state-of-the-art performance in mammogram classification, and successfully extending to DBT (17); However, these approaches introduced additional constraints on model design.

Creating high-quality annotations, which are essential for accurate AI algorithm development, is challenging in DBT. DBT images provide more precise visualization of masses by minimizing tissue superimposition. However, annotating every slice in a DBT study is time-consuming and labor-intensive. To reduce cost and time, only the center slice of the biopsied case can be annotated; however, this can lead to incorrect z-axis localization of annotations (18).

Finally, DBT images exhibit significant variability across vendors, adversely affecting the generalizability of AI applications. Differences in factors such as rotation angles of acquisition, number of images captured per scan, and reconstruction methods used to generate 3D images result in more pronounced discrepancies between manufacturers than those observed with DM (19). This variability can be particularly detrimental to DBT because of the limited availability of training and testing data.

CLINICAL APPLICATIONS OF AI FOR DBT

IMPROVED DIAGNOSTIC PERFORMANCE

The main goal of AI development for DBT is to enhance cancer detection and distinguish malignant from benign lesions (Figs. 1, 2). Many studies showed that when compared with traditional DBT interpretation without AI, AI algorithms significantly increased the sensitivity of DBT cancer detection. In a systematic review and meta-analysis of four DBT with AI studies, the area under the receiver operating characteristic curve (AUC) for standalone AI was significantly higher than that for radiologists (0.90 vs. 0.79; $p < 0.001$) (20). Conant et al. (21) compared the performance of 24 radiologists (including 13 breast radiologists) reading 260 DBT examinations (including 65 cancer cases), both with and without AI. The authors found that the performance of the radiologists in detecting malignant lesions with AI resulted in a higher mean AUC than that without AI (0.852 vs. 0.795). The average difference in the AUC was 0.057 ($p < 0.01$). Sensitivity increased from 77.0% without AI to 85.0% with AI (8.0%; $p < 0.01$), and specificity increased from 62.7% without AI to 69.6% with AI (6.9%, non-inferiority; $p < 0.01$). The recall rate for non-cancer cases decreased from 38.0% without AI to 30.9% with AI (-7.2%; non-inferiority; $p < 0.01$). Pinto et al. (22) performed a retrospective observer study of 190 single-view wide-angle DBT examinations and found that when interpreting images with AI support, the AUC was higher than that without AI support (0.88 vs. 0.85; $p = 0.01$). Sensitivity improved with AI support (86% vs. 81%; $p = 0.006$), with no differences in specificity (73% vs. 71%; $p = 0.48$) or reading time (48 s vs. 45 s; $p = 0.35$). In another retrospective analysis of 15999 DM and DBT examinations (15998 women with 113 cancers), standalone AI demonstrated an AUC of 0.93 for DM and 0.94 for DBT (23). AI demonstrated non-inferior sensitivity for both DM and DBT when compared with single- or double-reader evaluations. Notably, although standalone AI reduced the recall rate for DM by 2% (from 5.1% to 3.1%; $p < 0.001$), it increased the recall rate for DBT by 12% (from 4.4% to 16.7%; $p < 0.001$). The authors explained that the high recall rate observed in that study reflected results from a real-life screening environment, and suggested that the difference compared to prior DBT AI studies (21) might be due to the studies being conducted with enriched samples (23).

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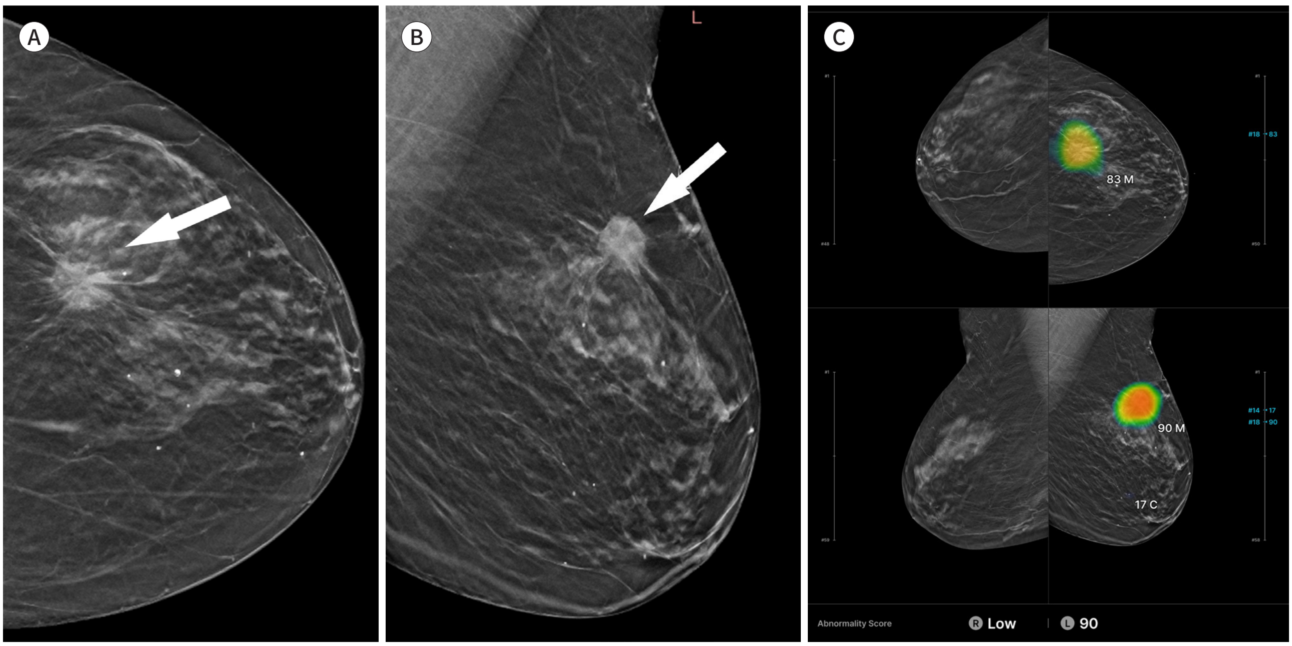
Fig. 1. A 76-year-old woman presented for diagnostic breast imaging due to a lump in the left upper outer breast.
A, B. DBT consisting of craniocaudal (A) and mediolateral oblique (B) views shows a 2 cm irregular spiculated mass with architectural distortion (arrows) in the left upper outer breast.
C. The artificial intelligence algorithm outlines lesions across various slices of the DBT, with maximum scores of 83 (slice 18) and 90 (slice 18) noted on craniocaudal and mediolateral oblique views, respectively. The mass was finally identified as invasive ductal carcinoma. Image courtesy of Lunit.
DBT = digital breast tomosynthesis

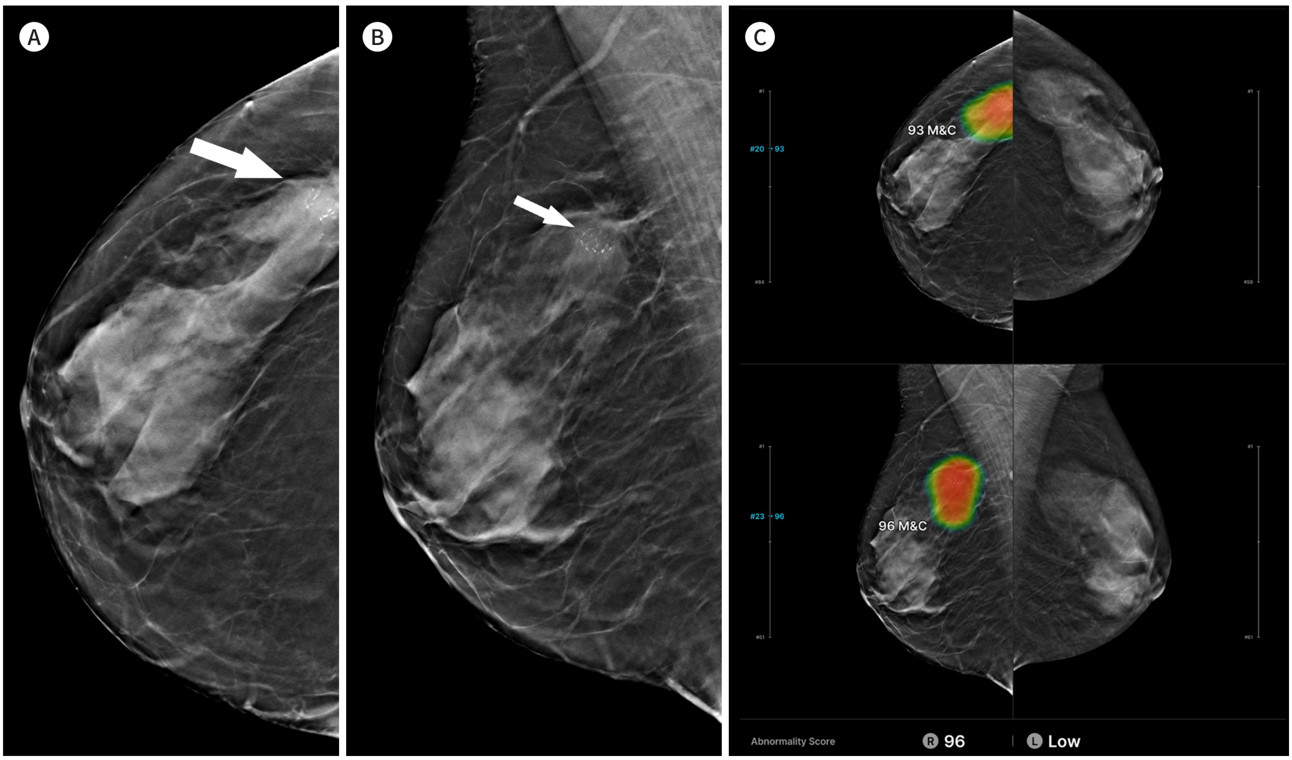


Most existing studies on AI for DBT have been conducted in women from the United States or Europe but studies evaluating the performance of AI in Asian women are rare. Park et al. (24) conducted a deep-learning-based AI algorithm study using DBT data from 258 women (65 cancers) collected from 14 South Korean and United States institutions. The stand-alone AI had an AUC of 0.9 and demonstrated a specificity (89.6%) higher than that achieved by radiologists (77.3%) (p < 0.001). In a reader study, the AUC for radiologists improved from 0.90 to 0.92 with AI aid (p = 0.003). When reading with AI, the radiologists' sensitivity increased from 85.4% to 87.7% (p = 0.04), with no significant difference in specificity.

DECREASED WORKLOAD

The acquisition time for DBT is longer than that for DM, and its interpretation time is reported to be almost twice that of DM (25, 26), which may critically affect the workload of radiologists. Unlike single images used for interpreting each plane in DM, radiologists must navigate through a series of stacked images for each mammographic projection in DBT, with the number of images per stack depending on the breast thickness under compression. A significant number of DBT images results in an increased workload, leading to longer interpretation times and radiologist fatigue. Therefore, AI applications would be even more impactful for DBT than for DM (10). In interpreting DBT images, the automated detection of abnormalities across multiple projection images can assist clinicians in localizing and evaluating the clinical significance of detected lesions. In one study, reading time was reduced by 52.7% (p <

Fig. 2. A 64-year-old woman presented for a screening examination.
A, B. DBT consisting of craniocaudal (A) and mediolateral oblique (B) views shows grouped pleomorphic calcifications with asymmetry in the right upper outer breast (arrows), originally interpreted by the radiologist as benign calcifications (BI-RADS 2).
C. The artificial intelligence algorithm identifies lesions across various slices of the DBT, with maximum scores of 93 (slice 20) and 96 (slice 23) noted on the craniocaudal and mediolateral oblique views, respectively. The mass was finally identified as invasive ductal carcinoma. Image courtesy of Lunit.
BI-RADS = Breast Imaging-Reporting and Data System, DBT = digital breast tomosynthesis



0.01) from 64.1 seconds without AI to 30.4 seconds with AI, along with improvements in all diagnostic metrics (21). The reader study from a cohort that included Korean women also demonstrated a decrease in reading time from 54.41 seconds without AI to 48.52 seconds with AI ($p < 0.001$) (24). However, in another study using single-view wide-angle DBT, no differences in reading time (48 s vs. 45 s; $p = 0.35$) were observed, but improvements in average sensitivity were noted. In that study, the use of the AI support system reduced the reading time by 8% for low-suspicion examinations (Transpara scores of 1–6) and increased the reading time by 27% for high-suspicion examinations (scores of 7–10) when compared with unaided reading. The authors suggested that reading time in their study was influenced by the reading strategies employed by readers. Although readers were encouraged to take advantage of the AI system while reading the examinations, they had the option of hiding the AI marks at the beginning, assessing the examination independently, and later revealing the AI marks to verify their evaluation. This process could potentially add extra time to the overall reading (22).

DBT AI has also been tested in triage mammographic examinations. In a retrospective study of 5182 DBT screening examinations, a simulated workflow was used to classify cancer-free examinations that could have been excluded from the screening worklist. In this simulation, using AI to automatically filter out cases resulted in a 39.6% reduction in workload,

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Table 1. FDA-Cleared AI Products for DBT

Use	Product Name	Manufacturer	Date of Initial FDA Approval	Modality
Computer-assisted detection and diagnosis	Genius AI Detection 2.0 with CC-MLOCorrelation	Hologic	11/18/2020	DBT
	Lunit INSIGHT DBT	Lunit	11/6/2023	DBT
	MammoScreen	Therapixel	11/26/2021	DBT, FFDM, SM
	ProFound AI Software V3.0	iCAD	10/4/2019	DBT
	Saige-Dx	DeepHealth	5/12/2022	DBT, FFDM, SM
	Transpara 1.7.2	ScreenPoint Medical B.V.	3/5/2020	DBT, FFDM
Triage	Saige-Q	DeepHealth	4/16/2021	DBT, FFDM
Breast density assessment	densityai	Densitas	2/19/2020	FFDM, SM
	Insight BD	Siemens Healthineers	2/6/2018	FFDM, DBT projections
	PowerLook Density Assessment V4.0	iCAD	4/5/2018	SM
	Quantra 2.2 Breast Density Assessment Software	Hologic	10/20/2017	FFDM, DBT projections
	Saige-Density	DeepHealth	12/16/2022	FFDM, SM
	Transpara Density 1.0.0	ScreenPoint Medical B.V.	12/11/2023	FFDM, SM
	Visage Breast Density	Visage Imaging	1/29/2021	FFDM, SM
	Volpara Imaging Software	Volpara Health Technologies Limited	1/7/2016	FFDM, DBT projections
	WRDensity	Whiterabbit.ai	10/30/2020	FFDM, SM
Breast arterial calcification detection	cmAngio V1.0	CureMetrix	10/5/2023	DBT, FFDM

Source: references 12 and 13.
AI = artificial intelligence, CC-MLO = craniocaudal-mediolateral oblique, DBT = digital breast tomosynthesis, FDA = Food and Drug Administration, FFDM = full-field digital mammography, SM = synthetic mammography

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non-inferior sensitivity (413 of 459 detected cancers; 90.0%; $p = 0.002$), and a 25% lower recall rate (358 recalls in 5182 examinations; 6.9%; $p = 0.002$). In a previous study, the AUC for standalone AI was higher than that of the average reader (0.84 vs. 0.81; $p = 0.002$) (27). Raya-Povedano et al. (28) retrospectively analyzed 15987 consecutive combined DM and DBT cases, and simulated the application of a previously validated AI model as an autonomous triaging system. When compared with the double reading of DBT images (568 h needed), DBT with AI resulted in a 72.5% less workload (156 h needed; $p < 0.001$), non-inferior sensitivity (95 of 113 cancers detected; $p = 0.38$), and a 16.7% lower recall rate ($p < 0.001$, 588 recalls in 15987 examinations).

INCREASED CONSPICUITY OF SUSPICIOUS LESIONS ON 3D DBT AND SM

Each DBT projection adds detector readout noise when compared with 2D mammography, which is propagated to the reconstructed DBT volume. This potentially obscures subtle signs of breast cancer such as microcalcifications (29). Researchers have attempted to improve the visibility of findings on DBT sections reconstructed from projection images by eliminating normal tissue that can obscure important findings or highlight suspicious findings (10). Gao et al. (29) tested a deep convolutional neural network framework for denoising DBT images by focusing on enhancing the conspicuity of microcalcifications and spiculations. The framework showed an improved contrast-to-noise ratio and detectability index for simulated microcalcifications in validation of DBT phantoms.

AI-based techniques to increase the conspicuity of suspicious lesions can also be applied to SM (30). Recently, SM has been commonly used to replace DM images, which may double the radiation dose when used in combination with DBT. Most studies comparing DM-DBT with SM-DBT have reported comparable recall and CDRs (31). Currently, AI is used to create SM images, replicate DM images, and highlight suspicious findings. In computer-aided detection (CAD)-based approaches (32-34), suspicious regions are identified on DBT slices and projected onto a 2D image to generate an SM image that offers a clearer representation of the suspicious findings. This SM image combines the advantages of a standard 2D breast view with enhanced visibility of suspicious areas in 3D slices. Fotin et al. (32) evaluated enhanced SM images in a study with five-readers, each reviewing 30 cases. This approach led to a 5.4% reduction in radiologist interpretation time, 6.7% increase in sensitivity, and 15.6% increase in specificity. Lotter et al. (17) developed an annotation-efficient deep learning AI model that classified an enhanced SM as showing cancer or no cancer. In a reader study, the AI model significantly outperformed five radiologists, improving sensitivity by 14% while maintaining the specificity of the "average reader." Using a commercially available system in which CAD detects and extracts suspicious masses, architectural distortions, and asymmetries from DBT planes, and blends them into SM to create CAD-enhanced images, radiologists can quickly review the enhanced images and navigate to the corresponding planes to confirm or dismiss potential lesions (35). A retrospective study involving six radiologists reviewing 80 DBT cases (including 23 malignant lesions) found that the concurrent use of CAD reduced reading time while maintaining similar sensitivity, specificity, and recall rates to reading without CAD (35).

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BREAST DENSITY ASSESSMENT

Mammographic breast density is an independent risk factor of breast cancer. However, its use in risk assessments and research is constrained by significant inter- and intraobserver variability in how radiologists classify breast density (36). To more accurately assess the amount of fibroglandular tissue relative to the total volume of the breast, volume-based density (VBD) estimation techniques are used with true 3D imaging modalities, such as MRI, or estimated from DBT projection images. A previous study found a significant correlation between VBD estimates from DBT and those from MRI ($r = 0.88$, $p < 0.001$), and differences in VBD estimates between DBT and MRI were not significant ($p = 0.26$) (37). A deep learning-based reconstruction algorithm for breast density estimation showed high accuracy (less than ±3%) when tested on breast phantoms (38). In a case-control study using contralateral DM-DBT in women with unilateral breast cancer and age- and ethnicity-matched controls, the volumetric percent density (VPD) was estimated from DBT and compared with breast density estimates from DM. The results demonstrated that volumetric density estimates calculated from DBT (odds ratio [OR], 2.3 per standard deviation [SD] of VPD%) had a stronger association with breast cancer than area-based percent density estimates from DM (OR, 1.3 per SD for raw DM and 1.7 for processed DM) and DM-derived VPD% (OR, 1.6 and 1.7 per SD) (39).

FUTURE CONSIDERATIONS

Many of the studies explored in this review focused on the value of AI for DBT, although this has not yet been fully explored in real-world clinical settings. Certain AI systems have primarily been investigated through retrospective studies and simulations. As has been observed in many other fields, building large-scale DM and DBT datasets for AI model development can lead to significantly improved models. Given the difficulty in obtaining labels for such large datasets, self-supervised learning (SSL) approaches, which involve training models to generate meaningful representations using unlabeled data, have become increasingly important. Unlike supervised learning, SSL allows for the creation of generalist models that can be fine-tuned for many downstream tasks without large-scale labeled datasets (40). These methods are expected to enhance both overall performance and generalization capabilities.

Despite these challenges, AI has a significant potential to transform the landscape of DBT and breast imaging, enhancing both patient experience and clinical outcomes. Prospective studies on the application of AI for DBT in clinical practice, particularly large-scale studies involving true screening populations, are required to assess the cost-effectiveness and real-world impact of AI models in assisting DBT interpretation.

CONCLUSIONS

Recent studies have highlighted several promising AI applications in DBT imaging workflows. AI has been demonstrated to improve radiologist CDRs and reduce the recall rates and reading times with DBT. Numerous studies confirmed that AI tools offer diagnostic performance comparable to that of radiologists in identifying and characterizing abnormal DBT findings. However, most of these applications are still in the research stage and larger prospective studies are required to demonstrate their clinical efficacy.

Supplementary Materials

Korean translation of this article is available with the Online-only Data Supplement at https://doi.org/10.3348/jksr.2025.0011.

Author Contributions

Conceptualization, C.J.M.; data curation, C.J.M.; formal analysis, C.J.M.; investigation, C.J.M., L.W.; resources, all authors; supervision, C.J.M.; writing—original draft, C.J.M., L.W.; and writing—review & editing, all authors.

Conflicts of Interest

Jung Min Chang has been an Section Editor of the *Journal of the Korean Society of Radiology* since 2024; however, she was not involved in the peer reviewer selection, evaluation, or decision process for this article. Otherwise, no other potential conflicts of interest relevant to this article were reported. All remaining authors have declared no conflicts of interest.

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Funding

None

REFERENCES

1. Peppard HR, Nicholson BE, Rochman CM, Merchant JK, Mayo RC 3rd, Harvey JA. Digital breast tomosynthesis in the diagnostic setting: indications and clinical applications. *Radiographics* 2015;35:975-990
2. Ko MJ, Park DA, Kim SH, Ko ES, Shin KH, Lim W, et al. Accuracy of digital breast tomosynthesis for detecting breast cancer in the diagnostic setting: a systematic review and meta-analysis. *Korean J Radiol* 2021;22:1240-1252
3. Chae EY, Kim HH. [Digital breast tomosynthesis screening]. *J Korean Soc Radiol* 2019;80:19-31. Korean
4. Marinovich ML, Hunter KE, Macaskill P, Houssami N. Breast cancer screening using tomosynthesis or mammography: a meta-analysis of cancer detection and recall. *J Natl Cancer Inst* 2018;110:942-949
5. U.S. Food and Drug Administration. MQSA national statistics. Available at. https://www.fda.gov/radiation-emitting-products/mammography-information-patients/mqsa-national-statistics. Accessed February 3, 2025
6. Niell BL, Jochelson MS, Amir T, Brown A, Adamson M, Baron P, et al. ACR appropriateness criteria® female breast cancer screening: 2023 update. *J Am Coll Radiol* 2024;21(6S):S126-S143
7. Bruno MA, Walker EA, Abujudeh HH. Understanding and confronting our mistakes: the epidemiology of error in radiology and strategies for error reduction. *Radiographics* 2015;35:1668-1676
8. Donald JJ, Barnard SA. Common patterns in 558 diagnostic radiology errors. *J Med Imaging Radiat Oncol* 2012;56:173-178
9. Korhonen KE, Weinstein SP, McDonald ES, Conant EF. Strategies to increase cancer detection: review of true-positive and false-negative results at digital breast tomosynthesis screening. *Radiographics* 2016;36:1954-1965
10. Geras KJ, Mann RM, Moy L. Artificial intelligence for mammography and digital breast tomosynthesis: current concepts and future perspectives. *Radiology* 2019;293:246-259
11. Goldberg JE, Reig B, Lewin AA, Gao Y, Heacock L, Heller SL, et al. New horizons: artificial intelligence for digital breast tomosynthesis. *Radiographics* 2023;43:e220060
12. American College of Radiology Data Science Institute. AI Central (breast cancer imaging). Available at. https://aicentral.acrdsi.org. Accessed January 18, 2025

13. U.S. Food and Drug Administration. Artificial intelligence and machine learning (AI/ML)-enabled medical devices. Available at. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices. Accessed January 18, 2025
14. Dang PA, Freer PE, Humphrey KL, Halpern EF, Rafferty EA. Addition of tomosynthesis to conventional digital mammography: effect on image interpretation time of screening examinations. *Radiology* 2014;270:49-56
15. Bai J, Jin A, Wang T, Yang C, Nabavi S. Feature fusion Siamese network for breast cancer detection comparing current and prior mammograms. *Med Phys* 2022;49:3654-3669
16. Carneiro G, Nascimento J, Bradley AP. *Unregistered multiview mammogram analysis with pre-trained deep learning models.* In Navab N, Hornegger J, Wells W, Frangi A, eds. *Medical image computing and computer-assisted intervention – MICCAI 2015.* Cham: Springer 2015:652-660
17. Lotter W, Diab AR, Haslam B, Kim JG, Grisot G, Wu E, et al. Robust breast cancer detection in mammography and digital breast tomosynthesis using an annotation-efficient deep learning approach. *Nat Med* 2021;27:244-249
18. Buda M, Saha A, Walsh R, Ghate S, Li N, Swiecicki A, et al. A data set and deep learning algorithm for the detection of masses and architectural distortions in digital breast tomosynthesis images. *JAMA Netw Open* 2021;4:e2119100
19. Tirada N, Li G, Dreizin D, Robinson L, Khorjekar G, Dromi S, et al. Digital breast tomosynthesis: physics, artifacts, and quality control considerations. *Radiographics* 2019;39:413-426
20. Yoon JH, Strand F, Baltzer PAT, Conant EF, Gilbert FJ, Lehman CD, et al. Standalone AI for breast cancer detection at screening digital mammography and digital breast tomosynthesis: a systematic review and meta-analysis. *Radiology* 2023;307:e222639
21. Conant EF, Toledano AY, Periaswamy S, Fotin SV, Go J, Boatsman JE, et al. Improving accuracy and efficiency with concurrent use of artificial intelligence for digital breast tomosynthesis. *Radiol Artif Intell* 2019;1:e180096
22. Pinto MC, Rodriguez-Ruiz A, Pedersen K, Hofvind S, Wicklein J, Kappler S, et al. Impact of artificial intelligence decision support using deep learning on breast cancer screening interpretation with single-view wide-angle digital breast tomosynthesis. *Radiology* 2021;300:529-536
23. Romero-Martín S, Elías-Cabot E, Raya-Povedano JL, Gubern-Mérida A, Rodríguez-Ruiz A, Álvarez-Benito M. Stand-alone use of artificial intelligence for digital mammography and digital breast tomosynthesis screening: a retrospective evaluation. *Radiology* 2022;302:535-542
24. Park EK, Kwak S, Lee W, Choi JS, Kooi T, Kim EK. Impact of AI for digital breast tomosynthesis on breast cancer detection and interpretation time. *Radiol Artif Intell* 2024;6:e230318
25. Gilbert FJ, Tucker L, Gillan MG, Willsher P, Cooke J, Duncan KA, et al. Accuracy of digital breast tomosynthesis for depicting breast cancer subgroups in a UK retrospective reading study (TOMMY trial). *Radiology* 2015;277:697-706
26. Skaane P, Bandos AI, Gullien R, Eben EB, Ekseth U, Haakenaasen U, et al. Comparison of digital mammography alone and digital mammography plus tomosynthesis in a population-based screening program. *Radiology* 2013;267:47-56
27. Shoshan Y, Bakalo R, Gilboa-Solomon F, Ratner V, Barkan E, Ozery-Flato M, et al. Artificial intelligence for reducing workload in breast cancer screening with digital breast tomosynthesis. *Radiology* 2022;303:69-77
28. Raya-Povedano JL, Romero-Martín S, Elías-Cabot E, Gubern-Mérida A, Rodríguez-Ruiz A, Álvarez-Benito M. AI-based strategies to reduce workload in breast cancer screening with mammography and tomosynthesis: a retrospective evaluation. *Radiology* 2021;300:57-65
29. Gao M, Fessler JA, Chan HP. Deep convolutional neural network with adversarial training for denoising digital breast tomosynthesis images. *IEEE Trans Med Imaging* 2021;40:1805-1816
30. Shin J, Woo OH, Shin HS, Song SE, Cho KR, Seo BK. Diagnostic performance of digital breast tomosynthesis with the two-dimensional synthesized mammogram for suspicious breast microcalcifications compared to full-field digital mammography in stereotactic breast biopsy. *J Korean Soc Radiol* 2022;83:1090-1103
31. Freer PE, Winkler N. Synthesized digital mammography imaging. *Radiol Clin North Am* 2017;55:503-512
32. Fotin SV, Yin Y, Haldankar H, Hoffmeister JW, Periaswamy S. Workflow improvements for digital breast tomosynthesis: computerized generation of enhanced synthetic images. Available at. https://doi.org/10.1117/12.2217182. Published 2016. Accessed January 20, 2025
33. James JJ, Giannotti E, Chen Y. Evaluation of a computer-aided detection (CAD)-enhanced 2D synthetic mam-

JOURNAL of THE KOREAN SOCIETY of RADIOLOGY

mogram: comparison with standard synthetic 2D mammograms and conventional 2D digital mammography. *Clin Radiol* 2018;73:886-892

34. Kim H, Hong J, Lee T, Choi YW, Kim HH, Chae EY, et al. A synthesizing method for signal-enhanced and artifact-reduced mammogram from digital breast tomosynthesis. *Phys Med Biol* 2020;65:215026
35. Balleyguier C, Arfi-Rouche J, Levy L, Toubiana PR, Cohen-Scali F, Toledano AY, et al. Improving digital breast tomosynthesis reading time: a pilot multi-reader, multi-case study using concurrent computer-aided detection (CAD). *Eur J Radiol* 2017;97:83-89
36. Acciavatti RJ, Lee SH, Reig B, Moy L, Conant EF, Kontos D, et al. Beyond breast density: risk measures for breast cancer in multiple imaging modalities. *Radiology* 2023;306:e222575
37. Pertuz S, McDonald ES, Weinstein SP, Conant EF, Kontos D. Fully automated quantitative estimation of volumetric breast density from digital breast tomosynthesis images: preliminary results and comparison with digital mammography and MR imaging. *Radiology* 2016;279:65-74
38. Teuwen J, Moriakov N, Fedon C, Caballo M, Reiser I, Bakic P, et al. Deep learning reconstruction of digital breast tomosynthesis images for accurate breast density and patient-specific radiation dose estimation. *Med Image Anal* 2021;71:102061
39. Gastounioti A, Pantalone L, Scott CG, Cohen EA, Wu FF, Winham SJ, et al. Fully automated volumetric breast density estimation from digital breast tomosynthesis. *Radiology* 2021;301:561-568
40. Huang SC, Pareek A, Jensen M, Lungren MP, Yeung S, Chaudhari AS. Self-supervised learning for medical image classification: a systematic review and implementation guidelines. *NPJ Digit Med* 2023;6:74

디지털 유방 토모신테시스에서 인공지능의 임상 적용

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디지털 유방 토모신테시스(digital breast tomosynthesis; 이하 DBT)는 유방암 검진에서 널리 활용되고 있으며, 디지털 유방촬영술(full field digital mammography)과 비교하여 암 발견율이 향상되고 소환율이 감소하는 결과를 가져왔다. 그러나 DBT의 우월한 성적에도 불구하고 이미지의 수 증가에 따른 판독 업무 증가와 판독 시간의 증가 등의 문제가 있다. 현재 개발되는 다양한 DBT 인공지능(artificial intelligence; 이하 AI)은 DBT의 장점을 강화하고 단점을 극복할 수 있는 많은 기회를 제공할 것으로 기대된다. AI 알고리즘은 유방암 검출 및 특성화에 있어 중요한 역할을 할 수 있다. AI의 적용은 판독 흐름을 간소화하고 영상의학과 의사가 영상을 판독하는데 데 소요되는 시간을 단축할 수 있으며, 합성 유방촬영(synthesized mammography)에서 병변의 가시성을 향상시킴으로서 방사선 노출을 줄일 수 있도록 도와준다. 본 종설에서는 DBT AI 기술과 임상 응용을 정리하고, 미래 발전 방향을 정리하고자 한다.

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