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REVIEW ARTICLE

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The Application of Artificial Intelligence in Detecting Breast Lesions with Medical Imaging: A Literature Review

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Abstract

Breast cancer is considered the most commonly diagnosed cancer among women worldwide. Several studies have shown that mammography screening could significantly decrease breast cancer mortality. Despite other screening modalities, such as MRI and ultrasound (US), mammography plays a vital role in detecting cancer and following up on it, due to its qualities and properties. The aim of this literature review is to look at recent studies that use AI with different medical imaging mammograms, MRI, and US, in detecting breast lesions.

A literature search was carried out using Google Scholar, Semantic Scholar, medRxiv, and PubMed databases for a period of the last four years. The search terms were "breast lesion," "breast imaging," and "breast cancer" combined with "machine learning," "deep learning," and "artificial intelligence." Among these studies, only the medical imaging related to breast lesions with AI was selected. A total of 25 articles were extracted from the following databases: 4 Google Scholar, 3 Semantic Scholar, 4 medRxiv, and 14 PubMed. Only papers related to breast lesions with medical imaging modalities were extracted, and all duplications were removed. In this study, the papers were reviewed by medical imaging professionals.

This literature review summarizes the most recent articles on utilizing artificial intelligence (AI) in detecting breast lesions for different imaging modalities: mammogram, ultrasound, and MRI. Reviewed studies showed that AI performance in detecting lesions was significant, associated with high accuracy, sensitivity, and specificity for these modalities.(**International Journal of Biomedicine. 2023;13(1):9-13.**)

Keywords: artificial intelligence • convolution neural network • machine learning • neural network artificial

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Abbreviations

AI, artificial intelligence; **AUC**, area under curve; **BI-RADS**, Breast Imaging Reporting and Data System; **DL**, deep learning; **CAD**, computer-aided detection; **CNN**, convolution neural network; **MRI**, magnetic resonance imaging; **ML**, machine learning; **NNA**, neural network artificial; **US**, ultrasound.

Introduction

Breast cancer is considered the most commonly diagnosed cancer among women worldwide.[1,2] Several studies have shown that mammography screening could significantly decrease breast cancer mortality.[3] Despite other screening modalities, such as MRI and ultrasound (US), mammography plays a vital role in detecting cancer and following up on it, due to its qualities and properties.[4] About 20%-30% of breast cancers can be missed in mammography because of poor positioning, interpretation error, and dense parenchyma-obscuring lesions.[5,6] By reviewing many images, radiologists have identified the mammographic differences between noncancer and cancer, and these images have been shared among radiologists, who utilized their morphological characteristics.[3] In order to enhance the radiologists' performance, the traditional computer-aided detection (CAD) system was introduced and used in 83% of

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digital mammography examinations.[7] CAD was developed to help mammogram interpretation, especially in terms of cancer detection i.e., sensitivity.[8-10] However, CAD efficiency is controversial as some studies suggest that CAD can improve cancer detection, while large studies illustrate conflicting results for assessing the radiologist's performance in 40 facilities over four-year intervals. They found that CAD led to reduced accuracy in detecting cancer and it increased biopsy recommendations.[11,12] Moreover, important information in CAD is susceptible to being lost when designing human-interpretation descriptors. In developed AI-based CAD, the artificial intelligence (AI) algorithms extract mammographic characteristics as descriptors. The main difference between self-learned and human-designed descriptors is the success factor of deep learning (DL) algorithms. Several studies have reported that AI could provide similar performance to medical image experts who can analyze many medical images.[13,14] The growing interest in the application of AI in medical imaging have resulted in several newer algorithms based on DL that have been developed and utilized in digital mammography, MRI, and US. Preliminary data demonstrated that the AI system can improve the radiologist's efficiency in terms of specificity, sensitivity, and time.[15-17]

The aim of this literature review is to look at recent studies that use AI with different medical imaging mammograms, MRI, and US, in detecting breast lesions.

Materials and Methods

A literature search was carried out using Google Scholar, Semantic Scholar, medRxiv, and PubMed databases for a period of the last four years. The search terms were "breast lesion," "breast imaging," and "breast cancer" combined with "machine learning," "deep learning," and "artificial intelligence." Among these studies, only the medical imaging related to breast lesions with AI was selected.

Results

A total of 25 articles were extracted from the following databases: 4 Google Scholar, 3 Semantic Scholar, 4 medRxiv, and 14 PubMed. Only papers related to breast lesions with medical imaging modalities were extracted, and all duplications were removed. In this study, the papers were reviewed by medical imaging professionals. Of the extracted articles, only 3 reported on medical imaging utilized with AI: 11 mammograms, 9 US, and 5 MRI. The AI types were varied among these articles, including DL, ML, and NNA. The classification was distributed as 17 DL and 8 neural networks. The number of patients in this literature ranged from 240 to 353,879, providing data for developing the AI, including 18 retrospective data, 4 prospective data, and 3 multi-case studies (Table 1).

Discussion

Mammography

Pacilè et al.[18] utilized 2 groups of a deep CNN named MammoScreen V1 and Therapixel, including 240 patients (120 benign and 120 malignant tumors) with 14 radiologists. The average area under curve (AUC) across readers was 0.79 with AI, and the average variation in AUC was 0.028 by using AI; the average sensitivity was enhanced when detecting malignant tumors using AI. Kim et al.[3] developed an AI algorithm based on a deep convolution neural networks (CNN) named ResNet-35. The data they used was collected from 5 different institutions located in the UK, USA, and South Korea. The number of all data was 170,000, including 75,000 benign and 37,000 malignant cases, with participation of 14 radiologists. By using AI, the performance of level was 0.94, which was significantly increased, compared with the radiologists' performance without AI assistance (0.81).

Moreover, AI was more sensitive in detecting cancer with masses. Frazer et al.[20] utilized multiple DL-based AI techniques, such as ResNet 50, as a backbone DL model that is pre-trained on the imageNet17 dataset. They also used 3 CNNs: inception-ResNet-V2, efficientNetB6, and NASNetLarg. The AUC was 0.89 based on 349 test cases. Another study showed that the AI reduced the false-positives for the proportion of breast screening in women from 89.9% to 62%, and the value of positive predictive recall (PPV-1) increased to 16.5%. Also, the sensitivity was enhanced for women with mass-related lesions by 98.5%.[22] Rodríguez-Ruiz et al.[25] used a DL-CNN system called Transpara, and the data included women from 2 institutions (in the USA and Europe). In general, the results indicate high performance in detecting cancer; with AI support, the AUC, sensitivity, and specificity were 0.89, 86%, and 79%, respectively, and the time of reviewing the case was similar between un-aided with AI (146 seconds) and aided with AI (149 seconds).

Ultrasound

Using AI applications, US demonstrated significant results. Xia et al.[28] utilized the S-detect AI system, which showed high efficiency for detecting malignant masses and was associated with high specificity, sensitivity, and accuracy of 93.8%, 95.8%, and 89.6%, respectively. Another study by Gao et al. used the RCNN network with 2 datasets from 2 different hospitals: dataset A contained 8966 nodules, and dataset B contained 2220 nodules. The number of benign cases was 788 and 929 for datasets A and B, respectively. Also, the number of malignant cases was 562 and 1291 for datasets A and B, respectively. For both datasets, the AUC of supervised learning and semi-supervised learning were: 94.2% vs. 93.7% and 92.3% vs. 92%, respectively.[29] Zhou et al.[33] used 3 different CNNs: Inception V3, Inception-ResNet V2, and ResNet-101 architectures with imageNet using 680 patients and 5 radiologists.

The best-performing CNN model, Inception V3, achieved an AUC of 0.89 (95% CI) in predicting the final clinical diagnosis of axillary lymph node metastasis in the independent test set. The model achieved 85% sensitivity (95% CI: 70%-94%) and 73% specificity (95% CI: 56% -85%), while the radiologists achieved 73% sensitivity (95% CI: 57%-85%) and 63% specificity (95% CI: 46%-77%).

Magnetic Resonance Imaging

A study performed by Dalmiş et al.[35] showed significant performance of AI with MRI modality. A prospective study

Table 1.
AI for detecting lesions for mammography, US and MRI.

Authors	Modality	Study type	Type of AI	Name of AI program	All data
Pacilè S. et al., 2020 [18]	Mammography	Multi-cases retrospective study	Dual groups of deep CNNs	MammoScreen V1; Therapixel, Nice, France	241 patient cases
Kim HE et al., 2020 [3]	Mammography	Retrospective, multireader study	Deep CNNs	ResNet-35	170,230 examinations
Rodriguez-Ruiz A, et al., 2019 [19]	Mammography	Multi-case study	Deep learning CNNs	Transpara 1.4.0, Screenpoint Medical BV, Nijmegen, the Netherlands	2653 examinations
Fraze HM, et al., 2021[20]	Mammography	Retrospective study Local Study &Global Study	Several DL-based AI techniques	1) ResNet50 2) Inception-ResNet-V2, EfficientNetB6 and NASNetLarge	28,694 examinations
Arasu VA, et al., 2022 [21]	Mammography	Retrospective, case-cohort study	1-Mirai (MIT): leverages a ResNet 2-GMIC: used CNN	1-Mirai algorithm 2-Algorithm of Globally Aware Multiple Instance Classifier (GMIC)	329,814 patients
Kerschke L, et al., 2022 [22]	Mammography	Retrospective study	DL	Transpara	2957 patients
van Winkel SL., et al., 2021 [23]	Digital breast tomosynthesis (DBT): Mammography	Several cases	Based on deep CNNs	Transpara™ 1.6.0	360 cases
Mansour S, et al., 2021 [24]	Mammography	Prospective study	Deep CNNs	Lunit INSIGHT MMG, v. 2019	2000 mammograms
Rodriguez-Ruiz A, et al., 2019 [25]	Mammography	Retrospective, multireader, multicase study	DL CNNs	Transpara (version 1.3.0)	240 examinations
Interlenghi M, et al., 2022 [26]	Ultrasound	Retrospective study	AI	Self-developed	928 ultrasound images
Shen Y, et al., 2021 [27]	Ultrasound	Reader study	AI	Self-developed	288,767 ultrasound exams
Xia Q, et al. 2021 [28]	Ultrasound	Retrospective study	DL system	S-Detect artificial intelligence system	40 patients
Gao, Liu et al., 2021[29]	Ultrasound	Retrospective study	DL	RCNN network	8966 nodules, 6746 nodules in Dataset A, 2220 nodules in Dataset B
Lyu SY, et al., 2022 [30]	Ultrasound	Retrospective study	Dual CNNs	AI-SONIC Breast system	92 patients
PhD XL, et al., 2022 [31]	Ultrasound	Retrospective study	DL 3D CNN	3D U-net	397 participants
Mango VL, et al., 2020 [32]	Ultrasound	Multicenter retrospective review	ML	Koios DS for Breast, Koios Medical	900 breast lesions
Zhou LQ, et al., 2020 [33]	Ultrasound	Retrospective study, Multicohort study.	Deep Nueral Network, CNNs	ResNet-101 Inception-ResNet V2 Inception V3, pretrained with ImageNet	680 patients
Zhou J, et al., 2020 [34]	MRI	Retrospective study	DL CNN	ResNet50 architecture	207 patients
Dalmiş MU, et al., 2019 [35]	MRI	Prospective study	DL architecture, independent CNNs	DenseNet	576 lesions
Adachi M, et al., 2020 [36]	MRI	Retrospective study	DL	RetinaNet	
Herent P, et al., 2019 [37]	MRI	Retrospective study	DL	50-layer residual neural network (ResNet-50)	335 MR images
Jiang Y, et al., 2021 [38]	MRI	Retrospective clinical reader study	Computer-assisted diagnostic MRI software	QuantX	111 examinations

associated with DL architecture used an independent CNN named DenseNet. About 576 images of lesions were used (208 benign lesions and 368 malignant lesions) from a dataset of Radboud University. The area under the ROC curve was 0.852 for the final AI system, which combines all imaging information with PI.

Another study by Adachi et al. demonstrated DL called RatinaNet that used 13 normal, 20 benign and 52 malignant cases with the participation of 4 radiologists to validate the study. The comparison between the radiologists' and AI performance was monitored. The results showed that the performance of the 4 radiologists with the AI was better than without using the AI. The AUC for the radiologists with AI was 0.925, 0.884, and 0.899, respectively. The AUC for the radiologists with AI was significantly higher than the radiologist's performance without AI (P=0.039).[36] Moreover, Herent et al.[37] utilized retrospective data with DL-AI that used a 50-layer residual neural network named ResNet-50. In this study, 335 MRI images were used: 212 benign lesions and 123 malignant lesions. Their model achieved a weighted mean AUC of 0.816 when using an independent challenge test. Jiang et al.[38] have evaluated whether the diagnostic performance of radiologists in differentiating cancer from noncancer with dynamic contrast, material-enhanced (DCE) breast MRI was improved when using an AI system, compared with conventionally available software. One hundred eleven women were evaluated with a total of 111 breast DCE-MRI examinations (54 malignant and 57 nonmalignant lesions). The average AUC of all readers improved from 0.71 to 0.76 (P=0.04) when using the AI system. The average sensitivity improved from 90% to 94% when BI-RADS category 3 was used as the cut point but not when using BI-RADS category 4a. The average specificity showed no difference when using either BI-RADS category 4a or category 3 as the cut point.

Conclusion

This literature review summarizes the most recent articles on utilizing AI in detecting breast lesions for different imaging modalities: mammogram, ultrasound, and MRI. Reviewed studies showed that AI performance in detecting lesions was significant, associated with high accuracy, sensitivity, and specificity for these modalities.

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