Artificial Intelligence in Breast Cancer: Imaging and Diagnosis

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Abstract: Artificial intelligence (AI) has infiltrated our everyday lives, and there have been extremely promising applications of AI in the area of health in the previous decade, including medical imaging, in vitro diagnostics, intelligent rehabilitation, and prognosis. Breast cancer is one of the most prevalent malignant tumors in women, and it poses a major danger to both physical and emotional health. Early detection of breast cancer by mammography, ultrasound, and magnetic resonance imaging (MRI) may greatly improve patients’ prognoses. AI has shown exceptional performance in picture recognition tasks and has been extensively researched in breast cancer screening. This study discusses the history of artificial intelligence (AI) and its applications in breast medical imaging (mammography, ultrasound, and MRI), such as lesion recognition, segmentation, and classification; breast density evaluation; and breast cancer risk assessment. In addition, we examine the limitations and future prospects of using AI in medical imaging of the breast.

Keywords: Artificial intelligence, magnetic resonance imaging, cancer

1. INTRODUCTION

AI is often characterised as "a system's capacity to properly understand external input, learn from such data, and apply those learnings to fulfil specified objectives and tasks via flexible adaptation." The enormous increase of computer functions connected to large data penetration during the last 50 years has pushed AI applications into new domains (1). AI may now be found in voice recognition, facial identification, autonomous vehicles, and other emerging technologies, and the use of AI in medical imaging has progressively become an important study area. Deep learning (DL) algorithms, in particular, have made great progress in image identification tasks. Methods ranging from convolutional neural networks to variational autoencoders have been discovered across a wide range of medical image processing applications, promoting the fast growth of medical imaging (2). In the realm of medical image analysis, AI has made significant contributions to early diagnosis, illness evaluation, and treatment response evaluations for diseases such as pancreatic cancer (3), liver disease (4), breast cancer (5), chest disease (6), and neurological tumors (7).
In 2018, around 2.1 million new instances of breast cancer were detected globally, accounting for almost one-fourth of all cancer cases among women (8). Breast cancer is the most often diagnosed cancer in most nations (154 of 185) and the leading cause of cancer mortality in more than 100 countries (9). Breast cancer has a significant influence on women's physical and emotional health, endangering their lives and wellbeing. Breast cancer detection and treatment have become serious public health issues across the globe. The precise diagnosis, particularly early identification and treatment of breast cancer, has a significant influence on the prognosis. Early breast cancer has a clinical cure rate of more than 90%; in the medium stage, it is 50-70 percent, and in the late stage, the therapeutic impact is extremely low. Mammography, ultrasound, and MRI are now crucial screening and additional diagnostic tools for breast cancer, as well as significant methods of detection, staging, effectiveness assessments, and follow-up exams (10).

Currently, radiologists view, analyse, and diagnose breast pictures. With a heavy and long-term workload, radiologists are more prone to misread pictures owing to weariness, resulting in a mistake or missing diagnosis, which AI may help to prevent. Computer-aided diagnosis (CAD) has been applied to eliminate human mistakes. A proper algorithm completes the processing and analysis of a picture in CAD systems (11). The most recent innovation is deep learning (DL), particularly convolutional neural networks (CNNs), which has made tremendous progress in medical imaging (12). This article provides a short history of AI before focusing on its applications in breast mammography, ultrasound, and MRI image processing. This study also explores the potential for AI's use in medical imaging.

2. BRIEF OVERVIEW OF AI

AI refers to the capacity of application computers to learn and solve issues by imitating humans or human brain processes (13). It has been more than 60 years since John McCarthy proposed the notion of artificial intelligence in 1956. AI technology has advanced at a breakneck pace in the last 10 years. As a branch of computer science, it aims to create a new type of intelligent machine that responds like a human brain; its application field is broad, and includes robots, image recognition, language recognition, natural language processing, data mining, pattern recognition, and expert systems, among other things (14, 15). AI may be used in the medical profession for health management, clinical decision support, medical imaging, illness screening and early disease prediction, medical records/literature analysis, and hospital administration, among other things. AI can evaluate medical pictures and data for illness screening and prediction, as well as assisting clinicians in diagnosis. In 2018, Al-antari MA et al. investigated a comprehensive integrated CAD system that can be utilised for detection, segmentation, and classification of masses in mammography, and its accuracy was more than 92 percent in all areas (16). Alejandro Rodriguez-Ruiz et al. collected 2654 exams and readings from 101 radiologists, using a trained AI system to score the possibility of cancer on a scale of 1 to 10, and discovered that using an AI score of 2 as the threshold could reduce the workload by 17 percent, proving that AI automatic preselection can significantly reduce radiologists' workload (17).

One of the most essential techniques to develop AI is via machine learning (ML). There are two types of machine learning: unsupervised and supervised. Unsupervised ML classifies radiomics features without relying on any information supplied by or defined by a previously accessible collection of imaging data of the same kind as the one under analysis. Supervised ML approaches are initially trained using an accessible data archive, which implies that the algorithm parameters are modified until the method delivers an ideal tradeoff between its ability to fit the training set and its generalisation power when a new data example comes. Sparsity-enhancing regularisation networks can generate predictions in the realm of supervised ML while also identifying the extracted characteristics that most influence such predictions (18). ML refers to computer techniques that use picture characteristics extracted by radiomics as input to predict illness outcomes on follow-up, such as linear
regression, K-means, decision trees, random forest, PCA (principal component analysis), SVM (support vector machine), and ANNs (artificial neural networks).

DL, one of the neural network-based AI systems, is constructed by developing models that mimic the human brain and is now regarded as the most advanced technology for picture categorization. Neural networks initially imitate nerve cells before attempting to replicate the human brain with the use of a simulation model known as a perceptron. A neural network is made up of layers that are continuous, such as the input layer, the hidden layer, and the output layer. The hidden layer contains a convolutional layer, a pooling layer, and a fully connected layer, while the input layer may handle multidimensional data. The feature map formed in the convolutional layer is first processed via a non-linear activation function before being transmitted to the pooling layer for downsampling. The output is then sent to the fully connected layer, which classifies the total conclusion, and the output layer sends data analysis findings directly. A multilayer perceptron is built by constructing and organising layers of perceptrons in which all nodes in the model are completely linked, allowing it to solve more complicated issues (19). CNNs' learning paradigm also includes supervised learning and unsupervised learning; supervised learning refers to the training technique in which both the observed training data and the accompanying ground truth labels for that data (also known as "targets") are necessary for training the model. Unsupervised learning, on the other hand, uses training data with no diagnostic or normal/abnormal labelling. In picture classification challenges, supervised learning seems to be the most preferred strategy at the moment (20).

3. APPLICATIONS OF AI IN MAMMOGRAPHY
Mammography is one of the most extensively used modalities for screening for breast cancer (21, 22). Mammography is a noninvasive detection technology with low discomfort, simple operation, excellent resolution, and good repeatability. The preserved picture is not restricted by age or body form and may be compared before and after. Mammography may detect breast lumps that physicians cannot palpate and can consistently distinguish benign lesions from malignant malignancies of the breast. Mammograms are presently obtained using full-field digital mammography (DM) devices and are available in both raw imaging data (for processing) and postprocessed data (for presentation) (23, 24). AI has been utilised in most research to analyse mammography pictures, mostly for the detection and categorization of breast mass and microcalcifications, breast mass segmentation, breast cancer risk assessment, and image quality enhancement.

4. DETECTION AND CLASSIFICATION OF BREAST MASSES
Masses are one of the most prevalent signs of breast cancer among the several abnormalities observed on mammograms. Because of variations in form, size, and borders, masses are difficult to identify and diagnose, particularly in the presence of thick breasts. As a result, mass detection is a critical stage in CAD. Some studies proposed a Crow search optimization-based intuitionistic fuzzy clustering approach with neighbourhood attraction (CrSA-IFCM-NA), and it has been demonstrated that CrSA-IFCM-NA effectively separated the masses from mammogram images and had good results in terms of cluster validity indices, indicating clear segmentation of the regions (24). Others created a fully integrated CAD system that used a regional DL approach You-Only-Look-Once (YOLO) and a new deep network model full resolution convolutional network (FrCN) and a deep CNN to detect, segment, and classify masses in mammograms, and used the INbreast dataset to verify that quality detection accuracy reached 98.96 percent, effectively assisting radiologists in making an accurate diagnosis (16, 25, 26).

5. DETECTION AND CLASSIFICATION OF MICROCALCIFICATIONS
Breast calcifications are little spots of calcium salts in the breast tissue that show on mammography as small white spots. Calcifications are classified into two types: microcalcifications and macrocalcifications. Macrocalcifications are huge, coarse calcifications that are typically benign and
age-related. Microcalcifications, with diameters ranging from 0.1 mm to 1 mm and with or without visible masses, may be early indicators of breast cancer (27). Several CAD methods are now being developed to identify calcifications in mammography pictures. Cai H et al. created a CNN model for the detection, analysis, and classification of microcalcifications in mammography images, confirming that the function of the CNN model to extract images outperformed handcrafted features; they achieved a classification precision of 89.32 percent and a sensitivity of 86.89 percent by using filtered deep features that are fully utilised by the proposed CNN structure for traditional descriptors (28).

Zobia Suhail et al. created a novel method for classifying benign and malignant microcalcifications by combining an improved Fisher linear discriminant analysis approach for the linear transformation of segmented microcalcification data with an SVM variant to distinguish between the two classes; 288 ROIs (139 malignant and 149 benign) in the Digital Database for Screening Mammography (DDSM) were classified with an average accuracy of 80%. (29). Jian W et al. created a CAD system based on the dual-tree complex wavelet transform (DT-CWT) to identify breast microcalcifications (30). Guo Y et al. suggested a novel hybrid approach for detecting microcalcification in mammograms by combining contourlet transform with nonlinking simplified pulse-coupled neural network (31). An artificial neural network can identify, segment, and categorise masses and microcalcifications in mammography, serving as a reference for radiologists and considerably enhancing radiologists' job efficiency and accuracy.

6. BREAST MASS SEGMENTATION

True mass segmentation is closely connected to the patient's successful therapy. Fuzzy contours were employed by some researchers to automatically segregate breast masses from mammograms, and the ROIs retrieved from the miniMIAS database were analysed. The average true positive rate was 91.12 percent, and the accuracy was 88.08 percent, according to the data (32). Due to low-contrast mammography pictures, uneven forms of masses, spiculated edges, and the existence of intensity changes in pixels, global segmentation of masses on mammograms is a complicated operation. Some researchers employed the mesh-free radial basis function collocation technique to evolve a level set function for segmentation of the breast and suspicious mass areas. The suspicious regions were then classified as abnormal or normal using an SVM classifier. The sensitivity and specificity for the DDSM dataset were found to be 97.12 percent and 92.43 percent, respectively (33). Plane fitting and dynamic programming were used to identify and categorise breast mass in mammography, considerably improving the accuracy of segmentation of breast lesions (34). Correct segmentation of breast lesions ensures appropriate disease categorization and diagnosis (35). The use of an autonomous picture segmentation method demonstrates the use and promise of deep learning in precision medical systems.

7. BREAST DENSITY ASSESSMENT

Breast density is a significant risk factor for breast cancer and is often assessed using two-dimensional (2D) mammography. Those with greater breast density are two to six times more likely to get breast cancer than women with low breast density (36). Mammographic density has historically been measured as the absolute or relative quantity (as a proportion of total breast size) occupied by dense tissue, which shows as white "cotton-like" patches on mammographic pictures (37). Accurate and consistent breast density assessment is very desired in the present context of breast density identification to give physicians and patients with better informed clinical decision-making assistance. Many research have indicated that AI technology may help with mammographic breast density measurement (BD). Mohamed AA et al. investigated a CNN model based on the Breast Imaging Reporting and Data System (BI-RADS) for BD categorization and classified the density of large (i.e., 22000 images) DM datasets (i.e., "scattered density" and "heterogeneous density"); they found that increasing the number of training samples resulted in a higher area under the receiver operating characteristic curve (AUC) of 0.94-0.98. (38). They also utilised a CNN model to demonstrate that
radiologists employed a medial oblique (MLO) view rather than a head-to-tail (CC) view to classify the category of BD (39). Le Boulc'h M and colleagues assessed the agreement between DenSeeMammo (an AI-based automatic BD assessment software approved by the Food and Drug Administration) and visual assessment by a senior and a junior radiologist on DM and discovered that the BD assessment between the senior radiologist and the AI model was basically the same (weighted=0.79; 95 percent CI:0.73-0.84). (40). Lehman CD et al. created and tested a DL model to evaluate BD using 58 894 randomly chosen digital mammograms, and they implemented the model using PyTorch and a deep CNN, ResNet-18. And it is concluded that the agreement between density assessments with the DL model and those of the original interpreting radiologist was good (k = 0.67; 95 percent CI: 0.66, 0.68), and in the four-way BI-RADS categorization, the interpreting radiologist accepted 9729 of 10763 (90 percent ; 95 percent CI: 90 percent, 91 percent) DL assessments (41). AI-assisted MBD evaluation may minimise variance among radiologists, better forecast the risk of breast cancer, and serve as a foundation for future diagnosis and treatment.

8. BREAST CANCER RISK ASSESSMENT

Breast cancer's high incidence and fatality rate endangers women's physical and emotional health. As Sun YS et al. concluded in 2017, there are many known risk factors for breast cancer, including ageing, family history, reproductive factors (early menarche, late menopause, late age at first pregnancy, and low parity), oestrogen (endogenous and exogenous estrogens), lifestyle (excessive alcohol consumption, too much dietary fat intake, smoking), and oestrogen (endogenous and exogenous estrogens).

According to the relevant literature, AI research in breast cancer risk prediction is also highly widespread. Nindrea RD et al. conducted a systematic review of published ML algorithms for breast cancer risk prediction between January 2000 and May 2018, summarised and compared five ML algorithms, including SVM, ANN, decision tree (DT), naive Bayes, and K-nearest neighbour (KNN), and confirmed that the SVM algorithm was able to calculate breast cancer risk with greater accuracy than other ML algorithms (43). According to some studies, mammography results, risk factors, and clinical findings were analysed and learned using an ANN in conjunction with cytopathological diagnosis to evaluate the risk of breast cancer for doctors to estimate the probability of malignancy and improve the positive predictive value (PPV) of the decision to perform biopsy (44). Yala A and his colleagues also created a hybrid DL model that uses both the full-field mammography and conventional risk variables, and discovered that it was more accurate than the Tyrer-Cusick model, which is currently used in clinical practise (45). As a consequence, AI predicts breast cancer risk with more accuracy than previous approaches, allowing clinicians to advise high-risk groups in the implementation of suitable measures to lower the occurrence of breast cancer.

9. IMAGE QUALITY ASSESSMENT

Accurate illness diagnosis is dependent on good picture quality. Clear pictures are favourable to the identification and diagnosis of microscopic lesions, and image quality has a substantial influence on the diagnosis rate and accuracy rate of AI for evaluating breast illnesses on mammography. One after the other, computer techniques for increasing picture quality have been devised. Multi-scale shearlet transform may provide multi-resolution findings because it offers additional information on the data phase, directionality, and shift invariance. This is useful for detecting cancer cells, especially those with tiny outlines. Shenbagavalli P and his colleagues used a shearlet transform image enhancement approach to improve mammography image quality and identified the DDSM database as benign or malignant with an accuracy of up to 93.45 percent (11). Teare P et al. used a novel form of a false colour enhancement method, contrast-limited adaptive histogram equalisation (CLAHE), to optimise the characteristics of mammography. Using dual deep CNNs at different scales for classification of mammogram images and derivative patches combined with a random forest gating network, they
achieved a sensitivity of 0.91 and a specificity of 0.80. (46). Because picture quality is the foundation of an accurate diagnosis, thorough image quality assessment and improvement methods must be implemented in order to successfully aid radiologists and ANN systems in further analysis and diagnosis (Table 1).

10. APPLICATIONS OF AI IN BREAST ULTRASOUND
Ultrasound offers several benefits as a diagnostic technology with a high usage rate, such as easy operation, no radiation, and real-time operation. As a result, ultrasound imaging has increasingly become a widely used imaging technique for the detection and diagnosis of breast cancer. To eliminate missing or misdiagnosed breast lesions due to a lack of physician expertise or subjective impact, and to achieve quantification and uniformity of ultrasound diagnosis, an AI system to identify and diagnose breast lesions in ultrasound pictures was created (47). According to related research (48, 49), AI systems are mostly employed in breast ultrasound imaging for the detection and segmentation of ROIs, feature extraction, and classification of benign and malignant lesions.

11. IDENTIFICATION AND SEGMENTATION OF ROIs
To correctly portray and identify breast lesions, the lesions must first be separated from the surrounding tissue. Manual segmentation of breast pictures was mostly performed by ultrasound physicians in the present clinical work; this procedure not only relies on the doctors' working expertise, but also requires time and effort. Furthermore, since breast ultrasound pictures have poor contrast, unclear borders, and a lot of shadows, an AI-based automated segmentation approach for breast ultrasound image lesions is presented. The method of segmenting breast ultrasound pictures entails detecting a ROI encompassing the lesion and delineating its outlines. Hu Y et al. suggested an automated tumour segmentation approach that merged a DFCN with a phase-based active contour (PBAC) model. Following training, 170 breast ultrasound pictures were detected and segmented, with a mean DSC of 88.97%, demonstrating that the suggested segmentation approach may partially substitute manual segmentation results in medical analysis (50). Kumar V. et al. proposed a multi-U-net algorithm and segmented masses from 258 women's breast ultrasound images, achieving a mean Dice coefficient of 0.82, a true positive fraction (TPF) of 0.84, and a false positive fraction (FPF) of 0.01, all of which are clearly better than the original U-net algorithm's results (51). To segment ultrasound pictures of breast cancers, Feng Y. et al. used a Hausdorff-based fuzzy c-means (FCM) method with an adaptive area selection approach. The neighbourhood surrounding each pixel is adaptively chosen for Hausdorff distance measurement based on mutual information between areas. The findings demonstrated that the adaptive Hausdorff-based FCM algorithm outperformed the Hausdorff-based and classic FCM methods (52). The detection and segmentation of lesions in breast ultrasound pictures saves ultrasound specialists a significant amount of time in swiftly identifying and diagnosing illnesses, as well as providing a basis and guarantee for the development of AI for automated diagnosis of breast disorders.
12. **FEATURE EXTRACTION**

The morphological and textural properties of the breast pictures are used by ultrasound specialists to locate and segment worrisome tumours. Shape, orientation, edge, echo type, back features, calcification location, and hardness are examples of these characteristics. Then, using the BIRADS scale, they categorise suspicious masses in order to measure the degree of cancer suspicion in breast masses. Morphological traits are critical for distinguishing between benign and malignant tumours, and acquiring them accurately places significant demands on the ultrasound examiner. AI algorithms have been used to extract features from breast ultrasound pictures in order to lessen reliance on the physician's expertise. According to Hsu SM et al research's morphological feature parameters (e.g., standard deviation of the shortest distance), texture features (e.g., variance), and the Nakagami parameter are combined to extract the physical features of breast ultrasound images. They classified the data using FCM clustering and achieved an accuracy of 89.4 percent, specificity of 86.3 percent, and sensitivity of 92.5 percent. The maximum discrimination performance of the optimal feature collection was independent of the type of classifier when compared to logistic regression and SVM classifiers, indicating that the combination of different feature parameters should be functionally complementary to improve the performance of breast cancer classification (53). By integrating feature learning and feature selection, Zhang et al. created a two-layer DL architecture to extract shear-wave elastography (SWE) features. When compared to the statistical features of quantified image intensity and texture, the DL features performed better in classification, with an accuracy of 93.4 percent, sensitivity of 88.6 percent, specificity of 97.1 percent, and area under the receiver operating characteristic curve of 0.947 percent (54). CAD systems (S-Detect, Samsung RS80A ultrasound system) used to evaluate the ultrasound characteristics of breast masses have been proven in relevant studies to greatly enhance the diagnosis performance of both expert and unskilled radiologists (Figure 1). CAD systems may be useful in improving breast lesion descriptions and determining treatment choices, and they increase the uniformity of breast mass features across observers (49, 55).

Because breast cancer has a high incidence and fatality rate among women all over the globe, several governments have implemented breast cancer screening programmes for women of suitable age. The most significant aspect of breast disease screening is distinguishing between breast cancer and benign...
breast illnesses. BIRADS is the primary classification system used by physicians to categorise lesions in breast ultrasound imaging. AI systems with benign and malignant categorization features have progressively been created to assist clinicians with varying levels of knowledge to achieve a consistent decision. Cirtisis A et al. used a deep convolution neural network (dCNN) to classify an internal data set and an external test data set and categorised breast ultrasound pictures into BI-RADS 2-3 and BI-RADS 4-5. The findings indicated that the dCNN had a classification accuracy of 93.1 percent (external 95.3 percent), while radiologists had a classification accuracy of 91.6 5.4 percent (external 94.1 1.2 percent). This demonstrates that dCNNs may be used to simulate human decision making (56). Becker AS et al. analysed 637 breast ultrasound pictures using DL software (84 malignant and 553 benign lesions). The programme was trained using a randomly selected subset of the photos (n=445, 70%), and the remaining instances (n=192) were utilised to verify the resultant model throughout the training process. The results were compared to three readers with varying levels of skill (a radiologist, a resident, and a qualified medical student), and the findings revealed that the neural network, which had only been trained on a few hundred instances, had equivalent accuracy to a radiologist's reading. The neural network performed better than a medical student who was taught with the identical training data set (57). This study suggests that AI-assisted categorization and diagnosis of breast illnesses may greatly reduce physicians' diagnostic time and enhance the diagnostic accuracy of novice clinicians (Table 2).

13. BENIGN AND MALIGNANT CLASSIFICATION
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14. APPLICATION OF AI IN BREAST MRI

MRI is the most sensitive method for detecting breast cancer and is generally recommended as a complement to mammography for high-risk patients (59). Through a variety of scanning sequences, MRI can completely examine the form, size, scope, and blood circulation of breast masses. However, because of the problems of limited specificity, high cost, lengthy examination time, and patient selectivity, it is not as widely utilised as mammography and ultrasound tests. The majority of research on breast imaging and DL have focused on mammography, with little evidence available for breast MRI (60). The detection, segmentation, characterization, and categorization of breast lesions are the primary goals of DL research in breast MRI (61–64). Ignacio Alvarez Illan et al. used a CAD system to identify and segment non-mass enhanced lesions on dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) of the breast, and the improved CAD system lowered and controlled the false positive rate, yielding good results (65). Herent P. et al. created a deep learning model to identify, describe, and categorise lesions on breast MRI (mammary glands, benign lesions, invasive ductal carcinoma, and other malignant lesions), and it performed well (60). Antropova N. et al. used maximum intensity projection images to include the dynamic and volumetric components of DCE-MRIs into breast lesion categorization using DL techniques. The findings shown that combining volumetric and dynamic DCE-MRI components may greatly enhance CNN-based lesion categorization (66). Jiang Y. et al. recruited 19 breast imaging radiologists (eight academics and eleven private practices) to classify DCE-MRI as benign or malignant, and compared the classification results obtained using only conventionally available CAD evaluation software, including kinetic maps, with those obtained using AI analytics via CAD software. The usage of AI systems was demonstrated to increase radiologists' performance in distinguishing benign and malignant breast tumours on MRI (67). Breast MRI is still required to assess people who are at high risk of developing breast cancer. The CAD method may increase examination sensitivity, lower false positive rates, and eliminate needless biopsies and psychological stress on patients (68). (Table 3).
15. CONCLUSION
AI, especially deep learning, is becoming more commonly employed in medical imaging and performs well in medical image processing tasks. AI can deliver objective and useful information to physicians while reducing their burden and the rates of missed diagnosis and misdiagnosis because of its benefits of high computation speed, strong repeatability, and little tiredness (72). At the moment, the CAD system for breast cancer screening is being extensively researched. These methods can recognize and segment breast lesions, estimate characteristics, categorize them, estimate BD and the risk of breast cancer, and assess treatment impact and prognosis in mammography, ultrasound, MRI, and other imaging tests (39, 73–78). These technologies have significant benefits and possibilities for alleviating doctor pressure, optimizing resource allocation, and enhancing accuracy.

16. CHALLENGES AND PROSPECTS
AI is still in the "weak AI" stage. Despite fast advancements in the medical industry over the last decade, it is still a long way from being completely integrated into doctors' practise and widespread use throughout the globe. CAD systems for breast cancer screening currently have numerous drawbacks, including a lack of large-scale public datasets, reliance on ROI annotation, high image quality requirements, geographical disparities, and overfitting and binary classification issues. Furthermore, AI is primarily aimed at one task training and cannot do several tasks at the same time, which is one of the hurdles and difficulties that DL encounters in the development of breast imaging. Meanwhile, they give a fresh push for the development of breast imaging diagnostic disciplines and demonstrate the enormous future potential of intelligent medical imaging.
Aside from standard imaging approaches, CAD systems based on DL are quickly evolving in the domains of digital breast tomosynthesis (79–81), ultrasound elastography (82), contrast-enhanced mammography, ultrasound, and MRI et al (83, 84). We think that artificial intelligence in breast imaging may be utilised to not only identify, categorise, and forecast breast disorders, but also to classify particular breast diseases (e.g., breast fibroplasia) and predict lymph node metastasis (85) and disease recurrence (86). It is expected that as AI technology advances, radiologists will achieve higher accuracy, greater efficiency, and more accurate classification and determination of adjuvant treatment for breast diseases, resulting in earlier detection, diagnosis, and treatment of breast cancer for the vast majority of patients.

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**REFERENCES**


