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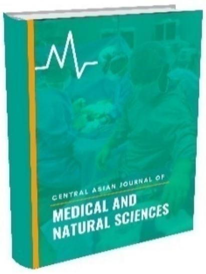

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Artificial Intelligence in Breast Cancer: Imaging and Diagnosis

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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 density evaluation, 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 ASSESMENT

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:0.73-084). (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 ASSESMENT

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 ASSESMENT

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.

TABLE 1 | Summary of key studies on the role of AI in mammography.

n	Task	Algorithms	No. of Cases	Results
1	detect, segment, and classify the breast masses	a completely integrated CAD system (the You-Only-Look-Once to detect, the full resolution CNN to segment, the deep CNN to recognize and classify)	112	ACC= 95.64%
2	detect, analysis, and classify microcalcifications	a deep CNN with the same 5 convolutional layers	990	ACC=89.32% Sen = 86.89%
3	classify microcalcifications	an improved fisher linear discriminant analysis approach combined with a support vector machine variant	288	ACC=96%
4	segment breast masses	a hybrid method based on the active contours and fuzzy logic	57	ACC=88.08% Sen=91.12%
5	detect and segment breast masses	globally supported radial basis function based collocation method	300	AUC=98% Sen=97.12% Spe=92.43%
6	categorize breast density	a two-class CNN-based deep learning model	7000	AUC=94.21%
7	estimate breast cancer risk	a back-propagation learning algorithm	655	AUC=95.5% Sen=82% Spe=90%
8	enhance image quality	shearlet transform and neural network	300	ACC=93.45%

AI, artificial intelligence; CAD, computer aided diagnosis; CNN, convolutional neural network; ACC, accuracy; Sen, sensitivity; AUC, the area under the receiver operating characteristic curve; Spe, specificity.

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).

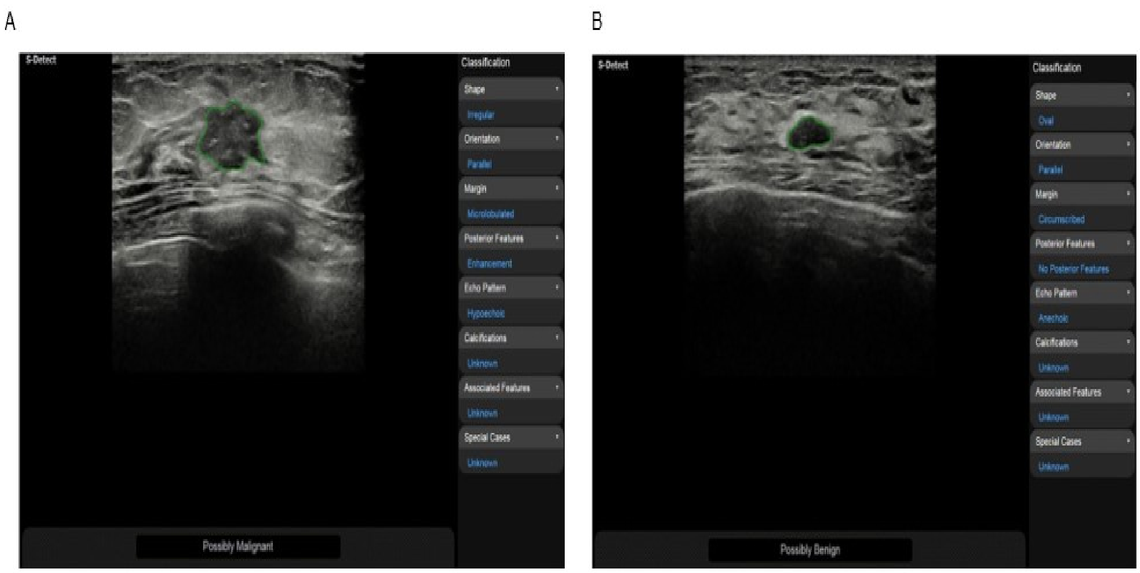

FIGURE 1 | (A) A 50-year-old woman was diagnosed with invasive cancer, and the results of CAD (S-Detect, Samsung RS80A ultrasound system) were"possibly malignant"; (B) A 48-year-old woman was diagnosed with adenosis, and the results of CAD were"possibly benign".

13. BENIGN AND MALIGNANT CLASSIFICATION

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).

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).

TABLE 2 | Summary of key studies on the role of AI in breast ultrasound.

n	Task	Algorithms	No. of Cases	Results	Ref.
1	segment breast tumors	a dilated fully convolutional network combined with an active contour model	170	AUC=79.5% ACC=71.9% Sen=71.2% Spe=72.6%	(50)
2	segment breast masses	the underlying multi u-net algorithm based on CNN fuzzy	433	Sen=84%	(51)
3	characterize breast tumors	c-means clustering algorithm	160	AUC=96% ACC=89.4% Sen=92.5% Spe=86.3%	(53)
4	detect, highlight, and classify breast lesions classify breast	deep CNN	101	AUC=83.8%	(56)
5	tumors	an industrial grade image analysis software (ViDi Suite v. 2.0)	192	AUC=98% Sen=97.12% Spe=92.43%	(57)
6	classify breast tumors	a two-layer DL architecture comprised of the point-wise gated boltzmann machine and the restricted boltzmann machine	227	ACC=93.4% Sen=88.6% Spe=97.1% AUC=94.7%	(54)
7	identify ALN involvement	DL radiomics	584	AUC=90.2%	(58)

AI, artificial intelligence; AUC, the area under the receiver operating characteristic curve; ACC, accu ficity; CNN, convolutional neural networks; DL, deep learning; ALN, axillary lymph node.

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 to 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 recognise and segment breast lesions, extract characteristics, categorise 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, optimising 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.

TABLE 3 | Summary of key studies on the role of AI in breast MRI.

n	Task	Algorithms	No. of Cases	Results
1	detect, characterize and categorize lesions	a supervised-attention model with deep learning	335	AUC=81.6%
2	classify lesions	radiomic analysis and CNN	1294	AUC=98%
3	characterize and classify lesions	the combination of unsupervised dimensionality reduction and embedded space clustering followed by a supervised classifier	792	AUC=81%
4	classify breast tumors	QuantX	111	AUC=76%
5	assess and diagnose contralateral BI-RADS 4 lesions	MRI radiomics-based machine learning	178	AUC=77% ACC=74.1%
6	assess tumor extent and multifocality	CADstream software (version 5.2.8.591)	86	AUC = 88.8% Spe=92.1% PPV=90.0%
7	early predict pathological complete response to neoadjuvant chemotherapy and survival outcomes	linear support vector machine, linear discriminant analysis, logistic regression, random forests, stochastic gradient descent, decision tree, adaptive boosting and extreme gradient boosting	38	AUC=86%

AI, artificial intelligence; MRI, magnetic resonance imaging; AUC, the area under the receiver operating characteristic curve; CNN, convolutional neural network; BI-RADS, Breast Imaging Reporting and Data System; ACC, accuracy; CAD, computer-aided detection; Spe, specificity; PPV, positive predictive value.

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 further 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

1. Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. Artificial Intelligence: Applications in Orthognathic Surgery. J Stomatol Oral Maxillofac Surg (2019) 120(4):347–54. doi: 10.1016/j.jormas.2019.06.001

2. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts H. Artificial Intelligence in Radiology. Nat Rev Cancer (2018) 18(8):500–10. doi: 10.1038/s41568-018-0016-5

3. Korn RL, Rahmanuddin S, Borazanci E. Use of Precision Imaging in theEvaluation of Pancreas Cancer. Cancer Treat Res (2019) 178:209–36. doi: 10.1007/978-3-030-16391-4_8

4. Zhou LQ, Wang JY, Yu SY, Wu GG, Wei Q, Deng YB, et al. Artificial Intelligence in Medical Imaging of the Liver. World J Gastroenterol (2019) 25 (6):672–82. doi: 10.3748/wjg.v25.i6.672

5. Arieno A, Chan A, Destounis SV. A Review of the Role of AugmentedIntelligence in Breast Imaging: From Automated Breast Density Assessment to Risk Stratification. AJR Am J Roentgenol (2019) 212(2):259–70. doi: 10.2214/AJR.18.20391

6. Qin C, Yao D, Shi Y, Song Z. Computer-Aided Detection in Chest Radiography Based on Artificial Intelligence: A Survey. BioMed Eng Online (2018) 17(1):113. doi: 10.1186/s12938-018-0544-y

7. Villanueva-Meyer JE, Chang P, Lupo JM, Hess CP, Flanders AE, Kohli M.Machine Learning in Neurooncology Imaging: From Study Request to Diagnosis and Treatment. AJR Am J Roentgenol (2019) 212(1):52–6. doi: 10.2214/AJR.18.20328

8. Cardoso F, Kyriakides S, Ohno S, Penault-Llorca F, Poortmans P, Rubio IT,et al. Early Breast Cancer: ESMO Clinical Practice Guidelines for Diagnosis, Treatment and Follow-Updagger. Ann Oncol (2019) 30(8):1194–220. doi: 10.1093/annonc/mdz173

9. Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A. GlobalCancer Statistics 2018: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA Cancer J Clin (2018) 68 (6):394–424. doi: 10.3322/caac.21492

10. Fiorica JV. Breast Cancer Screening, Mammography, and Other Modalities.Clin Obstet Gynecol (2016) 59(4):688–709. doi: 10.1097/GRF. 0000000000000246

11. Shenbagavalli P, Thangarajan R. Aiding the Digital Mammogram for Detectingthe Breast Cancer Using Shearlet Transform and Neural Network. Asian Pac J Cancer Prev (2018) 19(9):2665–71. doi: 10.22034/APJCP.2018.19.9.2665

12. Abdelhafiz D, Yang C, Ammar R, Nabavi S. Deep Convolutional Neural Networks for Mammography: Advances, Challenges and Applications. BMC Bioinf (2019) 20(Suppl 11):281. doi: 10.1186/s12859-019-2823-4

13. Hamet P, Tremblay J. Artificial Intelligence in Medicine. Metabolism (2017) 69S:S36–40. doi: 10.1016/j.metabol.2017.01.011

14. Viceconti M, Hunter P, Hose R. Big Data, Big Knowledge: Big Data forPersonalized Healthcare. IEEE J BioMed Health Inform (2015) 19(4):1209–15. doi: 10.1109/JBHI.2015.2406883

15. Obermeyer Z, Emanuel EJ. Predicting the Future - Big Data, MachineLearning, and Clinical Medicine. N Engl J Med (2016) 375(13):1216–9. doi:10.1056/NEJMp1606181

16. Al-Antari MA, Al-Masni MA, Choi MT, Han SM, Kim TS. A Fully IntegratedComputer-Aided Diagnosis System for Digital X-Ray Mammograms via Deep Learning Detection, Segmentation, and Classification. Int J Med Inform (2018) 117:44–54. doi: 10.1016/j.ijmedinf.2018.06.003

17. Rodriguez-Ruiz A, Lang K, Gubern-Merida A, Teuwen J, Broeders M,Gennaro G, et al. Can We Reduce the Workload of Mammographic Screening by Automatic Identification of Normal Exams With Artificial Intelligence? A Feasibility Study. Eur Radiol (2019) 29(9):4825–32. doi: 10.1007/s00330-019-06186-9

18. Tagliafico AS, Piana M, Schenone D, Lai R, Massone AM, Houssami N. Overview of Radiomics in Breast Cancer Diagnosis and Prognostication. Breast (2020) 49:74–80. doi: 10.1016/j.breast.2019.10.018

19. Yanagawa M, Niioka H, Hata A, Kikuchi N, Honda O, Kurakami H, et al.Application of Deep Learning (3-Dimensional Convolutional Neural Network) for the Prediction of Pathological Invasiveness in Lung Adenocarcinoma: A Preliminary Study. Med (Baltimore) (2019) 98(25): e16119. doi: 10.1097/MD.0000000000016119

20. Le EPV, Wang Y, Huang Y, Hickman S, Gilbert FJ. Artificial Intelligence in Breast Imaging. Clin Radiol (2019) 74(5):357–66. doi: 10.1016/j.crad.2019.02.006

21. Welch HG, Prorok PC, O'Malley AJ, Kramer BS. Breast-Cancer Tumor Size, Overdiagnosis, and Mammography Screening Effectiveness. N Engl J Med (2016) 375(15):1438–47. doi: 10.1056/NEJMoa1600249

22. McDonald ES, Oustimov A, Weinstein SP, Synnestvedt MB, Schnall M, ConantEF. Effectiveness of Digital Breast Tomosynthesis Compared With Digital Mammography: Outcomes Analysis From 3 Years of Breast Cancer Screening. JAMA Oncol (2016) 2(6):737–43. doi: 10.1001/jamaoncol.2015.5536

23. Alsheh Ali M, Eriksson M, Czene K, Hall P, Humphreys K. Detection ofPotential Microcalcification Clusters Using Multivendor for-Presentation Digital Mammograms for Short-Term Breast Cancer Risk Estimation. Med Phys (2019) 46(4):1938–46. doi: 10.1002/mp.13450

24. S P, NK V, S S. Breast Cancer Detection Using Crow Search OptimizationBased Intuitionistic Fuzzy Clustering With Neighborhood Attraction. Asian Pac J Cancer Prev (2019) 20(1):157–65. doi: 10.31557/APJCP.2019.20.1.157

25. Jiang Y, Inciardi MF, Edwards AV, Papaioannou J. Interpretation Time Usinga Concurrent-Read Computer-Aided Detection System for Automated Breast Ultrasound in Breast Cancer Screening of Women With Dense Breast Tissue. AJR Am J Roentgenol (2018) 211(2):452–61. doi: 10.2214/AJR.18.19516

26. Fan M, Li Y, Zheng S, Peng W, Tang W, Li L. Computer-Aided Detection ofMass in Digital Breast Tomosynthesis Using a Faster Region-Based Convolutional Neural Network. Methods (2019) 166:103–11. doi: 10.1016/ j.ymeth.2019.02.010

27. Cruz-Bernal A, Flores-Barranco MM, Almanza-Ojeda DL, Ledesma S, IbarraManzano MA. Analysis of the Cluster Prominence Feature for Detecting Calcifications in Mammograms. J Healthc Eng (2018) 2018:2849567. doi: 10.1155/2018/2849567

28. Cai H, Huang Q, Rong W, Song Y, Li J, Wang J, et al. Breast Microcalcification Diagnosis Using Deep Convolutional Neural Network From Digital Mammograms. Comput Math Methods Med (2019) 2019:2717454. doi:10.1155/2019/2717454

29. Suhail Z, Denton ERE, Zwiggelaar R. Classification of Micro-Calcification in Mammograms Using Scalable Linear Fisher Discriminant Analysis. Med Biol Eng Comput (2018) 56(8):1475–85. doi: 10.1007/s11517-017-1774-z

30. Jian W, Sun X, Luo S. Computer-Aided Diagnosis of Breast Microcalcifications Based on Dual-Tree Complex Wavelet Transform. BioMed Eng Online (2012) 11:96. doi: 10.1186/1475-925X-11-96

31. Guo Y, Dong M, Yang Z, Gao X, Wang K, Luo C, et al. A New Method of Detecting Micro-Calcification Clusters in Mammograms Using Contourlet Transform and non-Linking Simplified PCNN. Comput Methods Prog BioMed (2016) 130:31–45. doi: 10.1016/j.cmpb.2016.02.019

32. Hmida M, Hamrouni K, Solaiman B, Boussetta S. Mammographic MassSegmentation Using Fuzzy Contours. Comput Methods Prog BioMed (2018) 164:131–42. doi: 10.1016/j.cmpb.2018.07.005

33. Kashyap KL, Bajpai MK, Khanna P. Globally Supported Radial Basis FunctionBased Collocation Method for Evolution of Level Set in Mass Segmentation Using Mammograms. Comput Biol Med (2017) 87:22–37. doi: 10.1016/ j.compbiomed.2017.05.015

34. Song E, Jiang L, Jin R, Zhang L, Yuan Y, Li Q. Breast Mass Segmentation inMammography Using Plane Fitting and Dynamic Programming. Acad Radiol (2009) 16(7):826–35. doi: 10.1016/j.acra.2008.11.014

35. Anderson NH, Hamilton PW, Bartels PH, Thompson D, Montironi R, SloanJM. Computerized Scene Segmentation for the Discrimination of Architectural Features in Ductal Proliferative Lesions of the Breast. J Pathol (1997) 181(4):374–80. doi: 10.1002/(SICI)1096-9896(199704)181:4<374:: AID-PATH795>3.0.CO;2-N

36. Fowler EEE, Smallwood AM, Khan NZ, Kilpatrick K, Sellers TA, Heine J.Technical Challenges in Generalizing Calibration Techniques for Breast Density Measurements. Med Phys (2019) 46(2):679–88. doi: 10.1002/mp.13325

37. Hudson S, Vik Hjerkind K, Vinnicombe S, Allen S, Trewin C, Ursin G, et al. Adjusting for BMI in Analyses of Volumetric Mammographic Density and Breast Cancer Risk. Breast Cancer Res (2018) 20(1):156. doi: 10.1186/s13058018-1078-8

38. Mohamed AA, Berg WA, Peng H, Luo Y, Jankowitz RC, Wu S. A Deep Learning Method for Classifying Mammographic Breast Density Categories. Med Phys (2018) 45(1):314–21. doi: 10.1002/mp.12683

39. Mohamed AA, Luo Y, Peng H, Jankowitz RC, Wu S. Understanding ClinicalMammographic Breast Density Assessment: A Deep Learning Perspective. J Digit Imaging (2018) 31(4):387–92. doi: 10.1007/s10278-017-0022-2

40. Le Boulc'h M, Bekhouche A, Kermarrec E, Milon A, Abdel Wahab C, Zilberman S, et al. Comparison of Breast Density Assessment Between Human Eye and Automated Software on Digital and Synthetic Mammography: Impact on Breast Cancer Risk. Diagn Interv Imaging (2020) 101(12):811–9. doi: 10.1016/j.diii.2020.07.004

41. Lehman CD, Yala A, Schuster T, Dontchos B, Bahl M, Swanson K, et al.Mammographic Breast Density Assessment Using Deep Learning: Clinical Implementation. Radiology (2019) 290(1):52–8. doi: 10.1148/radiol. 2018180694

42. Sun YS, Zhao Z, Yang ZN, Xu F, Lu HJ, Zhu ZY, et al. Risk Factors andPreventions of Breast Cancer. Int J Biol Sci (2017) 13(11):1387–97. doi: 10.7150/ijbs.21635

43. Nindrea RD, Aryandono T, Lazuardi L, Dwiprahasto I. Diagnostic Accuracyof Different Machine Learning Algorithms for Breast Cancer Risk Calculation: A Meta-Analysis. Asian Pac J Cancer Prev (2018) 19(7):1747–52. doi: 10.22034/APJCP.2018.19.7.1747

44. Sepandi M, Taghdir M, Rezaianzadeh A, Rahimikazerooni S. Assessing BreastCancer Risk With an Artificial Neural Network. Asian Pac J Cancer Prev (2018) 19(4):1017–9. doi: 10.31557/APJCP.2018.19.12.3571

45. Yala A, Lehman C, Schuster T, Portnoi T, Barzilay R. A Deep LearningMammography-Based Model for Improved Breast Cancer Risk Prediction. Radiology (2019) 292(1):60–6. doi: 10.1148/radiol.2019182716

46. Teare P, Fishman M, Benzaquen O, Toledano E, Elnekave E. MalignancyDetection on Mammography Using Dual Deep Convolutional Neural Networks and Genetically Discovered False Color Input Enhancement. J Digit Imaging (2017) 30(4):499–505. doi: 10.1007/s10278-017-9993-2

47. Akkus Z, Cai J, Boonrod A, Zeinoddini A, Weston AD, Philbrick KA, et al. ASurvey of Deep-Learning Applications in Ultrasound: Artificial IntelligencePowered Ultrasound for Improving Clinical Workflow. J Am Coll Radiol (2019) 16(9 Pt B):1318–28. doi: 10.1016/j.jacr.2019.06.004

48. Wu GG, Zhou LQ, Xu JW, Wang JY, Wei Q, Deng YB, et al. Artificial Intelligence in Breast Ultrasound. World J Radiol (2019) 11(2):19–26. doi: 10.4329/wjr.v11.i2.19

49. Park HJ, Kim SM, La Yun B, Jang M, Kim B, Jang JY, et al. A Computer-AidedDiagnosis System Using Artificial Intelligence for the Diagnosis and Characterization of Breast Masses on Ultrasound: Added Value for the Inexperienced Breast Radiologist. Med (Baltimore) (2019) 98(3):e14146. doi: 10.1097/MD.0000000000014146

50. Hu Y, Guo Y, Wang Y, Yu J, Li J, Zhou S, et al. Automatic TumorSegmentation in Breast Ultrasound Images Using a Dilated Fully Convolutional Network Combined With an Active Contour Model. Med Phys (2019) 46(1):215–28. doi: 10.1002/mp.13268

51. Kumar V, Webb JM, Gregory A, Denis M, Meixner DD, Bayat M, et al.Automated and Real-Time Segmentation of Suspicious Breast Masses Using Convolutional Neural Network. PloS One (2018) 13(5):e0195816. doi: 10.1371/journal.pone.0195816

52. Feng Y, Dong F, Xia X, Hu CH, Fan Q, Hu Y, et al. An Adaptive Fuzzy CMeans Method Utilizing Neighboring Information for Breast Tumor Segmentation in Ultrasound Images. Med Phys (2017) 44(7):3752–60. doi: 10.1002/mp.12350

53. Hsu SM, Kuo WH, Kuo FC, Liao YY. Breast Tumor Classification Using Different Features of Quantitative Ultrasound Parametric Images. Int J Comput Assist Radiol Surg (2019) 14(4):623–33. doi: 10.1007/s11548-018-01908-8

54. Zhang Q, Xiao Y, Dai W, Suo J, Wang C, Shi J, et al. Deep Learning BasedClassification of Breast Tumors With Shear-Wave Elastography. Ultrasonics (2016) 72:150–7. doi: 10.1016/j.ultras.2016.08.004

55. Choi JH, Kang BJ, Baek JE, Lee HS, Kim SH. Application of Computer-AidedDiagnosis in Breast Ultrasound Interpretation: Improvements in Diagnostic Performance According to Reader Experience. Ultrasonography (2018) 37 (3):217–25. doi: 10.14366/usg.17046

56. Ciritsis A, Rossi C, Eberhard M, Marcon M, Becker AS, Boss A. AutomaticClassification of Ultrasound Breast Lesions Using a Deep Convolutional Neural Network Mimicking Human Decision-Making. Eur Radiol (2019) 29 (10):5458–68. doi: 10.1007/s00330-019-06118-7

57. Becker AS, Mueller M, Stoffel E, Marcon M, Ghafoor S, Boss A. Classification of Breast Cancer in Ultrasound Imaging Using a Generic Deep Learning Analysis Software: A Pilot Study. Br J Radiol (2018) 91(1083):20170576. doi: 10.1259/bjr.20170576

58. Zheng X, Yao Z, Huang Y, Yu Y, Wang Y, Liu Y, et al. Deep learningradiomics can predict axillary lymph node status in early-stage breast cancer. Nat Commun (2020) 11(1):1236. doi: 10.1038/s41467-020-15027-z

59. Sheth D, Giger ML. Artificial Intelligence in the Interpretation of Breast Cancer on MRI. J Magn Reson Imaging (2020) 51(5):1310–24. doi: 10.1002/ jmri.26878
60. Herent P, Schmauch B, Jehanno P, Dehaene O, Saillard C, Balleyguier C, et al.Detection and Characterization of MRI Breast Lesions Using Deep Learning. Diagn Interv Imaging (2019) 100(4):219–25. doi: 10.1016/j.diii.2019.02.008
61. Xu X, Fu L, Chen Y, Larsson R, Zhang D, Suo S, et al. Breast RegionSegmentation Being Convolutional Neural Network in Dynamic Contrast Enhanced MRI. Annu Int Conf IEEE Eng Med Biol Soc (2018) 2018:750–3. doi: 10.1109/EMBC.2018.8512422
62. Truhn D, Schrading S, Haarburger C, Schneider H, Merhof D, Kuhl C.Radiomic Versus Convolutional Neural Networks Analysis for Classification of Contrast-Enhancing Lesions at Multiparametric Breast MRI. Radiology (2019) 290(2):290–7. doi: 10.1148/radiol.2018181352
63. Gallego-Ortiz C, Martel AL. A Graph-Based Lesion Characterization andDeep Embedding Approach for Improved Computer-Aided Diagnosis of Nonmass Breast MRI Lesions. Med Image Anal (2019) 51:116–24. doi:10.1016/j.media.2018.10.011
64. Vidic I, Egnell L, Jerome NP, Teruel JR, Sjobakk TE, Ostlie A, et al. SupportVector Machine for Breast Cancer Classification Using Diffusion-Weighted MRI Histogram Features: Preliminary Study. J Magn Reson Imaging (2018) 47 (5):1205–16. doi: 10.1002/jmri.25873
65. Illan IA, Ramirez J, Gorriz JM, Marino MA, Avendano D, Helbich T, et al.Automated Detection and Segmentation of Nonmass-Enhancing Breast Tumors With Dynamic Contrast-Enhanced Magnetic Resonance Imaging. Contrast Media Mol Imaging (2018) 2018:5308517. doi: 10.1155/2018/ 5308517
66. Antropova N, Abe H, Giger ML. Use of Clinical MRI Maximum IntensityProjections for Improved Breast Lesion Classification With Deep Convolutional Neural Networks. J Med Imaging (Bellingham) (2018) 5 (1):014503. doi: 10.1117/1.JMI.5.1.014503
67. Jiang Y, Edwards AV, Newstead GM. Artificial Intelligence Applied to Breast MRI for Improved Diagnosis. Radiology (2021) 298(1):38–46. doi: 10.1148/ radiol.2020200292
68. Meyer-Base A, Morra L, Meyer-Base U, Pinker K. Current Status and FuturePerspectives of Artificial Intelligence in Magnetic Resonance Breast Imaging. Contrast Media Mol Imaging (2020) 2020:6805710. doi: 10.1155/2020/ 6805710
69. Hao W, Gong J, Wang S, Zhu H, Zhao B, Peng W. Application of MRIRadiomics-Based Machine Learning Model to Improve Contralateral BIRADS 4 Lesion Assessment. Front Oncol (2020) 10:531476. doi: 10.3389/ fonc.2020.531476
70. Song SE, Seo BK, Cho KR, Woo OH, Son GS, Kim C, et al. Computer-aideddetection (CAD) system for breast MRI in assessment of local tumor extent, nodal status, and multifocality of invasive breast cancers: preliminary study. Cancer Imaging (2015) 15(1):1. doi: 10.1186/s40644-015-0036-2
71. Tahmassebi A, Wengert GJ, Helbich TH, Bago-Horvath Z, Alaei S, Bartsch R,et al. Impact of Machine Learning With Multiparametric Magnetic Resonance Imaging of the Breast for Early Prediction of Response to Neoadjuvant Chemotherapy and Survival Outcomes in Breast Cancer Patients. Invest Radiol (2019) 54(2):110-7. doi: 10.1097/RLI.0000000000000518
72. Morgan MB, Mates JL. Applications of Artificial Intelligence in Breast Imaging. Radiol Clin North Am (2021) 59(1):139–48. doi: 10.1016/j.rcl.2020.08.007

73. Hupse R, Samulski M, Lobbes MB, Mann RM, Mus R, den Heeten GJ, et al.Computer-Aided Detection of Masses at Mammography: Interactive Decision Support Versus Prompts. Radiology (2013) 266(1):123–9. doi: 10.1148/ radiol.12120218

74. Quellec G, Lamard M, Cozic M, Coatrieux G, Cazuguel G. Multiple-InstanceLearning for Anomaly Detection in Digital Mammography. IEEE Trans Med Imaging (2016) 35(7):1604–14. doi: 10.1109/TMI.2016.2521442

75. Mendelson EB. Artificial Intelligence in Breast Imaging: Potentials and Limitations. AJR Am J Roentgenol (2019) 212(2):293–9. doi: 10.2214/ AJR.18.20532

76. Qi X, Zhang L, Chen Y, Pi Y, Chen Y, Lv Q, et al. Automated Diagnosis ofBreast Ultrasonography Images Using Deep Neural Networks. Med Image Anal (2019) 52:185–98. doi: 10.1016/j.media.2018.12.006

77. Kooi T, Litjens G, van Ginneken B, Gubern-Merida A, Sanchez CI, Mann R,et al. Large Scale Deep Learning for Computer Aided Detection of Mammographic Lesions. Med Image Anal (2017) 35:303–12. doi: 10.1016/ j.media.2016.07.007

78. Kim J, Kim HJ, Kim C, Kim WH. Artificial Intelligence in Breast Ultrasonography. Ultrasonography (2021) 40(2):183–90. doi: 10.14366/ usg.20117

79. Sechopoulos I, Teuwen J, Mann R. Artificial Intelligence for Breast Cancer Detection in Mammography and Digital Breast Tomosynthesis: State of the Art. Semin Cancer Biol (2020) 72:214-25. doi: 10.1016/j.semcancer.2020.06.002

80. Skaane P, Bandos AI, Niklason LT, Sebuodegard S, Osteras BH, Gullien R, et al. Digital Mammography Versus Digital Mammography Plus Tomosynthesis in Breast Cancer Screening: The Oslo Tomosynthesis Screening Trial. Radiology (2019) 291(1):23–30. doi: 10.1148/radiol.2019182394

81. Lotter W, Diab AR, Haslam B, Kim JG, Grisot G, Wu E, et al. Robust BreastCancer Detection in Mammography and Digital Breast Tomosynthesis Using an Annotation-Efficient Deep Learning Approach. Nat Med (2021) 27(2):244– 9. doi: 10.1038/s41591-020-01174-9

82. Zhang Q, Song S, Xiao Y, Chen S, Shi J, Zheng H. Dual-Mode ArtificiallyIntelligent Diagnosis of Breast Tumors in Shear-Wave Elastography and BMode Ultrasound Using Deep Polynomial Networks. Med Eng Phys (2019) 64:1–6. doi: 10.1016/j.medengphy.2018.12.005

83. Adachi M, Fujioka T, Mori M, Kubota K, Kikuchi Y, Xiaotong W, et al.Detection and Diagnosis of Breast Cancer Using Artificial Intelligence Based Assessment of Maximum Intensity Projection Dynamic Contrast-Enhanced Magnetic Resonance Images. Diag (Basel) (2020) 10(5):330. doi: 10.3390/ diagnostics10050330

84. Dalmis MU, Gubern-Merida A, Vreemann S, Bult P, Karssemeijer N, Mann R,et al. Artificial Intelligence-Based Classification of Breast Lesions Imaged With a Multiparametric Breast MRI Protocol With Ultrafast DCE-MRI, T2, and CT scan.