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The application of mammography imaging in the diagnosis and prediction of breast diseases

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Highlights

Computer-assisted detection, diagnosis, and prediction systems play an effective role in diagnosing and treating female breast diseases and monitoring the course of disease. Especially in mammography imaging, they provide key support for the early diagnosis of breast cancer. This highlights the significance of modern technology in enhancing breast disease management and improving women's health.

Abstract

Breast diseases pose a significant threat to women's health, so early detection and treatment are extremely important. In this context, early disease identification has become crucial in the diagnosis and treatment of breast diseases. This paper begins by outlining the pivotal role of mammography in the early diagnosis of breast cancer, comparing the structural similarities and differences between normal and diseased breast tissues. This comparison underscores the primary role of mammography in the diagnosis and treatment of breast diseases. Additionally, our paper provides an overview of fundamental concepts related to breast cancer detection, diagnosis, and prediction systems. It delves into the latest research developments in auxiliary diagnostic detection, examination, and risk prediction systems associated with breast cancer. Our objective is to offer a comprehensive understanding of the role of computer-aided detection, diagnosis, and prediction systems in breast diseases, fostering further development and application. This work aims to explore and drive innovation in the field, enhance early detection rates of breast diseases, and guide readers towards novel directions, thus contributing to female healthcare management.

Keywords: Mammography, imaging, computer-aided diagnosis, deep learning, multi-modality

Introduction

Since 1991, the incidence of breast cancer has been on the rise, establishing it as the predominant cause of mortality among women aged 20 to 59. According to the global cancer statistics report released by the American Cancer Society in January 2023, breast cancer has become the most prevalent cancer among women. It was estimated that in 2023, there would be 300,590 new cases of breast cancer in the United States with 297,790 female cases, constituting for 31% of all cancers in women [1].

The strategies pertaining to early detection and treatment of breast cancer have garnered substantial attention and witnessed notable advancements [2]. The mortality rate linked to breast cancer in women attained its apex in 1989 and since then has exhibited a declining trajectory. This downward trend can be attributed to advancements in early detection technologies, particularly notable enhancements in mammography, ultrasound, and treatment modalities, resulting in a substantial 42% reduction in the mortality rate [3]. Practice has proven that imaging plays a very important role in the detection, diagnosis, and prediction of

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breast diseases. Timely screening and early intervention and treatment have demonstrated significant efficacy in enhancing patient survival rates [2].

In the realm of breast disease diagnosis, the main examination methods encompass X-rays, ultrasound, MRI, computed tomography, among others. Mammography X-ray examination is simple to operate and low in cost, so it is the preferred imaging diagnostic method [4]. Computer-aided diagnosis (CAD) system, an integration of medical imaging and computer science, colloquially referred to as the "radiologist's auxiliary visual aid", is meticulously crafted to expedite the overall comprehension of mammograms by radiologists. Empirical observations have substantiated that the capacity of the CAD systems can improve the early detection rate of cancers. For example, the study by Morton and his team showed a 7.62% increase in the detection of breast cancers using CAD in cases with benign or negative results [5]. The CAD system exhibits proficiency in prognosticating the malignancy level of breast lesions. Illustratively, a study conducted by Ramadan et al. in 2016 employed a feature selection algorithm and a support vector machine classifier to analyze features such as morphology, size, and margins of breast masses to predict their malignancy, and showed an accuracy rate of 84.7% [6].

In recent times, deep learning (DL) has demonstrated significant achievements across diverse domains, encompassing applications such as automatic speech recognition and optical character recognition, natural language processing, as well as object detection, recognition, and classification. These milestones signify not only a notable progression within the sphere of machine learning but also herald a new epoch in the domain of computer vision [7]. Consequently, DL methodologies have sparked unparalleled enthusiasm in various sectors of pattern recognition and artificial intelligence (AI), notably including the domain of CAD in the field of medicine. CAD integrates machine learning techniques and interdisciplinary knowledge to analyze medical imaging and non-imaging data, facilitating the provision of analytical outcomes to clinicians. The outcomes generated by the CAD system function as a secondary evaluation or decision support for patients at diverse stages of the healthcare continuum [8]. This underscores the scalability and dependability of CAD as a decision support tool for clinicians, particularly in the realm of breast imaging applications.

This paper, firstly, introduces the detection methods of breast X-ray imaging, emphasizing its significance in the early diagnosis of breast cancer. By comparing the structures of normal and pathological breast tissues, the pivotal role of breast X-ray mammography in the diagnosis and treatment of breast diseases is elucidated. Subsequently, the article provides a brief overview of the fundamental concepts related to breast cancer detection, diagnosis, and prediction systems. It further delves into recent research developments, with a specific focus on advancements in breast cancer auxiliary diagnostic detection and risk prediction systems. The purpose of this paper is to review breast cancer CAD systems and related technologies based on mammography imaging, with an aim to attract more attention to the field of breast cancer CAD research and advance studies on breast cancer detection, diagnosis, and prediction systems.

Applicability of mammography imaging in the diagnosis and treatment of breast diseases

Imaging modalities have long been indispensable in both the initial screening and later-stage assessment of breast cancer. Currently, in the diagnostic process of breast cancer, physicians prefer non-invasive examination techniques to minimize adverse effects on patients' body. Ultrasound, mammography, and MRI are commonly employed detection modalities in the medical staff's pursuit of accurate disease determination. They can effectively participate in the process of detecting and classifying breast lesions [9]. Simultaneously, they can contribute to the preoperative staging, efficacy evaluation, and prognosis monitoring processes. Mammography images can fully reflect the anatomy of the whole breast, presenting most of the features for qualitative diagnosis, and in particular, clearly showing the micro calcified foci of breast lesions. Therefore, most studies adopt molybdenum images, a considerable number of studies utilize ultrasound images, and a minority of studies used MRI [10].

During the mammography, a patient is first palpated by an experienced doctor before film taking. The patient undergoes the routine ultrasound examination first, followed by photography. Bilateral breast axial craniocaudal (CC) view (the patient's bilateral breasts are placed flat between two splints, and the mammography X-ray is irradiated vertically from top to bottom) and the mediolateral oblique (MLO) view (the patient is placed in the upright position, placing the film beneath the breast externally, and the X-ray is projected at an angle of 45° from the lower part of the breast) are usually

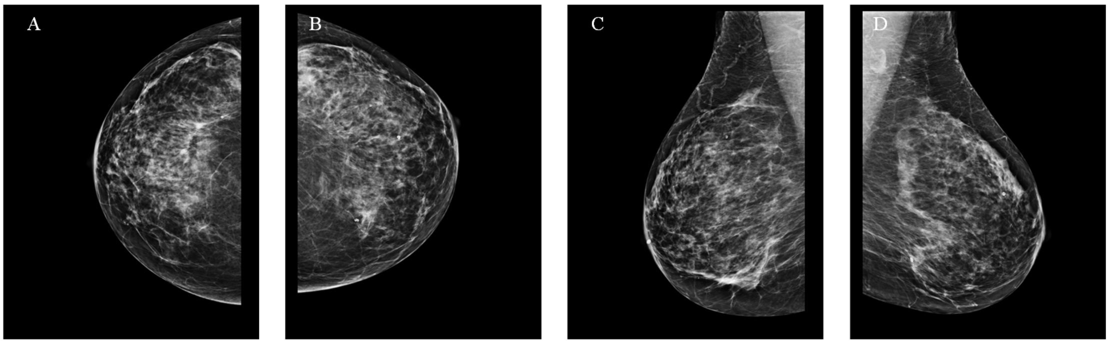

Figure 1. Example of the available views from a mammographic session. (A) Right CC view; (B) Left CC view; (C) Right MLO view; (D) Left MLO view. This figure was cited from the Chinese Mammography Database. CC, craniocaudal; MLO, medial-lateral oblique.

chosen for imaging (**Figure 1**). **Figure 1** was cited from the Chinese Mammography Database.

In mammography images depicting normal breast tissue, distinct anatomical components, such as the nipple, areola, skin, subcutaneous fat, and glandular tissue, are typically discernible. Conversely, mammographic images of patients afflicted with breast tumors often present of calcifications, masses, or a combination of both. Calcifications can manifest in both benign and malignant neoplasms. For clinicians, factors such as the size, shape, and distribution of calcifications hold diagnostic significance. Masses usually exhibit varying shape and margin distortion, presenting as round, oval, lobulated, or irregular entities with indistinct boundaries, accompanied by spiculations and infiltrations, often featuring higher densities in relation to the surrounding glandular tissue. Because breast cancer is a malignant tumor that results from the abnormal proliferation of ductal or lobular epithelial cells in breast tissue, a high prevalence is found in the breast epithelial tissue [11].

In mammography images, normal breast tissue and cancer-affected breast tissue exhibit distinct structural differences, including density, morphology, borders, and microcalcifications. Breast cancer tissue typically appears as areas of high density in mammography images, whereas normal breast tissue is characterized by uniformly distributed low-density areas [12]. Morphologically, breast cancer tissue may present as irregular nodules, patches, or masses, while normal breast tissue generally exhibits a more uniform appearance. The borders of breast cancer tissue tend to be less defined, often displaying spiculated or irregular edges, whereas the borders of normal breast tissue are clearer [13]. In mammography images, breast cancer tissue may manifest as atypical microcalcifications, a feature that is generally absent in normal breast tissue. These structural variances play a crucial role in early diagnosis and quantitative analysis of breast cancer. Early detection of breast cancer can enhance the likelihood of successful treatment and reduce the risk of patient mortality. Mammography imaging aids clinicians in detecting abnormal breast tissue and identifying potential tumors at an early stage.

With mammography imaging technology, physicians can utilize features, such as image density, morphological characteristics, boundary clarity, and microcalcifications, to identify potential abnormal tissues. With their medical expertise and clinical experience, physicians can assess these image features and make accurate diagnoses by integrating them with other clinical information. Furthermore, advanced imaging techniques, such as digital mammography and breast ultrasound, provide more detailed information about breast tissue, assisting doctors in precise diagnosis and formulating treatment plans [14].

In the diagnosis of suspected breast lesions in females, X-ray mammography and breast ultrasound exhibit comparable diagnostic accuracy, albeit with X-ray mammography images demonstrating notably higher specificity than breast ultrasound, characterized by robust targeting capabilities and heightened sensitivity. The rapid advancements in computerized imaging and digital image processing technologies have propelled the progress of mammography, yielding clearer images with enhanced contrasts [15]. Leveraging low-energy, long-wavelength X-rays with limited penetration, mammography is particularly well-suited for breast tissue examination [16]. Globally, it is widely acknowledged as the foremost screening tool for breast cancer. In the United States, mammography has been integrated into routine screenings for women as an essential diagnostic tool. Per the guidelines of the American Cancer Society, routine mammograms are recommended every one to two

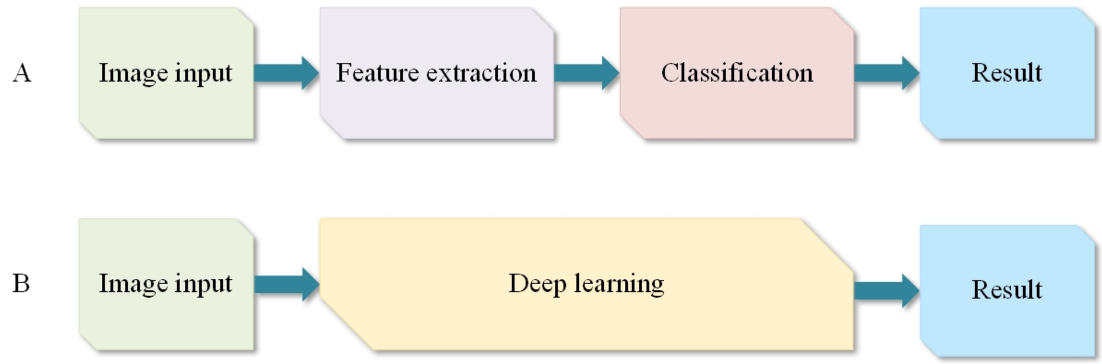

Figure 2. Traditional CAD and AI-CAD processes. (A) Human defines features: CAD; (B) AI extracts features from learning data: Deep Learning AI-CAD. CAD, computer-assisted diagnosis; AI, artificial intelligence.

years for women aged 40 to 49, which significantly enhances the early detection of breast cancer [17].

Application of mammography imaging in the diagnosis and treatment of breast diseases

Imaging technology is a crucial means for the diagnosis, staging, and assessment of breast cancer. Studies using computers to automatically analyze radiographic images emerged in the 1960s. Some researchers attempted to use computers to automatically detect breast abnormalities, a pursuit constrained by computational resource limitations and challenges associated with acquiring high-fidelity digitized image data [18]. Despite the initial feasibility of these early endeavors, they garnered limited attention. Over the subsequent five decades, significant advancements have unfolded in the domain of medical imaging technology. By 2017, a study showed that the sensitivity of breast cancer screening with mammography images had increased from 78.7% to 86.9% [19].

In the quest to enhance the lucidity of patient lesion details and enable refined and accurate diagnostic assessments, ongoing advancements in medical imaging technology persist, accompanied by a proliferation of data. Iterative reviews or the involvement of multiple radiologists in the interpretation of the same mammographic image have the potential to diminish misdiagnosis rates. However, this approach can be exceedingly labor-intensive and costly, exerting a substantial burden on healthcare systems. In 1966, Ledley proposed CAD system in an article published in Science [20]. This system integrates computer technology with medical diagnosis, utilizing robust computational capabilities to analyze medical images and assist physicians in disease diagnosis. The initial CAD systems can be categorized into two types: one is CADe that used for computer-aided detection, in which the computer annotates and indicates the location of suspected lesion areas in the medical image, followed by the doctor's diagnosis of the condition and management of the patient; and the other is CADx that used for computer-aided diagnosis, in which the preliminary task of annotating lesion areas is given to a person or a computer, with the computer generating the final diagnosis results and displaying them to the physician, such as the probability of malignancy. CAD has been used to screen mammography images for over 20 years. In recent years, the convergence of AI and computer-aided detection and diagnosis has led to the emergence of AI-CAD, which harnesses the potential of cutting-edge techniques such as machine learning and DL for intricate medical image analysis and diagnostics. By leveraging these cutting-edge technologies, AI-CAD surpasses traditional CAD systems, better comprehending the complex features of medical images and providing more accurate diagnostic results (**Figure 2**). This system not only facilitates the identification of anomalous regions but also delivers refined diagnostic recommendations based on extensive data, thereby amplifying a more significant role in clinical applications.

Overall, CADe provides comprehensive detection support, while CADx emphasizes rapid diagnosis of abnormal regions. AI-CAD, on the other hand, has made significant strides in both aspects, leveraging advanced AI technologies to enhance diagnostic accuracy and efficiency.

Mammography used in the detection of breast diseases

The purpose of CADe is to automate the localization of disease classification and to integrate the physician's judgement to form a practical and useful diagnostic prediction. Huo et al. investigated a CADe based on mammography im-

Table 1. Some neural network architectures for medical tissue segmentation and classification

Network name	Reference
CNN	Cai et al. (2020) [53] Chakravarthy and Rajaguru (2022) [54]
U-Net	Ronneberger et al. (2015) [55]
VGGNet	Simonyan and Zisserman (2014) [56]
DenseNet	Huang et al. (2017) [57]
ImageNet	Sert et al. (2017) [58]
UNETR	Hatamizadeh et al. (2022) [59]
Transunet	Chen et al. (2021) [60]
Doubleu-net	Jha et al. (2020) [61]
Swin-unet	Cao et al. (2022) [62]
Medical SAM adapter	Wu et al. (2023) [63]

Note: CNN, Convolutional Neural Network; VGG, Visual Geometry Group; UNETR, U-net Transformer.

ages, in which a radiologist or an experienced X-ray examiner manually scored the appearance of the mass in the image and then followed up with a computer [21]. In the preliminary investigation, four features, namely spiculation, edge density, and two density correlation metrics of the mass, were extracted and subsequently subjected to classification utilizing a neural network and a hybrid classifier, ultimately generating the detection outcomes. Subsequent to the initial study, Huo et al. made several iterative improvements to the methodology. The first improvement involved the application of region growing and radial edge gradients to extract spiculation features, introducing a rule-based method and the integration of an artificial neural network as a hybrid information processing approach [22]. In Huo's earlier study, they used the patient's mammography images in MLO position and head-to-tail CC position, while in the subsequent study, images in special positions (such as spot compression or spot magnification views) were also added. Studies have shown that mammography images with special views are more helpful for radiologists in distinguishing benign and malignant lesions than images with standard views [23].

Liao et al. developed a DL system based on DenseNet combined with quality algorithms [24]. The system exhibited high sensitivity in detecting breast mass, outstanding performance in diagnosing benign-malignant asymmetric lesions, and proficiency in diagnosing such lesions in both dense and non-dense breasts. This system demonstrated an excellent performance compared with junior radiologists. Balaji et al. proposed a breast cancer detection method based on Chimp Optimization Algorithm Based Type-2 Intuitionistic Fuzzy C-Means Clustering (COA-T2FCM), combining type-2 intuitionistic fuzzy C-means clustering and an oppositional function [25]. The method was tested on three datasets, exhibiting high accuracy and similarity. Similarly, Pal et al. employed a hybrid segmentation technique based on Fruitfy optimization algorithm and Fuzzy C-Means clustering, utilizing extended Gabor wavelet transform for MRI image feature extraction, enabling early diagnosis of breast cancer. Research findings indicated a superior performance and accuracy (96.50%) of the hybrid segmentation technique, holding promising implications for precise localization of breast cancer lesions [26].

The optimization of mammography imaging for breast cancer detection is fundamentally grounded in two key dimensions: patient positioning and the application of CADe strategies in image processing.

Strategically adjusting the patient's posture to an optimal position is a pivotal factor influencing the efficacy of breast X-ray mammography image detection. This adjustment is not merely a procedural formality but a critical determinant in mitigating the complexities associated with image interpretation. The optimization strategy serves not only to alleviate challenges posed by anatomical complexities but also provides a stable and reliable foundation for CADe systems.

Simultaneously, the development and application of CADe strategies offer new possibilities for optimizing diagnostic accuracy and the workflow of healthcare professionals. Beyond their conventional role as diagnostic aids, improved CADe trategies are poised to yield profound impacts, including heightened accuracy in breast cancer diagnosis, reduced cognitive burden on healthcare professionals, and alterations to existing diagnostic patterns. These advancements hold promise to simplify processes and foster an environment conducive to improving diagnostic outcomes, shaping the future landscape of breast X-ray mammography imaging in breast cancer detection. This progress not only strengthens the theoretical foundations of mammography imaging but also

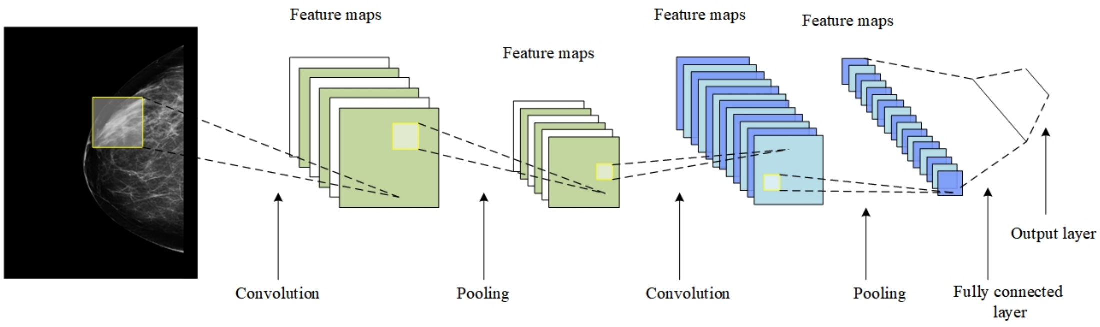

Figure 3. Convolutional neural networks. The input images in the neural network shown was cited from the Chinese Mammography Database.

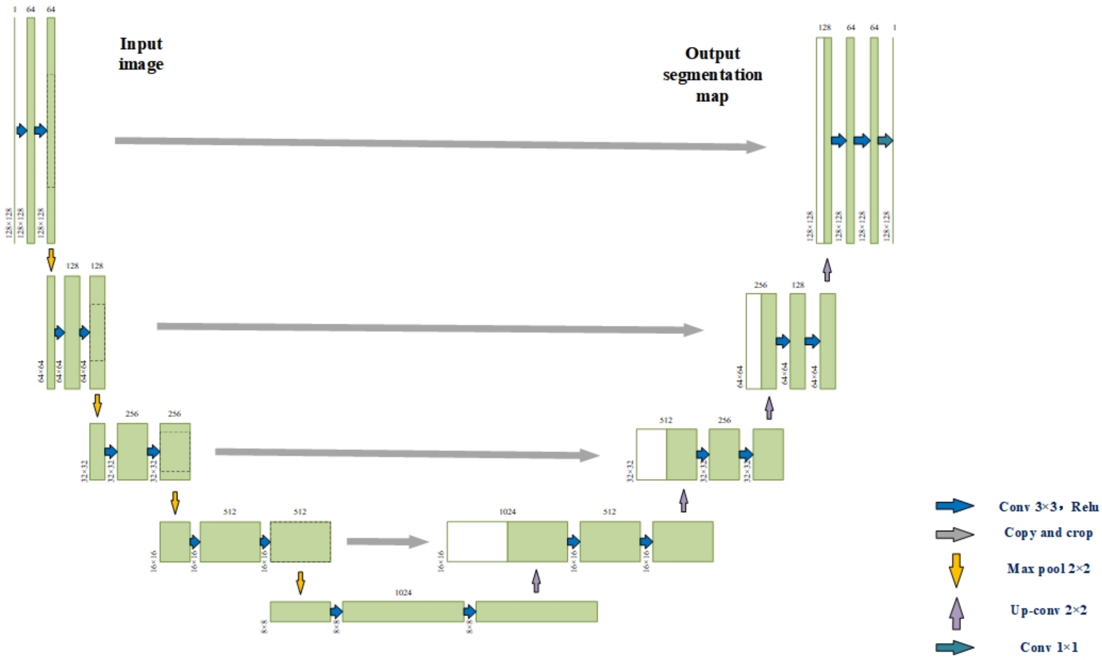

Figure 4. U-net architecture. This figure was adapted from [34].

provides valuable insights for future research and clinical practices.

Mammography used in the diagnosis of breast cancer

In the mid-1980s, the University of Chicago began to focus on CADx for the diagnosis of breast cancer based on mammography images [27]. Early-stage breast cancer usually presents tiny masses and microcalcifications that are challenging to detect in medical images. Applying CAD in the diagnosis of breast cancer can improve the accuracy of the localization and identification of lumps and calcification sites and to reduce identification errors due to the overlapping of structures or the presence of speckles in the image pictures.

Convolutional Neural Networks (CNNs), which originated as a new neural network in the early 1980s, were introduced into the field of medical image analysis in 1993 and are now widely used for solving a variety of technical problems in medical imaging (**Figure 3**) [28-30]. The input images in the neural network shown in **Figure 3** was cited from the Chinese Mammography Database. Most of studies adapted some well-known CNN architectures, such as modified versions of the architectural frameworks of AlexNet, various iterations of GoogleNet, and diverse iterations of Microsoft's ResNet, with alterations in the hyperparameters or kernel layers of the original structures [31-33]. **Table 1** lists some neural network architectures for medical tissue segmentation and classification. Drawbacks of DL include the requirement for large datasets for training and uncertainties in the diagnostic significance of many deep-learned image features. This uncertainty diminishes the interpretability of deep neural network outputs, making the assessment of the importance of imaging information and the role of each feature in classification performance rather challenging.

Almajalid et al. designed a DL framework with a segmentation architecture and applied it to the assisted diagnosis of breast cancer based on molybdenum target images called U-net (**Figure 4**) [34]. **Figure 4** is adapted from [34]. U-net is a CNN framework that has been widely adopted by numerous researchers in subsequent studies. Given the significant time cost associated with manual segmentation, automatic segmentation of images has become an inevitable trend. Ragab et al. devised an ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification (EDLCDS-BCDC) on ultrasound images, which incorporates chaotic krill herd algorithm and Kapur entropy techniques and uses optimal multilevel thresholding for image segmentation to identify regions affected by tumors [9]. Integration of three DL models (Visual Geometry Group (VGG)-16, VGG-19, and SqueezeNet) is used for feature extraction. Cat swarm optimization based on the multi-layer perceptron model is also used to classify breast cancer images to determine the presence of cancer. In contrast to the current prevalent learning approach, Chaudhury introduced a novel DL framework for diagnosing and classifying breast cancer using the concept of transfer learning [35]. Migration learning aims to acquire specific information from one problem to solve other similar problems. As a result, Chaudhury designed an attribute mining structure that uses CNN architectures such as GoogleNet, VGGNet, and residual networks that have been previously trained and fed into a fully linked layer to classify malignant and benign cells using an average pooling classification method. Wang et al. proposed a new model named DisAsymNet, employing self-adversarial learning guided by an asymmetric attention transformer to understand the differences between asymmetric and symmetric images for classification and diagnosis [36].

Qi et al. developed an automatic breast cancer diagnosis system that can be installed on a smartphone [37]. The scheme used molybdenum target images as input. Firstly, noise in the captured images was reduced, and high-quality images were reconstructed. Then, an initial subsystem was designed using a stacked denoising autoencoder framework and a generative adversarial network. Ultimately, a deep convolutional neural network was employed to capture the high-level features of the images and conduct binary classification of breast images, discerning between benign and malignant diagnoses. Ting et al. recommended a convolutional neural network algorithm to improve the classification of breast cancer laceration, which helps professionals diagnose the disease and classify the molybdenum images as benign, malignant, or healthy [38]. Kaur et al. developed a new algorithm with multiple support vector machines (MSVM) and DL mechanisms as the basis for proposing an automated system for breast cancer molybdenum images using k-mean clustering, and MSVM hybrid accelerated the recovery of features to obtain better classification results [39]. Following rigorous quantitative analysis and experimental validation, the study recommended the adoption of a multi-layer perceptron and J48+K mean clustering WEKA approach to achieve heightened accuracy. Baccouche et al. investigated an end-to-end based You Only Look Once (YOLO) fusion model for breast lesion detection and classification [40]. Their results indicated that using the YOLO model held promise in capturing overlooked lesions in early screening views that were clearly visible in the latest screening images.

Within the domain of CADx for diagnosing breast cancer through mammography images, it becomes apparent that the predominant strategies center on the DL-based classification of benign and malignant cancer images, as well as the segmentation of lesions within these images. Simultaneously, apart from efforts aimed at augmenting the precision of neural network diagnostic outcomes, there is a discernible research emphasis on the lightweighting network models [41].

This highlights a theoretical framework wherein the primary emphasis lies in the application of DL methodologies for the classification of breast cancer images and the delineation of lesions, underscoring a pivotal role for AI in diagnostic processes [42]. Concurrently, the research thrust towards lightweighting network models reflects a strategic exploration into optimizing computational efficiency without compromising diagnostic accuracy. This dual focus on classification and lightweighting is indicative of a nuanced approach within theoretical frameworks, aiming to balance diagnostic efficacy with computational feasibility in the context of breast cancer diagnosis through CADx methodologies.

Mammography used in the prediction of breast cancer

In recent years, research efforts have not only been dedicated to the advancement of medical imaging technology and the enhancement of image clarity but have also embraced the integration of multimodal information. This includes the integration of textual and image data into the research scope, aiming to establish breast cancer risk prediction models. These models enable risk assessment and screening for high-risk individuals, facilitating targeted intervention measures.

For instance, Kyono et al. developed a machine learning approach to identify normal cases in screening mammography [43]. Utilizing a Deep Convolutional Neural Network with multitask learning, it was trained to extract imaging features for prediction. The predictions from multiple views were combined with non-imaging patient data and input into another deep network for assessing case abnormalities. Kumar used the voting classifier technique to predict breast cancer and proposed a new model combining three classifiers, J48, Bayesian, and support vector machine, and used the voting fusion technique in the classification of benign and malignant tumors [44]. The study by Akselrod-Ballin et al. combined machine learning and DL to apply mammography images and electronic health records to construct a risk prediction model based on imaging histological features and clinical histological features [45]. The research employed standard breast image views alongside comprehensive clinical history as input, extracting medical imaging features and clinical case attributes as feature sets. By combining the eXtreme Gradient Boosting method and the minimum area under the Receiver Operating Characteristic curve method, the predictive results were binarily classified as cancer-positive or normal. Their model outperformed the commonly used Gail model, exhibiting superior sensitivity and specificity compared to the established benchmarks of the breast cancer surveillance consortium.

A team of researchers from the Computer Science and Artificial Intelligence Laboratory at the University of Massachusetts Institute of Technology and Massachusetts General Hospital has created a DL model capable of automatically predicting whether a patient is likely to develop breast cancer within the next five years based on mammographic images [46]. The utilized model incorporated full-field-of-view mammography images and considered several conventional risk factors, encompassing breast cancer diagnosis, imaging follow-up spanning at least five years post-diagnosis, age, weight, height, age at menarche, menopausal status, comprehensive family history of breast and ovarian cancer, BRCA mutation status, history of atypical hyperplasia, history of lobular carcinoma in situ, and breast density. The results demonstrated that the model was able to learn subtle patterns of malignancy signs in breast tissue with a 13% improvement in accuracy over the current clinical standard, the Tyrer-Cusick model (version 8). The study has also re-affirmed that mammograms and traditional risk factors contain complementary information and that traditional risk factors can also have a critical impact on breast cancer developement.

Qian et al. proposed a multi-path DL architecture based on multi-modal breast ultrasound images [47]. Their dataset selected patients with three imaging modes: ultrasound B-mode, color Doppler ultrasound, and elastography. Different weights were assigned to images from different imaging modes in the predictive model. Their research showed that the AI model was as good at predicting breast cancer risk as the 7 experienced radiologists in the study. Ali et al. introduced a label-free breast cancer detection tool based on a small data set [48]. The image data set used a combination of three nonlinear imaging modes (coherent anti-Stokes Raman-scattering, two-photon excited autofluorescence, and second harmonic generation), demonstrating that multi-modal imaging can improve the efficiency and accuracy of predictive diagnosis for small sample sizes of patients. Siviengphanom et al. demonstrated that the overall radiological profile of mammograms could be used to predict difficult-to-interpret cases and that a model that used either CC-view or MLO-view images alone was more accurate than a model used both CC and MLO views [49]. It was suggested that model with dual CC+MLO bits had lower performance, and quantitative overall radiomic features extracted from mammograms could help to accurately differentiate between hard-to-interpret normal cases and easy-to-interpret normal cases.

The assessment of bilateral breast asymmetry holds significance in the evaluation of cancer risk, as the presence of tumors often induces asymmetry in breast size. Studies by Li et al. have successively proposed breast cancer short-term risk prediction models based on local regional bilateral asymmetry features, and on global regional features combined with local regional features [50, 51]. Furthermore, the research conducted by Wengert et al. substantiates the pivotal role of a comprehensive evaluation of multimodal imaging in enhancing the accuracy of breast density measurement [52]. Breast density, as identified through multimodal imaging, emerges as a promising factor for risk prediction and stratification in the context of breast cancer.

In the realm of breast disease prediction, the application of mammography images has become a focal and highly discussed topic. By integrating mammography images with multimodal imaging, such as ultrasound images, and incorporating patient pathological information, we are advancing toward achieving a more precise prediction of breast diseases.

This discourse emphasizes the pivotal role of utilizing mammography images in breast disease prediction. The effective integration of these images with other modalities or patient pathology data provides us with a deliberate strategy to enhance the accuracy of auxiliary predictions. It underscores the potential synergies between different sources of medical information in shaping the theoretical framework for advancing breast disease prediction.

Conclusion and outlook

CAD plays a crucial role in the research and development of medical imaging, particularly in the field of mammography with molybdenum target images. Firstly, through a comprehensive examination of patient positioning, we can better understand how to improve the readability of molybdenum target images and the accuracy of breast disease diagnosis. Appropriate imaging positions can effectively enhance the display of breast morphology and details, assisting doctors in more accurately identifying and diagnosing breast diseases. Simultaneously, through the study of lightweight network models, it is possible to optimize the computational efficiency of models without compromising diagnostic accuracy, making it more practical for real-world applications and providing better support for molybdenum-targeted breast disease auxiliary diagnosis systems. By improving the performance of neural networks, we will further enhance the accuracy of breast disease diagnosis based on molybdenum target images, potentially predicting the likelihood of breast diseases. Finally, in the field of breast disease prediction, the integration of mammography images with other modal imaging and patient pathological information can further improve the prediction accuracy. However, despite some progress, continued in-depth research is needed to further optimize the performance of CAD systems and enhance their practical value in clinical practice.

References

[1] Siegel RL, Miller KD, Wagle NS, et al. Cancer statistics, 2023. CA Cancer J Clin 2023;73:17-48.
[2] Wilson J, Sule AA. Disparity in early detection of breast cancer. Treasure Island (FL). StatPearls Publishing, 2020.
[3] Siegel RL, Miller KD, Fuchs HE, et al. Cancer statistics, 2022. CA Cancer J Clin 2022;72:7-33.
[4] Ammar MB, Ayachi FL, de Paiva AC, et al. Harnessing Deep Learning for Early Breast Cancer Diagnosis: A Review of Datasets, Methods, Challenges, and Future Directions. Int J Comput Digital Syst 2024;15:1-13.
[5] Morton MJ, Whaley DH, Brandt KR, et al. Screening mammograms: interpretation with computer-aided detection-prospective evaluation. Radiology 2006;239:375-383.
[6] Ramadan SZ. Methods Used in Computer-Aided Diagnosis for Breast Cancer Detection Using Mammograms: A Review. J Healthc Eng 2020;2020:9162464.
[7] Esteva A, Chou K, Yeung S, et al. Deep learning-enabled medical computer vision. NPJ Digit Med 2021;4:5.
[8] Chan HP, Samala RK, Hadjiiski LM, et al. Deep learning in medical image analysis. Adv Exp Med Biol 2020;3-21.
[9] Ragab M, Albukhari A, Alyami J, et al. Ensemble Deep-Learning-Enabled Clinical Decision Support System for Breast Cancer Diagnosis and Classification on Ultrasound Images. Biology (Basel) 2022;11:439.
[10] Zhang X, Guo H. Research on an improved algorithm for image dehazing in underground coal mine. Journal of Physics: Conference Series (1693): The 2020 3rd International Conference on Computer Information Science and Artificial Intelligence (CISAI) 2020 25-27 September 2020, Inner Mongolia, China. IOP Publishing 2020;012153.
[11] Harbeck N,Gnant M. Breast cancer. Lancet 2017;389:1134-1150.
[12] Shrivastava N, Bharti J. Breast tumor detection and classification based on density. Multimed Tools Appl 2020;79:26467-26487.
[13] Durur Subaşı I. Breast imaging for non-radiologists. Erciyes Med J 2022;44:129-137.
[14] Arıbal E. Future of Breast Radiology. Eur J Breast Health 2023;19:262.
[15] Nyayapathi N. Development of Photoacoustic Technologies for Breast Cancer Imaging. New York (US). State University of New York 2020.
[16] Zhong LC, Yang T, Gu LP, et al. The diagnostic performance of shear wave velocity ratio for the differential diagnosis of benign and malignant breast lesions: Compared with VTQ, and mammography. Clin Hemorheol Microcirc 2021;77:123-131.
[17] Monticciolo DL. Current guidelines and gaps

in breast cancer screening. J Am Coll Radiol 2020;17:1269-1275.
[18] Winsberg F, Elkin M, Macy Jr J, et al. Detection of radiographic abnormalities in mammograms by means of optical scanning and computer analysis. Radiology 1967;89:211-215.
[19] Lehman CD, Arao RF, Sprague BL, et al. National performance benchmarks for modern screening digital mammography: update from the Breast Cancer Surveillance Consortium. Radiology 2017;283:49.
[20] Ledley RS. High-speed automatic analysis of biomedical pictures. Science 1964;146:216-223.
[21] Huo Z, Giger ML, Vyborny CJ, et al. Automated computerized classification of malignant and benign masses on digitized mammograms. Acad Radiol 1998;5:155-168.
[22] Huo Z, Giger ML, Vyborny CJ, et al. Analysis of spiculation in the computerized classification of mammographic masses. Med Phys 1995; 22:1569-1579.
[23] Huo Z, Giger ML,Vyborny CJ. Computerized analysis of multiple-mammographic views: Potential usefulness of special view mammograms in computer-aided diagnosis. IEEE Trans Med Imaging 2001;20:1285-1292.
[24] Liao T, Li L, Ouyang R, et al. Classification of asymmetry in mammography via the DenseNet convolutional neural network. Eur J Radiol Open 2023;11:100502.
[25] Balaji P, Muniasamy V, Bilfaqih SM, et al. Chimp Optimization Algorithm Influenced Type-2 Intuitionistic Fuzzy C-Means Clustering-Based Breast Cancer Detection System. Cancers 2023;15:1131.
[26] Pal S, Maity S, Adhikari S, et al. Breast Cancer Detection Using Hybrid Segmentation Using FOA and FCM Clustering. Proceedings of Springer (1450): Proceedings of 3rd International Conference on Mathematical Modeling and Computational Science. ICMMCS 2023. Advances in Intelligent Systems and Computing. Springer Cham 2023;65-78.
[27] Giger ML, Doi K, MacMahon H. Image feature analysis and computer☐aided diagnosis in digital radiography. 3. Automated detection of nodules in peripheral lung fields. Med Phys 1988;15:158-166.
[28] Fukushima K, Miyake S. Neocognitron: A new algorithm for pattern recognition tolerant of deformations and shifts in position. Pattern Recognit 1982;15:455-469.
[29] Lo SCB, Lin JS, Freedman MT, et al. Computer-assisted diagnosis of lung nodule detection using artificial convoultion neural network. Proceedings of SPIE (1898): Medical Imaging 1993: Image Processing 1993;859-869.
[30] Zhang W, Li R,Deng H, et al. Deep convolutional neural networks for multi-modality isointense infant brain image segmentation. Neuroimage 2015;108:214-224.
[31] Fujita H. AI-based computer-aided diagnosis (AI-CAD): the latest review to read first. Radiol Phys Technol 2020;13:6-19.
[32] Szegedy C, Liu W, Jia Y, et al. Going deeper with convolutions. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2015;1-9.
[33] He K, Zhang X, Ren S, et al. Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition 2016;770-778.
[34] Almajalid R, Shan J, Du Y, et al. Development of a deep-learning-based method for breast ultrasound image segmentation. 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA) 2018; 1103-1108.
[35] Chaudhury S, Shelke N, Sau K, et al. A Novel Approach to Classifying Breast Cancer Histopathology Biopsy Images Using Bilateral Knowledge Distillation and Label Smoothing Regularization. Comput Math Methods Med 2021;2021:4019358.
[36] Wang X, Tan T, Gao Y, et al. DisAsymNet: Disentanglement of Asymmetrical Abnormality on Bilateral Mammograms Using Self-adversarial Learning. Proceedings of Springer (14226): Medical Image Computing and Computer Assisted Intervention–MICCAI 2023. Cham. Springer Cham 2023;57-67.
[37] Qi X, Yi F, Zhang L, et al. Computer-aided diagnosis of breast cancer in ultrasonography images by deep learning. Neurocomputing 2022;472:152-165.
[38] Ting FF, Tan YJ, Sim KS. Convolutional neural network improvement for breast cancer classification. Expert Syst Appl 2019;120:103-115.
[39] Kaur P, Singh G, Kaur P. Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification. Inform Med Unlocked 2019;16:100151.
[40] Baccouche A, Garcia-Zapirain B, Zheng Y, et al. Early detection and classification of abnormality in prior mammograms using image-to-image translation and YOLO techniques. Comput Methods Programs Biomed 2022;221:106884.
[41] Mall PK, Singh PK, Srivastav S, et al. A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities. Healthc Anal 2023;100216.
[42] Ranjbarzadeh R, Dorosti S, Ghoushchi SJ, et

al. Breast tumor localization and segmentation using machine learning techniques: Overview of datasets, findings, and methods. Comput Biol Med 2023;152:106443.

[43] Kyono T, Gilbert FJ,van der Schaar M. Improving workflow efficiency for mammography using machine learning. J Am Coll Radiol 2020;17:56-63.

[44] Kumar UK, Nikhil MS,Sumangali K. Prediction of breast cancer using voting classifier technique. 2017 IEEE international conference on smart technologies and management for computing, communication, controls, energy and materials (ICSTM) 2017;108-114.

[45] Akselrod-Ballin A, Chorev M, Shoshan Y, et al. Predicting Breast Cancer by Applying Deep Learning to Linked Health Records and Mammograms. Radiology 2019;292:331-342.

[46] Yala A, Lehman C, Schuster T, et al. A deep learning mammography-based model for improved breast cancer risk prediction. Radiology 2019;292:60-66.

[47] Qian X, Pei J, Zheng H, et al. Prospective assessment of breast cancer risk from multimodal multiview ultrasound images via clinically applicable deep learning. Nat Biomed Eng 2021;5:522-532.

[48] Ali N, Quansah E, Köhler K, et al. Automatic label-free detection of breast cancer using nonlinear multimodal imaging and the convolutional neural network ResNet50. Transl Biophotonics 2019;1:e201900003.

[49] Siviengphanom S, Gandomkar Z, Lewis SJ, et al. Global Radiomic Features from Mammography for Predicting Difficult-To-Interpret Normal Cases. J Digit Imaging 2023;36:1541-1552.

[50] Li Y, Fan M, Cheng H, et al. Assessment of global and local region-based bilateral mammographic feature asymmetry to predict short-term breast cancer risk. Phys Med Biol 2018;63:025004.

[51] Li Y, Fan M, Liu S, et al. Prediction of Short-Term Breast Cancer Risk Based on Deep Convolutional Neural Networks in Mammography. J Med Imaging Health Inform 2019;9:1663-1672.

[52] Wengert GJ, Helbich TH, Leithner D, et al. Multimodality Imaging of Breast Parenchymal Density and Correlation with Risk Assessment. Curr Breast Cancer Rep 2019;11:23-33.

[53] Cai G, Guo Y, Chen W, et al. Computer-aided detection and diagnosis of microcalcification clusters on full field digital mammograms based on deep learning method using neutrosophic boosting. Multimed Tools Appl 2020;79:17147-17167.

[54] Chakravarthy SS, Rajaguru H. Automatic detection and classification of mammograms using improved extreme learning machine with deep learning. Innov Res BioMed Eng 2022;43:49-61.

[55] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. Proceedings of Springer (9351): Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Springer Cham 2015;234-241.

[56] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition (Preprint). ArXiv 2015.

[57] Huang G, Liu Z, Van Der Maaten L, et al. Densely connected convolutional networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2017;4700-4708.

[58] Sert E, Ertekin S, Halici U. Ensemble of convolutional neural networks for classification of breast microcalcification from mammograms. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2017;689-692.

[59] Hatamizadeh A, Tang Y, Nath V, et al. UNETR: Transformers for 3d medical image segmentation. 2022 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) 2022;574-584.

[60] Chen J, Lu Y, Yu Q, et al. Transunet: Transformers make strong encoders for medical image segmentation (Preprint). ArXiv 2021.

[61] Jha D, Riegler MA, Johansen D, et al. Doubleunet: A deep convolutional neural network for medical image segmentation. 2020 IEEE 33rd International symposium on computer-based medical systems (CBMS) 2020;558-564.

[62] Cao H, Wang Y, Chen J, et al. Swin-Unet: Unet-Like Pure Transformer for Medical Image Segmentation. Proceedings of Springer (13803): Computer Vision–ECCV 2022 Workshops. Springer Cham 2023;205-218.

[63] Wu J, Fu R, Fang H, et al. Medical sam adapter: Adapting segment anything model for medical image segmentation (Preprint). ArXiv 2023.