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EDITORIAL

Artificial Intelligence in Breast Cancer Diagnosis: Current Trends, Limitations, and Future Prospects

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Abstract

Breast cancer continues to be a predominant cause of cancer-related fatalities among women worldwide. Timely and precise diagnosis is essential for successful intervention and enhanced patient outcomes. Artificial intelligence (AI), especially deep learning (DL) methodologies, is swiftly revolutionizing breast cancer diagnostics, providing unparalleled prospects to improve the accuracy and efficacy of detection and characterization. This editorial paper explores the crucial role of AI in breast cancer imaging, analyzing its utilization in computer-aided diagnosis (CAD) and its capacity to address the intrinsic limits of manual assessment. The article will examine several DL approaches utilized for classification, segmentation, and detection, emphasize notable findings, and describe large language models for breast cancer diagnosis. Additionally, the editorial will rigorously examine the existing limitations, significant obstacles, and ethical implications related to the extensive implementation of AI in clinical practice. Ultimately, it will focus on the future, delineating emerging patterns and the progression of AI in influencing the next generation of precision medicine for breast cancer patients.

Keywords: breast cancer, artificial intelligence, deep learning, large language models, computer aided diagnosis, segmentation, medical imaging.

1 Introduction

Breast cancer poses a serious global health burden [1], with nearly 2.3 million new cases diagnosed around the world each year, resulting in 685,000 recorded mortalities [2], making it the most commonly diagnosed cancer in females [2, 3]. Timely identification and precise diagnosis are essential for enhancing survival rates as well as therapeutic efficacy, with five-year survival rates surpassing 90% when diagnosed at primary stages [4]. Self-examination of breasts and clinical assessments are critical techniques for identifying breast cancer. In conjunction with clinical examinations and physical assessments, medical imaging is essential for the early identification of breast cancer. Conventional

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diagnostic approaches have traditionally depended on radiologists' professional opinions when interpreting medical imaging studies, including mammography, ultrasound, magnetic resonance imaging (MRI), thermography, and histopathology. The limitations of inferring the existence of cancer are problematic due to variability between interpretive observers, possible cognitive fatigue [5], and the potential inability to discern subtle pathological changes, particularly when breast tissue is dense.

As the global burden of breast cancer continues to rise, record levels of incidence have created unprecedented pressures to provide screening and diagnostic services [3]. This increase has stressed healthcare infrastructure and emphasized the shortcomings of traditional diagnostic methods, which frequently depend on subjective assessments and encounter capacity restrictions [5]. In this context, artificial intelligence (AI) has arisen as a crucial innovation, providing scalable solutions to improve diagnostic precision, optimize workflows, and facilitate earlier detection [6]. AI systems utilize sophisticated machine learning algorithms to process and analyse larger, complex imaging datasets with better accuracy, which can mitigate variability in interpretation and enhance risk discrimination [7]. In addition, personalized treatment planning may be facilitated by these new technologies, helping practitioners optimize treatment outcomes [8].

Nevertheless, the journey toward clinical integration is fraught with challenges. One challenge is assuring the validity and generalizability of AI models, particularly when accounting for the biological heterogeneity of breast cancer subtypes and the potential of bias in datasets [9]. Additionally, the opaque or "black box" features of many deep learning systems can interfere with clinical decision making, as clinicians rightly demand transparency for the rationale of algorithmic decisions [10]. The regulatory frameworks will also have to continue to keep pace with the rapid evolution of AI, while balancing advancement with patient safety [11], and many healthcare systems will encounter pragmatic barriers to integrating AI, like adapting clinical workflows to incorporate the technology. While there are many hurdles to cross, successful implementation can only be achieved collaboratively through different disciplines where AI developers, clinicians, and policymakers work together towards better solutions. Solutions that are technologically sophisticated but clinically meaningful, ethically supported, and equitably implemented [12]. The primary objective is evident: to leverage AI's capabilities to revolutionize breast cancer treatment while carefully tackling the complications of practical application.

The purpose of this editorial article is to provide an overview of the growing space of AI applications in breast cancer diagnosis. The article will examine the integration of AI into diverse imaging procedures, analyze the progression of computer-aided diagnostic (CAD) systems, and emphasize the particular deep learning methodologies propelling these improvements. Furthermore, the editorial will explore significant limitations and hurdles and ethical concerns that must be addressed to facilitate the safe and efficient use of AI in clinical practice, and a vision for AI's future directions in breast cancer as we move closer to an era of precision medicine that utilizes technology to enhance patient care and patient outcomes.

2 Imaging Techniques and Limitations of Manual Breast Cancer Diagnosis

2.1 Imaging Techniques

An accurate diagnosis of breast cancer incorporates many imaging modalities, and no one modality is perfect, as each has its strengths and flaws. There are five main imaging techniques used for screening and diagnosis of breast cancer: mammography, ultrasound, magnetic resonance imaging (MRI), thermography, and histopathology.

2.1.1 Mammography

Mammography is the most popular screening examination for breast cancer, and allows the detection of both microcalcifications and masses, often the first signs of possible malignancy [13]. This imaging modality employs low-dose X-rays to achieve internal visualization of breast composition, thus allowing early identification of lesions or anomalies by experts in radiology [14]. Digital breast tomosynthesis (DBT) has provided additional value to screening mammography by allowing three-dimensional visualization of superimposed breast tissues, thus lessening the effects of overlapping tissue and allowing for a better assessment of breast cancers [15]. Mammography has limitations, particularly in women with dense breast tissue, because if an abnormality is present in dense breast tissue, there may not be an opposing tissue density to reveal the abnormality, which leads to lower sensitivities and more false negatives. Additionally, mammography is also associated with low-level ionizing radiation.

2.1.2 *Ultrasound*

Ultrasound of the breast is commonly performed in conjunction with mammography - ultrasound is a good supplement to mammography in characterising breast masses, dense breast, or inconclusive mammogram studies. Ultrasound has the advantage of being radiation-free and allows for differentiation of solid masses versus fluid-filled cysts. Its ability to provide imaging in real time is also advantageous for biopsy guidance. However, ultrasound is highly operator dependent, and performance can vary widely depending on the sonographer's skill and experience. Compared with mammography, ultrasound is less specific and has a higher number of false positives [16].

2.1.3 *Magnetic Resonance Imaging*

Magnetic Resonance Imaging (MRI) is likely to be the most sensitive imaging method available for detecting breast cancer, particularly in high-risk women and for assessing disease extent for newly diagnosed patients. MRI does not involve ionizing radiation and provides excellent anatomic and functional information. On the other hand, MRI is expensive, takes a long time, has a high rate of false positives leading to unnecessary biopsies, and is not appropriate for all patients, such as those with metallic implants [17].

2.1.4 *Histopathology*

Histopathological analysis is considered to be the common way to identify cancerous conditions [18, 19]. Histopathology entails removing suspicious breast tissue, followed by microscopic examination of the tissue to reveal any abnormalities. Histopathology is the gold standard in diagnosing tumors, determining the stage of the disease, and providing therapeutic guidance. However, the details within histopathological slides can become complicated and prevent definitive separation of benign or malignant anomalies [20].

2.1.5 *Thermography*

Thermal imaging, or thermography, is a new non-invasive imaging technique that measures temperature differences on the breast surface caused by malignant tissue with increased metabolic activity and angiogenesis [21, 22]. Although thermal imaging cannot compete with conventional imaging modalities, it provides distinct advantages such as real-time imaging, no radiation exposure, and the potential for a patient to be screened more frequently without discomfort. Several new studies are showing effective results by combining thermal imaging with machine learning algorithms to detect breast cancer with sensitivity rates of 85-95% when performed in a controlled environment [23].

2.2 Limitations of Manual Diagnosis

Despite the extensive level of competency of the radiologist and pathologists, traditional manual interpretation of breast imaging examinations does have major limitations that can diminish diagnostic accuracy and patient outcomes. One of the main limitations is inter-observer variability. Inter-observer variability is attributed to differences in training, levels of experience, fatigue, and subjective interpretation of imaging results, particularly for subtle pathological changes or borderline lesions. Intra-observer variability is a further complication with regard to manual diagnosis. A radiologist may provide two different interpretations of the same imaging study when reviewed at different time points [24].

Intra-observer variability is an additional challenge to manual diagnosis [25]. Similarly to inter-observer variability, the same radiologist may interpret the same image at two separate time intervals differently. Another further limitation is the demonstrated variability among radiologists, especially in busy practice settings, where the radiologist may suffer performance degradation, or it may be fatigue, during the latter half of an extended reading session. In addition, when considering reading quality in the context of the modern world, interpreting advanced modalities with increasingly higher numbers of imaging examinations for routine screening creates significant excess workloads that risk diagnostic accuracy and efficiency [26].

Furthermore, the issue of dense breast tissue can obscure cancerous lesions on a mammogram, so the possibility of manual detection is challenging and, in some cases, simply not viable. A radiologist manually looks at these complex images to detect breast cancer, while another radiologist offers a second opinion. Each radiologist must carefully evaluate the images captured before rendering a report; even the most skillful radiologist can report falsely negative exams [27]. In addition, early breast cancers, even more so than established cancers, can be identified on a mammogram as very subtle changes such as tiny microcalcifications or architectural distortions. These subtle changes can be difficult to detect, even by radiologists, and among normal variations of breast tissue, the potential for missed cancer is increased [28]. Besides, the standardization process for thermal imaging, environmental sensitivity, and a lack of specificity limit clinical implementation. Furthermore, the review of histopathological images is time-consuming, requires substantial expertise, and is dubious since different specialists will not always agree about the diagnosis. Furthermore, even experts can make mistakes in analyzing findings [29, 30]. The shortage of appropriately trained professionals dismisses most of the evaluations of histopathology properly and timely.

Manual interpretation relies on human radiologists, who can introduce both false positives (considered benign findings that are incorrectly interpreted as cancer, which ultimately results in unnecessary biopsies and anxiety for patients) and false negatives (skipped cancers where patients are delayed in treatment, which may worsen their prognosis). Balancing the competing metrics of sensitivity and specificity is a perpetual struggle for radiologists [31]. The limitations of manual interpretation indicate a significant need for advanced tools to assist radiologists, to eliminate variation, and to ensure an accurate and efficient diagnosis for patients with breast cancer. Computer-aided diagnosis (CAD) systems, and more recently, AI-enabled systems, can provide a transformative opportunity to address each issue.

3 Computer-Aided Diagnosis in Breast Cancer

Computer-aided diagnosis (CAD) systems have developed significantly since they were first developed in the 1960s. They have gone from working as rule-based expert systems to employing currently available machine learning and deep learning frameworks. CAD developed its original functionality using hand-crafted feature extraction and regular machine learning algorithms (such as support vector machines, decision trees, k-nearest neighbors, and artificial neural networks) to process breast image datasets [32]. These early systems were powerful but only produced modest improvements in diagnostic accuracy due to the reliance on defined human features, and did not allow for more complicated, nuanced learning based on raw images or scan data.

Modern systems now use more powerful computational methods, such as deep learning, to improve the performance of diagnoses and potential to avoid limitations associated with classical machine learning methods [33, 34]. More recent approaches can process multiple image data simultaneously, while incorporating clinical data, patient demographic data, and history of imaging studies to inform their diagnostic evaluation [35]. Studies allowing for CAD to be part of the clinical workflow have been shown to improve the detection of cancers, decrease the time to read images, and the confidence of radiologists to make decisions [36].

The transformation from conventional CAD systems to AI-based systems signals a revolutionary development in diagnostic capabilities. AI-assisted CAD systems can learn relevant features from large databases autonomously without the need for explicit programming and can begin to identify subtle pathological topographical features that a human may miss. Moreover, they will get better with routine exposure to new cases and will adapt continuously to current clinical practices or changes in imaging technologies. AI-powered systems can also run in real-time, providing a clinician with instantaneous feedback on image acquisition and the interpretation process.

4 Deep Learning in Breast Cancer CADs

Deep learning-based CAD systems serve as a potent tool in breast cancer classification, segmentation, and detection, superseding traditional methods in accuracy and efficiency. In classification, deep learning models can distinguish, for example, benign versus malignant lesions, while in segmentation, the tumor boundaries are delineated, which is important for medical decision making. For detection, these models can localize suspicious regions with a high level of sensitivity, even in early-stage cancers. Thus, deep learning CAD systems greatly reduce human error, improve diagnostic consistency, allow for earlier intervention, and lead to better patient outcomes.

4.1 Classification

Deep learning, especially convolutional neural networks (CNNs), has become the most popular way to classify breast cancer. It has shown remarkable outcomes in interpreting medical images. CNNs are developed to operate with grid-like data structures like photographs. They use convolutional layers to automatically find hierarchical characteristics in raw pixel data. CNNs are good at classifying breast cancer because they can learn complicated spatial correlations, texture patterns, and morphological features that set malignant tumors apart from benign ones.

Among CNNs, AlexNet, VGGNet, ResNet,

EfficientNet, Inception, and DenseNet are just a few of the famous CNN architectures that have been used successfully to classify breast cancer. These structures have been altered and enhanced for implementation in medical imaging, with changes made to fit the specific needs of breast imaging data. For example, transfer learning methods have worked very well. In these methods, networks that have already been trained on huge natural image datasets are refined using smaller medical imaging datasets [37]. This method solves the problem of having insufficient annotated medical imaging data by using the general feature extraction skills obtained from large datasets of natural images.

Vision Transformers (ViTs) are a novel type of deep learning model that has shown promise in analyzing medical images, including breast scans [38]. ViTs work differently from CNNs because they break images into patches and use self-attention mechanisms to find global dependencies and long-range interactions within images [39]. This method has been shown to be especially good at picking up on tiny pathological details and contextual information that typical CNN architectures could miss. Recent research has demonstrated that ViT-based methods can do just as well as other methods at classifying breast cancer, and they can also be more interpretable due to attention visualization techniques.

Many studies have demonstrated that deep learning techniques perform well in classifying histopathological images of breast cancer into various types. The authors of reference [40] applied a self-learning approach together with transfer learning to classify breast cancer through histopathological images. They adopted many pre-trained CNNs with the self-learning method, including Inception V3, VGG19, AlexNet, ResNet-18, GoogleNet, ShuffleNet, MobileNet, ResNet-101, Inception ResNet V2, and SqueezeNet. They concluded that a self-learning method produces accurate tumor diagnosis in the sub-images (as opposed to classifying the whole image). The self-learning method achieved 99.1% accuracy after four iterations when correcting the labels using InceptionNet-V3's model. The study [41] introduced the Efficient Channel Spatial Attention Network (ECSAnet), an architecture based on EfficientNetV2, enhanced with a convolutional block attention module (CBAM) and supplementary fully connected layers. In a separate study, the authors [42] developed a new deep learning-based ensemble classifier to identify breast cancer. By combining three well-established transfer learning algorithms (AlexNet, ResNet, MobileNetV2), the model achieved better accuracy and efficiency, using smaller datasets. In study [43], the authors developed a CAD system for the identification of breast cancers using an image fusion method, which combines different visual forms of representation as well as several CNN architectures applied to ultra-sound images. The CNN-based approaches from the study included VGGNet, ResNet, and DenseNet.

4.2 Segmentation

Image segmentation is an important preprocessing step when analyzing images for breast cancer, as it allows the regions of interest, lesion edges, and anatomical structures to be accurately defined for subsequent quantitative analysis. Accurate segmentation allows for measurement of lesion size, shape analysis, texture analysis, and keeping track of treatment response over time. Segmentations were traditionally accomplished by radiologists manually contouring objects or using semi-automated tools such as region-growing, thresholding, and edge-detection algorithms. These methods were subject to high variability across users and were slow for the radiologists to perform.

Deep learning-based segmentation methods are becoming popular as they provide automated and accurate segmentation that can be reproduced across images. The U-Net architecture, designed for biomedical image segmentation, has become the standard for many medical imaging applications because of its encoder-decoder structure with skip connections, allowing it to maintain spatial information while segmenting an object and capturing detailed boundaries [44]. Variants have been designed for breast cancer segmentation that improve segmentation of breast tissue by incorporating attention mechanisms, residual connections, and multi-scale feature extraction.

Advanced segmentation networks, including DeepLab, SegNet, and Fully Convolutional Networks (FCNs), have been applied to breast cancer segmentation in various imaging modalities. These methods incorporate different architectural benefits in segmentation strategy; for example, DeepLab uses atrous convolutions to extract multi-scale features [45], SegNet utilizes an encoder-decoder architecture with memory-efficient upsampling [46], and FCNs offer end-to-end segmentation that can be trained at once [47]. More recently, transformer-based segmentation approaches have shown promise for the analysis of breast cancers. Swin-Unet, a U-structure transformer-based architecture, is able to achieve higher performance across medical image segmentation tasks through a drawback-free U-structure that combines global modeling in transformers and convolutional layers [48]. These types of architectures demonstrated particular advantages in managing complex lesion morphologies or heterogeneous tissue patterns, often exhibited in breast imaging.

Many studies have recently focused on breast cancer segmentation issues using deep learning methods. For example, a study created a deep learning automatic segmentation model from Res-UNet for preoperative MRI in breast patients, and showed it is valuable for quantifying tumor size and characteristics [49]. The research [50] introduced an architecture named Connected-UNets, which interlinks two UNets through enhanced altered skip connections. The authors incorporated Atrous Spatial Pyramid Pooling (ASPP) into the two conventional UNets to enhance the contextual information within the encoder-decoder network design. The suggested design was implemented on the Attention UNet (AUNet) and the Residual UNet (ResUNet). Other studies showed promise for AI-based automatic segmentation of breast cancer on dynamic contrast-enhanced MRI (DCE-MRI) examinations and accurately outlining tumor regions [51]. Many studies are therefore developing CNN-based segmentation models, with improved accuracy and tuning for reduced computational costs. Furthermore, the study [52] has compared SegNet and U-Net deep learning approaches to obtain whole breast segmentation.

4.3 Detection

Object recognition in breast cancer imaging is essential for recognizing alarming lesions, microcalcifications, and structural deformities within intricate anatomical structures. Conventional detection methods depended on sliding window techniques, integrated with manual feature extraction and traditional machine learning classifiers. Nonetheless, these approaches were computationally intensive, necessitated significant parameter optimization, and frequently failed to identify nuanced disease results.

The You Only Look Once (YOLO) architecture has become a prominent method for real-time object recognition in medical imaging [53], particularly in breast cancer identification [54]. YOLO's single-stage detection framework analyzes complete images in a single forward pass, facilitating rapid detection while preserving excellent accuracy. The architecture segments input photos into grids and forecasts bounding boxes and class probabilities for each grid cell, enabling the concurrent detection of many objects within images [55]. Enhanced versions of YOLO, including YOLOv3, YOLOv4, and YOLOv5, have been effectively utilized for breast cancer detection, demonstrating enhancements in small object identification, multi-scale processing, and model tuning.

RetinaNet exemplifies a sophisticated detection methodology that tackles the issue of class imbalance frequently observed in medical imaging datasets. The design employs focal loss functions that adaptively modify loss contributions according to classification complexity, facilitating efficient training on datasets with a substantially greater number of background areas compared to positive findings [56]. This technology has demonstrated notable efficacy in identifying tiny microcalcifications and minor lesions that typical detection techniques may overlook.

Faster R-CNN [57] and its variations exemplify two-stage detection methodologies that integrate region proposal generation with refinement phases to attain elevated detection precision. These algorithms initially create prospective object regions and subsequently classify and improve these regions to yield final detections. Although computationally more demanding than single-stage methods, two-stage detectors frequently attain enhanced accuracy for complex detection applications involving small or low-contrast lesions.

Recent research has shown the efficacy of deep learning detection methods in breast cancer detection procedures. McKinney et al. [6]created an AI system for breast cancer screening using mammography that surpassed six radiologists in cancer detection and lowered both false-positive and false-negative rates. The system employed ensemble methods that integrate numerous detection networks to attain reliable performance across various patient demographics and imaging methodologies. Researchers have utilized YOLO-based methodologies to identify microcalcifications in mammography, attaining sensitivity rates of 90% for clinically significant lesion sizes [58].

5 Large Language Models in Breast Cancer Diagnosis with Medical Imaging

The incorporation of AI, especially large language models (LLMs), is transforming medical image processing by optimizing interpretation and improving diagnostic proficiency. In the realm of breast cancer, LLMs exhibit considerable potential to aid in this vital domain by evaluating medical pictures and related data to offer decision support; yet, they are not a substitute for qualified physicians [59]. LLMs in the field of radiology may serve multiple points along the diagnostic workflow, including informing requests for imaging studies and protocols, and providing assistance in the generation and interpretation of reports. LLMs can provide data that analyzes and summarizes information from radiology reports, may aid in clinical decision support, and can improve workflow efficiency through automated repetitive processes, such as protocoling and writing reports. Furthermore, multimodal LLMs that integrate imaging data with clinical and laboratory information can support physicians in proposing differential diagnoses and improving processes during triage [60, 61].

A number of studies have explored the use of LLMs for breast cancer diagnosis with generally optimistic but varied results. Some studies have focused on the use of LLMs to stratify breast imaging data along the Breast Imaging Reporting and Data System (BI-RADS), which is a well-known classification for reporting and categorizing breast lesions. In an international analysis of 2,400 breast imaging reports in English, Italian, and Dutch, Cozzi et al. [62] reported moderate agreement with radiologists in BI-RADS classification for GPT-3.5, GPT-4, and Google Bard (Gemini), with enough discrepancy to potentially impact patient management. The authors point to the need for heightened regulatory scrutiny of such LLMs that are publicly available.

A separate study [63] examined the efficacy of various LLMs, including ChatGPT and Glass AI, in determining the most suitable imaging scan for diverse clinical presentations. The findings indicated that Glass AI, possessing supplementary training in medical texts, outperformed ChatGPT markedly, especially in the breast imaging panel. This indicates that specialized training is essential for the proper utilization of LLMs in this field. A thorough study of large language models in breast cancer management revealed that their accuracy varied between 50% and 98%, with optimal performance observed in information extraction and question-answering tasks. Nonetheless, their efficacy in delivering clinical decision assistance for breast tumor boards was suboptimal, varying between 50% and 70% [64].

The study [65] examined the capacity of LLMs to utilize five breast-related medical classification systems in the field of plastic surgery to aid in the diagnosis and treatment process. There were fifty clinical scenarios evaluated, with the responses rated from 0 to 2 based on accuracy. Gemini was superior to ChatGPT-4 with 98% vs 71%. Both models produced acceptable scores for the Baker and UTSW classifications, and Gemini outperformed ChatGPT-4 in Fischer, Kajava, and Regnault classifications. Overall, these results indicate that LLMs may assist with clinical decision-making in plastic surgery after refinement.

6 Challenges and Ethical Considerations of AI

Despite substantial progress in AI applications for breast cancer diagnosis, numerous severe constraints, challenges, and intricate ethical considerations persist. Overcoming these complex concerns is essential for the responsible, equitable, and effective development and implementation of AI technologies, eventually helping all patients and healthcare systems while assuring successful clinical integration and widespread acceptance.

6.1 Challenges

6.1.1 Data-Related Challenges

A primary problem that arises from the fundamental aspect of AI is data. Healthcare AI systems require access to extensive amounts of sensitive patient data, encompassing medical records, radiological images, genetic data, and clinical results. This poses significant issues about data privacy and security, as the collection and processing of such sensitive information introduces new vulnerabilities to cyberattacks, unwanted access, and misuse. Comprehensive security protocols, rigorous regulatory structures, and principled data governance principles are vital for safeguarding patient confidentiality and preserving public trust [66].

The quality, volume, and variety of training data significantly impact the effectiveness and validity of AI models. In healthcare, data is frequently dispersed among multiple systems, missing, inconsistent, or of poor quality. A major issue is algorithmic bias, wherein AI models are trained on datasets that replicate current biases in healthcare, such as inadequate representation of specific ethnic groups, genders, or socioeconomic backgrounds, which could perpetuate or exacerbate these discrepancies. This may result in inequitable consequences, including misdiagnosis or inadequate suggestions for treatment for underrepresented patient populations, hence worsening existing health disparities [67, 68]. The absence of adequate, high-quality, and representative datasets from varied populations continues to be a significant obstacle in creating genuinely generalizable and equitable AI systems.

6.1.2 *Technical and Implementation Challenges*

Numerous sophisticated AI models, function as 'black boxes,' signifying that their fundamental decision-making mechanisms are obscure and challenging for humans to comprehend. The absence of comprehensibility constitutes a substantial obstacle to clinical implementation. Clinicians may exhibit reluctance to trust or depend on AI suggestions if they are unable to understand the underlying rationale or verify the AI's logic. This opacity presents difficulties for authorization from regulators, accountability in instances of error, and the ongoing enhancement and refining of the models [69]. Attempts are in progress to create Explainable AI (XAI) to tackle this problem; however, it continues to pose a hard technical barrier.

Ensuring ongoing clinical performance of AI in practice is challenging: machine learning models can drift over time based on changing disease patterns and can sometimes be suboptimal when data is missing or incomplete with accuracy decreasing in conditions of use like differences in patient population. These issues, combined with bias and fairness considerations, highlight the need for verification, validation and routine monitoring when used in practice and real-world settings [70].

The seamless integration into current healthcare workflows poses significant implementation hurdles. Healthcare systems frequently exhibit complexity, characterized by established norms and legacy IT. The integration of new AI technologies necessitates substantial modifications to infrastructure, comprehensive training for healthcare personnel, and meticulous attention to the presentation and implementation of AI insights to avoid disrupting patient care or exacerbating clinician workload [71]. The expenses associated with the development, deployment, and maintenance of advanced AI systems in healthcare are considerable, possibly restricting their accessibility, particularly for smaller healthcare institutions or those in developing areas [72].

Notwithstanding their apparent promise, the application of LLMs in breast cancer diagnostics presents several hurdles. A major issue is the occurrence of "hallucination," in which the model produces inaccurate information that can be effortlessly combined with factual data. Additional drawbacks encompass the potential to exacerbate healthcare disparities, insufficient transparency in the decision-making process, and the necessity for rigorous validation prior to clinical implementation. The dependability of LLMs may be compromised by biases present in their training data and deficiencies in domain-specific expertise. Consequently, although LLMs are positioned to significantly enhance workflows and assist multidisciplinary teams, their effective incorporation into clinical practice will rely on adequate training, validation, and ethical governance, with human oversight serving as an essential protection [64, 73].

6.2 Ethical Considerations

The ethical ramifications of AI in medical diagnosis are significant and necessitate meticulous consideration. A fundamental inquiry involves accountability and liability: when an AI system renders an erroneous diagnosis or suggests a defective treatment, who assumes responsibility? Is the responsibility attributed to the AI developer, the doctor utilizing the tool, the hospital, or a combination thereof? Defining explicit accountability and culpability for AI-induced errors presents a multifaceted legal and ethical dilemma that needs comprehensive regulatory frameworks [74].

Additionally, there is an apprehension that the dehumanization of medical care may result from excessive dependence on technology. Although AI can improve productivity, it is devoid of emotional intelligence, empathy, and the capacity to deliver comprehensive, compassionate care fundamental to the doctor-patient relationship. The lack of an emotional connection between the healthcare provider and the patient is a notable disadvantage. Preserving the human aspect in healthcare, with AI functioning as an auxiliary instrument rather than a substitute for human engagement, is essential.

The growing automation facilitated by AI raises apprehensions regarding potential job displacement in specific healthcare positions, especially those associated with routine diagnostic functions. Although AI is frequently portrayed as a supportive instrument, the enduring effects on the healthcare workforce require meticulous evaluation, strategic workforce planning, and retraining programs to facilitate a seamless transition and capitalize on AI's advantages without detrimental social repercussions [75]. The swift advancement of AI technology frequently surpasses the establishment of suitable regulatory frameworks, necessitating that policymakers remain vigilant to guarantee patient safety as well as effectiveness [76].

7 Future Directions and Emerging Technologies

The prospects of AI applications in breast cancer diagnosis are highly promising, thanks to multiple developing technologies and methodologies set to overcome existing limitations and enhance diagnostic skills. A significant potential path is the advancement and extensive implementation of XAI. As AI models grow more intricate and their predictions affect medical outcomes, their 'black box' nature becomes progressively troublesome. XAI seeks to render AI decision-making clear and comprehensible to human users, especially physicians. This entails creating methodologies that elucidate the rationale behind a certain diagnosis, the derivation of a therapy suggestion, or the characteristics in an image that prompted a particular conclusion. By elucidating the AI's rationale, XAI will enhance confidence among healthcare practitioners, streamline regulatory approval, and promote ongoing learning and enhancement of AI systems. Future AI solutions will probably have inherent interpretability capabilities, enabling physicians to check and comprehend the AI's reasoning, thereby fostering a more collaborative and informed decision-making process [77].

Federated learning exemplifies an innovative method for training AI models on decentralized datasets while safeguarding patient privacy and data security. This method facilitates cooperation among healthcare organizations while safeguarding sensitive patient information, perhaps resulting in more resilient and broadly applicable models. Federated learning methodologies have demonstrated significant potential in medical imaging applications, where data sharing limitations and privacy issues constrain the accessibility of extensive training datasets. Federated learning enhances a model's ability to be generalized and effective by facilitating cooperative model training among multiple entities, all while adhering to data governance standards. Numerous studies have shown the effective use of federated learning in breast cancer detection and classification tasks, achieving performance at the same level as centralized training methods.

Multi-modal AI methodologies that incorporate data from several imaging techniques, clinical information, and molecular indicators signify a viable pathway for breast cancer diagnosis. These methodologies can utilize supplementary information from various data sources to attain more thorough and precise diagnostic evaluations. Deep learning architectures developed for multi-modal data integration, featuring cross-attention processes and fusion networks, have demonstrated encouraging outcomes in amalgamating diverse data sources to enhance diagnostic efficacy. Screening techniques for breast cancer that employ and integrate various imaging modalities signify a prospective advancement in the field. Such protocols can enhance scanning rate, modality choice, and risk-based screening procedures tailored for specific patient features and risk factors. AI systems may modify suggested screenings dynamically depending on prior imaging results, familial history, and additional risk variables to deliver individualized screening methods.

Edge computing and mobile AI apps signify innovative methods for enhancing access to breast cancer screening and detection in resource-constrained environments. Tailored compact AI models for mobile devices and portable imaging devices facilitate screening in remote areas and underserved populations. These methodologies can close healthcare access disparities and facilitate early identification in environments lacking conventional screening infrastructure.

8 Conclusion

The incorporation of AI technology into breast cancer diagnosis signifies a significant progression in medical imaging and clinical practice. Deep learning methodologies, encompassing convolutional neural networks, vision transformers, and sophisticated detection frameworks like YOLO, have exhibited exceptional proficiency in breast cancer detection and classification across many imaging modalities. These technologies provide substantial enhancements in diagnostic precision, consistency, and efficiency relative to conventional manual methods.

Concurrently, LLMs are starting to assume a supplementary role in breast cancer detection, especially when included in multimodal frameworks that merge medical images with clinical text data. Such models improve diagnostic workflows by facilitating automated report production, correlating picture attributes with textual information, and assisting in the understanding of radiological and pathological data. As LLMs progress in comprehending and reasoning across visual and textual modalities, they possess the capacity to enhance decision support, transparency, and communication between AI systems and physicians substantially. Their incorporation into diagnostic frameworks signifies a pivotal advancement in the development of intelligent, comprehensive methods for thorough breast cancer management.

Notwithstanding considerable advancements, some hurdles persist, notably data quality concerns, model generalizability, regulatory mandates, and obstacles to clinical incorporation. Confronting these problems necessitates ongoing collaboration among academics, physicians, regulatory bodies, and healthcare systems to guarantee the safe, effective, and equitable deployment of AI technologies.

The potential application of AI in breast cancer diagnosis is highly promising, as emerging technologies like federated learning, multi-modal integration, and edge computing are set to enhance accessibility and diagnostic precision. As these technologies advance, they will likely assume a more significant role in facilitating early detection, precise diagnosis, and enhanced outcomes for breast cancer patients globally.

The effective integration of AI in breast cancer diagnosis necessitates constant expenditure in research, infrastructure, and clinical validation, while prioritizing patient-centered care and clinical value. With suitable development, validation, and implementation procedures, AI technologies can markedly enhance breast cancer outcomes and revolutionize clinical practice for the advantage of both patients and healthcare providers.

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Conflicts of Interest

The author declares no conflicts of interest.

AI Use Statement

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Ethical Approval and Consent to Participate

Not applicable.

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