Artificial Intelligence in Breast Cancer Screening in Inducing Diagnostic Accuracy with Early Detection

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Abstract

Background: The integration of artificial intelligence (AI) into breast cancer screening has shown promise in overcoming these limitations, potentially improving diagnostic accuracy and patient outcomes. Methods: This study reviews the current imaging modalities for breast cancer detection, including mammography, magnetic resonance imaging (MRI), dynamic contrast-enhanced MRI (DCE-MRI), magnetic resonance elastography (MRE), magnetic resonance spectroscopy (MRS), positron emission tomography-computed tomography (PET-CT), ultrasound, breast-specific gamma imaging (BSGI), and molecular image-guided sentinel node biopsy. It also explores the role of AI in enhancing diagnostic precision through advanced computational techniques, such as deep learning and machine learning models, focusing on object detection, segmentation, and tumor classification. Results: Mammography remains the gold standard for breast cancer detection but poses risks, such as overdiagnosis and radiation exposure. Alternative methods, like MRI, DCE-MRI, and BSGI, offer advantages in specific scenarios but also have limitations, such as low specificity and higher costs. AI systems have demonstrated superior performance in breast cancer prediction compared to human experts by reducing false-positive and false-negative rates. AI integration enhances screening programs by improving the detection accuracy of imaging biomarkers and facilitating automated interpretation. Conclusion: The incorporation of AI in breast cancer screening represents a significant advancement in early detection and diagnosis, improving treatment outcomes.

Keywords: Breast cancer screening, Artificial intelligence (AI), Imaging modalities, Diagnostic accuracy, Machine learning

Significance | This review discusses the AI to improve diagnostic accuracy in breast cancer screening, potentially reducing false positives and negatives and improving patient outcomes.

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1. Introduction

Breast cancer is a leading cause of mortality among women worldwide. Cancer, which may occur due to personal or environmental reasons, is now one of the most common diseases across the globe. This disorder can affect many body regions and cause cells to grow irregularly due to uncontrolled cell division. The body parts mainly affected by cancer are the breast, prostate, lung, skin, and pancreas. Death cases due to cancer are increasing day by day. In women, mortality cases are mostly due to breast cancer, but if detected early with proper treatment, many lives can be saved. Early detection of breast cancer is mainly done by different imaging techniques like mammography, ultrasound, computed tomography imaging (CT), thermal imaging, and magnetic resonance imaging (MRI). The outcome of these imaging procedures depends on

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different factors, and it is advised to use more than one method to verify the results properly. Among all the imaging methods, mammography is the most important and widely accepted method by the medical fraternity (Coleman, 2017). Even though it is termed the gold standard, it poses many risks for patients; thermography has therefore become more important in recent years due to its lower risks compared to mammography. Digital infrared thermography has not yet been used as a primary tool for early diagnosis because it relies on skin disease and temperature. However, promising results show that radiologists can combine it with mammography to assess the status of the breast for proper breast cancer assessment and diagnosis. Detecting patients by means of different imaging modalities is one of the treatments (Basilion, 2001). Although screening programs exist worldwide, the interpretation of mammograms is compromised by high rates of false-positive and false-negative results (Basilion, 2001). Despite the availability of multiple imaging techniques for early detection, the limitations of traditional methods, such as mammography, necessitate the development of more accurate diagnostic tools. Here we present an artificial intelligence (AI) system capable of outperforming human experts in breast cancer prediction.

2.Present scenario of breast cancer diagnosis:

2.1. Mammography

In mammography x-ray of the breast is done to detect abnormalities in tissues of breast. The technique is performed to get an x-ray image by applying a small radiation dose through the breast after compressing the breast between two plates. Mammograms are used for both screening and diagnosis of breast cancer (Bhan et al, 2013) .If a woman experiences symptoms like, a lump in her breast Mammography screening may be carried out to detect any early signs of breast cancer and treatment can be started too early to decrease mortality (Sundaram et al, 2014).

2.2. Disadvantages

Over diagnosis is the main disadvantage of mammography that detect a cancer that would never have had an effect on the health of the women or consequences on her life – like a cancer that develops very slowly or a benign cancer. As such, women in the screening program if detected with a benign cancer receive treatment for breast cancer that would not be necessary, making her suffer from the side effects of these treatments, have to live with the fear of having been diagnosed with cancer and have to frequently visit medical with repeated diagnosis to ensure that the cancer does not return (Heywang et al, 2011).

2.3. Magnetic Resonance Imaging

In MRI technique radio frequency of low-energy waves and a magnetic field are employed to obtain MRI images showing internal structures of breast. It is a non-invasive and non-ionizing diagnostic imaging tool. MRI data reveals the size of the cancer and also predict whether the tumour is metastatic or not in women already diagnosed with breast cancer. The major drawback of MRI is that it can identify tumours accurately if the size is less than or equal to 2 cm, but larger sized breast tumours are often overestimated than the actual lesion, leading to greater mastectomy rates (Jethava et al, 2015).

2.4. DCE-MRI

The process involves delivering a paramagnetic contrast agent via the veins, which amplifies the visible tissue pattern. The methodology above is a non-invasive method of imaging that allows for the quantitative assessment of tissue vascularization, interstitial space composition, and lesion differentiation (Rahbar et al, 2016). DCE-MRI has demonstrated significant use in the prognostication of tumor angiogenesis, as well as in the prognostication of overall recurrence and survival among individuals diagnosed with breast cancer (Gillman et al, 2014). The diagnosis of lymph node metastases resulting from heightened angiogenesis in breast tumors is facilitated by the ability to predict angiogenesis. The primary benefit of conducting DCE-MRI is acquiring a three-dimensional image, which facilitates the visualization of the disease's scope well before any morphological alterations and enables the prediction of overall response before or during therapy (Chol et al, 2016). However, the primary drawback of DCE-MRI is its lack of specificity (Amornsiripanitch et al, 2019).

2.5. MRE

In-vivo, cross-sectional MRE imaging is a non-invasive, non-ionizing technique that can yield data concerning mechanical characteristics of tissue (Patel et al, 2021). Increased cell count, collagen, and proteoglycan content render malignant breast tissue more rigid than benign lesions and healthy breast tissue (Hawley et al, 2017). Manual palpation is inferior to MRE scanning concerning specificity and sensitivity. Spatial resolution and the ability to identify small focal lesions are the main drawbacks of MRE in breast tumors, owing to the overlapping flexibility regions of soft neoplasms and unyielding benign lesions (Lorenzen et al, 2002).

2.6. MRS

By implementing strong magnetic fields (typically 11–14 T) on body fluids, cell extracts, and tissue samples, magnetic resonance spectroscopy (MRS) can ascertain the chemical composition of the test region through the measurement of a chemical "spectrum" in the region (Bolan et al, 2003). While the specificity of MRS is capable of reaching 88%, its primary drawbacks are the need for slightly larger lesions and low sensitivity in detecting the total choline (tCho) signal (Flavell et al, 2016)

PET-CT combines Positron Emission Tomography (PET) and PET in Conjunction with CT Scanning. The positron emission tomography (PET) imaging technique is a significant non-invasive diagnostic procedure. The technique employs 2-deoxy-2-(18F) fluoro-D-glucose (FDG), a PET radiotracer authorized by the US FDA that capitalizes on the augmented glucose metabolism observed in cancer cells (Kadoya et al, 2013). Due to the accelerated proliferation and elevated glucose metabolism rate of cancer cells relative to normal cells, FDG-PET radiotracers gain intracellular uptake through the glucose transporter and subsequently accumulate within the cells. When investigating primary tumors, the combination of PET and CT (PET-CT) provides more excellent resolution and sensitivity than PET scans alone (Narayanan et al, 2011).

2.7. Molecular Image-Guided Sentinel Node Biopsy

Determine whether patients benefit from early detection of breast cancer. The finest slightly invasive method known as Sentinel lymph node biopsy (SLNB) is recommended as per the SLNB report, an optimal therapeutic approach is being pursued to treat cancer (cox et al, 2008). As compared to conventional axillary lymph node dissection SLNB involves less post-operative complications (Chen et al, 2006).

2.8. BSGI

Breast-specific gamma imaging (BSGI) is a special type of nuclear medicine imaging test that can detect subcentimeter mammographically obscured breast cancer.In terms of sensitivity and specificity, it is comparable to magnetic resonance imaging.

In BSGI, Technetium Tc99m Sestamibi or similar radiotracer is injected into the patient's bloodstream, followed by visualization of the breast using a special camera (Gong et al, 2015). The advantage of BSGI is that it is unaffected by breast density a major drawback of mammography. Modern BSGI has improved sensitivity in detecting subcentimeter lesions compared to scintigraphy. The main disadvantage of this technique is that the entire body is exposed to radiation, making it difficult to use the technique for frequent breast cancer screenings (Surti et al, 2013).

2.9. Ultrasound

Though mammography is the widely used technique for detection of breast cancer, it is not suitable in case of women with dense breasts and in such cases, ultrasound is used as a supplemental tool in analysing. It also analyses mistrustful zones not observed especially on a mammogram (Candelaria et al, 2011). This system is widely available and the patient is not going through exposure to radiation during analysis making it a better choice than other methods. The technique is having some limitations like it failed to detect microcalcifications and early signs of cancer. These limitations make its use restricted in screen for breast cancer but are used in some special situations only.

2.10. Digital pathology and cancer management

The availability of modern and advanced techniques has made it easier to store and manage large amounts of information. Improvements in machine learning have permitted the integration of digital pathology with artificial intelligence, enabling more accurate and efficient image-based diagnoses. This advance opens up new avenues in the diagnosis and treatment of cancer (Niazi et al., 2019). This technology can display complex signaling pathways that connect cancer cells as high-resolution images. Another significant advantage is the observation of full-size images of tissue samples, allowing sub-visual morphometric phenotypes, thus improving patient care (Bera et al., 2019). Compared to traditional techniques, digital methods enable the quick, accessible collection, integration, and analysis of large amounts of data. The technique has the potential to obtain more reliable and accurate data at larger volumes and generate results with a significant number of summaries and comparisons. Preparation of AI algorithms requires high-quality training images that have been manually examined by a pathologist, and any areas of abnormal or pathological significance have been identified (Sobhani et al., 2021). The qualitative evaluation enables rapid and precise identification of cell types and provides an adequate idea of morphological, histological, and biologically relevant patterns. It also allows access to data from the tissue side that cannot be evaluated manually and reduces the error rate compared to manual methods (Tizhoosh & Pantanowitz, 2018).

3. Artificial intelligence and screening of breast cancer

By producing accurate diagnosis news reports, integrating artificial intelligence into screening processes, such as evaluating biopsy slides, increases the rate of successful treatments. In recent years, interest in this field of study has increased due to the improved accuracy of diagnosing outcomes. It appears that the application of artificial intelligence to breast cancer detection has a promising future. Unquestionably, computerized radiology holds an essential position within the discipline of medical imaging, particularly for the early identification and analysis of breast tumors. It involves the application of various computational techniques, such as computer vision, lesion detection, and pattern recognition, to assist in the analysis of medical images. The goal is to improve the efficiency and accuracy of diagnostic procedures, often automating tasks that were traditionally performed by human experts. Computational radiology involves extracting imaging biomarkers from medical images. These biomarkers serve as quantitative measures that can be used to model therapy responses and provide predictive and prognostic information about the disease. The two fundamental elements of artificial intelligence—machine learning and deep learning—play crucial roles in breast cancer detection. Large datasets of medical images are used to train machine learning models. These models can then generalize patterns and assist in the automated interpretation of new images (Erickson et al., 2017). The application of deep learning, as a subfield of machine learning, employs artificial neural networks, including numerous layers, to autonomously acquire hierarchical representations from data. This method has proven significant efficacy in tasks related to picture classification and recognition, rendering it an advantageous approach for the diagnosis of breast carcinoma (Coleman, 2017). AI in breast cancer screening has made significant strides, and its primary applications often involve object detection (segmentation) and tumor classification. These two aspects contribute to breast cancer screening using AI (Tran et al., 2021). Schematic diagram elucidating advancement of A.I in Health care system has been depicted in **Figure (1).**

3.1. Object Detection (Segmentation)

Segmentation involves identifying and delineating the boundaries of objects within an image. In breast cancer screening, this typically means identifying and outlining regions of interest, such as tumour's or suspicious masses. Accurate segmentation is crucial for subsequent analysis and characterization of the identified regions.

3.2. Tumor Classification

Once regions of interest are identified through segmentation, the next step is to classify these regions as either benign or malignant. The subsequent information concerns the categorizing aspect of artificial intelligence in the context of breast cancer screening. Like other machine learning models, deep learning models are trained using datasets containing labeled images. This training methodology facilitates the acquisition of knowledge about patterns that can be employed to identify tumors, distinguishing between malignant and benign types. Classification methods often depend on information obtained from segmented images when making forecasts. Many models exist that encompass traditional machine-learning techniques and complex deep-learning structures. Radiomics, an extensively employed methodology in artificial intelligence (AI) systems, encompasses extracting quantitative attributes from medical pictures referred to as features. The facilitation of this process is commonly achieved through pattern recognition algorithms that can distinguish images and generate a number set that represents quantitative attributes of the observed image region (Van Timmeren et al., 2020). Radiomics operates on the underlying premise that the extracted properties comprise diverse activities occurring at both the genetic and molecular levels. The application of machine learning in disease comprehension utilizes computational methods that leverage visual data acquired via radiomics. Machine learning in radiomics can be categorized into two main classifications: unsupervised and supervised. Unsupervised machine learning is a computer method that allows for identifying patterns and classifying information without relying on pre-existing data or assistance from the given image. Supervised machine learning, in contrast, initiates the process by training artificial intelligence models using pre-existing data (Tagliafico et al., 2020). Deep learning is a computational approach that employs a multi-neural layer or network to analyze a picture, transforming the image into a numerical representation that encapsulates its distinctive characteristics. The methodology described exhibits similarities with automated machine learning. A high-resolution mammographic image is obtained for analysis, utilizing sophisticated computer methods to detect possible anomalies such as breast masses, perform mass segmentation, evaluate breast density, and estimate the likelihood of malignancy. Breast mass identification plays a crucial role in computer-aided diagnostic (CAD) procedures due to their high prevalence among persons diagnosed with breast cancer (S P et al., 2019). Calcifications manifest as diminutive spots on mammography, presenting in two distinct forms: microcalcifications and macrocalcifications. Currently, computer-aided diagnostic (CAD) systems exhibit proficiency in identifying microcalcifications (Cruz-Bernal et al., 2018). Segmentation of breast masses, recognized as authentic segmentation, profoundly impacts the diagnostic process. Employing blurred contours facilitates the automatic segmentation of breast masses from mammograms. The intricacies of segmentation in breast imaging arise from individual irregularities, making detection challenging. AI-driven precise segmentation significantly enhances patient prognostication (Hmida et al., 2018).

4. Current challenges and futuristic forecasts of artificial intelligence in the management of breast carcinoma

Artificial intelligence (AI) has emerged as a game-changer in cancer treatment, offering promising outcomes. The potential for a paradigm shift is on the horizon, with AI reshaping and influencing current treatment methodologies. The key question is to define the boundaries that distinguish AI from human intelligence. AI's effectiveness relies heavily on data from diverse populations, raising concerns about the inherently different processes of data development among people of various socioeconomic backgrounds (Xu et al., 2021). The incidence of cancer varies significantly among racial groups, underscoring the need for AI to produce unbiased outcomes that serve as standards and credibility benchmarks (Yuan et al., 2018). To ensure the widespread acceptance of AI, it's essential to foster a culture of independent reproduction and generation of AI machines, akin to scientific discoveries. This necessitates the availability of a publicly accessible shared code, implying equal data distribution among all participants (Glicksberg et al., 2019). The focus of AI models in cancer management is primarily on image data, posing a challenge in incorporating patient biographies from electronic health records across different medical facilities. The integration of user-friendly software and accessible databases into global hospital software systems is a complex task that requires the collaborative efforts of the engineering and medical communities (Bhinder et al., 2021). One of the key challenges in AI implementation is to instill confidence among medical professionals, who need comprehensive training on the practical application of AI technology (Subramanian et al., 2020). However, applying AI methods involves many ethical

Table 1. General Illustration of imaging modalities for breast tumour lymph node cataloguing

Serial No	Name of Imaging Techniques	Sample size	References
1.	CECT—contrast enhanced computer tomography	348 nodes	Yang et al. 2020
2.	Mammography	75 nodes	Abel et al. 2022
3.	CNN de novo	937 nodes	Guo et al. 2020
4.	PET-CT	100 nodes	Song et al. 2021
5.	Ultrasound randomics (Google Cloud AutoML Vision)	317 nodes	Tahmasebi et al. 2021
6.	T1-post contrast dynamic	275 nodes	Ha et al. 2018
7.	Standard breast MRI	259 nodes	Ren et al. 2020

**CECT—contrast enhanced computer tomography, PET—positive emission tomography, MRI-magnetic resonance imaging*

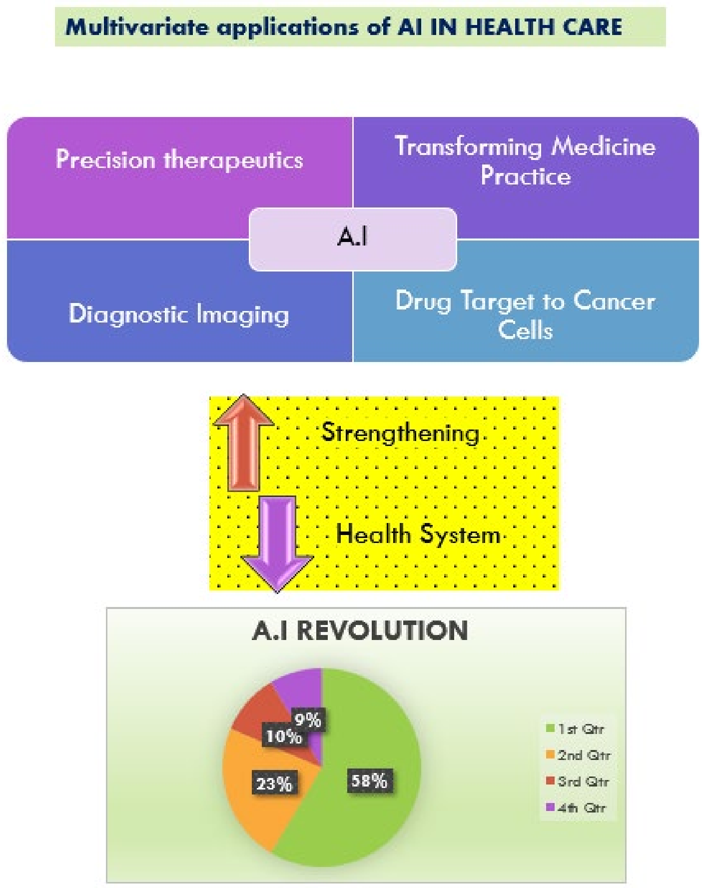

Figure 1. Schematic diagram elucidating advancement of A.I in Health care system

considerations, including consent, data confidentiality, privacy violations, and patient autonomy. Stringent protocols and legal frameworks are in place to prevent any breach of confidentiality and respond to potential unethical practices (Subramanian et al., 2020).Artificial intelligence (AI), machine learning (ML), and deep learning (DL), in particular, are highly suitable candidates for enhancing and augmenting the current diagnostic methodologies employed in the diagnosis of ALN metastasis (Painuli et al., 2022). This is due to the recent developments that have taken place in the discipline. Deep learning (DL) and machine learning (ML) are two instances of machine learning. Considerable research efforts have been devoted in recent years to advancing deep-learning models that are technologically advanced and can detect breast cancer through the analysis of radiological images. By integrating fuzzy ensemble modeling techniques with deep convolutional neural networks (CNN), researchers have achieved a remarkable accuracy rate of 99.32% when applying CNN to detecting breast cancer from mammograms (Hardy & Harvey, 2020). This represents a noteworthy accomplishment. Furthermore, there has been an investigation into using artificial intelligence-based approaches to assess clinicopathological factors, including HER-2, ER, PR, and patient age, to forecast the presence of lymph node metastasis in breast cancer (Adler-Milstein et al., 2021; Altameem et al., 2022; Vrdoljak et al., 2023; Arya et al., 2021; Dileep & Gianchandani, 2022). The various imaging approaches that are currently being utilized in the application of artificial intelligence to the cataloging of numerous breast cancers are enlisted in Table 1 (Yang et al., 2020; Abel et al., 2022; Guo et al., 2020; Song, 2021; Tahmasebi et al., 2021; Ha et al., 2018; Ren et al., 2020).

5. Conclusion

Breast cancer stands as a significant challenge in the medical domain, impacting both healthcare professionals and patients. Implementing artificial intelligence into numerous screening methods has made it simpler to detect cancer early. AI can identify breast bulk, segment breast tissue, and evaluate its density. It can also detect calcification, which facilitates patient diagnosis and care. Additional research and technological breakthroughs have the potential to overcome these limitations, making powered by AI screening methods more widely adopted. This has the potential to enhance the overall quality of life for individuals affected by cancer. Its non-invasive characteristics render it a viable choice, and through continued research, there is potential to enhance the capabilities of AI even further.

However, challenges remain in standardizing AI models across diverse populations and integrating them into existing healthcare systems. Continued research and development are necessary to fully realize the potential of AI in breast cancer management, ensuring equitable access and unbiased diagnostic results.

Author contributions

AKP, PP, PKP, SKS, and BRJ planned, wrote, and conceptualized the study design. Authors RNY, SD, and BNR collected and analyzed the literature, performing advanced analysis and referencing. All authors reviewed and approved the final manuscript.

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Competing financial interests

The authors have no conflict of interest.

List of Abbreviations

MRE: Magnetic resonance elastography
MRS: Magnetic resonance spectroscopy
BSGI: Magnetic resonance spectroscopy
US FDA: United states Food and Drug Administration
CAD: computer-aided diagnostic
AI: Artificial Intelligence
CTCs: circulating tumour cells
PET: Positron Emission Tomography
MRI: Magnetic Resonance Imaging
ER: estrogen receptor,
PR: progesterone receptor
HER-2: human epidermal growth factor receptor 2
FR: Folate receptor
DCE-MRI: Dynamic Contrast Enhanced MRI

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