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Review Article

A Comprehensive Review on Breast Cancer Detection and Using Machine Learning Techniques: Methods, and Challenges Ahead

Mohadeseh Parhizkari[1*], Mahdi Shabanzadeh[2], Fatemeh Abbasi[3], and Sadra Saremi[4]

[1]Department of Biomedical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran
[2]Department of Biomedical Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[3]Chemistry Department, College of Sciences, Shiraz University, Shiraz 71946-84795, Iran
[4]Department of Physics, Iran University of Science and Technology, Tehran 16846-13114, Iran

Corresponding Author: Mohadeseh Parhizkari; email: st_m_parhizkari@azad.ac.ir

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Abstract

Breast cancer (BC) continues to be a major global health concern, with rising incidence rates each year. Timely identification is essential for enhancing patient outcomes, but conventional diagnostic techniques often fall short in terms of precision and effectiveness. This review explores the role of artificial intelligence (AI) and machine learning in transforming BC detection, with a focus on advancements up to 2024. A thorough review of recent studies was conducted, emphasizing the application of machine learning in BC detection across diverse data sources, including microarray data, medical imaging such as mammography, ultrasound, (Magnetic Resonance Imaging) (MRI), and histopathology, and clinical records. The analysis traces the progression from traditional machine learning methods to sophisticated deep learning frameworks, especially convolutional neural networks (CNNs), and assesses their effectiveness in real-world clinical environments. Advances in AI have led to notable gains in diagnostic accuracy, with deep learning models delivering exceptional performance in experimental studies. Hybrid imaging strategies that integrate multiple imaging modalities with AI algorithms have proven particularly effective, especially in detecting abnormalities in dense breast tissue. Innovations like transfer learning and explainable AI have enhanced the adaptability and transparency of these models. Nevertheless, issues related to data quality, computational demands, and the lack of standardized protocols remain unresolved. Although AI-driven detection systems exhibit considerable potential in research contexts, their broader adoption in clinical practice faces several hurdles. Future progress will depend on overcoming challenges such as data standardization, improving model interpretability, and optimizing computational efficiency. Combining AI technologies with established diagnostic practices offers a promising approach to advancing the accuracy and accessibility of BC detection.

Keywords: breast cancer detection, machine learning, deep learning, computer-aided detection

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1. Introduction

In modern healthcare, cancer represents a significant global challenge, with numerous aggressive forms identified. Of these, BC ranks among the most frequently occurring. This condition transcends geographical boundaries and cultural differences, profoundly affecting women's health across the globe. While predominantly impacting women, BC also occurs in men, albeit at substantially lower rates. Ranking as the second primary cause of female mortality, its incidence continues to rise each year [1]. Statistical reports from the American Cancer Society indicate that BC has claimed the lives of nearly 3.3 million women in the United States historically. Globally, annual diagnoses approach 2.3 million individuals, highlighting the disease's widespread impact [2, 3].

Data from Iran's Ministry of Health reveals more than 6,000 new BC cases are diagnosed yearly nationwide, resulting in over 2,000 fatalities. Comparative analyses show that Iranian mortality rates from BC exceed those in industrialized nations. Specifically, Iran experiences a 25% mortality rate versus 15% in developed countries [4].

These statistics underscore the critical importance of timely BC identification. Implementing early detection strategies remains a vital approach for decreasing cancer-related deaths, especially in BC cases. Contemporary medical practice predominantly utilizes mammographic imaging techniques as primary diagnostic tools for this purpose.

The intricate nature of mammography, coupled with the substantial volume of data, the limited accuracy of mammographic images, and other contributing factors, pose significant challenges for the early detection of BC [5]. Research indicates that the extensive data and the potential for human error are primary contributors to misdiagnoses, particularly in the initial stages of the disease. Consequently, there is a pressing need for an efficient and reliable approach to accurately diagnose BC. Computer-aided detection (CAD) systems have emerged as a valuable tool in handling large datasets and improving the diagnostic accuracy of BC, especially in mammography. CAD leverages AI techniques, including machine vision algorithms, machine learning, and statistical pattern recognition, to evaluate mammographic images [6]. Over recent years, AI has thus gained a prominent role in disease detection. Among the key domains of AI is machine learning, which focuses on analyzing diverse data types—such as text, audio, and images—to uncover underlying patterns and insights.

By combining machine learning and machine vision, efficiency in processing images, in general, and medical images, in particular, has increased a lot. Some researchers have discussed methodologies for BC detection with the use of tools of machine learning in collaboration with machine vision [1, 5, 7]. Machine learning is one of the most important techniques for the extraction of information and knowledge from information. It generates tools with high effectiveness in discovering information/knowledge. With the rapid growth in the creation of information, tools for machine learning can manage such information. Machine learning involves algorithms for classification, regression, etc [6]. Out of numerous algorithms for machine learning, deep learning is most effective in the analysis of information, in general, and unstructured information, in particular. Deep learning, a subset of machine learning, involves working with images (unorganized information) directly. Thus, deep learning can be used for classification and other operations of machine learning through learning and extraction of correct features in an unsupervised environment. Deep learning requires high-processing tools such as graphical processing tools (GPUs). Despite such algorithms having a long background and dating back to the 1940s, these have become widespread in AI in numerous areas ever since 2012 when proper tools for them started getting produced [2]. Deep learning involves algorithms such as CNN and their variants, and these have been utilized for the classification of an image.

Despite high efficiency in an image's classification through deep learning, deep learning suffers from certain limitations, such as [8]: 1) powerful processing tools, and 2) a high level of training information, sometimes in terms of thousands and even in terms of millions. Considering these two restrictions, researchers utilize the principle of transfer learning to bypass them . The following sections present an overview of tools utilized for BC detection with the use of machine learning, such as machine learning algorithms and datasets utilized in this field.

2. Data

As per analyzed articles, the following types of data are utilized for BC detection with the use of machine learning tools:

2.1. Microarray Data

Microarrays are one of the most significant breakthroughs in experimental molecular biology, allowing for the analysis of gene expression levels of tens of thousands of genes at a single run. Microarrays are utilized in gene expression analysis, genome mapping, Single Nucleotide Polymorphism (SNP) differentiation, activity of transcription factors, toxicity, pathogen detection, and many other applications. Microarrays allow scientists to pose questions that have long been considered unapproachable through an analysis of the expression level of thousands of genes at a single run. Microarray is nothing but a glass slide with DNA molecules spotted at definite locations termed as spots or probes. Typical microarray platform and experimental and data analysis architecture and flow is pictorially represented in Figure **1** [9].

Research utilizing microarray analysis for BC detection has documented significant improvements in recent years, particularly in discovering new biomarkers and molecular signatures. Dorabad et al. (2024) conducted a thorough meta-analysis of microarray analysis for the investigation of miRNAs deregulation in BC, utilizing Agilent microarray chips for analysis of tumor and adjacent tissue, reporting new information about potential therapeutic targets [11]. Other improvements in molecular signatures have been documented by Samara et al. (2024), who utilized miRNAs discovered through microarray analysis, reporting high accuracy with a high level of sensitivity over 98% [12]. The application of microarray technology for subclassification has been aided by Sirek et al. (2024) work, in which individual expression profiles for individual subclasses of BC have been confirmed through Reverse Transcription-quantitative Polymerase Chain Reaction (RT-qPCR), and therapeutic intervention potential markers have been proposed [13].

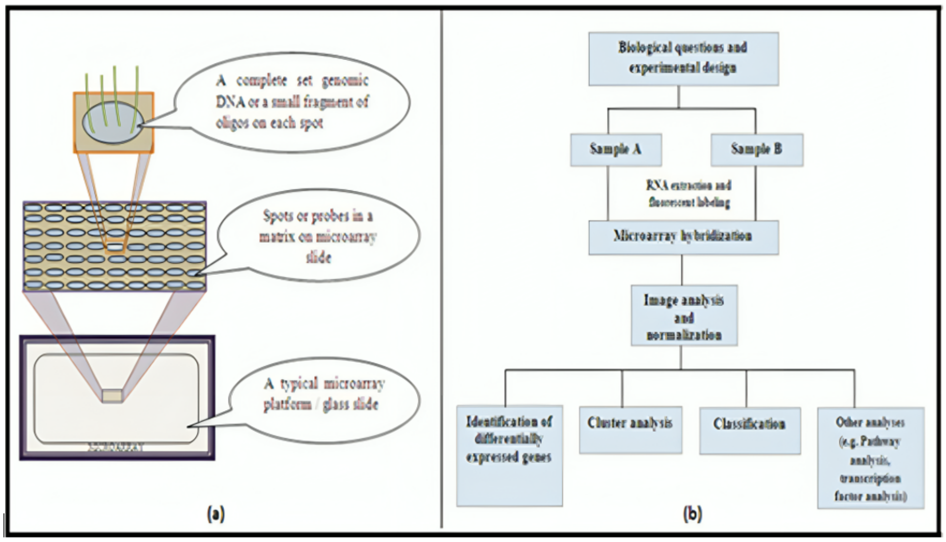

Figure 1: a) A typical microarray platform and its architecture, b) Experimental workflow and data analysis perspectives typically [10].

Recent advances in microarray analysis techniques have aided in a deeper level of understanding of individual breast subclasses of cancer. Vora et al. (2024) have performed GeneSpring GX software analysis for miRNAs with differential expression in triple-negative BC, providing important information about such an aggressive subclass [14]. Suhiman et al. (2024) have constructed complex predictive subclassification models for BC through analysis of RNA-microarray, with considerable improvement in diagnostics and patient stratification [15]. Integration with immune-related gene analysis has been aided through Krishnamoorthy et al. (2024)'s work, in which microarray datasets have been analyzed through Weighted Gene Co-Expression Network Analysis (WGCNA), and important immune-related genes in triple-negative BC have been identified [16].

The application of complex machine algorithms in microarray analysis capabilities has aided in considerable early detection capabilities. Rahman et al. (2024) have displayed increased accuracy in diagnostics through the use of complex algorithms in microarray datasets [17]. Golestan et al. (2024) have performed an integrative analysis combining bioinformatic analysis with experimental confirmation in identifying and confirming new BC markers, providing a deeper level of disease mechanism [18]. All such studies in current times represent the continued development and utility of microarray technology in the investigation and diagnostics of BC, particularly when performed in combination with complex analysis techniques. Medical imaging plays a key role in BC detection nowadays. Techniques of machine vision represent one of the most prevalent AI tools in medical image analysis. Some of the imaging techniques used for the detection of BC are MRI [19-21], ultrasound imaging [22, 23], Digital Mammography (DM) [24, 25], Computed Tomography (CT) scan [26, 27], Positron Emission Tomography (PET) scan [28, 29], Histopathology (HP) [30, 31], and Thermal Imaging (TI) [32, 33] (Table **1**).

Table 1: Distribution of document types related to cancer from the Web of Science database.

Imaging Method	Advantages	Disadvantages
DM	a) First theoretical method b) Easy and economical	a) High radiation b) Unsuitable for dense samples
BUS (Breast Ultrasound)	a) No radiation b) Suitable for dense samples c) Real-time imaging	a) Highly operator-dependent
CT	a) Accurate 3D representation of anatomy and soft tissue samples	a) High cost b) High radiation
HP	a) Color imaging Subtype (type) cancer identification	a) Highly expert-dependent b) Time-consuming
MRI	a) Stage determination of BC b) High accuracy in soft tissue signals	a) Unsuitable for pregnant women b) Unsuitable for individuals with magnetic objects in their bodies
TI	a) Functional information acquisition	a) Low accuracy b) Only used as an assistant method, not as a primary diagnostic method
PET	a) Monitors BC progression and destructive performance	a) Cannot detect small samples

Recent advances in AI-based analysis of medical imaging have transformed BC detection potential. Studies have established that deep learning algorithms in mammography, particularly CNNs, have tremendously improved diagnostic accuracy [34]. All these advances demonstrate AI potential in augmenting early detection protocols, especially in screening programs where fast and accurate diagnosis is paramount.

The combination of CAD systems with conventional imaging techniques has yielded encouraging outcomes in clinical practice. AI-enhanced systems have shown notable advancements in detecting and classifying breast masses [35]. Furthermore, innovative deep-learning architectures that utilize advanced computational methods have achieved considerable success across various imaging modalities, such as ultrasound and histopathology imaging [36].

Recent studies indicate a significant rise in the use of AI for BC imaging in recent years. This trend is particularly evident in the creation of deep learning algorithms tailored for different imaging techniques [37]. The proliferation of AI applications has strengthened diagnostic capabilities across diverse healthcare environments, offering particular advantages in areas with limited access to specialized radiologists. Research has demonstrated the efficacy of AI-powered imaging systems in identifying subtle abnormalities and non-palpable breast masses [38]. These developments play a crucial role in standardizing and improving BC screening programs worldwide, while also enhancing diagnostic precision and reducing variability in interpretation.

Table **2** outlines the imaging methods used for BC detection, along with their respective advantages and disadvantages. While each method has its strengths and limitations, mammography remains the most widely used approach for BC detection. Table **2** lists several datasets utilized for BC detection, including links for access. According to reviews, some of these datasets are private and restricted, while others are publicly available to researchers.

Table 2: Some commonly used datasets in BC detection studies.

Dataset Name	**Imaging Method**	**Ref.**
Integrated Relative Modelling Approach (IRMA)	DM	[28]
Mammographic Image Analysis Society (MIAS)	DM	[29]
Digital Database for Screening Mammography (DDSM)	DM	[30]
INbreast	DM	[31]
Breast Ultrasound Images (BUSI)	BUS	[32]
Reference Image Database to Evaluate Therapy Response (RIDER)	MRI	[33]
Duke-Breast-Cancer-MRI (DBC-MRI)	MRI	[39]
Breast Image Classification Benchmark on Histopathologica (BICBH)	HP	[40]
Cancer Histopathological Images (BreakHis)	HP	[41]
Deuterium metabolic imaging MRI (DMI-IR)	TI	[42]
Open Access Series of Breast Ultrasonic Data (OASBUD)	BUS	[43]
UDIAT (Diagnostic Imaging Centre)	BUS	[44]
Dynamic contrast-enhanced MRI (DCE-MRI)	MRI	[45]

Figure **2** depicts the workflow of image analysis for BC detection. As illustrated in Figure **2**, the machine vision process for BC detection involves several key steps: image preprocessing, feature extraction, data dimensionality reduction (using techniques like feature selection), and finally, classification, clustering, and image segmentation. Various methods exist for extracting features from images. However, given the widespread adoption of deep learning techniques in image analysis and classification in recent years, where feature extraction and selection are automated within the network architectures—this review emphasizes deep learning approaches in medical image processing for BC detection.

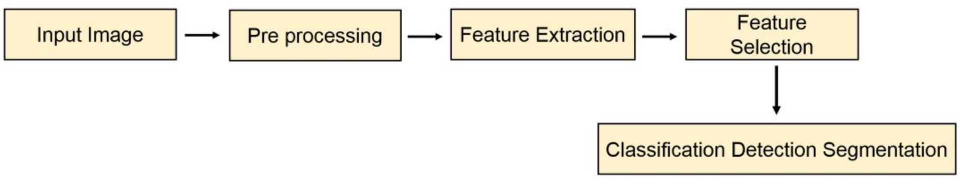

Figure 2: The process of image-based methods in BC detection.

3. Machine Learning Algorithms in BC Detection

Machine learning encompasses a variety of techniques for tasks such as detection, classification, clustering, segmentation, regression, and other forms of data analysis. The data used in these processes

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can take various formats, including tabular data, images, and text. Rather than delving into the theoretical aspects of machine learning and its algorithms, this section focuses on the practical implementation of conventional machine learning approaches. These include methods like Support Vector Machines (SVMs), k-nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Decision Trees, which are commonly used to classify extracted features from medical images and preprocessed datasets.

Selvaraj S and Rezaee K *et al*. [10, 46] employed microarray data for BC detection. Rezaee K *et al*. [46] applied statistical techniques and medical analysis, whereas Selvaraj S *et al*. [10] utilized machine learning tools and methodologies. Due to the high-dimensional nature of microarray data, where the number of features often exceeds the number of samples, preprocessing and dimensionality reduction play a critical role. In the referenced study, researchers used a wrapper-based feature selection approach in combination with a KNN classifier. Following this step, both traditional classification algorithms and deep learning models were implemented for classification and detection, demonstrating the superior performance of deep learning methods over conventional approaches.

Benjelloun M *et al*. [47] investigated gene replacement as a method for BC identification. They emphasized that the classification process involves predicting gene markers, identifying specific genes, and diagnosing gene replacement to determine the presence or absence of cancer. Their findings suggested that multiple approaches could be applied, including regression models, probabilistic methods, SVMs, Neural Networks (NNs), and genetic learning techniques. Additionally, they highlighted significant opportunities to establish connections between nucleotide sequences and feature extraction, given the vast amount of data encoded within DNA sequences.

Wisesty U *et al*. [48], gene expression data, and DNA mutation profiles were analyzed to predict BC. The study employed SVMs, decision trees, and random forest algorithms for classification and prediction tasks. The authors assessed the accuracy and error rates of these algorithms using two different data extraction tools, Weka and Spark. Their comparative analysis revealed that SVM outperformed the other methods, achieving an accuracy of 99.68% in Spark and 98.03% in Weka.

Furthermore, Rabiei *et al*. [8] utilized personal health data to predict BC through machine learning techniques. The primary objective of their study was to assess the effectiveness of various machine learning models in accurately predicting BC.

Alghunaim S *et al*. [49], gathered BC patient data from the Iranian Breast Cancer Center and evaluated it using three machine-learning approaches. The study compared the performance of Decision Tree (C4.5), ANN, and SVM based on accuracy, sensitivity, and specificity metrics. The authors specifically emphasized the Multilayer Perceptron (MLP) model to assess the ANN algorithm's accuracy. Their findings revealed that SVM outperformed the other methods, achieving a prediction accuracy of 95.7% for BC.

Israni P *et al*. [50], a parallel genetic algorithm was employed to enhance the MLP neural network for BC detection, utilizing the Wisconsin Breast Cancer Dataset (WBDC) dataset. Unlike image-based methods, their approach relied on a preprocessed dataset. The study demonstrated that optimizing the MLP neural network significantly improved the detection capabilities of the system.

Rezaeipanah A. *et al*. [51], introduced an advanced intelligent technique for detecting BC in mammographic images. The method involved image processing to identify and highlight mass regions within the images. After eliminating noise, a fuzzy inference system was applied to enhance edges, and a logical coordinate filter was used to pinpoint and mark mass areas. The proposed approach exhibited strong performance in accurately detecting BC.

Abaspur Kazerouni I *et al*. [52], the authors conducted a comparative analysis of multiple classification algorithms. They evaluated eight classification algorithms on eight Natural-Color Dataset (NCD), employing 10-fold cross-validation. The performance of these algorithms was measured using the Area Under the Curve (AUC) metric. The study highlighted that NCD often contain noisy data and irrelevant features. Among the tested algorithms, KNN, SVM, and NN demonstrated robustness against noise. Additionally, the authors suggested that preprocessing techniques could effectively address the issue of irrelevant features, thereby improving classification accuracy.

Kanyongo W *et al*. [53] explored the effectiveness of neural networks in cancer diagnosis, particularly in early-stage detection. Their findings indicated that neural networks showed significant promise in identifying tumor cells. However, they also noted that the imaging methods used in such analyses demand substantial computational resources for image preprocessing tasks.

Mahmood M *et al*. [54], conducted a study to compare five nonlinear machine learning algorithms-MLP, KNN, classification and regression tree (CART), SVM, and Gaussian Naive Bayes-for BC detection. The primary goal was to evaluate the efficiency and effectiveness of these algorithms in detecting BC. The authors individually measured the accuracy of each algorithm using the WBCD and applied K-Fold validation for accuracy prediction. The results revealed that the MLP algorithm achieved the highest accuracy of 96.70%, outperforming KNN, CART, and Gaussian Naive Bayes.

4. Deep Learning Algorithms in BC Detection

Deep learning represents an advanced extension of ANN, characterized by multi-layered architectures. These algorithms are capable of processing vast amounts of natural data and can effectively recognize diverse data types across various categories. This article highlights research focused on deep learning applications in BC detection, without delving into the technical intricacies of the algorithms.

In 2021, Gohargani and Rezagholi [55] introduced a method utilizing CNN for BC detection through mammographic images. Their simulation results demonstrated that CNN outperformed existing neural networks in terms of accuracy and efficiency. The proposed CNN-based algorithm achieved approximately 95% accuracy, precision, and sensitivity. In contrast, the Generalized Regression Neural Network (GRNN) and MLP algorithms yielded results below 90%, with GRNN performing slightly better than MLP.

In 2023, Prodan M *et al*. [56] employed deep learning techniques, including CNN and Vision Transformer models, for mammographic image analysis in BC detection. Their innovative approach incorporated effective data augmentation and preprocessing techniques, which significantly enhanced the performance of their models.

In 2022, Boudouh *et al*. [57] proposed a tumor detection model leveraging transfer learning and data augmentation to mitigate overfitting. They evaluated three pre-trained CNN architectures-AlexNet, VGG16, and VGG19-on a dataset of 4,000 preprocessed images sourced from two databases: the Digital Database for Screening Mammography and the Chinese Mammography Database. Among the architectures, AlexNet and VGG16 exhibited strong performance in tumor detection.

In 2020, Shen *et al*. introduced an end-to-end training approach utilizing deep learning for local image patch classification. They trained a patch classifier on the Digital Database for Screening Mammography (DDSM) dataset, which included well-annotated regions of interest, and then applied transfer learning to the INbreast dataset. The study employed VGG-16 and ResNet-50 architectures in two phases: patch classifier training and whole-image classifier training. The transfer learning approach yielded the best performance on the INbreast test set, achieving an AUC of 0.95 [58].

In 2021, Salama *et al*. [59] developed a framework for image segmentation and classification of BC to aid radiologists in early detection and enhance diagnostic efficiency. The framework incorporated multiple deep learning models, such as InceptionV3, DenseNet121, ResNet50, VGG16, and MobileNetV2, to classify mammographic images as benign or malignant. Additionally, a modified U-Net model was utilized for segmenting breast regions in Cranio-Caudal (CC) and Mediolateral Oblique (MLO) views. To address the challenge of limited labeled data, the method employed transfer learning and data augmentation techniques.

In 2022, Maqsood *et al*. [60] proposed a five-stage method for BC image detection and classification. The stages included contrast enhancement, the use of a Transferable Texture Convolutional Neural Network (TTCNN) architecture, transfer learning, feature combination, and feature selection. This approach achieved high accuracy rates of 99.08%, 96.82%, and 96.57% on the DDSM, IN breast, and MIAS datasets, respectively. However, the authors noted that the method's performance could vary depending on factors such as background noise or overfitting in different images.

Luo *et al*. [61] introduced a framework known as the Segment-based Attention Network (SBANet), a segmentation-to-classification model specifically developed for BUS images. The framework begins by training a segmentation network to generate images that improve tumor segmentation. For the classification phase, features are extracted from both the segmentation-enhanced images and the original reference images. Experimental evaluations demonstrate that this segmentation-to-classification approach achieves a diagnostic accuracy of 90.78%.

In another study, Ding *et al*. [23] employed the ResNetGAP network to perform simultaneous tumor classification and localization. The network was trained using BUS and Endoscopic Ultrasound (EUS) images across different channels, with data from 264 patients included in the study. The model achieved a classification accuracy of 88.6% and a sensitivity of 95.3%. However, a significant limitation of this work is the absence of EUS images for testing purposes.

To tackle challenges such as data limitations, misclassifications, and prediction errors, Jabeen *et al*. [62] developed a fully automated system based on a modified version of the DarkNet53 deep learning model. The model was trained on augmented BUS images using transfer learning techniques. Optimal features were selected through a combination of modified differential evolution and gray wolf optimization algorithms. Furthermore, a probabilistic approach was employed to integrate the selected features before applying machine learning algorithms for classification. The proposed framework achieved an impressive accuracy of 99.1%.

In a separate study, Joseph *et al*. [63] introduced a method that combines handcrafted feature extraction techniques with deep neural networks for multi-class classification of BC using mammographic images. The preprocessing phase included data augmentation, noise removal, and segmentation to enhance classification performance and mitigate overfitting. Data augmentation played a critical role in improving accuracy, with the approach achieving accuracies of 97.87, 97.60, 96.10, and 96.84%.

Shen *et al*. [58] introduced an end-to-end deep learning approach designed to detect BC in mammography images with high precision, significantly reducing false positives. Their algorithm leverages clinical regions of interest (ROI) annotations for initial training and can be further enhanced using datasets without ROI annotations. The research highlighted the importance of patch-based classification for improving image classification accuracy, noting that while larger or more patches enhance accuracy, they also increase computational demands. Additionally, the study demonstrated that integrating VGG and ResNet architectures led to improved performance, with full-resolution digital mammography images delivering superior results.

Sahu *et al*. [64] conducted a study utilizing five hybrid CNN models for BC detection using both BUS and DM images. The hybrid approach combined the strengths of multiple networks, outperforming individual base classifiers. The system's efficiency and accuracy were heavily dependent on reliable chip-on components and probability-based elements. The proposed model was evaluated on datasets from two distinct BC imaging modalities (BUS and DM) and achieved higher accuracy than existing state-of-the-art methods, such as ShuffleNet and ResNet. Specifically, the hybrid model achieved 99.17% and 98.00% accuracy in detecting anomalies and malignancies in the DM dataset, and 96.52% and 93.18% in the BUS dataset.

Demir *et al*. [65] proposed an innovative method based on a Convolutional LSTM (CLSTM) model using HP images. By combining CNN and LSTM, the model benefited from CNN's ability to extract meaningful features and LSTM's strength in processing sequential data and identifying relationships among similar samples. Furthermore, the researchers replaced the softmax classifier with an optimized SVM classifier, achieving 100% accuracy across all magnification factors, which outperformed the softmax classifier.

Patil *et al*. [66] developed a framework employing CNN and Recurrent Neural Network (RNN) architectures for analyzing DM images. The framework consists of four key stages: preprocessing, tumor segmentation, feature extraction, and data classification. To enhance segmentation accuracy, a region-growing optimization algorithm was implemented. The results indicated that the diagnostic accuracy of this framework surpassed that of earlier models. In Table **3**, a summary of some significant machine learning (deep learning) methods in BC detection is provided.

Table 3: Summary of some significant machine learning (deep learning) methods in BC detection.

Challenges	Performance	Type of Data	Technique Used	Number of Images	Journal	Author and Year (*et al.*)
The method has a two-stage classification process, which increases complexity and training time and does not have end-to-end efficiency.	Acc 90.78, Sensitivity 91.18, Specificity 90.44, F1-score 91.46, and AUC 95.49	BUS	SBANet and channel attention	A: 160 benign and 132 malignant B: 786 benign and 916 malignant	Pattern Recognition	Luo [61] 2022
Random data augmentation is used, so results may be biased towards a particular class.	Acc 88.6	BUS	ResNET-GAP	29 B and 135 M	IEEE Journal of Biomedical and Health Informatics	Ding [23] 2022
Lack of explanation and interpretation of the model's capabilities in disease diagnosis.	Acc 99.1	BUS	Transfer learning	133 N, 210 M, and 487 B	Sensors	Jabeen [62] 2022
The proposed method has not been tested on any other dataset, making the model not generalizable.	Acc 97.87, 97.60, 96.10, and 96.84	HP	Handcrafted and DCC	82 patients, 2480 B, and 5429 M	Intelligent Systems with Applications	Joseph [63] 2022
Mammograms are reduced in size to fit GPU memory, and the datasets used are not representative samples.	AUC of 0.88, sensitivity: 86.1%, specificity: 80.1%	DM	Resnet-50 and VGG16	2478 images from 1249 patients	Scientific Reports	Shen [58] 2019
Combined results of parse learning and transfer learning have not been reported.	Acc 99.17 and 98.00 with the DDSM dataset. 96.52, 93.18 with BUSI dataset	BUS, DM	Hybrid CNN	BUS: B 487, M 210, N 133 DM: N 2728, M 3596, B 3360	Biomedical Signal Processing and Control	Sahu [64] 2023
CLSTM has a complex structure.	Acc 100	HP	CLSTM	429 M, 2480 B	Biocybernetics and Biomedical Engineering	Demir [65] 2021
A mean filter is used for noise removal, but it has the drawback of removing fine details and thin lines in the image, even at low noise levels.	Acc 93.59	DM	CNN, RNN	Not mentioned	Evolutionary Intelligence	Patil [66] 2021

BC remains the most common cause of death among women globally, making early detection a critical factor in reducing mortality rates. Various imaging techniques are currently used to gain a more detailed understanding of BC. However, manually analyzing large volumes of diverse images is both time-consuming and prone to errors, often resulting in misdiagnoses and increased false positives. As a result, there is a pressing need for automated solutions to address these challenges. Medical image analysis using CAD systems has emerged as a highly effective tool for the early detection of BC. CAD systems are designed to support healthcare professionals by providing accurate interpretations of medical images. These systems enable radiologists to identify abnormalities more efficiently and reduce the likelihood of incorrect diagnoses. However, CAD systems often detect a higher number of false features than genuine abnormalities, requiring physicians to carefully analyze the results. This limitation increases the time required for diagnosis and restricts the number of cases radiologists can evaluate. Despite these challenges, advancements in AI, particularly deep learning, have revolutionized the image analysis process, offering significant support to radiologists in the early detection of BC.

Studies have demonstrated that deep learning-based CAD systems can deliver reliable results in medical image analysis. However, several obstacles hinder their widespread adoption in clinical practice. A major challenge is the scarcity of comprehensive datasets for training deep learning models in medical imaging. Since these algorithms depend on large, high-quality datasets, the availability of suitable data is crucial for optimal performance. Creating such datasets is difficult due to the time-intensive nature of annotating medical images and the need to minimize human error. Additionally, the imbalance between abnormal and normal cases makes data collection expensive and complex. Data availability is further influenced by factors such as the number of patients undergoing specific tests, access to imaging equipment, and regulatory constraints across different healthcare centers. For instance, DM datasets are typically larger, encompassing data from thousands of patients, while MRI and PET/CT datasets are smaller due to fewer patients. This disparity has led to more algorithms being developed and validated on DM datasets compared to others, largely due to the wider accessibility of DM equipment. To address these issues, a collaborative, multicenter approach is recommended to create large, diverse datasets that include a wide range of patient demographics, clinical histories, imaging modalities, and treatment methods. Such datasets would significantly improve the performance, accuracy, and reliability of deep learning algorithms.

Most existing imaging datasets are limited in scope, posing a challenge for deep learning models, which require extensive training data to achieve optimal results. Addressing data scarcity is essential, and several potential solutions have been proposed. One promising approach is the aggregation of data from multiple healthcare centers to create a larger, more comprehensive dataset. However, this must be done while adhering to strict patient privacy regulations to ensure ethical and legal compliance.

5. Machine Vision Methods in BC Detection

Machine vision involves computational techniques and algorithms tailored to analyze and interpret medical images for BC detection. These methods utilize a range of imaging modalities, such as mammography, ultrasound, MRI, and histopathology, alongside advanced image processing algorithms to identify and classify potential malignancies. The fusion of AI with conventional imaging techniques has transformed diagnostic capabilities, enabling more precise and efficient detection of BC features. Recent innovations in this field have prioritized improving detection accuracy, minimizing false positives, and enhancing early diagnosis through automated analysis systems [67-78].

Recent progress in machine vision techniques has significantly advanced BC detection across various imaging modalities. The combination of AI with traditional imaging methods has led to notable improvements in diagnostic accuracy and efficiency. This section explores key developments and methodologies in machine vision applications for BC detection.

The integration of radiomics and deep learning has become a pivotal advancement in BC diagnosis. Oladimeji *et al*. (2024) showcased the efficacy of combining radiomics with deep learning models, employing mutual information-based feature selection and SHAP explainability. Their method significantly enhanced tumor subtype identification and delivered interpretable results for clinical use [79].

Multimodal machine learning approaches have demonstrated considerable potential in risk stratification. Qian *et al*. (2024) developed an integrated model that combined clinical, imaging, and genomic data, achieving superior predictive accuracy in BC risk assessment [80]. This multimodal strategy overcomes the limitations of single-modality analysis, offering a more comprehensive understanding of patient-specific risk factors.

Computational methods have substantially improved ultrasound imaging techniques. Sushanki *et al*. (2024) conducted an extensive review of machine learning and deep learning applications in ultrasound imaging, emphasizing the effectiveness of transfer learning and segmentation-enhanced classification for analyzing dense breast tissues [81]. Their findings underscore significant advancements in accurately identifying malignant regions within complex tissue structures.

In histopathology analysis, AI applications have revolutionized traditional diagnostic methods. Ray *et al*. (2024) investigated deep-transfer learning models for analyzing histopathological images, achieving exceptional accuracy in detecting nuclear atypia and tumor grading [82]. Their work highlights the potential of automated systems to support pathologists in the diagnostic process.

The incorporation of IoT and 5G technologies with machine vision methods represents a major leap forward in real-time diagnosis. Saroğlu *et al*. (2024) examined the impact of these technologies on processing efficiency and diagnostic accuracy [83]. Their research emphasized the potential for enhanced real-time analysis and remote diagnostic capabilities.

Deep learning applications in mammography analysis have produced promising results in recent developments. Ahmad *et al*. proved CNN-based approach is superior to traditional diagnostic methods in lesion detection. [35] Their model offered remarkable enhancements in the accuracy of early detection, especially in complex instances involving denser breast tissue.

These improvements in machine vision techniques have collectively resulted in better and faster BC detection systems. The combination of different computational techniques with conventional imaging techniques has improved the diagnosis through various healthcare facilities. Nevertheless, there are still issues with the unity of these approaches for their clinical application and the variability of their effectiveness in different patients.

6. Deep Learning for Automated Image Analysis in BC Detection

Deep learning is a game changer in the field of automated medical image analysis for BC detection. This computational approach uses sophisticated neural networks to learn for itself how to recognize patterns in medical imaging data without being programmed to do so, outperforming conventional computer vision techniques. Deep learning models, including CNNs, have shown great potential in various modalities such as mammography, ultrasound, MRI, and histopathology [84-88].

Advanced deep learning architectures have revolutionized the way of BC diagnosis. Ahmad *et al*. (2024) have gotten unprecedented enhancement in mammographic analysis through the use of CNN, which provided better detection of lesions especially in the dense breast tissue [35]. This improvement was subsequently improved by Qian *et al*. (2024) who designed a large-scale framework that combines clinical, imaging, and genomic information for accurate diagnosis [80].

In the field of pathological image analysis, Ekta *et al.* (2024) proposed the “Auto-BCS” system, a hybrid deep learning framework designed for real-time examination of pathological images [89]. This system has demonstrated remarkable efficacy in aiding clinical decision-making by swiftly and accurately detecting cancerous areas. In a related advancement, Ketfi and Belahcene (2024) improved automated segmentation methods for ultrasound imaging, creating models that excel at defining tumor boundaries even under difficult imaging conditions [90].

Notable strides have also been achieved in histopathological analysis using transfer learning techniques. Duodu *et al*. (2024) explored the fusion of IoT technologies with deep learning, unveiling new opportunities for remote screening and real-time diagnostic solutions [91].

A key breakthrough in clinical applications has been the improvement of interpretability in results. Oladimeji *et al*. (2024) effectively combined SHapley Additive exPlanations (SHAP) with CNN architectures, enhancing the transparency and clinical utility of deep learning outputs [79]. This development tackles the essential need for explainability in AI-powered medical diagnostics.

Together, these innovations mark a substantial leap forward in automated image analysis. Nevertheless, challenges remain in standardizing these methods across various healthcare environments and ensuring reliable performance across diverse patient groups. Ongoing advancements in these technologies hold the potential to further refine BC detection and diagnosis, ultimately contributing to better patient outcomes through earlier and more precise identification.

7. Multi-Modal Imaging Applications in BC Detection

The detection of BC has seen remarkable progress with the adoption of multi-modal imaging techniques, which integrate data from mammography, ultrasound, and MRI to overcome the limitations of single-modality approaches. Although mammography is widely used for screening, it struggles with dense breast tissues, while ultrasound, despite its utility, is subject to operator variability. MRI, while highly sensitive, is costly and not universally accessible. Multi-modal imaging combines the advantages of these techniques, improving diagnostic precision and early detection by merging complementary data. Utilizing advanced machine learning and deep learning frameworks, multi-modal methods synthesize diverse imaging inputs to offer a holistic perspective on BC characteristics. This integration not only enhances the detection of malignancies in challenging cases but also facilitates early diagnosis and personalized treatment plans, representing a significant advancement in BC detection [92-97].

Recent studies have highlighted substantial advancements in multi-modal integration strategies. Sushanki *et al*. (2024) introduced a novel framework that merges mammographic and ultrasound data using deep learning models, achieving higher classification accuracy for dense breast tissues [81]. This work was further advanced by Nakach *et al.* (2024), who developed refined fusion techniques combining MRI and ultrasound data, leading to improved accuracy in risk prediction [92].

The incorporation of explainable AI into multi-modal approaches has added a critical layer of reliability to diagnostics. Makhlouf *et al*. (2024) effectively integrated explainable AI methods with various imaging modalities, boosting the interpretability of results without compromising diagnostic precision [98]. Their approach proved particularly effective in evaluating complex cases involving mammography, ultrasound, and histopathology images.

Progress in hybrid modeling has also enhanced diagnostic performance. Sahu *et al.* (2024) created advanced CNN models that utilize combined mammogram and ultrasound data, achieving exceptional sensitivity and specificity in detecting early-stage malignancies [64]. Similarly, Luo *et al*. (2024) proposed an innovative framework that integrates tomosynthesis with ultrasound imaging, demonstrating significant improvements in identifying lesions [61].

Radiomics has emerged as a critical component in multi-modal imaging, offering new insights into BC analysis. Conti *et al*. (2024) showcased the efficacy of integrating pretreatment ultrasound and tomosynthesis radiomics to predict therapy response [99]. Their research underscores the prognostic potential of analyzing combined multi-modal data. Further advancing this domain, Guo *et al*. (2024) developed knowledge-enhanced deep learning models capable of effectively merging spatio-temporal features from diverse imaging modalities [100].

These innovations in multi-modal imaging mark a substantial leap forward in BC detection, particularly for complex and high-risk scenarios. By combining multiple imaging techniques and leveraging advanced computational approaches, diagnostic accuracy and reliability in clinical practice continue to improve, paving the way for more effective patient care.

The quality and diversity of datasets also pose significant challenges. Ahmad *et al*. (2024) showed that the effectiveness of AI systems is highly dependent on access to high-quality, diverse training data [35]. This reliance often results in limited generalization capabilities across different patient demographics and imaging scenarios.

Computational infrastructure demands further complicated implementation. Wahed *et al*. (2025) highlighted the extensive computational resources required for training and deploying sophisticated neural networks, especially in healthcare settings with limited resources [101]. Their findings indicated that these requirements often render advanced AI systems unfeasible for broad adoption.

Operational challenges were also emphasized by Ijaz *et al*. (2024), who identified issues such as insufficient labeled datasets and computational constraints as major barriers to AI system performance, particularly in resource-limited environments [102]. The study called for standardized data collection methods and innovative augmentation techniques to improve the reliability and robustness of AI-based diagnostic tools.

Carriero *et al*. (2024) further explored challenges related to system scalability and data augmentation [93]. Their research demonstrated how these limitations hinder the practical application of AI systems in clinical settings, especially when addressing diverse patient populations and varying imaging conditions.

8. Conclusion

Early detection of BC significantly improves survival rates, and advancements in technology have made this increasingly feasible. AI-based methods in medical image analysis now allow for the automated extraction of crucial features from extensive datasets, enhancing the accuracy of BC diagnosis. This study reviews recent literature on the application of deep learning to various medical imaging modalities for BC detection. It also evaluates the strengths and limitations of deep learning techniques by analyzing medical images. The scope of this study spans from cancer detection and segmentation to image generation and processing. While deep learning methods have achieved remarkable results, several challenges must be addressed before these technologies can be fully adopted in clinical settings. Ethical issues, particularly regarding the explainability and interpretability of AI systems, also require careful consideration. This analysis underscores potential future directions and obstacles in implementing AI-based approaches for BC detection using diverse medical images. It emphasizes the urgent need for a comprehensive, fully automated framework capable of reliably identifying BC with minimal human intervention.

Ethical Issue

Authors are aware of and comply with, best practices in publication ethics specifically about authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

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