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\textbf{Abstract}

Breast cancer stands as a pressing health concern for women across the globe with millions of new cases worldwide each year. The diagnostic procedures often rely on expert analysis and interpretation, which can be subject to errors and limitations. This review offers an in-depth examination of the potential role of artificial intelligence as a transformative tool in the diagnosis of breast cancer. The focus is on the recent advancements within machine learning and deep learning, subsets of artificial intelligence that have shown promise in enhancing the accuracy and efficiency of breast cancer detection and classification. The paper discusses studies published in 2023, which have utilized artificial intelligence models with diagnostic medical datasets to identify, classify and predict the presence of breast cancer with increased precision. By exploring a multitude of approaches, such as federated learning, hybrid deep and machine learning models, and optimization algorithms applied to classification and predictive tasks, this review encapsulates the current state of machine learning and deep learning applications in breast cancer diagnosis.
The Transformative Potential of Artificial Intelligence in the Diagnosis of Breast Cancer: A Review

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Abstract

Breast cancer stands as a pressing health concern for women across the globe with millions of new cases worldwide each year. The diagnostic procedures often rely on expert analysis and interpretation, which can be subject to errors and limitations. This review offers an in-depth examination of the potential role of artificial intelligence as a transformative tool in the diagnosis of breast cancer. The focus is on the recent advancements within machine learning and deep learning, subsets of artificial intelligence that have shown promise in enhancing the accuracy and efficiency of breast cancer detection and classification. The paper discusses studies published in 2023, which have utilized artificial intelligence models with diagnostic medical datasets to identify, classify and predict the presence of breast cancer with increased precision. By exploring a multitude of approaches, such as federated learning, hybrid deep and machine learning models, and optimization algorithms applied to classification and predictive tasks, this review encapsulates the current state of machine learning and deep learning applications in breast cancer diagnosis.

Keywords: Artificial Intelligence, Breast Cancer, Medical Imaging, Machine Learning, Deep Learning.
1. Introduction

Breast cancer, a malignancy originating from breast tissue, is the most prevalent and one of the most lethal types of cancer affecting women worldwide. This disease can manifest in different forms, ranging from localized tumors to aggressive cancers that spread rapidly to other parts of the body [1,2].

1.1.1 Etiology and Prevalence

The etiology of breast cancer is multifactorial, involving genetic, environmental and hormonal factors[3]. Epidemiologically, breast cancer represents a significant portion of cancer diagnoses in women, with numerous cases recorded annually across the globe. In the year 2020, breast cancer diagnoses reached 2.3 million among women globally, leading to 685,000 fatalities. By the close of 2020, 7.8 million women had been diagnosed with breast cancer in the last five years that were still alive, solidifying its status as the most widespread cancer worldwide. This form of cancer affects women in every country, emerging at any age post-puberty, with incidence rates rising notably in later stages of life [4]. In the United States in 2023, there were 297,790 newly reported cases of breast cancer, and 43,170 women died of the disease [5]. The mortality rate, although decreasing due to advances in detection and treatment, remains concerningly high.

1.1.2 Classification and Pathophysiology

Breast cancers can be categorized based on their pathophysiology into several types: benign, in-situ carcinoma, and invasive carcinoma [6]. A benign tumor is usually a mild abnormality within the breast structure and is considered non-cancerous [7]. In-situ carcinoma denotes cancer cells that are confined within the ducts and lobules, posing a limited threat when detected early [8]. In contrast, invasive carcinomas have the potential to metastasize, spreading to distant organs and thus representing a more severe threat to patient health [9].

1.1.3 Diagnostic Modalities

Early and accurate diagnosis of breast cancer is crucial for effective treatment, potentially reducing mortality rates. The diagnostic methods include:

a) Mammography: An X-ray based technique that is considered the gold standard for early breast cancer screening [10].
b) Ultrasound: Provides detailed imaging of breast tissue and is often used to supplement mammographic findings [11].

c) Computed Tomography (CT): Helps in assessing the degree of dissemination of the disease [12].

d) Magnetic Resonance Imaging (MRI): Offers high-resolution images and is particularly helpful in assessing invasive cancers [13].

e) Positron Emission Tomography: Often combined with CT to evaluate cancer metastasis [14].

f) Breast Thermography: Measures breast surface temperatures and may detect early vascular changes associated with tumor growth [15].

g) Histopathological Examination: The definitive diagnostic approach involves microscopic analysis of tissue biopsies, typically using H&E staining to differentiate between normal and cancerous cells [16].

Despite the effectiveness of these methods, challenges persist, including false positives/negatives and the need for a more accurate understanding of tumor biology.

1.1.4 The Challenges of Current Diagnostic Practices

The standard diagnostic pathway often requires interpretation by experienced radiologists or pathologists, and several limitations are associated with human analysis:

1. Expert Availability: There is limited access to breast cancer specialists in remote or underdeveloped regions.

2. Diagnostic Complexity: There is a need for domain expertise to analyze multi-class images accurately.

3. Workload and Fatigue: Professionals are often tasked with reviewing large volumes of imaging data, leading to potential diagnostic errors.

4. Subtleties of Imaging: Breast tumors and tissue structures can be challenging to distinguish, increasing the difficulty of accurate manual analysis.

1.2.1 The Advent of AI in Breast Cancer Diagnosis
Given these challenges, there is an increasing interest in leveraging artificial intelligence (AI) to augment the detection and classification of breast cancer. AI technologies can analyze complex medical images with high precision, minimizing human error. The potential of AI encompasses machine learning algorithms and deep learning models which promise to transform the field of oncology by providing more accurate, efficient, and accessible diagnostic tools.


Machine learning (ML) and deep learning (DL) are subsets of AI that have shown incredible promise in a multitude of fields [17–21], including medical diagnosis and specifically, in breast cancer diagnosis. They are usually involved in the development of algorithms that can learn from and make predictions or decisions based on data.

Machine Learning, at its core, is the process by which computers are trained to learn from and interpret data without being explicitly programmed for every possible scenario [22,23]. In the context of breast cancer diagnosis, ML algorithms can be trained on a dataset consisting of various patient records, mammogram images, biopsy results, and more. By identifying patterns and relationships within this data, ML algorithms can help predict the likelihood of breast cancer, classify tumors into benign or malignant, and even predict patient outcomes such as survival rates.

There are different types of ML approaches that are relevant to breast cancer diagnosis:

i) Supervised Learning: Algorithms are trained on labeled data, meaning the data is already tagged with the correct answer (e.g., cancerous or non-cancerous). The algorithm then applies what it has learned to new, unlabeled data [24].

ii) Unsupervised Learning: Algorithms are used to identify patterns in data but the data is not labeled. This approach is often used for clustering similar cases and anomalies, which can be particularly useful for identifying unusual or aggressive forms of breast cancer[25].

Deep Learning, on the other hand, is a subset of ML that uses neural networks with multiple layers (hence ‘deep’) to progressively extract higher-level features from raw data [26,27]. This ability to automatically discover the representations needed for feature detection or classification makes DL especially suited for complex tasks like image recognition, which is critical for breast cancer diagnosis.
In breast cancer detection, DL usually involves convolutional neural networks (CNNs) that are trained using large sets of labeled images – for example, mammograms or ultrasounds. Each layer of a CNN is able to detect features at a different level of complexity. The first layer might detect edges and simple patterns, while deeper layers might identify more complex structures pertinent to distinguishing between benign and malignant tumors.

DL models are particularly adept at handling the high dimensionality of medical imaging data, making them excellent at diagnosing breast cancer, often surpassing human performance in terms of accuracy. Researchers train these models using vast datasets of breast imagery, which might feature minute signs of early cancer that even experienced radiologists could miss.

However, the robust performance of DL models is based on the quality and quantity of annotated data. Since acquiring a large, well-labelled dataset is often challenging in the medical field due to privacy concerns and the time-consuming nature of expert annotation, DL researchers must often find innovative ways to leverage existing datasets or augment data to improve model performance.

Once trained, DL models can quickly evaluate new images and provide diagnostic assessments, including the likelihood of malignancy and the identification of tumor boundaries. This not only aids in early detection but can also help in planning treatments and surgeries by providing detailed insights into tumor size, shape and potentially behavior.

One of the main advantages of DL in breast cancer diagnosis is its ability to continuously improve. As these models are exposed to more data over time, they refine their predictive capabilities, and their diagnostic accuracy can potentially increase. This aspect is vital in its contribution to personalized medicine, wherein treatment plans and diagnostic tools are tailored specifically to individual patient profiles.

Despite these benefits, some challenges surround the integration of ML and DL into clinical settings for breast cancer diagnosis. The black-box nature of these models often makes it difficult for clinicians to understand the reasoning behind specific diagnoses or predictions [28]. Consequently, there is a drive within the field to develop more interpretable ML models that can explain their outputs, thereby increasing trust and adoption among healthcare professionals [29].

Furthermore, ethical considerations around data privacy, potential biases in training data resulting in unequal care and regulatory approvals also play a critical role. Ensuring fairness and
transparency in these AI systems is essential, particularly as they start to play a more integral role in life-impacting decisions such as breast cancer diagnosis[30–32].

Machine learning and deep learning represent transformative technologies in the fight against breast cancer. ML ability to parse through and learn from vast amounts of data and deep learning's has shown proficiency in image recognition both have the potential to enhance diagnosis, treatment planning, and outcome prediction [33]. As these technologies continue to evolve, their integration into healthcare systems promises to help in the timely and accurate diagnosis of breast cancer, ultimately leading to better patient care and survival outcomes. However, the success of these AI applications will depend on continuous collaboration between technologists, clinicians, and ethical regulators to ensure that the benefits are maximized while minimizing potential risks.

This review will explore the studies that were published in 2023 in which AI tools are currently being developed and used for the diagnosis of breast cancer. Table 1 summaries the studies discussed in this literature review.

Table 1 summaries the studies using machine learning and deep learning in 2023

<table>
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<td>Neelima et al., 2023</td>
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<td>Aslan (2023)</td>
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<td>Accuracy 98.56% on MIAS data set. Accuracy of 92.26% on inbreast data set.</td>
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Gad et al., 2023 | RF | Accuracy 97.2%, F1 score of 97.3%
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Botlagunta et al., 2023 | DT and RF | Accuracy 83% respectively, F1 score of 83% and 85% respectively. AUC of 0.87 and 0.85 respectively
Farooq et al., (2023) | NCA-KNN | Accuracy 97.5%
Zourhri et al., (2023) | Transfer Learning VGG19 | Accuracy 98.44%
Chebbah et al., (2023) | SVM | Accuracy 94.4% and F1 score of 91.2%
Jiang et al., (2023) | FW-PHHO-ELM | Accuracy 98.76%
Rahman et al., (2023) | AdaBoost, XGBoost, gradient boosting | Accuracy 98.60%, 97.20% and 95.80% respectively. AUC 1.00, 0.99 and 0.98 respectively

3. Application of Artificial Intelligence in Breast Cancer Diagnosis

Scientists are carrying out huge amounts of work and AI could revolutionize medical sciences. Researcher predict the probability of breast cancer in patients using ML models. These include multilayer perceptron, k-nearest neighbour (KNN), random forest (RF), gradient boosting, bagging and AdaBoost. Testing and training were conducted on the Wisconsin repository's breast cancer diagnostic medical dataset, consisting of 569 observations and 32 features. After the data cleaning, exploratory analysis, training, testing, and validation, the model performance was evaluated based on parameters like classification accuracy and F1 score. Multilayer perceptron, gradient boosting, bagging, KNN AB, and RF models yielded an accuracy of 95%, 94%, 94, 94% 93% and 91% respectively, positioning them as suitable models for breast cancer identification and prediction. A macro f1 score of 95%, 95%, 94%, 93%, 93% and 91% was achieved by multilayer perceptron, KNN, bagging, AdaBoost, gradient boosting and RF classifier respectively [34].

Kumbhare et al., (2023) utilizes federated learning (FL), a new form of AI training, applied specifically for breast cancer detection. Without centralizing data, FL allows individual hospitals to utilize the extensive datasets from multiple unaffiliated hospitals. Digital database for screening mammography (DDSM) dataset was used to collect mammogram images which assisted in
creating an efficient deep-learning model using FL. Combining DL and meta-heuristic learning, the study aims to propose a model for breast cancer diagnosis involving three steps: image collection, feature extraction, and classification phase. FL reduces processing time and enhances model performance by collecting mammogram images from affected individuals. The DenseNet architecture was then used to extract features from these images, which were further classified using enhanced recurrent neural networks (E-RNN). Optimization of certain parameters in the RNN network was done using the hybrid dragon-rider optimization (HDRO), combining dragonfly algorithm (DA) and red deer algorithm (RDA) for accurate classification results. The effectiveness of the breast cancer diagnosis model was shown, with an accuracy of 95% and Matthews correlation coefficient of 91% [35].

Researcher focuses on an effective approach to early breast cancer detection, with designs to minimize human errors through data mining technologies. The study's systematic process involves initial data pre-processing and upgrading image quality, segmenting cancerous cells from healthy tissue, and outlier exclusion, followed by the assembly of a classification model utilizing deep neural networks. The classification model is based on majority voting, using several key features derived from images, and designed for diagnosing the invasive ductal carcinoma grade. The methodology was tested on two histopathological microscopic datasets of invasive ductal carcinoma patients. The model achieved success in rapid and precise cancer diagnosis, attaining average accuracies of 92.65% and 93.34% [36].

A hybrid DL and ML data mining approach for breast cancer prediction was investigated. The technique addresses imbalances in data distribution impacting prediction accuracy by utilizing a combination of linear discriminant analysis, wild horse optimization and advanced Elman recurrent neural network (AERNN) methods. The linear discriminant analysis model facilitates feature removal, the wild horse optimization model manages feature reduction and tunes AERNN's hyper-parameters and the optimized AERNN model advances classifications. Using, the hybrid model on the Wisconsin diagnosis breast cancer dataset, 60% for training and 40% for testing, facilitated feature extraction and reduction, thus enhancing classification efficiency. performance metrics demonstrate a superior outcome with precision at 98.51%, recall at 98.65%, accuracy at 97.88%, an F1 score of 98.32% and low error evaluations of RMSE (1.006) and MAE (1.986) [37].
Researchers examined the application of ML methods in classifying breast cancer mass pathology using mammogram annotations from radiologists in the breast cancer digital repository. It evaluated the efficacy of precomputed features in the breast cancer digital repository and the combination of discrete wavelet with radon transform utilizing four serial feature selections and three genetic algorithms. The fusion of features from different mammographic views (craniocaudal and mediolateral oblique) yielded improved classifier performance. The study deployed deep transfer learning (DTL) for mass classification, leveraging the weight of NASNetLarge, ResNet50, and Xception networks. An ensemble of DTL models outperformed individual DTL models. The devised ensemble (EDTL) demonstrated high classification performance with AUC scores of 88.43 and 90.89 on region of interest (ROI) and ROI union datasets respectively. [38].

Neelima et al., (2023) study focused on the breast cancer early detection and diagnosis system implementing ML techniques. The researchers utilized the Wisconsin diagnostic data set to evaluate the effectiveness of two ML algorithms, decision tree (DT) and support vector machine (SVM). The performance of the combined fuzzy based SVM and DT model surpassed other singular ML models based on measures such as precision, accuracy, specificity, and recall. The outcomes showed that the fuzzy-based SVM and DT classifiers could detect breast cancer with high accuracy (98.2%), precision (97.6%), recall (96.5%) and specificity (97.8%), thus implying the potential of this system in enhancing patients' survival rates [39].

Aslan (2023) carried out an analysis of mammography images using the mammographic image analysis society (MIAS) [40] and inbreast datasets [41], with a goal to classify the images into three categories: normal, benign, and malignant. The images underwent preprocessing and were later introduced into two unique end-to-end deep networks. The first network was purely a CNN while the second was a hybrid, incorporating both CNN and bidirectional long short-term memories (BiLSTM). Upon comparison, the CNN-BiLSTM showed higher classification accuracy on the MIAS dataset as compared to CNN with accuracy of 98.56% and 97.60% and f1 score of 97.61% and 98.56% respectively. For inbreast data the CNN and CNN-BiLSTM achieve 91.67% and 92.26% accuracy and 87.89%, and 88.53% F1 score [42].

Gad et al., (2023) studies focused on the importance of feature selection in ML models. The researchers used a unique strategy for feature selection, leveraging a Pigeon-Inspired Optimizer—a continuous swarm intelligent algorithm. This method was applied to the Wisconsin breast cancer
dataset, both for the training and testing phases of the ML models. The most optimal performance was demonstrated by the RF model, showing 97.2% accuracy, a 97.3% F1-score, recall, and precision rates. [43].

In a study aimed at developing a non-invasive diagnostic system for the classification of metastatic breast cancer, researchers implemented various ML algorithms on blood profile data and evaluated their predictive capabilities using cross-validation criteria such as accuracy and AUC. Statistical validity of the findings was supported by a welch unpaired t-test. Notably, the refinement of blood profile data by outlier removal substantially heightened the accuracy of the ML models. Among different models, best results were achieved by DT and RF classifier with an equal accuracy rate and f1 score of 83% and 85% and an AUC of 0.87 and 0.85 respectively[44].

In the context of improving diagnostic methodologies for breast cancer subtypes, a study has utilized Fourier transform infrared spectroscopic imaging combined with ML to enhance the clinical application and prognostic stratification associated with breast cancer molecular subtypes. The developed method specifically couples a KNN with neighborhood components analysis (NCA), crafting an NCA-KNN framework that allows for the precise differentiation of breast cancer cell lines without augmenting model complexity or computational load. This method harnesses Fourier transform infrared imaging data, resulting in significant improvements in classification accuracy (97.5%), specificity (96.3%), and sensitivity (98.2%), notably with few co-added scans and limited acquisition times. Comparative analysis revealed that the NCA-KNN model outperformed the SVM benchmark model by 9% in accuracy, indicating its superior diagnostic efficacy. The findings of this study underscore the potential of the NCA-KNN approach as a critical diagnostic tool for the classification of breast cancer subtypes, ultimately contributing to targeted therapeutic interventions [45].

Researcher employed transfer learning techniques for breast cancer diagnosis using ultrasound imagery, utilizing pre-trained models such as VGG16, VGG19, MobileNetV2, and ResNet50V2. Analyzing a dataset of 9016 ultrasound images encompassing benign and malignant cases, the research identified the VGG19 network as the superior classifier, achieving an accuracy of 98.44% in differentiating between benign and malignant breast tumors [46].

Chebbah et al., (2023) studied a computer-aided diagnosis system employing AI and thermography to assist in the diagnosis of breast diseases. The data comprised of 170 infrared breast images and
employed the U-net model for automatic segmentation, yielding an intersection over the union metric of 89.03%. Subsequently, textural and vascular network analyzes were conducted on the segmented images to extract relevant features. Utilizing these features, supervised learning classifiers were engaged to differentiate between normal and abnormal thermograms. The system’s performance on a SVM resulted in an accuracy of 94.4%, precision of 96.2%, recall of 86.7%, F1-score of 91.2%, and a true negative rate of 98.3% [47].

Researchers developed a novel hybrid model intended to enhance the detection of breast cancer by integrating an optimization algorithm and ML, applying a feature weighting (FW) strategy to address the challenge posed by nonlinear and imbalanced data distribution. The process began with the application of K-Means-based feature weighting, which successfully improved the separation between benign and malignant samples. Following this, a Particle Swarm Optimization algorithm was used to augment the search capabilities of the Harris Hawks Optimization (HHO) algorithm. This optimized HHO, termed PHHO, was then employed to fine-tune an extreme learning machine (ELM). The validity and performance of the proposed FW-PHHO-ELM model were evaluated using the Wisconsin diagnosis breast cancer dataset. The model demonstrated superior performance metrics, achieving an accuracy of 98.76%, a sensitivity of 97.37%, and a specificity of 99.46% [48].

In the objective pursuit of enhancing breast cancer stage prediction accuracy, another study evaluates the effectiveness of boosting classification algorithms, namely XGBoost, AdaBoost, and gradient boosting. Leveraging the Wisconsin breast cancer dataset, the research hones in on fine-tuning hyperparameters within these classifiers to discern between 'Benign' and 'Malignant' forms of the disease. AdaBoost classifier achieved an 98.60% model accuracy and an AUC of 1.00. XGBoost and gradient boosting achieved an accuracy of 97.20% and 95.80% with an AUC of 0.99 and 0.98 respectively [49].

Utilizing a multi-class MIAS dataset encompassing benign, malignant, and normal mammogram images, this study created a new framework to enhance early breast cancer detection. The methodology initiated with morphological operations for isolating the breast region in images, followed by bicubic interpolation for super-resolution enhancement—with a field-first application—thus refining image details for effective diagnosis. Subsequent image augmentations expanded the dataset to 1932 images, enriching the variety for improved classifier performance.
Orienting towards feature-based classification, the study crafted a unique 11-feature vector leveraging frequency and spatial data, sidestepping the resource demands of direct image analysis. KNN, SVM, DT, artificial neural network and CNN showed accuracy greater than 99%. SVM, DT, artificial neural network and CNN showed F1 scores greater than 99% while KNN showed 98.78% [50].

Maaliw et al., (2023) designed and evaluated a DL architecture named AWFCNET for image classification within mammogram analysis. They incorporated a ResNeXt-101 convolutional network enhanced by attention-aware mechanisms, alongside a fusion classifier that leveraged three recurrent neural networks. Preprocessing steps included color shifting and image enhancement techniques. The results indicated a high degree of model efficacy, achieving an accuracy of 98.10% on a mammogram dataset, validated through 10-fold cross-validation [51].

Alhasani et al., (2023) used the Wisconsin Diagnostic Breast Cancer dataset and subjected it to information gain feature selection to enhance the attribute set, followed by the implementation of various ML classifiers for breast cancer categorization. Specifically, the classifiers tested included the SVM, Naive Bayes and C4.5 DT algorithms. The results indicated a remarkable 100% classification accuracy for the C4.5 DT, with corresponding weighted averages for precision and recall. The SVM achieved slightly lower metrics with an accuracy of 98.42% and weighted precision and recall of 98.17% and 98.58%, respectively. The Naive Bayes classifier lagged behind with an accuracy of 96%, yet the weighted precision was markedly low at 18.57%, and recall stood at 50% [52].

**Conclusion**

The potential role of artificial intelligence (AI) in the diagnosis of breast cancer is substantial and evolving. AI technologies, particularly machine learning and deep learning, are proving to be valuable techniques in analyzing medical images, identifying patterns and enhancing diagnostic accuracy. The advancements in AI-driven diagnostic tools as presented throughout the various studies in 2023 affirm the capability of AI. However, the adoption of AI in clinical practice also poses non-trivial challenges. The inherent complexity of AI decision-making processes and the need for interpretability, data privacy considerations, potential biases in datasets and the requirement for ethical guidelines and regulatory compliance are evident hurdles. The future of AI in breast cancer diagnosis hinges on ongoing interdisciplinary collaboration between data
scientists, clinicians, ethicists and regulatory bodies. This will ensure the implementation of AI solutions that are transparent, equitable and enhance the diagnostic process, ultimately leading to better prognostic outcomes for patients. AI holds the promise of revolutionizing breast cancer diagnosis by providing sophisticated tools that offer earlier, more accurate detection, and personalized therapy options. However, sustained efforts are necessary to translate these technological advancements into standard clinical practice, maximizing their impact on patient care and outcomes.

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