Artificial Intelligence and Machine Learning for Breast Cancer Detection - A Survey

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Abstract: One of the leading causes of mortality for women globally is breast cancer. The probability of survival can be considerably increased with early identification and treatment. Artificial intelligence can potentially increase the efficacy and accuracy of breast cancer screening. The use of machine learning algorithms and deep learningtechniques is covered in this paper, along witha summary of the current status of Artificial Intelligence for breast cancer diagnosis. Besides,some difficulties that must be overcome to successfully use AI in breast cancer detection and diagnosisare also outlined. It also analyses the benefits and drawbacks of adopting the technology for breast cancer detection. The utilization of numerous algorithms and approaches, including image processing, feature extraction, and classification, is covered in this paper. It also looks at the possible advantages and drawbacks of applying AI and ML to diagnosing breast cancer, including data privacy, bias, and interpretation concerns. The paper concludes that AI and ML can improve breast cancer diagnosis, especially regarding accuracy and lowering false positives. The study indicates that AI has the potential to enhance breast cancer diagnosis and, with further research and development, might become a crucial tool.

KEYWORDS: Machine learning, Random Forest, Breast cancer detection, Artificial Intelligence**.**

1 INTRODUCTION

Breast cancer remains one of the most widespread cancers among women globally, and early detection plays a critical role in improving treatment outcomes and survival rates. While traditional screening methods such as mammograms and ultrasounds are effective, they still carry the risk of false positives and false negatives. The American Cancer Society's latest projections suggest that in 2022, there will be 281,550 new cases of invasive breast cancer and 49,290 new cases of non-invasive breast cancer in the United States. Additionally, approximately 43,600 deaths due to breast cancer are anticipated in the same year. Machine learning (ML) and artificial intelligence (AI) have emerged as promising technologies to enhance the accuracy and efficiency of breast cancer screening. By analyzing large datasets, AI and ML algorithms can identify patterns and features that may be difficult for human clinicians to detect, improving diagnostic performance and reducing the risk of misdiagnosis.

This paper goes through the various methods and algorithms employed by AI and ML, such as feature extraction, image processing, and classification, for analysing medical images. It also looks at the possible advantages and drawbacks of applying AI and ML to the early identification of breast cancer, including the requirement for excellent data and potential algorithmic biases. The study concludes by discussing the benefits and problems related to the application of AI and ML in healthcare settings, including the necessity of regulatory monitoring and the significance of protecting patient privacy.

AI has become a potent tool for breast cancer diagnosis, enabling more precise and effective diagnostics. AI algorithms may analyse medical images such as mammograms and ultrasounds to detect questionable regions, which can then be further assessed by radiologists or other healthcare practitioners. The establishment of CAD systems is one of the most promising uses of AI for breast tumor detection. These systems analyse medical images using machine learning algorithms to detect regions of interest, such as tumors or lesions. CAD systems can help radiologists diagnose more precisely, lowering the risk of incorrect diagnoses or needless biopsies. AI refers to using a computer, robot, or other machine to carry out intelligent behaviour that resembles a human. Ultrasound and X-ray mammography are two techniques for breast cancer that AI have aided.

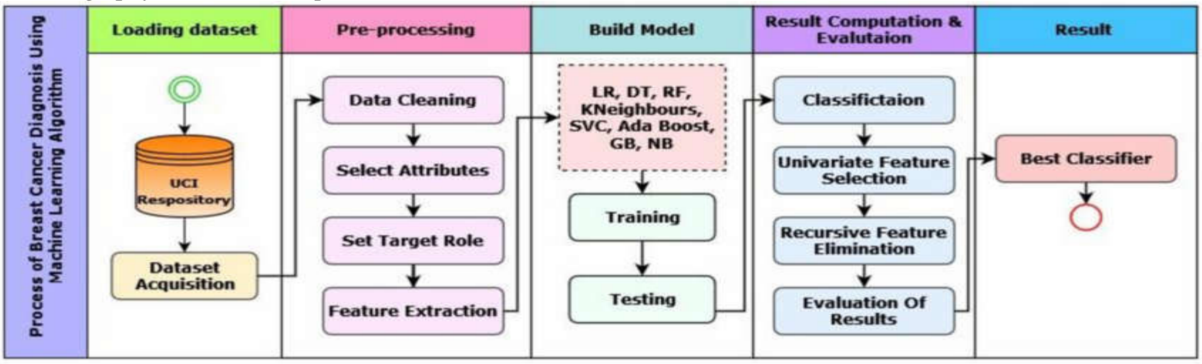

Fig 1. Fundamental workflow of machine learning models for breast cancer detection(*The-Proposed-Architecture-of-the-Breast-Cancer-Detection*, n.d.)

Retrospective studies have been investigated by (B. Lin et al., 2023)employing DL-based algorithms for their values in screening for different malignancies. Early diagnosis through frequent mammography examinations and other diagnostic testing remains vital to enhance breast cancer outcomes. Algorithms based on AI and ML demonstrate promise in increasing the correctness and accuracy of breast cancer evaluation, potentially leading to earlier identification and improved treatment choices for patients.Individual diagnostic findings might vary significantly based on age, family history, and other risk factors. As a result, patients must evaluate their breast cancer concerns with their physician and get frequent examinations as indicated.

Overall, this review emphasizes the potential of AI and ML to improve patient outcomes and breast cancer diagnosis. Healthcare workers may improve breast cancer screening and diagnostic accuracy and efficiency by utilizing these state-of-the-art technologies, eventually saving lives and enhancing patient quality of life.

2.MATERIALS AND METHODOLOGY AND CONTRIBUTIONS

A thorough summary of the AI and ML techniques utilized for finding breast cancer is given in this survey.

2.1Artificial intelligence

Using this approach, even for breast cancers with complex morphology, such as ductal cancer in situ, invasive lobular cancer, micropapillary carcinoma, and tubular carcinoma, AI has shown potential benefits in overcoming mammographic constraints. The study done by (Raafat et al., 2022) has a limitation. One of the limitations is that the sample size is limited. They did not investigate how a human translator would interact with the output of an AI system or how AI might impact radiologists' ultimate judgment. AI overcomes mammographic limitations. This is the principal merit of this study. They collected data from 123 patients for this study. However, the source is not publicly available. This method has 96.6% sensitivity.

Compared to prior machine learning-based algorithms, AI-based CAD can considerably minimize the number of false positive marks on a retrospective test set. The reader can inquire about it by clicking on a certain breast area. The algorithm then displays the amount of suspicion if anything in that area has been found. They have not yet been tested in the real world, but (Wallis, 2021) has the potential to be superior to the current tools since they can interface with tomosynthesis, cut down on false positive calls, and fundamentally change how information is presented to the reader. History has demonstrated that reader studies and retrospective analyses don't always forecast actual performance.

2.1.1 Artificial Intelligence and Morphometric Methods

The result from this method suggested by (Ogony et al., 2022) shows a sustained increase in Terminal duct lobular units (TDLUs) numbers, and the mean acini region is smaller in parous women than nulliparous women. Moreover, within five years of childbearing, protective immunity significantly rises. It shows that the quantitative characteristics of standard breast samples differ depending on demographics and breast cancer risk factors. Artificial intelligence (AI) techniques to quantify morphologic traits and the participation of young women, whose medical samples of body cells are rarely accessible, are important strengths of this investigation. This analysis's advantages include utilizing the distinct, labelled Komen Tissue Bank (KTB) samples and verifying AI results by masked visual evaluation. Data for this study were gathered from the Komen Tissue Bank. This case's sample size was minimal, which affected the outcome of this model.

2.1.2 Artificial Intelligence Data Challenges on Ultrasound, CT, and MRI

The purpose of the study done by (Lassau et al., 2019) suggested that the primary goals of this data challenge were (1) to educate radiologists about the updated General Data Protection Regulation (GDPR) while simultaneously creating a large-scale, multicenter database comprising ultrasound, CT, and MRI images; (2) to build a collaborative ecosystem involving radiologists, researchers, startups, major companies, and engineering students; and (3) to make the new data challenge platform accessible to all French healthcare sector stakeholders.These five challenges brought together a sizable community of radiologists, engineers, researchers, and businesses in a relatively short time. Three of the five radiological modalities produced reliable findings, suggesting that artificial intelligence is a valuable tool in these radiology modalities.

2.1.3 Thermalytix Risk Score (TRS)

In the Research proposed by (Kakileti et al., 2020)to identify a high-risk target group for routine screening and enable early-stage breast cancer diagnosis at scale, the authors suggested and assessed a novel customized risk framework dubbed TRS.This approach utilizes thermal imaging combined with AI to generate a breast health risk score automatically. The score primarily consists of the vascular score and the hotspot score. The vascular score identifies asymmetric vascular activity, while the hotspot score highlights abnormalities based on uneven or asymmetric heat patterns observed on the skin's surface. The proposed AI-driven personalized risk scoring method performs betterthan traditional, general risk assessment techniques by leveraging thermal imaging patterns of the breast for more accurate risk evaluation. The suggested risk framework solution may be used by women of all ages, from 18 to 82, including those with thick breasts. It is automated, reasonably priced, non-invasive, non-contact, and radiation-free. The suggested score may also classify people into one of the four risk categories and recommend the required screening frequency. Also, the automatically labelled thermal scans pinpoint any probable aberrant locations, which may enable the doctor to provide patients with more individualized therapy.

2.2 Artificial Neural Networks (ANN)

The main objective of this pilot project done by (Herman-Saffar et al., 2018)is to create a statistical strategy that can be used to model data received from various detection techniques. The proposed article provides an ANN-based data analysis method that may be utilized to create a trustworthy predictive model. The approach is used in light of findings from pilot research in which urine and exhaled breath samples from women with early-stage breast cancer (BC) and a control group of healthy people were examined. This pilot investigation used two distinct commercial electronic noses to assess breath samples. By analysing urine samples and exhaled air, the methods utilized in this study explore the prospect of detecting early breast cancer (BC). Based on a straightforward, non-invasive study of exhaled air and a urine sample, the established statistical analysis approach permits reliable categorization of individuals as healthy or suffering from BC.

The approach offeredby (Sarvestani et al., 2023)used to automatically categorize benign and malignant forms of segmented ROI clusters, assisting in the detection of breast cancer was presented. It was used to draw attention to tiny masses in mammographic pictures. The primary purpose of this approach was to locate masses and microcalcification in various places of the mammography picture and then classify the crowds as benign or malignant to utilize as data samples. This approach has a 93% accuracy rate. This research also makes use of fuzzy systems and Gabor filters. The data showed that this technology might be utilized to ensure breast tumor identification.

ANN has been used to produce a powerful and precise prediction strategy that is superior to traditional statistical approaches and has been successfully applied to various clinical circumstances. This study done by (Li et al., 2022) verified and provided superior ANN modelling for assessing the likelihood of a BRCA1/2 deleterious variant in bilateral breast cancer patients without the need for extra testing. There were several drawbacks to this study. One restriction was that this method did not recommend specific medications; instead, it analysed a patient's odds of having BRCA1/2 dangerous mutations. Another drawback was that the majority of the BBC patients had originated from a single Chinese hospital. As a result, this method was not applicable in every situation. A larger examination and extra outside verification are required to fully verify its broad applicability. They obtained data from Fujian Medical University Union Hospital for their investigation. This dataset was also accessible through the BioProject repository.

Although further study is needed to analyse and examine the effectiveness of the recently created ANN methodology for PRS generation, it has the potential to replace traditional approaches. The 24 single nucleotide polymorphisms (SNPs) and related polygenic risk score (PRS) may provide additional risk data to aid in the risk classification of breast cancer in China's overall population. This procedure has a drawback. Compared to the emergence of PRSs in women of European ancestry, the PRSs' overall performance is less ideal. (Hou et al., 2022)Data for this investigation was obtained from the GWAS dataset and the external case-control dataset.

2.3 Machine Learning

Machine learning (ML) has become a potential approach for increasing the efficacy and accuracy of breast cancer screening. A thorough review of the use of ML in the identification of breast cancer is presented in this survey, which includes the following:

2.3.1 Random Forest

(An et al., 2022) were able to demonstrate that plasma metabolomics analysis provided a high confidence level when assessing diagnostic signs for breast cancer. They employed a machine learning model. There were certain limits to this strategy. The first was that the sample size was tiny. There was just one center from which all individuals were recruited, and no cohort for measuring attributes was developed. The second was that proteomics study samples were always insufficient, and the results were never verified. The final point was that while these newly found metabolites had been associated with breast cancer, the particular mechanism was yet unknown.

2.3.2 Random Forest (RF), Support Vector Machine (SVM), Multilayer Perceptron (MLP) and AdaBoost.

(Brahimetaj et al., 2022)Employed a machine learning model in their investigation. Their research was the largest to look at the feasibility of developing a CAD system that exclusively employed Mucinous carcinoma (MC) characteristics extracted from high-resolution 3D images to identify cancers. There were several drawbacks to this study. One of the constraints was that there was input data for all samples but not for individual MCs, which was their main shortcoming. Another was that examined samples were obtained as long as 10 years ago. Back then, many fewer routine test results were collected than now. As a result, it was impossible to relate its findings to specific cancer biomarkers. They obtained data from the university hospital in Brussels for their investigation. This study had an accuracy of 84.04%.

2.3.3 Recursive Feature Elimination Random Forest (RFE-RF)

By integrating radionics and molecular subtypes, (Sutton et al., 2020) developed and evaluated a machine learning technique that correctly predicted pathological complete response (pCR) on MRI with an AUROC of 0.88 in a separate test set. Their findings suggested that utilizing feature classifiers based on radiomics to anticipate pCR post-NAC might have a therapeutic advantage. This approach had certain drawbacks. One of the disadvantages was that the Recursive feature elimination (RFE) with the RFE-RF classifier only received internal validation from single institutional research and no external validation. Another restriction was that the MRI was performed with two different breast coils and field strengths.

2.3.4 XGBoost, Random Forest (RF) And Logistic Regression (LR)

(Liu et al., 2022)developed a framework using image attributes and machine learning to predict breast cancer metastasis and recurrence from histopathology images. They trained the model on 127 patient samples from the Cancer Hospital and validated it on 88 FFPE samples from TCGA. Using just eight texture and color features in these models achieved strong predictive performance through cross-validation.The performance of the suggested assessment framework was then assessed using data from the actual world, such as our clinical data and TCGA data.

2.3.5 6 ML Models (Support Vector Machine (kernel SVM and the sigmoid SVM), Random Forest, Decision Tree, K-Nearest Neighbors, and Gaussian Naïve Bayes)

Breast MRI scans come with their own set of problems. As a result, this work analysed the effects of radionics fat suppression (FS) on the outcomes and performances of the Machine Learning Algorithm (MLA). This study by (Laajili et al., 2021) involved identifying if a breast nodule was benign or cancerous. They mixed 10 FS approaches with six categorization models. Predictive modelling and FS were essential steps in the radionics process because of the abundance of data provided by radionics. So, this study could aid in determining the ideal method for fusing various strategies for the best performances and outcomes.

2.3.6 9 ML Models (LightGBM, K-nearest neighbor, Catboost, Decision tree, Random Forest, Gradient booster, Neural network model, Support vector machine, XGBoost)

Machine learning was utilized to develop nine models capable of forecasting chemotherapy patients' 5-year Overall survival (OS) and Breast cancer-specific survival (BCSS). They used the SEER database in this investigation. (Huang et al., 2022) gathered data from the SEER database on 4,696 individuals. This database was used to test all of these models. They then received LightGBM, which outperformed all other models. K-nearest neighbor provided 0.879 accuracy, Catboost provided 0.905 accuracies, Decision Tree provided 0.908 accuracies, Random Forest provided 0.869 accuracies, Gradient Booster provided 0.882 accuracies, LightGBM provided 0.882 accuracies, Neural Network Model provided 0.886 accuracies, Support Vector Machine provided 0.882 accuracies, and XGBoost provided 0.879 accuracies. A k-nearest neighbor provided 0.844 accuracies, Catboost provided 0.877 accuracies, Decision Tree provided 0.882 accuracies, Random Forest provided 0.837 accuracies, Gradient Booster provided 0.849 accuracy, LightGBM provided 0.851 accuracy, Neural Network Model provided 0.86 accuracy, Support Vector Machine provided 0.854 accuracy, and XGBoost provided 0.865 accuracy respectively in the case of a 5-year OS. The 5-year BCSS average accuracy was 0.886, while the 5-year OS average was 0.857. There was no information in the dataset on the details of chemotherapy. This was the shortcoming of this study.

2.3.7 10 ML Models (Naïve Bayesian Classifier, Support Vector Machines with Polynomial and Radial Basis Function Kernels, Multivariate Logistic Regression, Nearest Neighbours, Ripple Down Rules, J48 And Alternating Decision Trees.)

Using stratified ten-fold cross-validation, machine learning approaches with and without ensemble methods were linked with multidisciplinary team (MDT) judgements for adjuvant cytotoxic, endocrine, and biologic/targeted treatment. A machine-learning technique based on clinicopathologic features could predict MDT decisions for adjuvant cancer medication treatment. This strategy, suggested by (F. P. Y. Lin et al., 2016),could directly assist decision-making, simplify the transfer of local expertise to more remote facilities, improve the quality of patient care, and improve clinical outcomes for cancer patients.

2.3.8 Radial Basis Function Network (RBFN)

The properties obtained from the Electrical Impedance Scanning (EIS) were used to create an intelligent system for identifying breast tissues. This experimentwas done by (Helwan et al., 2017)carried out using two different kinds of neural networks. A comparison was conducted between similar network types based on various parameters defined during the training process. This comparison aimed to evaluate each network's performance and identify which performed best for the classification task. The results revealed that a Backpropagation Neural Network (BPNN) with more hidden layers outperformed the others when trained and tested on omitted data.In comparison to the other backpropagation networks, this network took less time to obtain the least minimum square error. On the other hand, for the RBFNs, different networks performed best during the training and testing phases.

2.3.9 Averaged-Perceptron (AP) Machine-Learning Classifier

The purpose of the study offered by(Birchha & Nigam, 2022)was to examine how well the averaged-perceptron machine-learning classifier performed on the Wisconsin original breast cancer dataset (WBC). The study primarily focused on two issues: first, does the averaged-perceptron classifier possess the necessary traits to outperform other classifiers in accuracy? Second, breast cancer is the main reason why women die from cancer; if found in its early stages, the disease is treatable. Less false-positive or false-negative breast cancer is forecasted thanks to technology.An excellent ML-enabled CAD system might provide a fast and inexpensive diagnosis method.

2.3.10Supervised Principal Component Analysis (SSSuperPCA)

Radiomics is a young discipline employing data-characterization techniques to extract significant quantitative information from biological pictures. Identifying distinctive imaging characteristics from biological images could be used to predict treatment response, predict prognosis, and offer a non-invasive method for individualized therapy.(Yan et al., 2020) suggested a cutting-edge machine learning method called stability selection SSSuperPCA. It extracted stable characteristics from large-scale radionics data and combined them with dimension reduction for right-censored survival outcomes.

2.3.11Unsupervised Domain Adaptation Method

The research by (Alirezazadeh et al., 2018) offersa brand-new unsupervised domain adaptation strategy based on representation learning suggested to address these issues. By gaining as much knowledge about a domain invariant space as feasible, this approach seeks to differentiate benign extracted feature vectors from those of malignant ones. The suggested strategy enabled classifiers to extract more discriminative features, increasing recognition rates. The labels were no longer proper because this approach used a correlation measure. Contrarily, this technique used manually created feature descriptors, less potent than convolution neural networks, to extract practical features. It was discussed how discriminative analysis might help breast cancer diagnostic methods. Although satisfactory results were obtained, it was obvious that the performance of the suggested system may be enhanced by using deep learning-based feature extraction approaches instead of manual descriptors and discriminative deep learning techniques. Future work will take this issue into account.

2.4 Ensemble Method

Ensemble methods have emerged as a powerful approach for enhancing the performance and reliability of breast cancer detection models. This survey comprehensively reviews ensemble techniques applied to breast cancer diagnosis. It highlights their ability to combine multiple models to improve accuracy, reduce variance, and deliver more robust screening outcomes. In the following discussion, various studies on ensemble methods and their effectiveness in breast cancer detection are reviewed:

2.4.1 Ensemble of Artificial Neural Network, Random Forest, and non-linear Support Vector Machine (EARN)

The search space for biomolecular and medical technology scientists in recognizing believable genetic variants to enable diagnosis and prognosis of complex illnesses can be drastically reduced using computational methods, such as ensemble machine learning methods, which are less expensive than biomolecular techniques. This study had a disadvantage in that while attempting to discover the finest MBCA drivers, and they met various challenges in the most recent research. The small size of the original mutation datasets was utilized in the whole-exome analysis of tumor tissues from people with advanced cancer. (Mirsadeghi et al., 2021)Used the TCGA dataset in their investigation. This approach had an accuracy of 88.89%.

2.4.2 CNN Ensemble Approach(GoogleNet, VGG11, MobileNetV3_Small)

(Majumdar et al., 2023) proposes a Gamma function-based ensemble of CNN models to improve breast cancer detection in histopathology images. Using a rank-based Gamma function fusion strategy, it combines decision scores from three transfer learning models—GoogleNet, VGG11, and MobileNetV3_Small. The method was tested on the BreakHis and ICIAR-2018 datasets, achieving outstanding classification accuracies across multiple magnifications (up to 99.16%). This ensemble approach outperforms individual CNNs and existing methods, offering a reliable AI-driven solution to assist pathologists, improve diagnostic precision, and reduce human errors in breast cancer screening.

2.5 Logistic Regression Method

A prediction model must be used to establish the elastic quantitative and semi-quantitative characteristics of solid breast lesions, and their diagnostic value must be assessed. An elastic ultrasound index forecast model that used quantitative and semi-quantitative data from the L9-3 study performed better, which could improve diagnostic precision for malignant breast tumors. This was a benefit of this research. The datasets used in this study were not available to the general public. As a result, the datasets utilized in the survey remain confidential. Changzhou First People's Hospital provided the statistics for the patients. The study by (Xie et al., 2022) included data from 129 female patients. Hence, the sample size was limited, which impacted the outcomes. The prediction model had an accuracy of 84.04%. When they increased the sample size, the model's performance improved.

The strategy suggested by Soumendu (Sen et al., 2022)was utilized to look into the differences in breast and cancer screening practices among Indian women of reproductive age based on regional and socioeconomic factors. Cancer awareness and education might reduce the frequency of cervical and breast cancers among Indian women of reproductive age. The sole drawback discovered was that this study could not assess cancer screening data for women over 50. Data for this study were gathered from Shinshu University Hospital patients. They considered two age groups in this study. The first considers ages 15 to 49, whereas the second considers ages 30 to 49. It was assumed that this study solely included reproductive-age women.

In the study suggested by (Dorling et al., 2022),estimates of relative risks for all of those categories, as well as the likelihood of a relationship with risks at the variation level, were provided, indicating that specific categories of missense variations in known carcinoma genetic variants were associated with increased risks of the illness. In comparison to others, the validation dataset was modest. This study gathered data from patients taking part in the BRIDGES initiative.

3. DISCUSSION

Breast cancer detection through machine learning (ML) has shown significant promise in improving diagnostic accuracy, especially with advanced imaging techniques. This literature review analyses various Convolutional Neural Networks (CNNs) and machine learning algorithms: RF, SVM, Logistic Regression, and Ensemble Methodschosen for their proven efficacy in medical imaging and classification tasks. These algorithms were selected based on their ability to handle high-dimensional and complex breast tissue features in imaging datasets. CNNs are particularly effective for image classification due to their hierarchical feature extraction, though they are computationally intensive and require large datasets to avoid overfitting. RF and SVM are robust classifiers for imbalanced datasets, with RF performing well on smaller datasets and SVM offering robust classification through hyperplane creation. Logistic Regression is efficient for binary classification but may struggle with complex relationships in data. Ensemble Methods combine multiple models to enhance accuracy, though they incur higher computational costs.

TABLE 1. The study reviews and contrasts recent methods for breast cancer prediction, focusing on the techniques, datasets, strengths, weaknesses, and performance outcomes.

Author	Method	Merits	Demerits	Database	Accuracy
(Wallis, 2021)	AI algorithms	AI has to be trained to look for high-risk malignancies in preference.	A screen reader's definition of a correct call cannot be used as a comparison.	Population data sets	NA
(Raafat et al., 2022)	AI algorithms	Potential benefits in overcoming mammographic constraints.	The sample size is limited.	Data is not publicly available.	NA
(Ogony et al., 2022)	AI and Morphometric Methods	It shows that the quantitative characteristics of normal breast.	Small sample size	Komen Tissue Bank	NA
(Lassau et al., 2019)	AI Algorithm	AI is a promising topic in these three modalities.	Did not predict the position and direction of the tears.	Multicentric prospective database	90%
(Kakileti et al., 2020)	TRS	More appropriate for poor nations.	The study can act as a roadmap	TRS	NA
(Herman-Saffar et al., 2018)	ANN	Classification accuracy will be higher.	The excellent models were reached after feature selection.	Data of one electronic nose	85%
(Sarvestani et al., 2023)	ANN	Used to classify benign and malignant automatically.	NA	DDSM	93%
(Li et al., 2022)	ANN	Superior to conventional statistical methods	It does not provide particular medication suggestions	Fujian Medical University Union.	NA
(Hou et al., 2022)	ANN	Additional risk data should be provided to help in the categorization.	Overall performance is less ideal.	GWAS dataset.	NA
(An et al.,	Random	Provides a high level of	The sample size was	Zhejiang	NA

8

2022)	Forest	confidence when investigating diagnostic signs for breast cancer.	limited.	University School of Medicine

TABLE 1. The study reviews and contrasts recent methods for breast cancer prediction, focusing on the techniques, datasets, strengths, weaknesses, and performance outcomes (Contd…).

Author	Method	Merits	Demerits	Database	Accuracy
(Brahimetaj et al., 2022)	RF, SVM, MLP, and AdaBoost.	Most significant research evaluating the feasibility of developing a CAD system	Input data for all samples but not for individual MCs.	University Hospital of Brussels.	84.04%
(Sutton et al., 2020)	RFE-RF	Utilizing feature classifiers based on radionics to anticipate pCR post-NAC	No external validation.	Electronic medical record.	NA
(Liu et al., 2022)	XGBoost, RF, and LR	Classification of breast cancer, in addition to enabling the integration of other novel aspects	Producing high-quality histopathology images from annotated data is difficult.	Clinical dataset from the Cancer Hospital	NA
(Laajili et al., 2021)	6 ML models	Produced the best outcomes for the majority of the prediction models.	Does not take into account the duplication of chosen characteristics.	MRI dataset	85%
(Huang et al., 2022)	9 ML models	LightGBM beat all other models and is a solid and helpful model for survival prediction.	The dataset does not contain any information regarding the specifics of chemotherapy.	SEER Database	0.886
(F. P. Y. Lin et al., 2016)	10 ML Models	Predict MDT decisions for adjuvant cancer medication treatment.	Chemo regimens were not entirely recorded in their data	NA	NA
(Helwan et al., 2017)	RBFN	The superiority pertains to accuracy, least error, most epochs, and training time.	This network did not perform better than the competing networks	Breast tissue database.	NA
(Birchha & Nigam, 2022)	AP ML classifier	The AP classifier-based proposed model received a higher sensitivity (recall) value of 1.	The AP model is only valid for the features and feature value range indicated in the WBC dataset.	Wisconsin Original Breast Cancer Dataset (WBC)	98.4%
(Yan et al., 2020)	SSSuperPCA	Outperform other regression and machine learning techniques.	It might produce biased results	Real radionics datasets	NA
(Alirezazadeh et al., 2018)	Unsupervised Domain Adaptation Method	It is simple to implement because it simply needs photos from the whole slide's histology.	Requires less processing time	BreaKHis dataset	NA

TABLE 1. The study reviews and contrasts recent methods for breast cancer prediction, focusing on the techniques, datasets, strengths, weaknesses, and performance outcomes (Contd…).

Author	Method	Merits	Demerits	Database	Accuracy
(Mirsadeghi et al., 2021)	EARN	It is less expensive than biomolecular techniques.	The small size of the original mutation datasets utilized	TCGA dataset	88.89%
(Majumdar et al., 2023)	CNN Ensemble Approach	Better generalization across different datasets and magnification levels.	Increased computational complexity compared to using a single model.	BreakHis&ICIAR-2018	96%-99%
(Xie et al., 2022)	Logistic Regression	Performed better	The sample size was small.	Changzhou First People's Hospital.	84.04%
(Sen et al., 2022)	Logistic Regression	Cancer education might reduce the number of cervical and breast cancers.	Unable to analyze cancer screening data for women beyond the age of 50.	National Family Health Survey-5	NA
(Dorling et al., 2022)	Logistic Regression	This study provides estimates of relative risks for all of those categories.	The validation dataset was modest.	Patients taking part in the BRIDGES experiment.	NA

Pre-processing is crucial in improving image quality and enhancing algorithms' ability to detect tumors and abnormal tissues. Techniques such as fuzzy segmentation highlight the breast tissue, aiding in better feature extraction. Noise removal and background subtraction further improve image clarity and focus on the relevant tissue regions, ensuring that the machine learning models perform optimally. While deep learning techniques like CNNs dominate the field, traditional machine learning methods like SVM and Logistic Regression have not been extensively explored for breast cancer detection, creating a gap in the literature. This review addresses these gaps by comparing both traditional and deep learning methods in breast cancer detection, highlighting the underutilization of conventional algorithms in the context of breast cancer diagnosis. The manuscript also emphasizes these algorithms' challenges, including model interpretability, data imbalance, and generalization issues. For example, CNNs, while highly effective, often function as black boxes, and both traditional and deep learning models struggle with imbalanced datasets unless specific techniques like resampling are employed. This study aims to bridge these gaps by comprehensively analysing different machine-learning methods for breast cancer detection. It focuses on their technical strengths, limitations, and the need for more research to address these challenges.

4. CONCLUSION

Recent advancements in machine learning (ML) and artificial intelligence (AI) have improved breast cancer screening, with models like SVM, ANN, and CNN showing high accuracy in detecting cancer from mammograms and ultrasounds. Deep learning, particularly CNNs, has enhanced diagnostic precision by reducing false positives and negatives, leading to the development of computer-aided detection (CAD) tools for radiologists. However, challenges remain, such as the need for large, diverse datasets, integration of multiple imaging modalities, and theblack-box nature of ML models, which makes them challenging to interpret and trust in clinical settings. Transparency in model decisions is essential for their safe use.

In conclusion, while ML and AI have the potential to improve breast cancer evaluation and patient outcomes significantly, more research and development are needed. Future efforts should focus on overcoming the limitations related to dataset size, model transparency, and the integration of multimodal imaging. Moreover, collaboration between medical professionals and AI researchers is essential to ensure these technologies are adapted to meet clinical needs and are safely incorporated into routine healthcare practices. These systems' continued refinement and validation will be crucial in realizing their full potential in improving breast cancer detection and diagnosis.

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