RESEARCH PAPER

Artificial Intelligence and Deep Learning Models in Breast Cancer Detection: A Decade Trend and Performance Analysis

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Received: 28th Feb, 2026; Revised: 6th March 2026; Accepted: 7th April, 2026; Available Online: 20th April, 2026

ABSTRACT

Breast cancer is one of the leading health challenges affecting women globally, and timely diagnosis is essential for improving survival and treatment outcomes. Over the past decade, advances in artificial intelligence (AI) and deep learning (DL) have significantly influenced medical imaging by enabling more consistent and accurate interpretation of mammographic, ultrasound, and histopathological images. The present review analyzes research published between 2017 and 2025 that applied AI-based techniques for breast cancer detection. The aim was to evaluate recent methodological developments, compare the diagnostic performance of different models, identify widely used datasets, and highlight current research gaps. A systematic literature search was performed using the databases PubMed, Scopus, IEEE Xplore, and Google Scholar. Only peer-reviewed articles written in English and reporting diagnostic performance metrics such as accuracy, sensitivity, specificity, or F1-score were included in the analysis. Studies lacking performance data, non-peer-reviewed publications, non-English papers, and studies focused solely on image segmentation without diagnostic relevance were excluded. A total of 43 studies satisfied the inclusion criteria. Information related to model architecture, dataset sources, and diagnostic outcomes was extracted, and temporal trends were illustrated graphically. Among the reviewed approaches, convolutional neural network (CNN) models constituted the largest proportion (approximately 46%), followed by hybrid approaches (24%) and ensemble or transfer-learning methods (20%). Transformer-based architectures accounted for nearly 10% of the studies and have shown increasing adoption since 2022. Reported diagnostic accuracy ranged from 91% to 99.9%, with an average value of approximately 96.8%. Frequently utilized datasets included MIAS, BUSI, BreakHis, and WBCD. Current developments emphasize the integration of multi-modal imaging data, wider use of transfer learning techniques, and the growing importance of explainable AI approaches. Overall, AI-driven models demonstrate strong potential to improve the detection of breast cancer. Future work should focus on improving model interpretability, addressing data privacy concerns, integrating multi-modal data sources, and validating these systems through prospective clinical studies to support real-world clinical implementation.

Keywords: *Breast cancer, artificial intelligence, deep learning, convolutional neural networks, hybrid models, transformer architectures, explainable artificial intelligence, systematic review.*

How to cite this article: Kiranmai S, Monica KL, Gardi A, Parveen MN, Joicee MR, Das PN, Surekha PV., Artificial Intelligence and Deep Learning Models in Breast Cancer Detection: A Decade Trend and Performance Analysis. Int J Drug Deliv Technol. 2026;16(52s): 463-470. DOI: 10.25258/ijddt.16.52s.58

Source of support: Nil.

Conflict of interest: None

INTRODUCTION

Breast Cancer: Epidemiology of the World

The most prevalent malignancy that has been diagnosed in women around the world is breast cancer. About 2.3 million new cases were diagnosed in 2022, and the disease claimed almost 670,000 deaths in the same year [20]. It was estimated that the overall burden will keep increasing and it is projected that by 2040, there will be an increase in the number of new cases by 47.8% of the current situation in 2022. This positive trend underlines the urgent need to enhance the practice of early detection and diagnosis [22].

Problems with Traditional Diagnostic Methods

Even though mammography, ultrasound tests and histopathological examinations are the main pillars of diagnosing breast cancer, each of the methods has been identified to have limitations.

- **Mammography**: Mammography is a method that is much commonly applied during regular screening; its sensitivity among people with dense breast tissue is low. Thick tissue may conceal any underlying lesion, and more likely give a false-negative result [4].
- **Ultrasound**: Although an ultrasound can be useful in distinguishing between cystic and solid lesion, ultrasound findings can be subject to operator variation

**Author for Correspondence: Baswaraj Chinchole* and it may not be very reliable in establishing the malignant potential of a lesion [4].

- **Histopathology**: A microscopic analysis of tissue samples is the only gold standard system of confirming a diagnosis. However, it involves invasive biopsy, has time consuming processing and interpretation. In addition, reporting variability may arise due to the fact that diagnostic conclusions may vary amongst the pathologists [2].

Those difficulties prove the necessity to find complementary or more progressive diagnostic solutions that could improve accuracy, decrease subjectivity, and improve the clinical workflow.

Emerging AI and DL Approaches in Breast Cancer Detection

Over the last ten years, the fields of artificial intelligence (AI) and deep learning (DL) have played an important role in the development of medical imaging. Among this landscape, convolutional neural networks (CNNs) and more recent transformer-based frameworks have demonstrated great proficiency in aiding automated assessment of breast cancer, and enhancing the accuracy of diagnostic interpretations [14].

Recent research studies have shown that: CNN-based systems have recorded accuracy at the classification to nearly 99.9 percent when used on mammographic data [14]. Transformer architectures are characterised by strengths in contextual cues and spatial relationships modeling across imaging features, which leads to better diagnostic performance [14]. These advancements show how the use of AI-based technologies can address some of the limitations of traditional methods of detection and provide more reliable and effective assessment of breast abnormalities. This review is based on the period between 2017 and 2025, as it is a stage of significant development of medical image analysis. Transfer-learning strategies, hybrid CNN models, and transformer-based approaches became popular during these years and contributed to the significant advancement in the use of AI to diagnose breast cancer jointly [14].

Objectives of the Review

- **Trend Analysis**: To analyze the development of the artificial intelligence and deep learning methods in detecting breast cancer in the years 2017-2025.
- **Performance Assessment**: To measure the diagnostic reliability, accuracy, and the overall effectiveness of the various AI and DL models that have been discussed in the literature.
- **Gap Identification**: To identify the current constraints, unresolved problems, and areas that need additional research.

This review aims to demonstrate the development of AI- and DL-based methods as well as underline their increasing importance in improving early breast cancer detection by synthesizing the findings of the published studies.

MATERIALS AND METHODS

Literature Sources and Search Methodology

A methodical literature review was conducted depending on PRISMA requirements. The search was carried out on the large academic databases Scopus, PubMed, IEEE Xplore, and Google Scholar to identify the relevant publications published since January 2017 and up to June 2025.

The search used different key words combinations such as:

- "Breast cancer"
- "Artificial Intelligence" OR "AI"
- "Deep Learning" OR "DL"
- "Convolutional neural networks" OR "CNN"
- "Transformer" OR "Hybrid models"
- "Classification" OR "Detection"

Inclusion Criteria

To include studies in this review they must have met the following criteria:

1. They used artificial intelligence or deep learning methods to recognize or classify breast cancer.
2. They described quantifiable diagnostic performance measures including accuracy, sensitivity, specificity, or F1-score.
3. They were found in peer-reviewed journals between 2017 and 2025.

Exclusion Criteria

The studies were not included in the analysis in case any of the following were the case:

1. The article had been published in a different language besides English [13].
2. The work touched upon segmentation tasks but it lacked any diagnostic evaluation.
3. The research was available in the form of a preprint or was not peer reviewed.
4. The authors did not give quantitative diagnostic measures [13].

Study Selection

The search of the database first retrieved 127 records. After the elimination of duplicates and the exclusion of studies that did not meet the inclusion criteria, the 43 studies were selected to be individually evaluated on a full-text basis. Study selection is described in PRISMA flowchart. The selection process and screening action were in accordance with the PRISMA 2020, and Figure 1 depicts the workflow.

Statistical Analysis

The data collected was summarized through descriptive types of analytical processes. The analysis focused on: yearly publication trends, allocation of model types, and Mean and range of accuracy. Graphs and charts defining these patterns were created with Microsoft Excel and Graph Pad Prism.

Quality Assessment and Risk of Bias

The quality of the methodology of each study was evaluated by the use of the QUADAS-2 tool of diagnostic accuracy research and the ROBINS-I framework of evaluating biasness in hybrid or retrospective studies. The areas of selection, performance, detection and reporting were all analyzed in case of bias. The majority of these studies were considered as having low to moderate risk as summarised in Table 2.

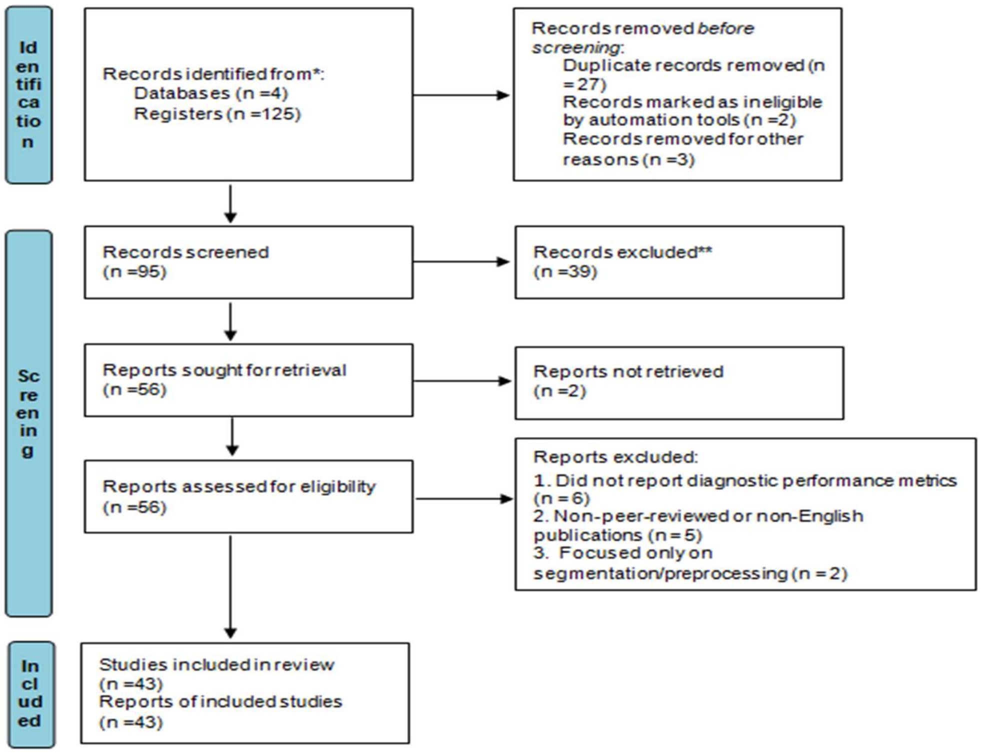

Figure. 1. PRISMA flowchart.

RESULTS

Year-wise Publication Trend (2017–2025)

A review of the 43 chosen articles revealed that the number of academic studies devoted to the topic of AI and DL methods used to detect breast cancer has steadily increased within the last decade. The recent studies in 2017-2019 were also rather few and mostly focused on early CNN models implemented on smaller datasets, such as WBCD and MIAS [10]. The amount of publications grew significantly starting in 2020, which is consistent with the general trend in AI-driven research in the field of healthcare during the COVID-19 crisis [17]. The maximal number of studies was found in the period between 2023 and 2025, as the use of the technique of transfer-learning, hybrid frameworks, and transformer-based architecture continued to expand. These are the trends depicted in Figure 2.

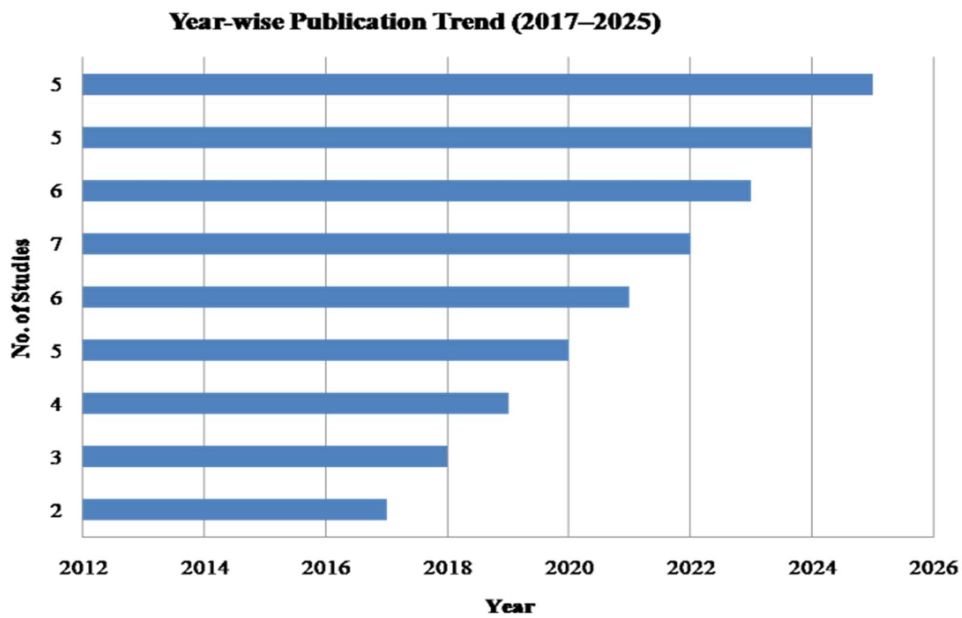

Figure. 2. Year-wise distribution of publications from 2017 to 2025 focusing on AI- and DL-based breast cancer detection methods.

Model Distribution and Performance Comparison
The majority of the research included utilized convolutional neural networks (CNNs), the most common of which is represented by 46 percent of the studies and is widely used as the solution to medical images interpretation. Hybrid models including those that combine CNNs with SVM, Random Forest classifiers, or attention mechanisms explained 24%. About one-fifth of the studies adopted ensemble strategies or transfer-learning models, such as models, such as ResNet, DenseNet, and EfficientNet. The remaining 10% (transformer-oriented models) pointed to the increased interest in attention-based models in the analysis of breast tissue [16]. Accuracies reported in the studies were as low as 91% and high as 99.9 with an average of 96.8% +- 2.3. There was a clear increase in diagnostic accuracy, which was observed over the years, as more sophisticated model designs were developed and more data augmentation was used. The following progression patterns are described in Figure 3 [21].

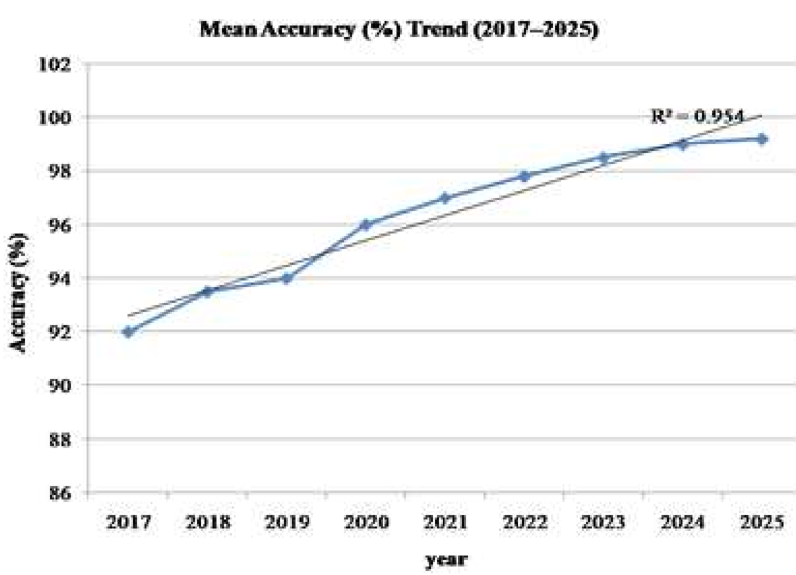

Figure 3. Year-wise trend of the average diagnostic accuracy of AI and DL models for breast cancer detection from 2017 to 2025.

Dataset Utilization Trends

The trend in the use of datasets has changed significantly in the last ten years. During the initial years, the most widely used resource was the Wisconsin Breast Cancer Dataset (WBCD) (28%), but mostly to support the studies that used the traditional CNN architectures [17]. The combination of the MIAS and BUSI datasets was approximately 33 percent of the dataset usage, especially in studies published in 2020 and those that focused on mammography and classification tasks based on ultrasound [16]. More recent years (2023-2025) also saw a strong transition to the use of individual clinical data and multi-modal sources of imaging, thus helping to increase the real-world applicability and model performance. The BreakHis histopathological data set also came to the forefront particularly in those investigations that use hybrid models and transformer-based models that seek to perform a detailed evaluation of the malignancy at the cellular level as shown in Figure 4 [21].

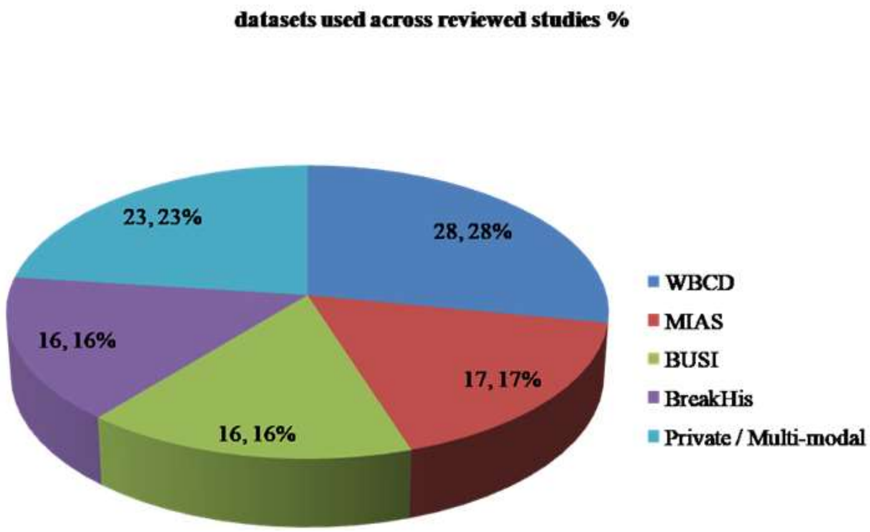

Figure. 4. Overview of dataset usage across the studies included in the review on AI- and deep-learning-based breast cancer detection.

Representative Study Summary

Table 1 describes a list of the prominent works that were published in 2017-2025 that illustrate how the data sets, modelling methods and diagnostic results changed over time. Throughout this period of time, deep-learning models, specifically convolutional networks and their hybrid versions were able to yield the most diagnostic results with majority of them reporting an accuracy rate between 97% and 100%. The research that included transfer-learning pipelines or explainable-AI elements exhibited evident benefits, having a higher level of transparency and better generalizability of their models. Table 1 briefly shows these trends.

Table 1: Representative studies and their performance metrics (2017–2025)

Author (Year)	Model Type	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	Key Findings
Zheng et al., 2020	CNN + AdaBoost	MRI	97.2	98.3	96.5	—	Deep learning assisted Adaboost improved early detection accuracy
Khater et al., 2025	ANN, KNN	WBCD	97.7–98.6	98.2	94.4	—	Explainable AI model highlighted key malignancy features
Abdullah et al., 2025	CNN	MRI	—	88	90	0.90	Deep learning achieved high diagnostic accuracy in MRI
Yari et al., 2020	ResNet50 / DenseNet 121	BreakHis	98–100	—	—	—	Transfer learning improved binary and multiclass classification

Quality Assessment of Included Studies
Quality of the methodological rigor of the chosen study was assessed with the help of the QUADAS-2 framework of diagnostic accuracy studies and the ROBINS-I tool of non-randomized research. In general, the majority of the studies presented a minimal amount of bias in the form of transparent reporting practices and the utilization of properly validated datasets. The risk was moderate in only one study (Khater et al., 2025), and it was mainly caused by the limited variability in the data used since it was summarized in Table 2.

Table 2. Methodological quality ratings for representative studies published between 2017 and 2025.

Study (Author, Year)	Dataset Used	Model	Bias Assessment Tool	Risk of Bias	Comment
Zheng et al., 2020	MRI dataset	CNN (AdaBoost)	QUADAS-2	Low	Clear metrics, validated dataset
Yari et al., 2020	BreakHis	ResNet50	QUADAS-2	Low	Multi-class validation
Khater et al., 2025	WBCD	ANN/KNN	ROBINS-I	Moderate	Limited dataset diversity
Goel et al., 2025	CBIS-DDSM	ANN	QUADAS-2	Low	Strong accuracy validation

Key Observations

- **Trends in Accuracy**: AI and DL models have steadily increased the average diagnostic accuracy over the decade, increasing to almost 99% by 2025, starting with about 92% in 2017. This is an indication of model architecture development and improvement in training methodologies [21].
- **Architectural Change**: The traditional CNNs were slowly replaced with hybrid and transformer-based architectures with focus on interpretability and better generalization [5].
- **Dataset Development**: Studies were no longer limited to small datasets that were publicly accessible but increasingly large, more diverse and multi-modal datasets, increasing their applicability to the real-world [16].
- **Drive toward Explainability**: Since 2022, it has become more and more commonly utilized to enhance the level of transparency and clinician trust in AI-driven decisions through the means of Explainable AI (XAI) [5].

DISCUSSION
The process of synthesizing the results of the 43 studies incorporated shows that there are some trends of improvements in performance, and methodological innovations in AI-assisted breast cancer detection over a decade.

Evolution of Model Performance
The review of the ten years of the past indicates the apparent evolution of AI and DL in the field of breast cancer diagnosis. Early methods were based on convolutional neural networks (CNNs), which provide useful features in distinguishing benign and malignant lesions over mammography, ultrasound, and histopathological images. The original CNN models were relatively simple (they were limited by the small datasets) and moderate-performing (up to 92-95%).

Since 2020, hybrid models that included CNNs with support vector machines (SVMs), random forests, or attention mechanisms incurred much better classification and often reached >98% accuracy [19]. With the advent of transformer-based architectures starting 2023, further positive results were achieved by seizing long-range dependencies in imaging data to enable detection of fine pathological features [6].

Dataset Expansion and Model Generalization
Gradually, research has shifted to major and more heterogeneous sources, BUSI, BreakHis and hospital-specific datasets as well as WBCD and MIAS. Multi-modal imaging has also been integrated which has also enhanced model robustness and clinical relevance. However, most of the models are still trained with geographically or demographically small size data that may restrict their extrapolation to other populations [8]. Possible solutions include federated learning and multi-institutional collaborations where the models can learn using larger datasets, and patient privacy is preserved.

Explainability and Clinical Integration
Explainable AI (XAI) approaches are increasingly introduced since 2022 in order to counter the black box characteristics of deep learning systems [3]. Grad-CAM, SHAP, and attention-based visualizations are methods that provide clinicians with understanding of AI predictions and, consequently, improve trust and ease clinical adoption [3]. Explainability has now been embraced as a key to regulatory compliance and successful implementation of AI as a routine part of diagnostic workflow.

Current Challenges

Although AI and DL models have achieved impressive results in terms of diagnostics, there are still a number of challenges.

- **Data Imbalance and Annotation Variability**: Most datasets are either biased towards benign or malignant and this can undermine model reliability [3].
- **Reproducibility Concerns**: It is hard to compare the results of different studies as they are affected by different preprocessing, data augmentation, and evaluation measures [12].
- **Clinical Integration Barriers**: Few models have been prospectively tested in a hospital environment or have been approved by the regulatory authorities.
- **Huge Computational Requirement**: Transformer-based systems have large demands on the use of GPUs limiting their use in institutions with limited resources [12].

The solutions to these challenges will include standardized data, open benchmarking platforms, and cloud computing solutions to support the sustainable and extensive use of AI in the medical field.

FUTURE DIRECTIONS

The future research opportunities are

- **Multi-Modal Integration**: Integrating mammography, ultrasound, and histopathology information in order to increase the accuracy of diagnosis and lower false-negative rates.
- **Federated and Privacy-Protecting Learning**: It is possible to train model in a decentralized way without sharing patient data to enhance generalization to a wide variety of populations.
- **Explainable and Trustworthy AI**: The introduction of interpretability mechanisms into the AI pipelines can increase the degree of transparency and build confidence in clinicians.
- **Few-Shot and Self-Supervised Learning**: These methods enable explicit model training with limited labeled data to overcome the shortage of labeled datasets.
- **Clinical validation and regulatory compliance**: The future research should focus on the multi-centric clinical trials and compliance with FDA or CE laws.
- **Ethical and social issues**: Equitable AI-driven healthcare should be addressed through bias reduction, evaluation of fairness, and open reporting [13].

Study Limitations and Future Scope

Despite the fact that this review is a complete description of the research conducted during 2017-2025, there are still certain limitations. There were some studies, which did not fully report the evaluation metrics including F1-score or AUC. Furthermore, the heterogeneity of datasets and protocols used to preprocess them makes it difficult to make direct comparisons across the studies. Future studies ought to engage meta-analytical methods, multi-institutional datasets, and emerging paradigms (e.g., federated learning and explainable AI) to enhance general clinical translation.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest associated with this work.

CONCLUSION

The systematic review outlines a decade of progress in AI and DL in the detection of breast cancer from 2017 to 2025. Convolutional neural networks (CNNs) are the most popular models, but models based on hybrid and transformer are also increasingly used to enhance accuracy, generalization, and interpretability. A combination of multi-modal imaging, transfer learning, and explainable AI has contributed to the high accuracy of diagnosis and increased trust in clinicians. Nonetheless, even with the high reported accuracies (91-99.9%), there are still difficulties in the diversity of the data set, its reproducibility, its clinical validation, and fair performance in different populations. Federated learning, few-shot/self-supervised learning methods, and prospective multi-centre studies should become the areas of the future research to make sure that AI models are clinically resilient, interpretable, and globally applicable. The current development of AI and DL in breast cancer detection proves the idea that it is capable of changing early diagnoses, increase the survival rates, and make the whole diagnostic practices more intelligent, data-driven systems.

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