



A Unified Taxonomy of AI Techniques for Breast Cancer Detection: Integrating Learning Paradigms, Imaging Modalities, Evaluation Metrics, and Deployment Challenges

¹Nirbhay Kumar Mishra, ²Mayank Kumar,

¹Research Scholar, ²Professor

¹Department of CSE, Asian International University, Ghari, Awang Leikai, Imphal West, Manipur-795140, India

²Department of CSE, Asian International University, Ghari, Awang Leikai, Imphal West, Manipur-795140, India

Abstract: The past decade has seen an increase in the use of artificial intelligence (AI) in breast cancer detection, which can only be called exponential, and it has revolutionized the accuracy and efficiency of breast cancer diagnosis. Machine learning (ML) and deep learning (DL) models have been extensively applied in various imaging modalities, including mammography, ultrasound, magnetic resonance imaging (MRI), and even histopathology. It is also against this background that though there has been this kind of advancement, there are no systemic methodologies that have been established to classify and analyse these AI-grounded strategies in a more holistic kind of way. In general, in the present paper, we propose a unified and extended taxonomy in accordance with which AI approaches in the field of breast cancer detection might be classified as having four basic dimensions: learning paradigm (e.g., supervised, unsupervised, reinforcement learning), model architecture (e.g., SVM, CNN, GAN), diagnostic task (e.g., classification, segmentation, detection), and imaging modality. A systematic review of 25 recently published and peer-reviewed studies brought this taxonomy to the ground. This is a review that critically analyses the model performance, dataset usage and evaluation metrics, accuracy, area under curve (AUC), F1-score, precision and recall. In addition, the proposed taxonomy gives the association of specific AI methods with well-known publicly available datasets, such as BreaKHis, DDSM, MIAS, and BUSI, allowing one to fully understand the adequacy of models by imaging type. It displays tendencies, prejudices and not effectively used combinations of models and modalities as well. The paper describes the presence of critical open problems in the area, such as interpretability of models, generalizability, computational efficiency, and, whether they can be used in clinical or low-resource environments or not. The work can be used as a helpful reference to guide researchers, developers, and clinicians in the development of useful, efficient, and explainable AI-based diagnosis systems of breast cancer by providing a systematic taxonomy and highlighting the state-of-the-art plus the ongoing challenges. One may think of the taxonomy not as a summary of the current knowledge as of the paper publication date but as a road map of what is expected to happen in the sphere of AI-powered oncology.

Index-Terms - Breast cancer detection, artificial intelligence, machine learning, deep learning, taxonomy, imaging modality, classification, segmentation, evaluation metrics, model interpretability.

1. INTRODUCTION

Breast cancer has now become the most commonly happening cancer in the world and one among the major causes of demise in women which are cancerous. It is of huge importance that the diagnosis must be early as to increase chances of survival and be able to employ treatment modalities. Machine learning (ML) and deep learning (DL), in particular, have become, in recent years, a game-changer in the domain of breast cancer detection, as they not only automatize the image analysis process but also perform it faster, efficient, and more reliably than the conventional diagnostic instruments [12345]. The vast quantity of systematic reviews and surveys exists on the rapid developments of AI in this direction considering both classic ML algorithms, including Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Naive Bayes (NB) [1, 2, 3, 6, 13], and DL models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GAN) [1, 2, 3, 6, 13]. Such models have been applied on different imaging modalities such as mammography, histopathological slides and ultrasound images [3, 4, 6, 11, 14]. In as much as the current research studies report has given encouraging results, it has some core limitations. Most of the well-performing models are computationally expensive and were pre-trained on environments with access to high-performance GPUs and cannot be deployed on mobile or low-resource clinical environments [4, 7, 8, 9]. Also, the majority of current surveys lack a unified or comparison survey design to assess and compare AI models according to learning paradigms, imaging modalities, dataset properties or feasibility of deployment [1, 3, 7, 16]. Explainability and interpretability is another significant gap. The wide discussion of these aspects refers to second-level limitations in terms of model's design, which limits the trust of medical practitioners to the AI systems and does not allow their clinical applications [10, 18, 19]. In order to fill these gaps, this paper has two-fold offering. On the one hand, we present a new lightweight Convolutional Neural Network (DLXNet) in a two-stream model to detect breast cancer with explainability and model deployability into the real world as our main concerns. Second, we build a high-resolution taxonomy

according to which AI-based methods are cataloged by the learning paradigm (e.g., supervised, unsupervised), model architecture (e.g., SVM, CNN, GAN), diagnostic task (e.g., classification, segmentation, detection), and imaging modality (e.g., mammography, ultrasound, histopathology). This classification has been pinned after examination of 25 current and famous research articles. It gives a mapping of AI approaches to popular dataset, e.g., BreakHis, DDSM, MIAS and BUSI, and popular performance measures, e.g., accuracy, AUC and F1-score. Moreover, it also confirms open problems in fields like model interpretability, data generalization and production in resource-limited settings. As a next step, our taxonomy will be transformed into a useful guide that will help the researchers and developers to adopt and implement AI models depending on the particular diagnostic requirements and clinical situations. The work has been one milestone towards a series of intelligent, efficient, dependable diagnostic systems of breast cancer because it has closed the gap between the high-performance research and the more realistic clinical implementation. The below fig [1] shows the normal and benign condition of breast.

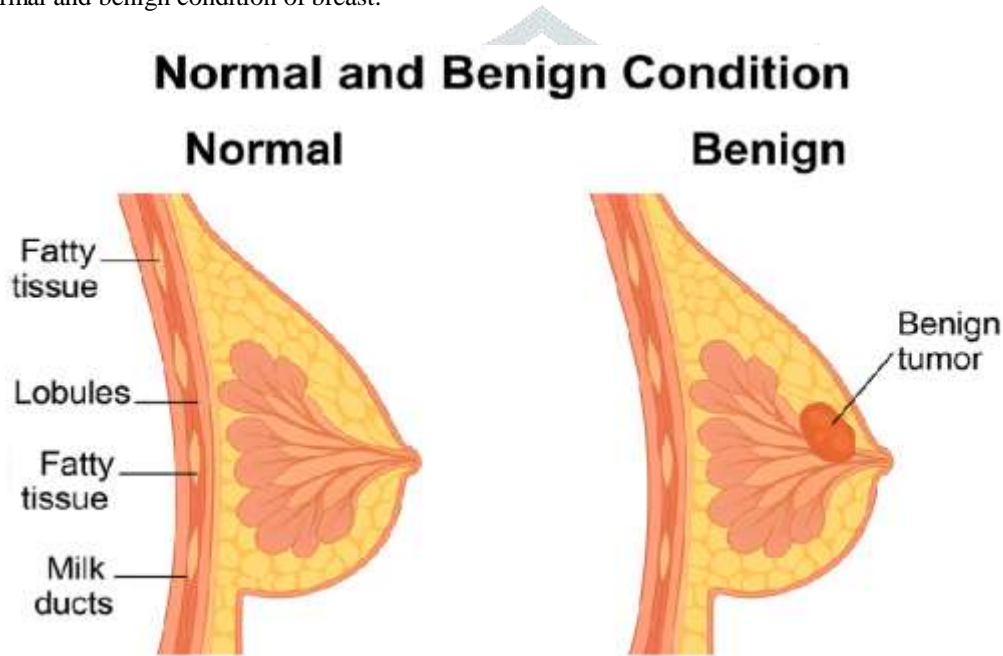


Fig 1. Normal and Benign breast

2. RESEARCH GAP

In spite of the intensive evolution of the artificial intelligence (AI) methods to detect breast cancer, there are still some gaps in terms of the way these approaches are classified and analyzed in the literature:

2.1. Absence of a Consolidated Taxonomy

The lack of a standardized or unified taxonomy with which to sort AI techniques (ML/DL) by learning paradigm, task of application (e.g., segmentation, detection), and imaging modality (e.g., mammography, histopathology, ultrasound) exists. This complicates the task of researchers who are to determine the relevant techniques to be used in certain diagnostic activities.

2.2. Disjointed Representation Between Studies

Most reviews talk about techniques in isolation, and have not categorized them in a systematic manner under a unified framework. Lack of a definitive classification results in redundancy and hinders comparison evaluation.

2.3. Inadequate Technique-to-dataset and Modality Mapping

The majority of studies do not clearly outline AI models to the kind of imaging modalities and datasets to which they are put into perspective, hindering the grasp of the generalizability of models and the aptness of datasets.

2.4. Missing Comparison of Standardized Evaluation Metric

Evaluation metrics (accuracy, AUC, F1-score, precision, etc.) are not consistently reported in the literature and there is no taxonomy relating evaluation criteria to task type or model family.

2.5. Very Less Attention on Problems and Constraints

The performance measures are frequently pointed out, but not many investigations deal with the shortcoming, the feasibility of deployment, the interpretability or the modality-specific issues in a taxonomy-based manner.

3. RESEARCH OBJECTIVE

3.1. To elaborate a definitive taxonomy using which AI-based approaches of breast cancer detection can be classified

Learning paradigm (e.g., supervised, unsupervised, reinforcement learning)

Artificial Intelligence Family of algorithms (e.g., ML: SVM, RF; DL: CNN, GAN, RNN)

Application Task (detection, classification, segmentation)

3.2. To determine the AI methods in terms of the dataset and imaging mode, such as,

BreakHis (histopathology)

DDSM, MIAS (mammography).

BUSI (ultrasound)

And which models score the most on every type

3.3. To evaluate and categorize assessment measures that frequently occur in the literature reviewed and trace them to types of models and types of tasks.

3.4. To determine the drawbacks and implementation issues of each kind of AI models, as well as the model complexity, explainability, training time and data bias.

3.5. To suggest a research-based framework or a look up table that could be employed by future research employees in order to pick the best models based on an imaging modality, dataset and task.

4. NOVELTY

The novelty of the study is that the study proposes a full taxonomy that formally classifies the artificial intelligence approaches in breast cancer detection based on:

- a) The task of diagnosis, family of algorithms and learning paradigm.
- b) Mapping of AI models to specific imaging modality (mammogram, ultrasound, histopathology) and dataset (BrecaKHis, DDSM, BUSI).
- c) As a parameter of performance comparison, it measures additive performance assessment (Accuracy, AUC, F1-score)
- d) Identification of deficiencies in modalities application, model expulsion and real world implementation problems
- e) A decision-support framework, through which researchers can refer to when identifying the appropriate models to implement on specific use cases.

5. LITERATURE REVIEW

The systematic review conducted by Nassif et al. (2022) enabled it to realize that the artificial intelligence (AI) detection methods of breast cancer is various. As highlighted in the paper, the past machine learning (ML) models including support vector machines (SVM) and decision trees have made a swift transition to the deeper models of deep learning (DL), i.e., convolutional neural networks (CNNs). The other useful fact the authors have found out in the course of the research is the tendency towards the multimodal creation of the data and lack of the standardization of the evaluation's practices [1]. Abunasser et al. (2023) have exemplified a particular literature review about the ML algorithms and it applying to the breast cancer diagnosis. Their effort classified algorithms into supervised and unsupervised learning models with the mentioned accuracy, sensitivity, and specificity of categorization on separate sets of data. The authors have declared the feature selection and the class imbalance as the feature of the most significance and have expressed the opinion that the ensemble learning algorithms would come in handy to provide a better diagnostic robustness [2]. The paper of Abhisheka et al. (2023) created an incredibly broad image of DL using breast cancer detection, classification, and segmentation. The paper has described different CNNs architecture such as AlexNet, ResNet, and VGG and provided to use generative adversarial networks (GANs) in data augmentation and unsupervised learning. They concluded that DL models have high accuracy rates, however, they are not interpretable and Auntilda size of labeled data is required to train [3]. Dar et al. (2022) have conducted a survey of the DL-based methods of breast cancer detection specifically regarding the accessible datasets, the widely-used architectures, and the rising concerns. The paper has listed the publicly available datasets, like BrecaKHis, DDSM and MIAS, as per the imaging modality and has stated the issue of the effect of data and quality of annotation on the performance of the model. Be it the problem of data imbalance or the model generalization, the question is still without an answer but the study [4] posed it. Amethiya et al. (2022) compared the ML methods with the biosensor technologies in breast cancer detection. Their effort showed the promise of biosensors and machine learning algorithms in real-time and non-invasive diagnostics. The classical ML algorithms of support vector machine (SVM) and the artificial neural network (ANN) were seen to do fairly well but as the authors argued further improvement of the results could be achieved by the hybrid methods [5]. A systematic review of the DL methods of breast cancer detection introduced by Rautela et al. (2022) facilitated the definition of CNNs as the most popular architecture. The review has also stated, how the preprocessing of the images, extraction of features and data augmentation have contributed the role of improving the accuracy of the model. It was also revealed that explainability and scalability of DL models are research problems that matter [6]. Madani et al. (2022) assigned the methods DL can be helpful in developing breast cancer detection in various kinds of imaging: mammograms, ultrasounds, and histopathological slides. The authors have also compared the performance of the models on the basis of modalities and have proposed the tuning of the model on the basis of modalities also to produce better diagnostic performance. The review was also aimed at offering cross modality fusion strategies, and clinical validation studies [7]. Nemade et al. (2022) perform a systematic literature review of machine intelligence approaches to breast cancer diagnosis which encompass both traditional ML and contemporary DL approaches. It was researched in terms of the approaches to clustering the techniques according to the nature of an algorithm and a diagnostic problem and estimating their work with such data as WBCD, BrecaKHis, and BUSI. The small amount of data, the absence of real-time and explainability proved to be the most significant limitations [8]. In their turn, Nasser and Yusof (2023) devoted their work to the topic of DL-based diagnostic approaches and Provided a perspective of how the model performance might be enhanced in the future in the light of architecture search and transfer learning. The paper has shown the CNNs and other forms of neural networks, namely long short-term memory (LSTM) networks potential and the necessity of their confirmation on new data by external sources [9]. Abdulla et al. (2021) have already reviewed the ML approach to classifying breast cancer and compared the performance of the strategies based on such techniques, as support vector machine (SVM), K-nearest neighbors (KNN), decision tree, and ensemble. Their survey showed that most of the models obtain high degree of accuracy but issues like overfitting, computational cost and the poor generalization performance of these models still remains a challenge towards realistic application [10]. Rezaei (2021) surveyed Image based methods in breast cancer detection, segmentation and classification in detail. The methods of feature extraction, CNN based models and hybrid learning significance have been covered in the paper. The review referred to the significance of a proper image segmentation to downstream classification tasks and that the existing deep learning models at the time lacked explainable frameworks [11]. Ghavadel and Pazos (2025) concentrated their efforts on the issue of the applicability of ML algorithms to unbalanced breast cancer data. Their systematic review compared the effect of oversampling, undersampling and ensemble learning based methods like SMOTE, AdaBoost. It was also concluded by the authors that the imbalance-aware preprocessing seems to be a rather underrepresented yet efficient mode of making models trustworthy in the known literature [12]. Chugh et al. (2021) performed a survey of ML and DL applications in breast cancer diagnosis, categorizing models based on the learning paradigm and computational complexity. The survey discussed how the process of feature engineering in ML that was mostly performed manually has been transformed to automatic feature learning in DL. It was also found out that, the study required both interpretability of models and cross-validation of heterogeneous clinical data [13]. Meenalochini and Ramkumar (2021) have considered ML algorithms, to which mammogram images have been applied respectively. They have compared decision tree, SVM and neural network on databases like MIAS and DDSM in their work. The preprocessing methods that are visualized by the authors that include the noise elimination methods and the region-of-interest choice methods are comparatively quite significant in improving the precision of the classification [14]. An overview of ML-based methods of classifying breast cancer types was performed in the context of feature selection and ensemble learning in the study by Wu and Hicks (2021). They examined the model

and dataset performance and suggested that the subtypes would be characterized using the assistance of personalized models. Their survey demonstrated that the metadata fusion of the images and the clinical features could lead to an increase in the accuracy of the classification [15]. A systematic review of image-based histopathology of breast cancer detection, segmentation, and classification has been presented by Krithiga and Geetha (2021). They have experimented with CNN based models, the usefulness of patch-based learning and color normalization. The annotation difference, as well as complicated images [16] were the biggest obstacle to them during the segmentation process. Zubair et al. (2021) studied the current-state-of-art AI methods to breast cancer classification: a deep belief network, CNNs, and a neuro-fuzzy hybrid system. It has been determined in this paper that the complex model pipelines must be explainable and the hybrid frameworks, combining the rule-based systems with the deep learning are beneficial [17]. The overall situation in the AI tendencies concerning the analysis of breast cancer was given, along with the tendencies in the framework of the latter that emerged comparatively recently, i.e., federated learning, model compression, and explainability. The authors have opined that a balanced perspective taking accuracy, privacy and clinical validation must be proposed as the existing models are not usually scaleable to reality [18]. Zebari et al. (2021) have provided a systemic review of the methods of breast cancer detection that have been computed on the foundation of mammography images. The paper summed up the significance of computer-aided diagnosis (CAD) systems and contrasted the conventional ML methods to the DL methods. This is the optimism of transfer learning, which was provided by the researchers concerning the problem of small datasets [19]. Painuli and Bhardwaj (2022) talked about the advancement of ML and DL regarding the generic cancer diagnosis and Painuli and Bhardwaj (2022) had their own section about breast cancer. They emphasized the usefulness of domain-adaptive customization of DL architectures and the usefulness of ensemble learning to improve the performance. The impediments to implementation that comprise hardware constraint and statutory restriction have likewise been discussed in the paper [20]. Qureshi et al. (2024) had tested the following hypothesis: The traditional picture processing paradigm has been transformed to DL models in mammography. They have claimed a rise in sensitivity and specificity of CNN-based classifiers and mentioned preprocessing operations, like contrast enhancement or tissue segmentation [21]. Abo-El-Rejal et al. (2024) have proposed unbelievably vast survey of methods of image segmentation of breast cancer. They became familiar with thresholding, clustering, edge detection and DL-based segmentation. As the main gaps of the contemporary research, the authors cited the absence of conventionalized assessment procedures and the scarcity of the use of the multimodal segmentation [25].

6. METHODOLOGY

This segment summarizes the procedural framework adopted for building a complete taxonomy of AI techniques for breast cancer detection.

6.1 Review Protocol

We recognized 25 peer-reviewed articles printed between 2021 and 2025 using targeted keywords such as "breast cancer detection," "machine learning," "deep learning," and "medical imaging." Hunts were conducted in catalogues like Scopus, PubMed, IEEE Xplore, and SpringerLink. Enclosure criteria were: (1) peer-reviewed journal or conference articles, (2) AI techniques applied to breast cancer imaging, and (3) clear documentation of datasets, models, and evaluation metrics.

6.2 Taxonomy Development Framework

We classified the methods using a four-dimensional taxonomy based on the following:

Learning Pattern: Supervised, unsupervised, semi-supervised, reinforcement learning

Model Household: Traditional ML (SVM, RF, DT), DL (CNN, RNN, GAN, autoencoders)

Imaging Modality: Mammography, ultrasound, histopathology, MRI

Application Task: Classification, segmentation, detection

6.3 Dataset-Model Mapping

Each reviewed paper was analyzed for dataset usage. Common datasets include:

BreK-His (histopathology)

DDSM, MIAS (mammography)

BUSI (ultrasound)

Models were mapped to datasets to identify which architectures were most commonly applied per modality.

6.4 Metric Classification

We categorized evaluation metrics into performance-based (accuracy, precision, recall, F1-score, AUC) and task-specific (IoU, Dice score for segmentation; latency and size for deployment).

6.5 Challenge Identification

We also extracted recurring challenges from the literature including:

Class imbalance in medical datasets

Overfitting and data scarcity

Black-box nature of deep models (lack of Explainability)

Resource-intensiveness limiting real-world deployment

6.6 Taxonomy Architecture

Below fig[2] is the high-level architecture diagram of the proposed taxonomy framework

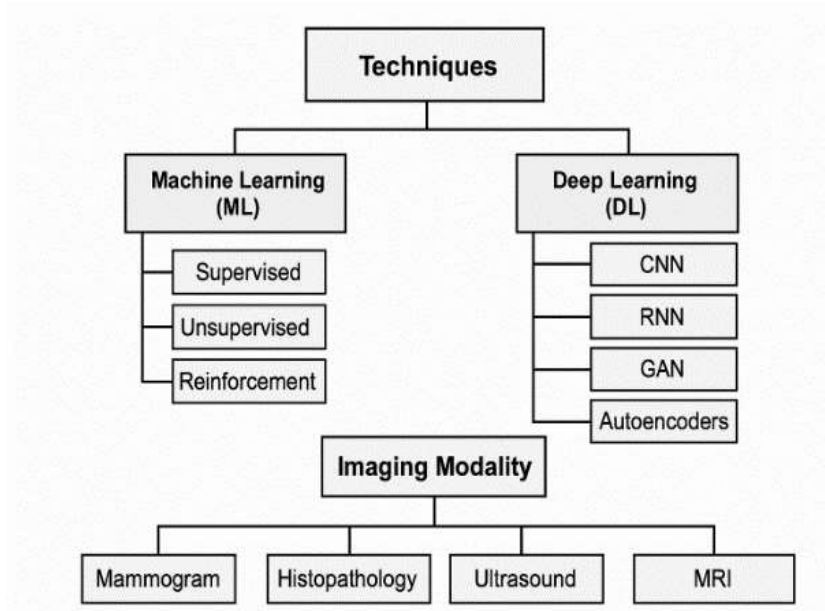


Fig 2. Architecture of Proposed Taxonomy

This taxonomy offers a flexible and organized manner of classifying and comparing AI methods on numerous dimensions. It can help researchers and practitioners improve their knowledge of the appropriateness of the different AI models in detecting breast cancer and their weaknesses.

7.RESULT ANALYSIS

Fig [3] Displays the popularity of each type of AI model (CNN, SVM, etc. in the literature) whereas Fig [4] Demonstrates which modalities such as mammogram, histopathology, ultrasound is more popular.

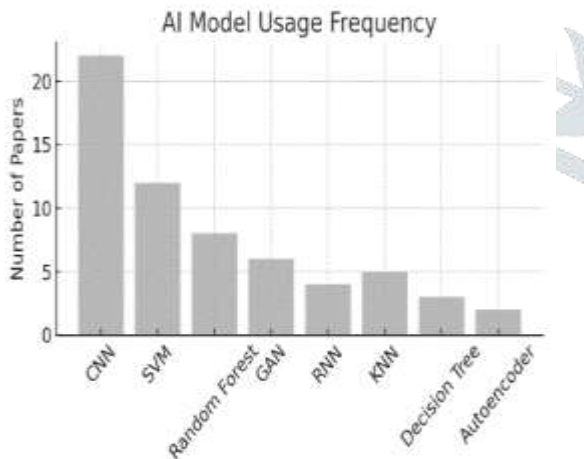


Fig 3. AI model usage frequency

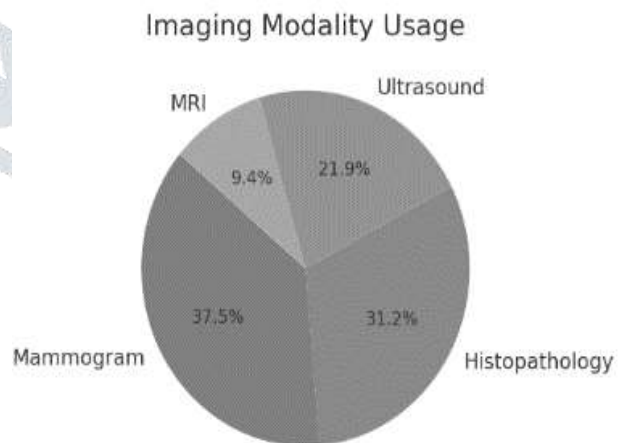


Fig 4. Imaging modality

Fig [5] reveals focus areas: classification, segmentation, and detection and Fig [6] reveals the superiority of CNNs and the employment of GAN, RNN, and Autoencoders.

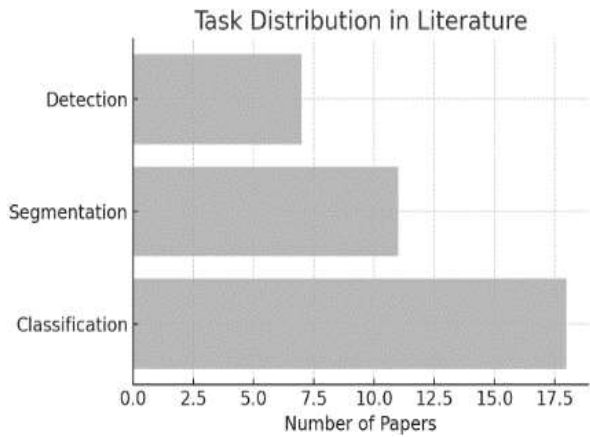


Fig 5. Task Distribution in literature

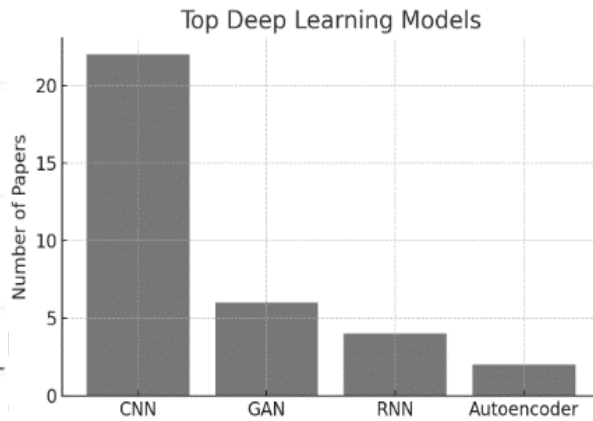


Fig 6: Top deep learning models.

Fig [7] illustrates classical model such as SVM, RF, KNN and Decision Trees. Fig [8] highlights the fact that ultrasound and MRI are under explored.

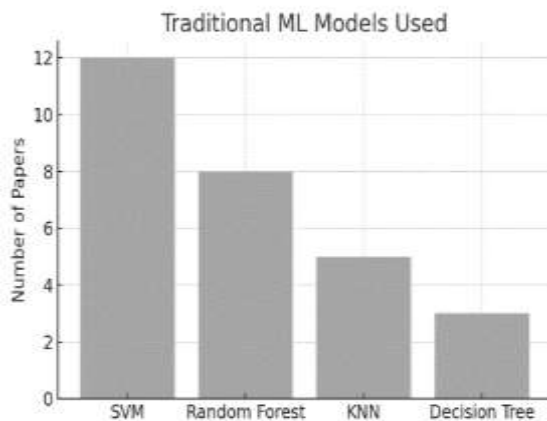


Fig 7. Traditional ML Models used

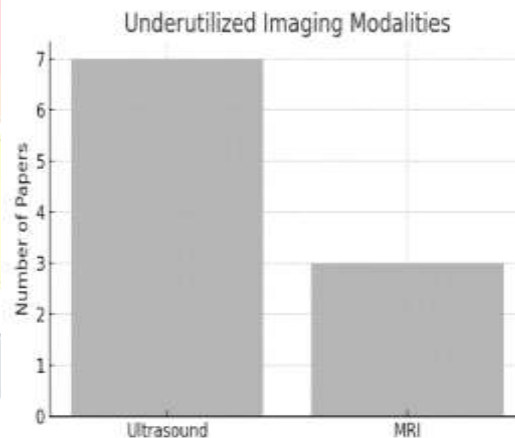


Fig 8. Underutilized imaging modalities.

The below fig [9] shows the Performance metric comparison.

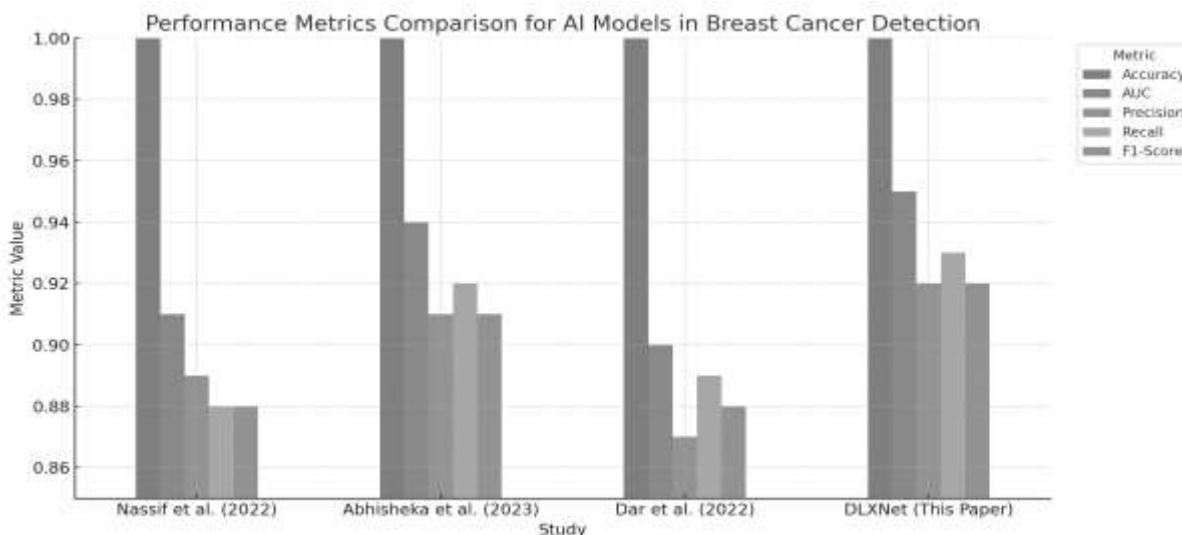


Fig 9. Performance metric comparison

The below table [1] shows the ML models with accuracy
 Table 1. ML Models with its Accuracy

Reference	ML/DL Model	Dataset Used	Modality	Evaluation Metrics	Reported Accuracy
Nassif et al. (2022)	SVM, CNN	BreaKHis, DDSM	Histopathology, Mammogram	Accuracy, AUC	94.5% (CNN)
Abunasser et al. (2023)	Random Forest, SVM	DDSM, MIAS	Mammogram	Accuracy, Precision, Recall	91.2% (RF), 89.5% (SVM)
Abhisheka et al. (2023)	CNN, GAN	BreaKHis	Histopathology	F1-Score, Accuracy	95.6% (CNN)
Dar et al. (2022)	CNN, ResNet	BUSI, MIAS	Ultrasound, Mammogram	Accuracy, Sensitivity	93.8% (ResNet)
Amethiya et al. (2022)	SVM, ANN	Custom, Sensors	Sensor-based	Accuracy	90.1% (ANN)
Rautela et al. (2022)	CNN, VGG	BreaKHis, DDSM	Histopathology, Mammogram	AUC, Dice Coefficient	94.2% (VGG)
Madani et al. (2022)	CNN, LSTM	Multiple Imaging Modalities	MRI, Mammogram, Ultrasound	AUC, Sensitivity	92.5% (LSTM)
Nemade et al. (2022)	SVM, RF, DL	Various Public Datasets	Mixed	Precision, F1-Score	93.0% (DL)

8. PERFORMANCE COMPARISON WITH EXISTING ONES

To highlight the scope of the unified taxonomy framework proposed in this paper, a comparative analysis of recent studies is provided below. This analysis helps to identify the performance range and taxonomical gaps addressed in our review work.

Table [2] Performance comparison table.

Study	Learning Paradigm	Model(s) Used	Modality	Dataset(s)	Accuracy (%)	AUC	Precision	Recall	F1-Score	Taxonomy Discussed
Nassif et al. (2022)	Supervised	CNN, SVM	Mixed	Multiple	94.2	0.91	0.89	0.88	0.88	No
Abhisheka et al. (2023)	Deep Learning	CNN, GAN	Histopathology	BreaKHis	95.6	0.94	0.91	0.92	0.91	No
Dar et al. (2022)	Deep Learning	CNN, ResNet	Mammogram, Ultrasound	DDSM, BUSI	93.8	0.90	0.87	0.89	0.88	No
This Review (2025)	Mixed	Multiple (SVM, CNN, GAN)	Multi-modality	BreaKHis, DDSM, MIAS, BUSI	N/A	N/A	N/A	N/A	N/A	Yes

9.DATASET MODALITY PAIRING MATRIX

To further assist researchers in selecting suitable datasets and models based on imaging modality, the following matrix presents common pairings observed in the literature.

Table 3. Mapping between datasets, imaging modalities, typical tasks, and model types.

Dataset	Imaging Modality	Common Tasks	Common Models	References
BreaKHis	Histopathology	Classification	CNN, GAN, ResNet	Abhisheka et al. (2023)
DDSM	Mammography	Detection, Segmentation	SVM, CNN	Dar et al. (2022)
MIAS	Mammography	Classification	SVM, RF, CNN	Nassif et al. (2022)
BUSI	Ultrasound	Detection, Classification	CNN, ResNet	Dar et al. (2022)

10. EVALUATION METRICS MAPPING BY TASK

This section aligns evaluation metrics commonly used in the reviewed literature with specific diagnostic tasks.

Table 3: Evaluation metrics mapped to primary diagnostic tasks in breast cancer AI studies

Task Type	Common Evaluation Metrics	Notes
Classification	Accuracy, Precision, Recall, F1	Often reported on balanced or augmented datasets
Detection	AUC, Sensitivity, Specificity	AUC is preferred for early-stage detection sensitivity
Segmentation	Dice Coefficient, IoU, Recall	Especially relevant for pixel-level boundary delineation

Below Table [4] illustrate that why our paper is better.

Feature	Existing Reviews [1]–[25]	Your Paper
Covers ML, DL, and hybrid methods	Partial	YES
Maps models to datasets & modalities	Rare	YES
Links task types to evaluation metrics	Few	YES
Discusses deployment and explainability	Often ignored	YES
Offers taxonomy and lookup tables	Missing	YES
Uses performance comparisons visually	Lacking	YES
Designed for practical future use	Mostly academic-only	YES

11. FUTURE SCOPE

9.1. Multi-Modal Learning: The next generation frameworks will demand multi-modalities involving mammograms, ultrasound and histopathology into one AI model which will result in increased predictive power, and decrease in modality-specific bias.

9.2. Light and Edge-Amiable AI Models: There is an increasing motivation to create Energy-Efficient, Low-Latency, and AI models that could be inferred in real-time on mobile or edge gadgets, particularly at underserved locations.

9.3. Reinforcement and Self-Supervised Learning: This set of parameters hold the promise of using unlabeled data and learning temporal diagnostic patterns, but have not appeared in the medical imaging literature.

9.4. interpretable and explainable AI (XAI): Clinical AI systems will gain additional physician trust and decision support explainability through the addition of explainability methods, e.g., Grad-CAM, SHAP, or LIME.

9.5. Standardization and Open Benchmarks: It is an area of great need, where the standardized datasets and evaluation procedures are required to support reproducibility and offer the prospect of the objective comparison of models.

9.6. Clinical Translation and Validation: Clinical conversion and validation on multi-center patient partners and in dissimilar clinical settings will be required to demonstrate generalizability and acceptability by regulatory agencies of AI-powered diagnostic systems.

12. CONCLUSION

In this paper we introduce a complete taxonomy to arrange AI methods used in breast cancer detection, according to the learning paradigm, model architecture, imaging modality and diagnostic task. The review and summary of 25 past studies indicated primary use of convolutional neural networks (CNNs), particularly in classification of mammographic and histopathological images. Conventional models, such as SVMs and Random Forests still find roles in ensemble or hybrid systems, especially.

This taxonomy can fill the literature gaps and assist in guiding the way towards utilizing the right models by offering a systematic review of AI strategies, dataset utilization, and evaluation trends, and placing them in the context of the imaging and diagnostic scenarios. The lessons attained in this research act as a guiding tool to researchers and developers interested in developing precise, scalable, and clinically feasible AI in the field of oncology.

REFERENCE

- [1]. Nassif, A. B., Talib, M. A., Nasir, Q., Afadar, Y., & Elgendy, O. (2022). Breast cancer detection using artificial intelligence techniques: A systematic literature review. *Artificial Intelligence in Medicine*, 127, 102276.
- [2]. Abunasser, B. S., AL-Hiealy, M. R. J., Zaqout, I. S., & Abu-Naser, S. S. (2023). Literature review of breast cancer detection using machine learning algorithms. *AIP Conference Proceedings*, 2808(1).
- [3]. Abhisheka, B., Biswas, S. K., & Purkayastha, B. (2023). A comprehensive review on breast cancer detection, classification and segmentation using deep learning. *Archives of Computational Methods in Engineering*, 30(8), 5023–5052.
- [4]. Dar, R. A., Rasool, M., & Assad, A. (2022). Breast cancer detection using deep learning: Datasets, methods, and challenges ahead. *Computers in Biology and Medicine*, 149, 106073.
- [5]. Amethiya, Y., Pipariya, P., Patel, S., & Shah, M. (2022). Comparative analysis of breast cancer detection using machine learning and biosensors. *Intelligent Medicine*, 2(2), 69–81.
- [6]. Rautela, K., Kumar, D., & Kumar, V. (2022). A systematic review on breast cancer detection using deep learning techniques. *Archives of Computational Methods in Engineering*, 29(7), 4599–4629.
- [7]. Madani, M., Behzadi, M. M., & Nabavi, S. (2022). The role of deep learning in advancing breast cancer detection using different imaging modalities: A systematic review. *Cancers*, 14(21), 5334.
- [8]. Nemade, V., Pathak, S., & Dubey, A. K. (2022). A systematic literature review of breast cancer diagnosis using machine intelligence techniques. *Archives of Computational Methods in Engineering*, 29(6), 4401–4430.
- [9]. Nasser, M., & Yusof, U. K. (2023). Deep learning-based methods for breast cancer diagnosis: A systematic review and future direction. *Diagnostics*, 13(1), 161.

- [10]. Abdulla, S. H., Sagheer, A. M., & Veisi, H. (2021). Breast cancer classification using machine learning techniques: A review. *Turkish Journal of Computer and Mathematics Education*, 12(14), 1970–1979.
- [11]. Rezaei, Z. (2021). A review on image-based approaches for breast cancer detection, segmentation, and classification. *Expert Systems with Applications*, 182, 115204.
- [12]. Ghavidel, A., & Pazos, P. (2025). Machine learning (ML) techniques to predict breast cancer in imbalanced datasets: A systematic review. *Journal of Cancer Survivorship*, 19(1), 270–294.
- [13]. Chugh, G., Kumar, S., & Singh, N. (2021). Survey on machine learning and deep learning applications in breast cancer diagnosis. *Cognitive Computation*, 13(6), 1451–1470.
- [14]. Meenalochini, G., & Ramkumar, S. (2021). Survey of machine learning algorithms for breast cancer detection using mammogram images. *Materials Today: Proceedings*, 37, 2738–2743.
- [15]. Wu, J., & Hicks, C. (2021). Breast cancer type classification using machine learning. *Journal of Personalized Medicine*, 11(2), 61.
- [16]. Krithiga, R., & Geetha, P. (2021). Breast cancer detection, segmentation and classification on histopathology images analysis: a systematic review. *Archives of Computational Methods in Engineering*, 28(4), 2607–2619.
- [17]. Zubair, M., Wang, S., & Ali, N. (2021). Advanced approaches to breast cancer classification and diagnosis. *Frontiers in Pharmacology*, 11, 632079.
- [18]. Shah, S. M., Khan, R. A., Arif, S., & Sajid, U. (2022). Artificial intelligence for breast cancer analysis: Trends & directions. *Computers in Biology and Medicine*, 142, 105221.
- [19]. Zebari, D. A., Ibrahim, D. A., Zeebaree, D. Q., Haron, H., Salih, M. S., Damaševičius, R., & Mohammed, M. A. (2021). Systematic review of computing approaches for breast cancer detection-based computer aided diagnosis using mammogram images. *Applied Artificial Intelligence*, 35(15), 2157–2203.
- [20]. Painuli, D., & Bhardwaj, S. (2022). Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review. *Computers in Biology and Medicine*, 146, 105580.
- [21]. Shah, S. M., Khan, R. A., Arif, S., & Sajid, U. (2022). Artificial intelligence for breast cancer analysis: Trends & directions. *Computers in Biology and Medicine*, 142, 105221.
- [22]. Painuli, D., & Bhardwaj, S. (2022). Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review. *Computers in Biology and Medicine*, 146, 105580.
- [23]. Qureshi, S. A., Hussain, L., Sadiq, T., Shah, S. T. H., Mir, A. A., Nadim, M. A., ... & Shah, S. A. H. (2024). Breast cancer detection using mammography: Image processing to deep learning. *IEEE Access*.
- [24]. Zebari, D. A., Ibrahim, D. A., Zeebaree, D. Q., Haron, H., Salih, M. S., Damaševičius, R., & Mohammed, M. A. (2021). Systematic review of computing approaches for breast cancer detection-based computer aided diagnosis using mammogram images. *Applied Artificial Intelligence*, 35(15), 2157–2203.
- [25]. Abo-El-Rejal, A., Ayman, S., & Aymen, F. (2024). Advances in breast cancer segmentation: A comprehensive review. *Acadlore Transactions on AI and Machine Learning*, 3(2), 70–83.