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Leveraging AI for the Next Era of Precision Oncology in Breast Cancer Detection

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Abstract: Cutting-edge progress in ML and DL techniques has led to substantial gains in the accuracy and reliability of breast cancer diagnostic systems. Conventional diagnostic means could have limited sensitivity and can be subjective; therefore, AI supported Computer-Aided Diagnosis (CAD) systems are introduced to overcome these issues. This review summarizes developments from 2022–2025 in ML and DL techniques applied to mammography, ultrasound, MRI, histopathology, and thermography. Deep learning methods, with convolutional neural networks at the forefront, have achieved notable accuracy across multiple imaging types, while emerging trends such as radiomics, deep reinforcement learning, hybrid ML–DL frameworks, and explainable AI (XAI) further enhance diagnostic performance and clinical trust. Challenges including data scarcity, model interpretability, and generalization remain, with promising solutions found in self-supervised learning, federated learning, and foundation models. These advancements collectively support earlier detection, improved treatment planning, and the advancement of precision oncology.

Keywords: Breast cancer detection, machine learning, deep learning, CNN, CAD systems, radiomics, explainable AI, federated learning

I. INTRODUCTION

Breast cancer still is one of the most common and deadly malignancies in women both in the Western World and worldwide with more than 2.1 million new cases per year and being on top of causes for cancer-related deaths [1][2][3]. Early detection is critical for reducing disease progression and improving survival outcomes, as timely diagnosis significantly enhances the effectiveness of therapeutic interventions [3][4][5]. Conventional screening techniques—such as mammography, ultrasound, and magnetic resonance imaging—have long formed the backbone of breast cancer diagnosis, yet these modalities frequently suffer from limitations in sensitivity, specificity, and interpretive consistency, particularly in dense breast tissues or early-stage manifestations [6][7][8]. Such challenges underscore the urgent need for more robust, reliable, and scalable diagnostic solutions.

The accelerating expansion of AI capabilities, supported by ML and DL approaches, have been revolutionizing the field of clinical oncology by offering automated high precision analysis of complex medical data, which is becoming an integral component for understanding biological systems. “AI-driven CAD systems are being widely deployed to assist radiologists by minimizing the likelihood of diagnostic errors, improving workflow efficiency, and providing more consistent assessments across diverse imaging modalities [9][10][11][12]. Over the past three years (2022–2025), rapid progress in ML and DL algorithms has yielded significant improvements in tumor detection, segmentation, classification, and prediction of treatment response. Techniques such as Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), radiomics-driven feature extraction, and hybrid ML–DL frameworks have demonstrated remarkable accuracy, achieving performance levels as high as 90–99% on mammography, ultrasound, and histopathological datasets [1][8][21][26].

In addition to enhancing diagnostic accuracy, emerging AI applications have expanded the scope of breast cancer analytics. From predicting pathological complete response (pCR) to neoadjuvant chemotherapy [14] to enabling fully automated tumor segmentation and efficient large-scale screening, AI continues to push the boundaries of precision medicine. Parallel advancements in deep reinforcement learning, explainable AI (XAI), and federated learning further promise to address key barriers such as interpretability, data scarcity, and privacy constraints [13][15][21][36].

Despite these advances, substantial challenges persist. Limited availability of high-quality annotated datasets, model generalization across heterogeneous populations, ethical concerns, and the "black box" nature of deep neural architectures

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continue to hinder widespread clinical deployment. Consequently, there is a growing emphasis on developing transparent, interpretable, and resource-efficient AI systems suitable for real-world medical environments.

This review paper presents a comprehensive discussion on current progress in ML and DL algorithms for breast cancer detection, covering the global research trends, advancements in imaging modalities, hybrid computational approaches, explainability frameworks, and clinical integration challenges. It also outlines emerging research directions, including foundation models, self-supervised learning, radiomic-DL fusion techniques, federated learning pipelines, and AI-driven precision treatment strategies. Through this review, the study aims to offer a consolidated perspective on current innovations while highlighting future pathways toward reliable, interpretable, and equitable AI-enabled breast cancer detection.

II. LITERATURE REVIEW

The detection of breast cancer has been thoroughly investigated using traditional diagnostic techniques like thermography, histopathology, ultrasound, MRI, and mammography. However, limitations in sensitivity, specificity, and inter-observer variability have motivated the adoption of AI-driven approaches, particularly Machine Learning (ML) and Deep Learning (DL), to improve diagnostic reliability and efficiency [6][7][8]. Over the past decade, and more notably between 2022 and 2025, advancements in computational modelling have significantly enhanced cancer detection performance across various imaging modalities.

A. ML and DL Integration in Computer-Aided Diagnosis

AI-assisted Computer-Aided Diagnosis (CAD) systems are increasingly being leveraged to reduce human error, expedite clinical workflows, and ensure consistent decision-making [9][10][11][12]. DL architectures—especially Convolutional Neural Networks (CNNs)—have become central to modern CAD pipelines due to their ability to extract hierarchical features from raw imaging data. Reported performance across different datasets has reached 90–99%, with specific models achieving 99.96% accuracy in mammography and 100% accuracy in ultrasound-based cancer detection [1].
Beyond static detection tasks, AI has also been applied in treatment prediction. Imaging data such as Diffusion-Weighted MRI (DWI) combined with DL models supports forecasting pathological complete response (pCR) to neoadjuvant chemotherapy (NAC), significantly aiding personalized treatment planning [14]. Automated tumor segmentation, a traditionally labor-intensive procedure, has also benefited substantially from DL-based optimization.

B. Developments Across Imaging Modalities

Deep reinforcement learning (DRL), an augmentation of reinforcement learning with deep neural networks, has shown considerable potential in medical imaging applications[1]. DRL frameworks learn sequences of actions that maximize expected rewards, and recent advancements include both model-free and model-based algorithms[1].

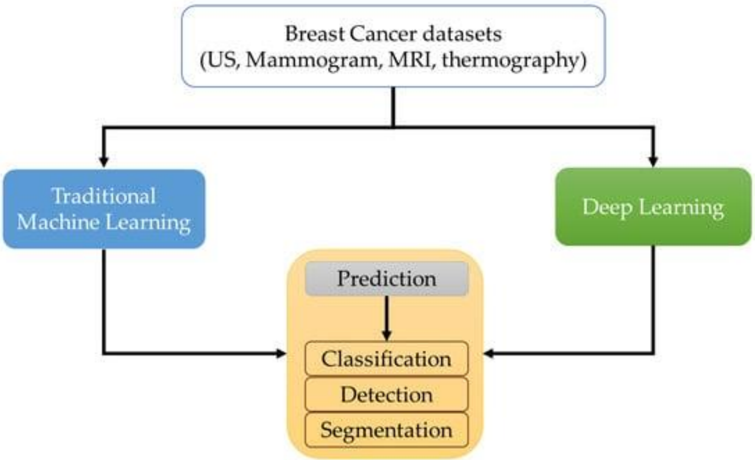

Fig. 1 Breast Cancer Detection [18]

These are distinct from methods focused on low-dimensional representations of dynamic medical data, such as cardiac motion, which also leverage advanced computational techniques to address challenges like natural circular patterns in data[2].

1) Mammography

Mammography remains the gold standard for early detection, though challenges persist in identifying subtle abnormalities. Deep learning models such as ResNet50 classify mammogram images (MLO and CC views) into cancerous and non-cancerous categories while employing saliency maps to enhance interpretability [21]. Novel architectures—such as Bi-xBcNet-96 incorporating "green AI" efficiencies—show promise in enabling resource-efficient clinical deployment [22]. Explainable AI (XAI) methods further enhance radiologist trust, offering transparent decision pathways for mammographic analysis [23].

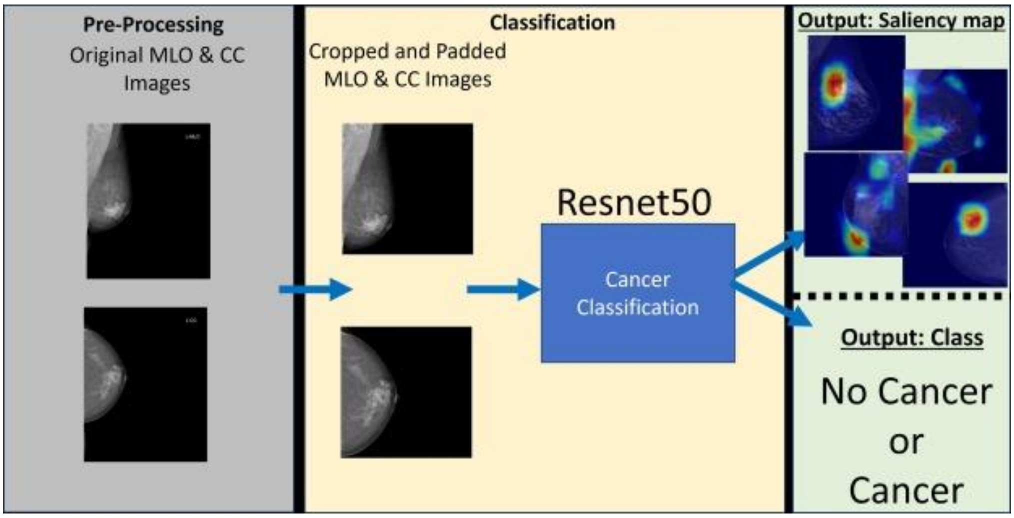

Fig. 2 Mammogram Processing with Resnet50 [21]

2) Histopathology

Histopathological imaging is essential for definitive diagnosis but is time-consuming and subject to variability [24]. DL solutions employing CNNs, GRUs, and Vision Transformers (ViTs) demonstrate substantial improvements in speed, reproducibility, and accuracy. ViT-based models, for instance, have achieved validation accuracies of 94% on large-scale patch datasets [26]. Advanced microscopy techniques, such as ultra-fast fluorescence confocal microscopy integrated with DL, further reduce dependencies on invasive procedures [25].

3) Ultrasound and MRI

In ultrasound imaging, hybrid architectures such as UGGNet, combining U-Net and VGG, provide enhanced segmentation of tumor regions [27]. MRI and digital breast tomosynthesis (DBT) offer superior resolution and depth, further improved through radiomics-driven feature engineering [28]. Algorithms such as SHGS-optimized DL models support late-onset metastasis prediction [29], while resource-efficient DL frameworks address gaps in diagnostic accessibility in developing regions [30].

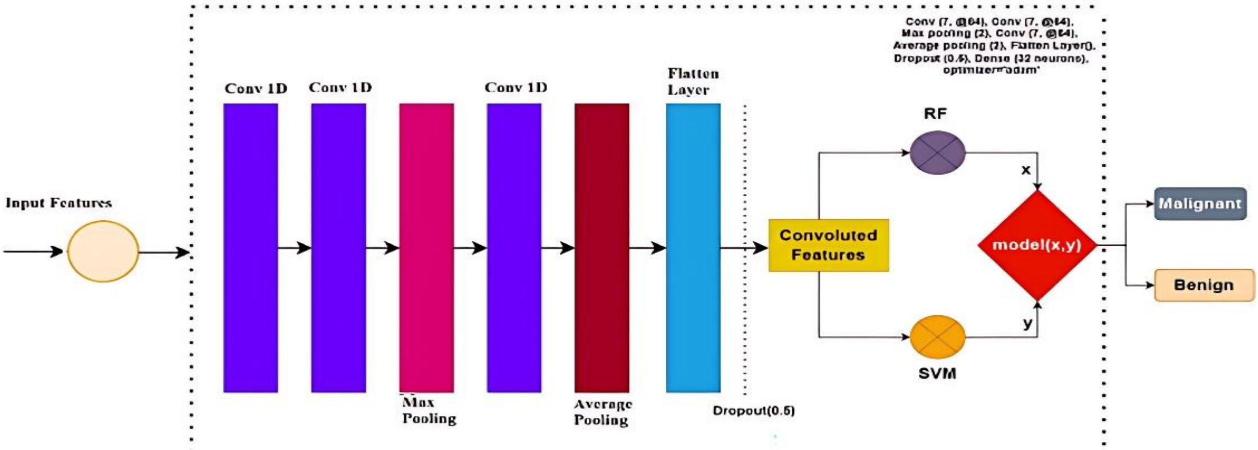

Fig. 3 Machine Learning Flowchart for Breast Cancer Detection [31]

C. Hybrid ML–DL Frameworks and Feature Engineering

Hybrid models combining CNN-based feature extraction with ML classifiers—such as SVM, Random Forest, and KNN—have demonstrated improved classification accuracy by merging DL's representational strength with ML's decision robustness [31]. Architectures such as BreastMultiNet integrate DenseNet201 and VGG19, followed by dense layers and softmax activation(f) for high-performance histological classification [11].

Techniques such as Wiener filtering and total variation–driven processing play a key role in elevating image clarity and strengthening model outcomes [32]. Feature selection remains essential for high-dimensional datasets, with radiomic feature filtering supported by mutual information and SHAP-based explainability proving highly effective [28][33]. Ensemble learning frameworks using U-Net transfer learning and XAI-driven interpretability also contribute to more reliable diagnostic pipelines [31].

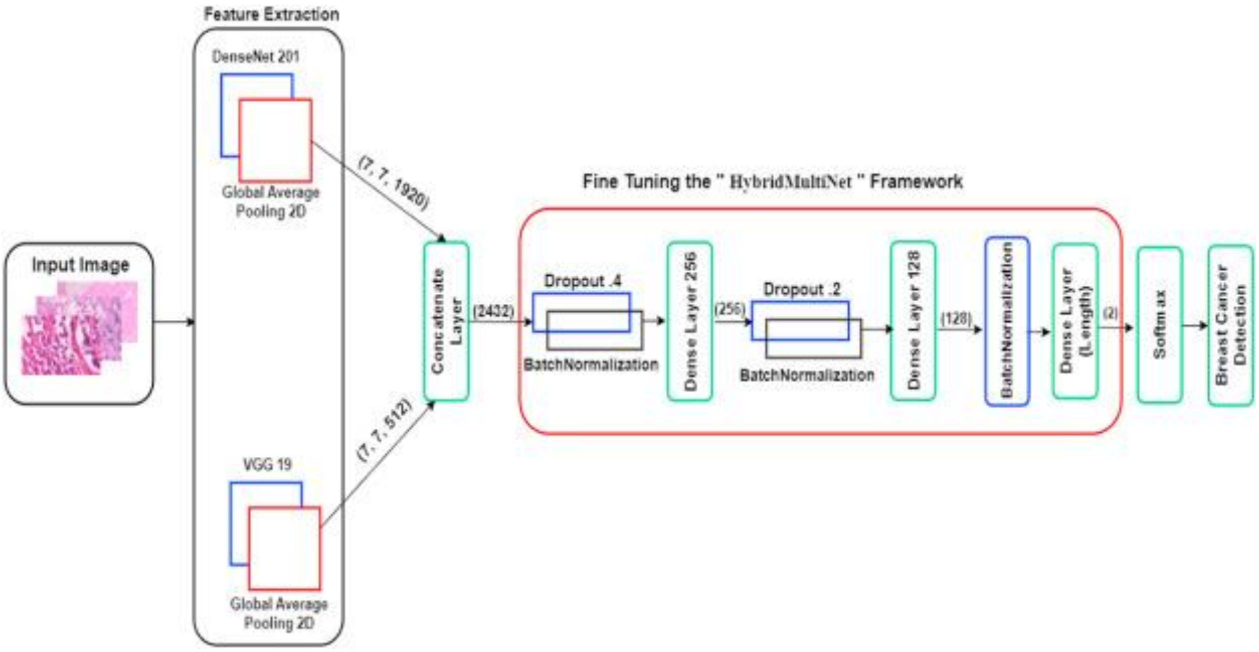

Fig.4 BreastMultinet Architecture [31]

D. Explainable Artificial Intelligence (XAI)

Due to the "black box" nature of DL models, XAI has become integral to medical AI research. Saliency mapping techniques provide visual justification for predictions, improving transparency and clinical acceptance [21][23][34][35]. XAI methods are particularly valuable in ultrasound-based tumor detection, where interpretability directly influences diagnostic confidence [35]. Quantitative evaluation of saliency performance is an emerging research focus, ensuring that interpretability metrics align with clinical expectations [21].

E. Emerging Trends and Future Directions

Several innovative trends are shaping future research. Self-supervised learning mitigates the problem of scarce annotated datasets by enabling model pre-training without manual labels [13] [24]. Federated learning allows collaborative training across institutions while preserving data privacy, addressing ethical and regulatory constraints [36]. Foundation models and generalist oncology models demonstrate potential for multi-task cancer diagnosis, including tumor classification, segmentation, and radiological assessment [13].

Additionally, combined ML–DL Quantitative Structure–Activity Relationship (QSAR) models support drug-efficacy prediction, offering new insights into personalized treatment design [37]. These advancements underscore AI's expanding role in early detection, prognostic prediction, and precision oncology.

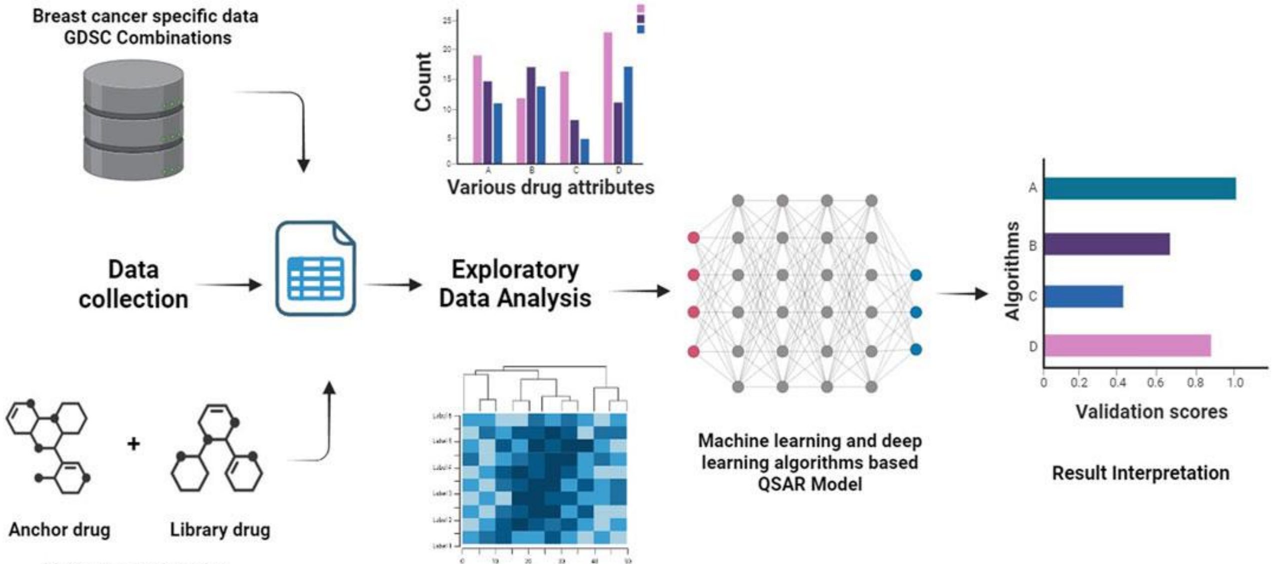

Fig. 5 QSAR Model Development Flowchart [37]

III. METHODOLOGY

This review adopts a structured and systematic methodology to synthesize recent advancements in Machine Learning (ML) and Deep Learning (DL) for breast cancer detection. The study follows a comprehensive search strategy across major scholarly databases including IEEE Xplore, PubMed, ScienceDirect, SpringerLink, and arXiv, focusing on publications from January 2022 to May 2025. Search queries combined relevant keywords such as breast cancer detection, machine learning, deep learning, CNN, XAI, mammography, ultrasound, MRI, histopathology, thermography, and radiomics, ensuring broad retrieval of AI-driven diagnostic research. To maintain scientific relevance and quality, inclusion criteria required studies to be peer-reviewed (or high-impact preprints), English-language, and focused on AI-based detection, segmentation, classification, or prediction tasks using medical imaging modalities. Additionally, only studies reporting measurable model performance metrics such as accuracy, AUC, sensitivity, specificity, Dice score, or IoU were considered. Papers unrelated to AI methods, lacking performance evaluation, or focused solely on hardware or non-imaging approaches were excluded.

All retrieved studies were screened, and key information was extracted regarding the imaging modality used, dataset characteristics, preprocessing strategies, ML/DL architectures, evaluation benchmarks, computational efficiency, and explainability methods. The selected papers were then organized into thematic groups covering modality-specific advancements, algorithmic innovations, hybrid ML–DL frameworks, radiomics and feature engineering approaches, reinforcement learning applications, and explainable AI techniques. Comparative analysis was performed to identify trends in diagnostic accuracy, segmentation quality, model robustness, and interpretability. Particular attention was given to the emergence of architectures such as CNNs, ResNets, DenseNet, Vision Transformers, U-Net variants, and hybrid pipelines combining DL feature extraction with ML classifiers like SVM, KNN, or Random Forest. Studies employing federated learning, self-supervised learning, saliency-based XAI, and resource-efficient architectures were also evaluated to understand solutions to data scarcity, privacy constraints, and clinical trust challenges.

Finally, insights from the analysed literature were synthesized to highlight major research trends, performance improvements across modalities, limitations of current approaches, and promising future directions. This methodology ensures that the review is comprehensive, analytically rigorous, and reflective of the most current innovations in AI-driven breast cancer detection.

IV. RESULTS AND DISCUSSION

Recent advancements in ML and DL have markedly improved the accuracy, robustness, and interpretability of breast cancer detection across various imaging modalities. The reviewed literature demonstrates that deep learning architectures—particularly CNN-based models, U-Net variants, and transformer-driven frameworks—consistently outperform traditional machine learning methods in both classification and segmentation tasks. Across mammography, ultrasound, MRI, histopathology, and emerging modalities such as DBT and thermography, DL models typically achieve

accuracy ranges between 90–99%, with several studies reporting near-perfect classification outcomes in controlled datasets [1][7][8][19][26]. For instance, CNN models applied to mammography have achieved accuracy levels of up to 99.96%, while ultrasound-based DL pipelines have reached 100% accuracy in small-scale evaluations [1]. Although these results underscore the impressive potential of DL methods, they also highlight the risk of dataset bias and limited generalizability—issues that remain central challenges in clinical deployment[38]
Mammography-based studies demonstrate significant gains through advanced architectures such as ResNet50, Bi-xBcNet-96, and hybrid XAI-integrated CNNs, which enhance lesion visibility and support radiologist decision-making by generating saliency maps and explainable feature attributions [20][21][22][23]. These models not only improve diagnostic accuracy but also contribute to more reliable tumor localization. Similarly, DBT-based approaches mitigate the limitations of 2D mammograms by leveraging volumetric information, enabling DL models to detect subtle structural variations associated with early-stage malignancy [28]. AI-driven radiomics has further strengthened diagnostic performance by extracting high-dimensional quantitative features—particularly when combined with mutual information-based feature selection and SHAP explainability, which improve interpretability while reducing redundancy in high-dimensional data [28][33].

Histopathology presents another domain where DL has achieved substantial success. Transformer-based models, such as ViT, and deep CNNs like DenseNet-121 and ResNet-50 have demonstrated high accuracy and strong generalization when trained on large-scale patch-based datasets [24][25][26]. Automated histopathological analysis is particularly valuable given the time-consuming and expertise-intensive nature of manual microscopic evaluation. Techniques combining ultra-fast fluorescence confocal microscopy with CNNs and GRUs have shown promise in detecting malignancies at early stages, providing a fast and minimally invasive alternative to standard protocols [25]. These advancements also align with broader trends toward digital pathology and computational histopathology [39].

Improvements in ultrasound and MRI analysis are equally notable. Models such as UGGNet—integrating U-Net with VGG—have enhanced segmentation precision, enabling more accurate delineation of tumor boundaries and surrounding tissue abnormalities [27]. In MRI applications, radiomics and DL models have contributed to better prediction of treatment response, such as pathological complete response to neoadjuvant chemotherapy, with automated segmentation playing a critical role in minimizing human variability [14][29]. Furthermore, resource-efficient and lightweight DL architectures have been proposed for metastatic breast cancer detection, ensuring feasibility in low-resource clinical environments where delayed diagnosis significantly impacts survival rates [30].

Hybrid ML-DL systems continue to gain traction due to their complementary strengths. CNNs are frequently employed as feature extractors, followed by ML classifiers such as SVM, Random Forest, or ensemble learning frameworks to refine the final prediction [31]. Models like BreastMultiNet exemplify this trend by combining DenseNet201 and VGG19 to produce multi-scale feature hierarchies for robust classification [11]. Additionally, studies integrating advanced preprocessing methods—such as Wiener filtering and total variation filtering—demonstrate improved diagnostic performance, especially in noisier imaging modalities like mammography and ultrasound [32].

Explainable Artificial Intelligence (XAI) remains a crucial component for clinical adoption. As DL models are often criticized for their “black box” nature, multiple studies evaluated saliency-based visualization techniques and post-hoc explainability methods that communicate the rationale behind predictions to clinicians [21][23][34][35]. Quantitative benchmarking of XAI performance further enhances reliability by establishing standardized criteria for explanation quality. In particular, multi-task BI-RADS–based frameworks demonstrate the ability to correlate model decisions with radiologically accepted descriptors, improving trustworthiness in real-world screening [35].

Despite the promising results, several challenges persist. Large, diverse, and well-annotated datasets remain limited, contributing to potential overfitting and reduced model generalization in clinical settings. Techniques such as self-supervised learning, federated learning, and multi-institutional model training offer promising solutions for overcoming these constraints while preserving patient privacy [13][24][36]. The emergence of foundation models and generalist medical AI systems also represents a significant shift toward more universal and adaptable frameworks capable of performing multiple oncology-related tasks with minimal fine-tuning [13]. Nevertheless, clinical integration requires rigorous validation, explainability, and regulatory approval to ensure safety, reproducibility, and fairness across diverse populations [40].

Overall, the current body of evidence demonstrates that ML and DL models have substantially advanced breast cancer detection, offering improved accuracy, efficiency, and interpretability across imaging modalities. However, translating these innovations into routine clinical practice will require continued progress in data sharing, explainability, robustness, and real-world validation. The rapid evolution of AI technologies, coupled with growing clinical collaboration, positions ML and DL as transformative tools in reducing global breast cancer mortality and improving personalized patient care.

V. CONCLUSION

This review investigated systematically the recent developments AI-driven detection methods for breast cancer utilizing different imaging modalities (mammography, ultrasound) and emerging histopathology image sources, including MRI as well as new thermal-imaging systems. The surveyed literature demonstrates that DL architectures—particularly CNNs, U-Net variants, DenseNet, ResNet, and Vision Transformers—continue to deliver state-of-the-art performance in classification, segmentation, and malignancy prediction tasks. Hybrid ML–DL frameworks further enhance diagnostic accuracy by combining deep feature extraction with traditional classifiers, while radiomics-driven pipelines complement imaging data through high-dimensional feature engineering. Recent progress in self-supervised learning, federated learning, and explainable AI offers practical solutions to persistent challenges such as data scarcity, privacy concerns, and clinical interpretability.

Despite these advancements, several limitations remain. Model performance still depends heavily on data quality, annotation consistency, and demographic diversity, limiting generalizability in real-world clinical settings. Many studies rely on small or institution-specific datasets, which restrict comparative benchmarking. Furthermore, explainability methods, although improving, are not yet sufficiently standardized for seamless integration into clinical workflows. Addressing these gaps requires the development of large, diverse, multi-center datasets, robust evaluation protocols, and clinically validated XAI frameworks. Interdisciplinary collaboration between clinicians, computer scientists, and regulatory bodies will be essential to ensure safe, transparent, and equitable deployment.

Overall, the evidence suggests that ML and DL technologies hold significant promise for early and accurate breast cancer detection. With continued innovation in data-centric learning, multimodal fusion, model interpretability, and ethical AI deployment, these methods are poised to become indispensable tools in future precision-diagnostic pipelines.

REFERENCES

[1] Md. A. Rahman *et al.*, “Advancements in Breast Cancer Detection: A Review of Global Trends, Risk Factors, Imaging Modalities, Machine Learning, and Deep Learning Approaches,” *BioMedInformatics*, vol. 5, no. 3, p. 46, Aug. 2025, doi: 10.3390/biomedinformatics5030046.

[2] G. Gurupakkiam and M. Ilayaraja, “A Survey on Breast Cancer Prediction using Various Deep Learning and Machine Learning Techniques,” *Proceedings of the 9th International Conference on Communication and Electronics Systems, ICCES 2024*, pp. 1872–1877, 2024, doi: 10.1109/ICCES63552.2024.10859664.

[3] Q. Q. Thabit, “Deep and Machine Learning for Improving Breast Cancer Detection,” *Engineering and Technology Journal*, vol. 8, no. 12, pp. 3156–3163, Dec. 2023, doi: 10.47191/ETJ/V8I12.06.

[4] N. K. Kashyap and S. Khurana, “Recent Advancements in Machine Learning Techniques for Breast Cancer Detection,” *2024 2nd International Conference on Advances in Computation, Communication and Information Technology, ICAICCIT 2024*, pp. 277–282, 2024, doi: 10.1109/ICAICCIT64383.2024.10912164.

[5] S. Yerraboina, H. Bommala, and V. Madireddy, “Breast cancer classification and prediction methods by employing machine and deep learning approaches-A survey,” *MATEC Web of Conferences*, vol. 392, p. 01137, 2024, doi: 10.1051/MATECCONF/202439201137.

[6] M. Aftab *et al.*, “AI in Oncology: Transforming Cancer Detection through Machine Learning and Deep Learning Applications,” Jan. 2025, Accessed: Nov. 11, 2025. [Online]. Available: https://arxiv.org/pdf/2501.15489

[7] G. M. Harshvardhan, K. Mori, S. Verma, and L. Athanasiou, “Machine learning applications in breast cancer prediction using mammography,” *Image Vis Comput*, vol. 152, p. 105338, Dec. 2024, doi: 10.1016/J.IMAVIS.2024.105338.

[8] L. Wang, “Mammography with deep learning for breast cancer detection,” *Front Oncol*, vol. 14, p. 1281922, Feb. 2024, doi: 10.3389/FONC.2024.1281922/FULL.

[9] J. Ahmad *et al.*, “Deep learning empowered breast cancer diagnosis: Advancements in detection and classification,” *PLoS One*, vol. 19, no. 7, Jul. 2024, doi: 10.1371/JOURNAL.PONE.0304757.

[10] “Comprehensive Study for Breast Cancer Using Deep Learning and Traditional Machine Learning,” *Zanco J Pure Appl Sci*, vol. 34, no. 2, Apr. 2022, doi: 10.21271/ZJPAS.34.2.3).

[11] M. M. Rahman, M. S. I. Khan, and H. M. H. Babu, “BreastMultiNet: A multi-scale feature fusion method using deep neural network to detect breast cancer,” *Array*, vol. 16, Dec. 2022, doi: 10.1016/J.ARRAY.2022.100256.

[12] G. Singh, A. Kamalja, R. Patil, A. Karwa, A. Tripathi, and P. Chavan, “a-comprehensive-assessment-of-artificial-intelligence-applications-for-cancer-diagnosis,” *Artif Intell Rev*, vol. 57, no. 7, Jun. 2024, doi: 10.1007/S10462-024-10783-6.

[13] R. Perez-Lopez, N. Ghaffari Laleh, F. Mahmood, and J. N. Kather, “A guide to artificial intelligence for cancer researchers,” *Nature Reviews Cancer 2024 24:6*, vol. 24, no. 6, pp. 427–441, May 2024, doi: 10.1038/s41568-024-00694-7.

[14] S. Nitzan, M. Gilad, M. Freiman, and E. Arazi, “Automated Prediction of Breast Cancer Response to Neoadjuvant Chemotherapy from DWI Data,” Apr. 2024, Accessed: Nov. 11, 2025. [Online]. Available: https://arxiv.org/pdf/2404.05061

[15] S. K. Zhou, H. N. Le, K. Luu, H. V Nguyen, and N. Ayache, “Deep reinforcement learning in medical imaging: A literature review,” *Med Image Anal*, vol. 73, p. 102193, Oct. 2021, doi: 10.1016/J.MEDIA.2021.102193.

[16] M. M. Rohé, M. Sermesant, and X. Pennec, “Low-dimensional representation of cardiac motion using Barycentric Subspaces: A new group-wise paradigm for estimation, analysis, and reconstruction,” *Med Image Anal*, vol. 45, pp. 1–12, Apr. 2018, doi: 10.1016/j.media.2017.12.008.

[17] A. M. Sharafaddini, K. K. Esfahani, and N. Mansouri, “Deep learning approaches to detect breast cancer: a comprehensive review,” *Multimedia Tools and Applications 2024 84:21*, vol. 84, no. 21, pp. 24079–24190, Aug. 2024, doi: 10.1007/S11042-024-20011-6.

[18] D. Al-Karawi *et al.*, “A Review of Artificial Intelligence in Breast Imaging,” *Tomography 2024, Vol. 10, Pages 705-726*, vol. 10, no. 5, pp. 705–726, May 2024, doi: 10.3390/TOMOGRAPHY10050055.

[19] K. Ishaq and M. Mustagis, “Computer Aided Detection and Classification of mammograms using Convolutional Neural Network,” Sep. 2024, Accessed: Nov. 11, 2025. [Online]. Available: https://arxiv.org/pdf/2409.16290

[20] A. Sahu, P. K. Das, and S. Meher, “Recent advancements in machine learning and deep learning-based breast cancer detection using mammograms,” *Physica Medica*, vol. 114, Oct. 2023, doi: 10.1016/j.ejmp.2023.103138.

[21] E. Cerekci *et al.*, “Quantitative evaluation of Saliency-Based Explainable artificial intelligence (XAI) methods in Deep Learning-Based mammogram analysis,” *Eur J Radiol*, vol. 173, Apr. 2024, doi: 10.1016/j.ejrad.2024.111356.

[22] N. A. El-Mawla, M. A. Berbar, N. A. El-Fishawy, and M. A. El-Rashidy, “A novel deep learning approach (Bi-xBcNet-96) considering green AI to discover breast cancer using mammography images,” *Neural Computing and Applications 2024 36:21*, vol. 36, no. 21, pp. 12701–12723, May 2024, doi: 10.1007/S00521-024-09815-7.

[23] M. Ahmed, T. Bibi, R. A. Khan, and S. Nasir, “Enhancing Breast Cancer Diagnosis in Mammography: Evaluation and Integration of Convolutional Neural Networks and Explainable AI,” *Proceedings of the IEEE International Multi Topic Conference, INMIC*, no. 2024, Apr. 2024, doi: 10.1109/INMIC64792.2024.11004362.

[24] S. Fatema, B. Nuwagira, S. Chakraborty, R. Gedik, and B. Coskunuzer, “TopOC: Topological Deep Learning for Ovarian and Breast Cancer Diagnosis,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 15239 LNCS, pp. 22–32, Oct. 2024, doi: 10.1007/978-3-031-73967-5_3.

[25] M. Mujahid, A. R. Khan, M. Kolivand, F. S. Alamri, T. Saba, and S. A. O. Bahaj, “Breast histopathological imaging using ultra-fast fluorescence confocal microscopy to identify cancer lesions at early stage,” *Microsc Res Tech*, vol. 87, no. 12, pp. 3047–3063, Dec. 2024, doi: 10.1002/JEMT.24677.

[26] S. Eskandari, A. Eslamian, N. Munia, A. Alqarni, and Q. Cheng, “Evaluating Deep Learning Models for Breast Cancer Classification: A Comparative Study,” p. 41, May 2025, doi: 10.1117/12.3047441.

[27] T. C. Minh, N. K. Quoc, P. C. Vinh, D. N. Phu, V. X. Chi, and H. M. Tan, “UGGNet: Bridging U-Net and VGG for Advanced Breast Cancer Diagnosis,” *EAI Endorsed Transactions on Context-aware Systems and Applications*, vol. 10, no. 1, Jan. 2024, doi: 10.4108/EETCASA.4681.

[28] O. O. Oladimeji, H. Ayaz, I. McLoughlin, and S. Unnikrishnan, “Mutual information-based radiomic feature selection with SHAP explainability for breast cancer diagnosis,” *Results in Engineering*, vol. 24, p. 103071, Dec. 2024, doi: 10.1016/J.RINENG.2024.103071.

[29] Y. Zhou, O. Arora-Jain, and X. Jiang, “Deep Learning to Predict Late-Onset Breast Cancer Metastasis: the Single Hyperparameter Grid Search (SHGS) Strategy for Meta Tuning Concerning Deep Feed-forward Neural Network,” Aug. 2024, Accessed: Nov. 14, 2025. [Online]. Available: https://arxiv.org/pdf/2408.15498.

[30] W. Gao, D. Wang, and Y. Huang, “Designing a Deep Learning-Driven Resource-Efficient Diagnostic System for Metastatic Breast Cancer: Reducing Long Delays of Clinical Diagnosis and Improving Patient Survival in Developing Countries,” *Cancer Inform*, vol. 22, Jan. 2023, doi: 10.1177/11769351231214446.

[31] R. M. Munshi, L. Cascone, N. Alturki, O. Saidani, A. Alshardan, and M. Umer, “A novel approach for breast cancer detection using optimized ensemble learning framework and XAI,” *Image Vis Comput*, vol. 142, p. 104910, Feb. 2024, doi: 10.1016/J.IMAVIS.2024.104910.

[32] Z. Zhu, Y. Sun, and B. Honarvar Shakibaei Asli, "Early Breast Cancer Detection Using Artificial Intelligence Techniques Based on Advanced Image Processing Tools," *Electronics 2024, Vol. 13, Page 3575*, vol. 13, no. 17, p. 3575, Sep. 2024, doi: 10.3390/ELECTRONICS13173575.

[33] K. S. Rekha, D. Divya, M. J. Amali, and N. Yuvaraj, "Hybrid ML-MDKL feature subset selection and classification technique accompanied with rat swarm optimizer to classify the multidimensional breast cancer mammogram image," *Optik (Stuttg)*, vol. 297, p. 171574, Feb. 2024, doi: 10.1016/J.IJLEO.2023.171574.

[34] S. Bai, S. Nasir, R. A. Khan, S. Arif, A. Meyer, and H. Konik, "Breast Cancer Diagnosis: A Comprehensive Exploration of Explainable Artificial Intelligence (XAI) Techniques," Jun. 2024, Accessed: Nov. 11, 2025. [Online]. Available: https://arxiv.org/pdf/2406.00532

[35] M. Karimzadeh, A. Vakanski, M. Xian, and B. Zhang, "POST-HOC EXPLAINABILITY OF BI-RADS DESCRIPTORS IN A MULTI-TASK FRAMEWORK FOR BREAST CANCER DETECTION AND SEGMENTATION," *IEEE Int Workshop Mach Learn Signal Process*, vol. 2023, p. 10.1109/mlsp55844.2023.10286006, 2023, doi: 10.1109/MLSP55844.2023.10286006.

[36] A. Ciobotaru, C. Corches, D. Gota, and L. Miclea, "Deep Learning and Federated Learning in Breast Cancer Screening and Diagnosis: A Systematic Review," *IEEE Access*, vol. 13, pp. 76322–76351, 2025, doi: 10.1109/ACCESS.2025.3560211.

[37] A. Karampuri and S. Perugu, "A breast cancer-specific combinational QSAR model development using machine learning and deep learning approaches," *Frontiers in Bioinformatics*, vol. 3, 2023, doi: 10.3389/FBINF.2023.1328262/PDF.

[38] J. Maicas, L. K. McMillan, K. V. Nguyen, R. Zamutto, G. Carneiro, and L. Petersson, "Deep reinforcement learning for active breast lesion detection from DCE-MRI," *IEEE Trans. Med. Imaging*, vol. 39, no. 3, pp. 954–963, Mar. 2020, doi: 10.1109/TMI.2019.2934021.

[39] F. Isensee, P. F. Jäger, S. A. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnU-Net: a self-configuring method for deep learning–based biomedical image segmentation," *Nat. Methods*, vol. 18, pp. 203–211, 2021, doi: 10.1038/s41592-020-01008-z.

[40] K. Han et al., "A survey on vision transformer models in medical image analysis," *IEEE Trans. Med. Imaging*, vol. 42, no. 5, pp. 1315–1335, May 2023, doi: 10.1109/TMI.2023.3239441.