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Mammogram Analysis for Breast Cancer Detection Using Deep Learning: A Review

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ABSTRACT

Breast cancer remains one of the most widespread and fastest growing diseases worldwide, particularly among women. Early detection is critical for effective management and improved patient outcomes. This review provides a comprehensive examination of deep learning techniques applied to breast cancer diagnosis such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures that leverage transfer learning. The performance of these models is analyzed across multiple datasets and imaging modalities, along with a critical assessment of their strengths and limitations. The study broadly explores imaging modalities such as mammography, ultrasound, magnetic resonance imaging, and histology, emphasizing their roles in breast cancer detection. Furthermore, the paper discusses the importance of large-scale and diverse datasets in training robust deep learning models, underscoring their importance in achieving generalizable results. Finally, it highlights the transformative potential of deep learning in improving diagnostic accuracy and identifies future research directions to advance this rapidly evolving field.

Keywords: Breast cancer, Deep learning, Convolution neural network (CNN), early detection, diagnosis.

1. INTRODUCTION

Improved patient outcomes will necessitate continuous advancements in detection techniques because breast cancer remains a major global health issue. Combining contemporary imaging technology with computational methods has produced innovative techniques[1]. Breast cancer ranks as the second deadliest illness for women and is a major cause of mortality for millions of women globally. The American Cancer Society indicates that around 20% of women diagnosed with breast cancer succumb to the disease[2]. Mammograms have been extensively studied, and they are now significant diagnostic tools for identifying breast cancer in patients. Deep learning has advanced quickly in recent years, which is helpful for studies on cancer. The goal of DL is to assist doctors in making assisted diagnoses and raising the standard of healthcare. Since DL doesn't require sophisticated feature extraction techniques, it has been used in numerous studies on mammogram image recognition [3]. There are various deep-learning models that can handle various tasks, including classification, visual tracking, object detection and semantic segmentation. To carry out the classifications, the researchers suggested a variety of models, including EfficientNet, MobileNet, GoogleNet, and AlexNet[4]. A number of tests, such as digital breast tomography, ultrasound, magnetic resonance imaging (MRI), and mammography, are recommended to diagnose breast tumors [4]. Mammography is a popular early screening method due to its high sensitivity to small lesions and low cost. Though, a number of factors, including the complexity of the breast structure, the details of the disease at an early stage, and the distraction and fatigue of the radiologists, can negatively affect the accuracy of the diagnosis in practice. This issue can be resolved with the use of computer-aided diagnosis to identify breast cancer [5]. Deep learning Techniques (DLT) have transformed the domain of computer vision, enabling various applications such as image classification, object detection, semantic segmentation, and medical image evaluation[6].

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Convolutional neural network (CNN) is a component of DLT that has been increasingly prominent over the past decade. CNN was proposed as early as 1993. Unfortunately, these projects remained in the experimental stage due to lack of computational resources. However, in recent years, the availability of advanced graphics processing units (GPUs) has greatly improved the performance of CNNs [7]. Many problems are solved by deep learning methods, which automate feature extraction and build models to fill the gaps. Convolutional neural networks (CNNs) extract spatial features efficiently but are unable to process temporal data. Different

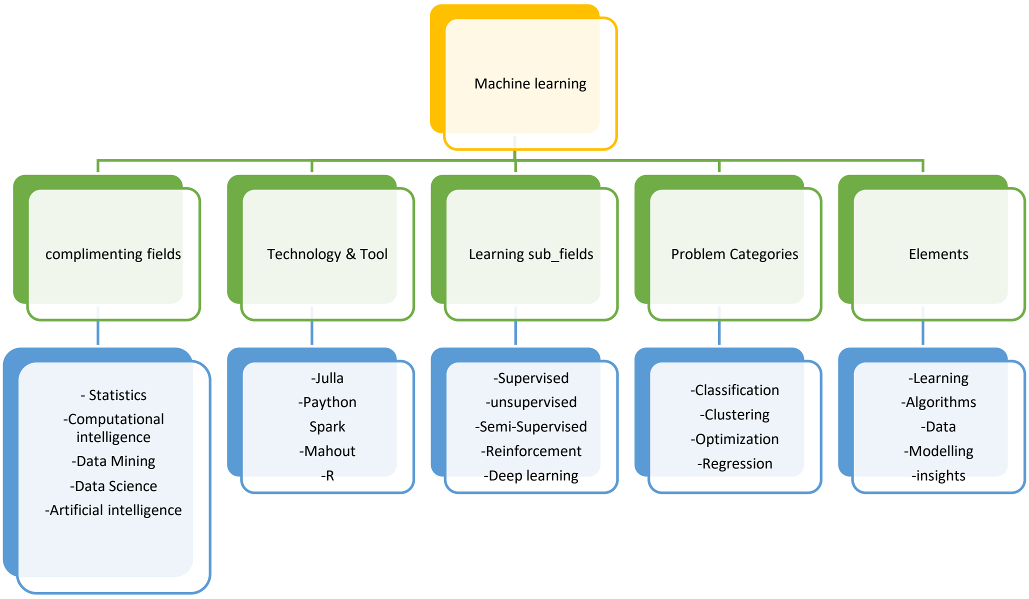

Figure 1. Machine Learning Parts.

types of machine learning and algorithms are depicted in Figure 1 [8].

The CNN, as a distinctive type of neural network layer named "convolutional," is used in place of a regular "fully connected" layer for at least one of the layers in the network. In a CNN model, there are three fundamental layers: convolutional, pooling, and full connection (FC), as shown in Figure 2 [9].

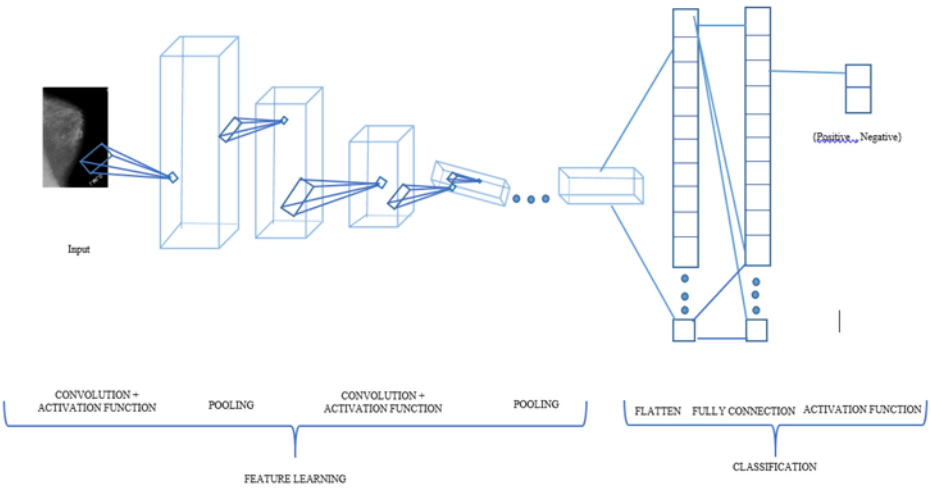

Figure 2. General block diagram of the convolutional neural network.

1.1. Related Works

The next section of this paper discusses various studies aimed at developing automated breast cancer detection systems. In recent years, a large number of articles have been published in this field, and the following are the contributions made by scientists as well as some observations.

In the work published by (J. Zheng et al.) [10], the authors used a (DLA-EABA) model, integrating CNNs, LSTMs, and AdaBoost, to enhance breast cancer detection. The model processes MRI, ultrasound, mammography, and tomosynthesis images, utilizing datasets from the Cancer Imaging Archive, and achieves an impressive 97.2% accuracy. However, its reliance on extensive training data presents a notable limitation.

In the same area, the research [11] by (X. Zhou et al.) discuss deep learning, the study assessed 19-layer deep convolutional neural network (CNN) designed for breast cancer classification using mammography images from the Break His dataset. The model demonstrates superior performance, achieving 84.5% accuracy, outperforming traditional SVM and Google Net models. However, challenges such as dataset imbalance and moderate accuracy highlight the need for enhanced feature extraction techniques and more diverse datasets.

In the work published by (F. Shahidi et al.) [12] researchers explored the application of advanced deep learning architectures for classifying breast cancer using histopathology images. The Inception-ResNet-V2 model achieved an accuracy of 99.79% for binary classification, while SENet-154 demonstrated state-of-the-art performance in multi-class tasks. Moreover In (P. E. Jebarani et al.) [13].This study presents a hybrid model integrating K-Means and Gaussian Mixture Models (GMM) for breast cancer detection, using the MIAS dataset. Preprocessed mammograms achieved a classification accuracy of 95.5%, distinguishing normal, benign, and malignant cases. However, the method's reliance on predefined parameters and susceptibility to imaging artifacts pose challenges.

The (K. Loizidou et al.) [14] presented a novel Computer Aided Diagnosis (CAD) technique for breast micro-calcification (MC) detection and classification is proposed, leveraging temporal subtraction of sequential mammograms and machine learning. By combining advanced classifiers and feature selection, the method achieved 99.55% accuracy using Support Vector Machines (SVM), outperforming the 91.42% accuracy without temporal subtraction. These findings underscore its effectiveness but call for further validation on larger datasets.

A study conducted by (N. Wu et al.) [15] researchers used a deep learning-based system using convolutional neural networks (CNNs) is proposed for breast cancer screening, trained on over 1,000,000 images. The model achieved an AUC of 0.895 in detecting cancer presence, matching radiologists' accuracy and improving results when combined with their assessments. However, the method requires further clinical validation and larger datasets. Moreover, (U. Naseem et al.) [16] proposed an ensemble machine learning model for automatic breast cancer diagnosis and prognosis using the Breast Cancer Wisconsin (Diagnosis) and (Prognosis) datasets. It combined classifiers such as SVM, LR, NB, and DT, achieving 98.83% accuracy on the diagnosis dataset. The model addressed class imbalance using up sampling techniques. Limitations included the challenges of handling skewed data and the need for pre-processing to optimize performance.

(S. Zahoor et al.) [4] focused on classifying breast cancer in mammogram images using a deep neural network and an Entropy-Controlled Whale Optimization Algorithm (MEWOA). It employed the CBIS-DDSM, INbreast, and MIAS datasets. The model utilized fine-tuned MobileNetV2 and NasNet Mobile for feature extraction, achieving accuracy rates of 99.7%, 99.8%, and 93.8%, respectively. Limitations included the high computational cost and the complexity of optimizing features for better classification results.

A study conducted by (D. G. Petrini et al.) [17] used on breast cancer diagnosis using two-view mammography with an Efficient Net-based convolutional network. It utilized the CBIS-DDSM dataset for training and testing. The model achieved high accuracy, with an AUC of 0.9344 in cross-validation. However, it faced limitations in terms of dataset size and model comparison under different test conditions.

The paper published by (S. Sharmin et al.) [18] proposed a hybrid deep learning and ensemble machine learning model for breast cancer detection, combining ResNet50V2 for deep feature extraction with LightGBM for classification. It utilized a histopathology image-based IDC dataset, achieving 95% accuracy, 94.86% precision, and

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94.32% recall. The model outperformed others, demonstrating superior robustness. Limitations included the focus on a specific cancer subtype (IDC) and the potential impact of image quality on performance.

Also, the research conducted by (T. Khater et al) [19]. proposed an explainable AI model for breast cancer classification using datasets like WBC and WDBC. It employed KNN, SVM, XG-boost, RF, and ANN models, achieving 97.7% accuracy with KNN and 98.6% with ANN. Key features identified included "bare nuclei" and "area worst," which were crucial in predicting malignancy. Limitations included computational complexity and the focus on specific datasets, which may not generalize to other cancer types. (Y. N. Tan et al.) [20] suggests a federated learning framework combining FedAvg-CNN with Mobile Net for breast cancer classification. It used mammogram images from the DDSM and CBIS-DDSM datasets, achieving up to 98% accuracy. The model ensured patient privacy but faced limitations with prolonged training time and reduced performance on non-IID data.

(D. Li et al.) [21] presented an classifying breast cancer in mammograms using deep learning. It employed the INbreast and CBIS-DDSM datasets with a CNN-based model incorporating a novel adaptive feature descriptor selection (AFDS) method, achieving high accuracy. The method outperformed state-of-the-art models in both datasets. Limitations included noise in mask maps and the triangle threshold strategy producing larger maps for extreme lesion cases. In research published by (Z. Sani et al.) [22] presented a novel group convolutional neural network (G-CNN) enhanced by discrete cosine transform (DCT) for breast cancer classification using mammography images. It utilized the MNIST-rotated and CBIS-DDSM datasets, achieving an accuracy of 94.84%. The model addressed issues of rotation invariance and equivariance, outperforming traditional CNN models. However, its limitations included the complexity of the model and the need for large datasets to perform optimally.

(J. Ahmad et al.) [23] introduced breast cancer detection using a deep learning model called BreastNet-SVM, which combined a modified AlexNet architecture with a Support Vector Machine (SVM) for classification. It utilized the Digital Database for Screening Mammography (DDSM) dataset, achieving an accuracy of 99.16%. The model was tested with different image sizes (16x16, 32x32, 48x48) and optimized using RMSprop, Adam, and SGD. The primary limitation was its reliance on a single dataset and the use of only three specific optimizers. The research by (S. Chakravarthy et al.) [24] discusses utilizing a Fusion of Hybrid Deep Features (FHDF) approach for breast cancer classification using CNNs (VGG16, VGG19, ResNet50, DenseNet121). It applied digital mammogram images from MIAS, CBIS-DDSM, and INbreast datasets, achieving maximum accuracies of 98.70%, 97.73%, and 98.83%, respectively. Despite its effectiveness in early tumor detection and classification, it struggled with computational complexity and slightly less precision in recognizing malignant cases.

The paper published by (H. O. Ahmed et al.) [25]. used mammogram images from the MIAS, CBIS-DDSM, and INbreast datasets to train and evaluate a Mixture of Experts (MoEffNet) model. The base model was EfficientNet, with variants B0, B1, B2, and B4. The MoEffNet model achieved high accuracy, with the best results being 99.6% on the CBIS-DDSM dataset using EfficientNet B2 and three experts. Limitations included the dependence on optimal expert configurations for complex datasets, with higher expert numbers leading to diminishing returns in simpler models.

The study presented by (P. S. C. Murty et al.) [1] a hybrid deep learning model for breast cancer diagnosis using the CBIS-DDSM and Wisconsin Breast Cancer datasets. The types of images analyzed included mammograms with diverse features like calcification and lesions. The model, combining CNNs with stochastic gradient descent (SGD), achieved high accuracy rates (up to 96%). Limitations included challenges with overfitting and the need for validation across different patient demographics and imaging qualities. (M. Anas et al.) [26] focused on enhancing breast cancer detection through an improved YOLOv5 network for classifying mammogram images. It utilized mammogram images from the INbreast, CBIS-DDSM, and BNS datasets. The model combined YOLOv5 with Mask RCNN for better segmentation and classification. The accuracy of the method increased significantly, achieving a 98% accuracy rate, with reduced false positives and false negatives. However, limitations included the model's complexity and the need for large datasets for optimal performance. The article (M. A. Rahman et al.) [27] proposed an enhanced machine learning model for early breast cancer detection using the Wisconsin Breast Cancer (Diagnostic) dataset, which includes 569 samples and 32 features. The authors applied an extreme Gradient Boosting classifier, achieving a high accuracy of 99.12%, with a precision of 0.9767, recall of 1.0, specificity of 0.9861, and an F1-score of 0.9882. The model outperformed previous approaches, demonstrating faster computational efficiency and reliability. However,

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the study's limitations include the reliance on feature selection and the computational intensity required for training the model. Data preprocessing techniques like SMOTE and feature selection were also employed. Table 1 demonstrates a comparison schedule of improving breast cancer detection.

Table 1: Overview of the literature on Mammogram Analysis for Breast Cancer Detection

Ref	Types of Images	Dataset	Base Model	Accuracy%	Limitations
[10]	MRI, ultrasound, mammography, tomosynthesis	Cancer Imaging Archive	DLA-EABA (CNNs + LSTMs + AdaBoost)	97.2%	Requires extensive training data
[11]	Mammography	BreakHis	19-layer CNN	84.5%	Dataset imbalance, moderate accuracy, needs better feature extraction
[12]	Histopathology	BACH	Inception-ResNet-V2, SENet-154	99.79%	Not specified
[13]	Mammography	MIAS	K-Means + GMM	95.5%	Relies on predefined parameters, imaging artifacts
[14]	Mammography	collected in Cyprus	SVM	Detection of True MCs: 99.02%	Limited validation on larger datasets
				Classification of MCs as benign or suspicious: 99.55%	
[15]	Mammography	Collected (1,000,000 images)	CNN	89%	Needs clinical validation, larger datasets required
[16]	Mammography	BCWisconsinDiagnosis	Ensemble (SVM, LR, NB, DT)	98.83%	Skewed data handling, pre-processing required
		BCWisconsinPrognosis		88.33%	
[4]	Mammography	CBIS-DDSM,	MobileNetV2+NasNet Mobile	93.8%	High computational cost, complex optimization
		INbreast		99.7%	
		, MIAS		99.8%	
[17]	Mammography	CBIS-DDSM	EfficientNet	85.13%	Small dataset size, limited test conditions
[18]	Histopathology	IDC	ResNet50V2 + LightGBM	95%	Focused on IDC subtype, image quality dependency
[19]	Digitized Breast Cancer Cell Images	WBCD	K-NN, ANN	97.7%	Computational complexity, limited generalization
		WDBC		98.6%	

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[20]	Mammography	DDSM,	FeAvg-CNN MobileNet	84.93% 95.93%	Long training time, reduced performance on non-IID data
			FeAvg-CNN Densenet121	83.75% 95.55%	
		CBIS-DDSM	FeAvg-CNN Xception	81.42% 94.80%	
[21]	Mammograms	INbreast,	CNN + AFDS	92.4% 97.2%	Noise in mask maps, triangle threshold limitations
		CBIS-DDSM		79.7% 86.2%	
[22]	Mammography	CBIS-DDSM	G-CNN with SE(2) + DCT	94.84%	Model complexity, needs large datasets
[23]	Mammography	DDSM	BreastNet-SVM (AlexNet SVM)	99.16%	Single dataset reliance, limited optimizers
[24]	Mammography	MIAS,	CNNs FHDF (VGG16, VGG19, ResNet50, DenseNet121)	98.70%	Computational complexity, less precision in malignancy recognition
		CBIS-DDSM,		97.73%	
		INbreast		98.83%	
[25]	Mammography	MIAS,	MoEffNet (EfficientNet variants)	99.4%	Reliance on optimal configurations, diminishing returns with higher experts
		CBIS-DDSM,		99.6%	
		INbreast		99.8%	
[1]	Mammography	CBIS-DDSM,	Hybrid Deep Learning Approach(CNN + SGD)	96%	Overfitting, validation across demographics and image qualities needed
		BC Wisconsin		96%	
[26]	Mammography	INbreast,	YOLOv5 + Mask RCNN	98%	Model complexity, large datasets needed
		CBIS-DDSM,		91.50%	
		BNS		Precision: 86% Recall: 77%	
[27]	Digitized images of Fine Needle Aspiration (FNA) biopsy samples	BC Wisconsin (Diagnostic)	XGBoost	99.12%	Feature selection reliance, computational intensity

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In conclusion, research demonstrated in this section that they have developed techniques and methods to improve and increase the functionality of breast cancer detection systems to some extent, using different processing methods and techniques on various related datasets.

2. CONCLUSION

This study presents an analysis of some recent research on approaches and strategies for breast cancer detection using deep learning techniques applied of various databases in this field such as DDSM, BCDR, IDC CBIS-DDSM, MIAS …etc. The findings show that deep learning models, such CNN, R-CNN, MLP, SVM…etc. Despite these advances, several challenges remain, including high computational costs, handling noisy or imbalanced data, and difficulty generalizing to new, unstructured environments. Future research should concentrate on improving attention mechanisms to extract the most important spatial and temporal features and maximizing the effectiveness of computation for real-time applications. This review functions as a thorough resource that highlights current developments in breast cancer detection while providing precise direction for further study with the goal of creating more adaptable and efficient solutions that satisfy the growing needs of practical applications in healthcare systems.

REFERENCES

[1] P. S. C. Murty, C. Anuradha, P. A. Naidu, D. Mandru, M. Ashok, A. Atheeswaran, et al., "Integrative hybrid deep learning for enhanced breast cancer diagnosis: leveraging the Wisconsin Breast Cancer Database and the CBIS-DDSM dataset," Scientific Reports, vol. 14, p. 26287, 2024.

[2] M. Madani, M. M. Behzadi, and S. Nabavi, "The role of deep learning in advancing breast cancer detection using different imaging modalities: a systematic review," Cancers, vol. 14, p. 5334, 2022.

[3] M.-L. Huang and T.-Y. Lin, "Double-Dilation Non-Pooling Convolutional Neural Network for Breast Mass Mammogram Image Classification," Bahrain Medical Bulletin, vol. 44, 2022.

[4] S. Zahoor, U. Shoaib, and I. U. Lali, "Breast cancer mammograms classification using deep neural network and entropy-controlled whale optimization algorithm," Diagnostics, vol. 12, p. 557, 2022.

[5] P. Kumar, S. Srivastava, R. K. Mishra, and Y. P. Sai, "End-to-end improved convolutional neural network model for breast cancer detection using mammographic data," The Journal of Defense Modeling and Simulation, vol. 19, pp. 375-384, 2022.

[6] R. Adam, K. Dell'Aquila, L. Hodges, T. Maldjian, and T. Q. Duong, "Deep learning applications to breast cancer detection by magnetic resonance imaging: a literature review," Breast Cancer Research, vol. 25, p. 87, 2023.

[7] S. Nadkarni and K. Noronha, "Breast cancer detection using ensemble of convolutional neural networks," International Journal of Electrical & Computer Engineering (2088-8708), vol. 14, 2024.

[8] M. M. Taye, "Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions," Computation, vol. 11, p. 52, 2023.

[9] I. Goodfellow, "Deep learning-ian goodfellow, yoshua bengio, aaron courville," Adapt. Comput. Mach. Learn, 2016.

[10] J. Zheng, D. Lin, Z. Gao, S. Wang, M. He, and J. Fan, "Deep learning assisted efficient AdaBoost algorithm for breast cancer detection and early diagnosis," IEEE Access, vol. 8, pp. 96946-96954, 2020.

[11] X. Zhou, Y. Li, R. Gururajan, G. Bargshady, X. Tao, R. Venkataraman, et al., "A new deep convolutional neural network model for automated breast Cancer detection," in 2020 7th International Conference on Behavioural and Social Computing (BESC), 2020, pp. 1-4.

[12] F. Shahidi, S. M. Daud, H. Abas, N. A. Ahmad, and N. Maarop, "Breast cancer classification using deep learning approaches and histopathology image: A comparison study," Ieee Access, vol. 8, pp. 187531-187552, 2020.

[13] P. E. Jebarani, N. Umadevi, H. Dang, and M. Pomplun, "A novel hybrid K-means and GMM machine learning model for breast cancer detection," IEEE Access, vol. 9, pp. 146153-146162, 2021.

[14] K. Loizidou, G. Skouroumouni, C. Nikolaou, and C. Pitris, "An automated breast micro-calcification detection and classification technique using temporal subtraction of mammograms," IEEE Access, vol. 8, pp. 52785-52795, 2020.

[15] N. Wu, J. Phang, J. Park, Y. Shen, Z. Huang, M. Zorin, et al., "Deep neural networks improve radiologists' performance in breast cancer screening," IEEE transactions on medical imaging, vol. 39, pp. 1184-1194, 2019.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[16] U. Naseem, J. Rashid, L. Ali, J. Kim, Q. E. U. Haq, M. J. Awan, et al., "An automatic detection of breast cancer diagnosis and prognosis based on machine learning using ensemble of classifiers," Ieee Access, vol. 10, pp. 78242-78252, 2022.
[17] D. G. Petrini, C. Shimizu, R. A. Roela, G. V. Valente, M. A. A. K. Folgueira, and H. Y. Kim, "Breast cancer diagnosis in two-view mammography using end-to-end trained efficientnet-based convolutional network," Ieee access, vol. 10, pp. 77723-77731, 2022.
[18] S. Sharmin, T. Ahammad, M. A. Talukder, and P. Ghose, "A hybrid dependable deep feature extraction and ensemble-based machine learning approach for breast cancer detection," IEEE Access, 2023.
[19] T. Khater, A. Hussain, R. Bendardaf, I. M. Talaat, H. Tawfik, S. Ansari, et al., "An explainable artificial intelligence model for the classification of breast cancer," IEEE Access, 2023.
[20] Y. N. Tan, V. P. Tinh, P. D. Lam, N. H. Nam, and T. A. Khoa, "A transfer learning approach to breast cancer classification in a federated learning framework," IEEe Access, vol. 11, pp. 27462-27476, 2023.
[21] D. Li, L. Zhang, J. Zhang, and X. Xie, "Convolutional feature descriptor selection for mammogram classification," IEEE Journal of Biomedical and Health Informatics, vol. 27, pp. 1467-1476, 2023.
[22] Z. Sani, R. Prasad, and E. K. M. Hashim, "Breast cancer classification using equivariance transition in group convolutional neural networks," IEEE Access, vol. 11, pp. 28454-28465, 2023.
[23] J. Ahmad, S. Akram, A. Jaffar, M. Rashid, and S. M. Bhatti, "Breast Cancer Detection Using Deep Learning: An Investigation Using the DDSM Dataset and a Customized AlexNet and Support Vector Machine," IEEE Access, 2023.
[24] S. Chakravarthy, N. Bharanidharan, S. B. Khan, V. V. Kumar, T. Mahesh, A. Almusharraf, et al., "Multi-class breast cancer classification using cnn features hybridization," International Journal of Computational Intelligence Systems, vol. 17, p. 191, 2024.
[25] H. O. Ahmed and A. K. Nandi, "High Performance Breast Cancer Diagnosis from Mammograms Using Mixture of Experts with EfficientNet Features (MoEffNet)," IEEE Access, 2024.
[26] M. Anas, I. U. Haq, G. Husnain, and S. A. F. Jaffery, "Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images," IEEE Access, 2024.
[27] M. A. Rahman, M. Hamada, S. Sharmin, T. A. Rimi, A. S. Talukder, N. Imran, et al., "Enhancing early breast cancer detection through advanced data analysis," IEEE Access, 2024.