Hybrid Approach for Breast Cancer Detection Using CNNs and Real-Time Risk Assessment

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***Abstract*—Breast cancer remains a leading cause of mortality among women, and early detection is crucial for improving patient outcomes. However, current detection methods, including mammography and BMI-based approaches, have limitations in terms of accuracy and reliability. This research proposes an innovative breast cancer detection using the Breast Cancer Detection and Risk Assessment (BCDRA) system. BCDRA integrates the features of convolutional neural networks (CNNs) and transfer learning, with an optimized feature selection process designed specifically for mammographic images and patient clinical data. The system follows a multi-stage pipeline: Data preprocessing and augmentation, Automated feature extraction using CNNs, Transfer learning for enhancing model accuracy, and Risk prediction using a hybrid classification-regression algorithm. This pipeline is supported by the Breast Cancer Prediction Algorithm (BCPA), which identifies early-stage anomalies and provides real-time risk assessment based on personalized risk factors such as age, family history, and genetic markers. By integrating a real-time risk assessment module and offering higher diagnostic precision, BCDRA aims to revolutionize breast cancer screening, allowing for earlier interventions and improved patient care, ultimately contributing to better survival rates. BCDRA implemented using both Python and R programming environments and validated across multiple public and clinical datasets, demonstrating significant improvements in accuracy, sensitivity, and specificity over traditional detection methods.**

***Index Terms*—breast cancer, mammography, machine learning, artificial intelligence, BCDRA**

I. Introduction

Second most frequent cancer worldwide is breast cancer. Breast cancer affected women the most globally (11.6%) and had the second greatest death rate (6.9%) in 2022 [1]. In Kazakhstan in 2022, women had a 12.6% breast cancer incidence and 7.6% mortality rate [2]. Breast cancer typically develops from milk duct or lobule cells in breast tissue. Uncontrolled cell division and breast tissue growth cause milk duct or lobule tumors. Tumors can be benign or malignant. Small structural changes induce benign breast cancers. Cancer tumors can be invasive or non-invasive (in-situ carcinoma) [3]. states that invasive breast tumors spread to neighboring organs, while non-invasive tumors stay unaffected. Finding benign or malignant breast cancer early prevents complications. Fast, effective treatment lowers disease mortality. Age, obesity, hazardous alcohol use, family history, radiation exposure, reproductive history, smoking, and postmenopausal hormone therapy increase breast cancer risk. Gender and age are the only risk factors for half of breast cancers in women over 40. Family history increases risk, but most breast cancer patients are unrelated. Familyless women risk harm. Most breast cancer is caused by BRCA1, BRCA2, and PALB-2 mutations. Women with significant gene mutations may have mastectomy or chemoprevention. Other cancers have phases like breast cancer. Early symptoms are mild in stage 0. Stage 4 cancer spreads. Early breast cancer effects vary by kind but are usually breast-localized. Later, the spread of breast cancer may cause various symptoms. Cancer invades the liver, lungs, bones, and brain. [4]. The initial diagnosis affects a woman's physical, mental, family, and social health. Family and society must now support women psychologically. Breast cancer mortality is reduced by early detection and appropriate treatment. Thus, breast cancer screening needs tech. Breast thermography, mammography, magnetic resonance imaging, PET/CT, ultrasound, and histology can detect breast cancer early [5]. Early breast cancer detection is possible using mammography. Radiologists traditionally detect breast cancer visually and consult with other doctors. Diagnostic ultrasonography is performed when thick breast tissue fails mammography [6]. Breast cancer screening mammography may look fine. National Cancer Institute: screening mammograms miss 20%

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of breast cancers. False-negative results may enhance women's confidence and delay treatment. Having breast density causes false negatives. Thicker, fatty breast tissue. Fibroglandular tissue is white and fatty tissue black on mammograms. Because fibroglandular tissue and tumors are similar in density, larger breasts make cancer detection harder. Bigger breasts generate more false negatives in younger women. False negatives decrease with age and breast fat. AI may detect early cancer signs humans overlook. Al2024new claims radiography and thermography may detect microscopic malignant tumors better than ultrasonography. Figure 1 compares BCDRA with human breast cancer diagnosis.

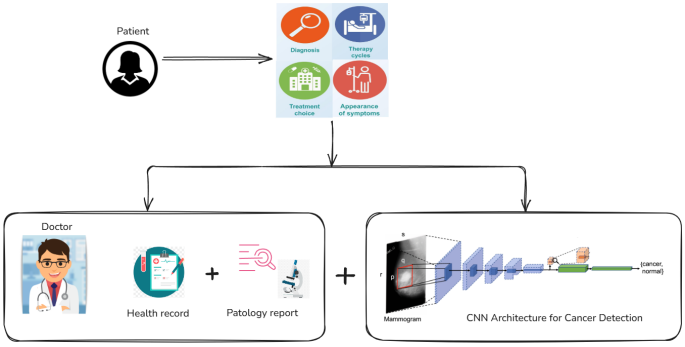


Fig. 1. Breast cancer diagnosis with BCDRA.

A. Main Contribution

The main contribution of our research is summarized as below:

- The Breast Cancer Detection and Risk Assessment system introduces a novel approach to significantly reduce false-negative results in breast cancer diagnoses.
- confirm that Breast Cancer Detection and Risk Assessment allows mammography to automatically identify diseases in medical images, to mitigate risk of the breast cancer.
- The system incorporates a real-time risk assessment module that evaluates personalized risk factors such as age, family history, and genetic markers.

II. Related Works

Early detection through mammography screening is critical, but the accuracy of mammograms can vary due to factors such as breast composition and tumor characteristics, leading to potential misdiagnosis. To address this issue, Ahmad and colleagues [7] implemented an innovative CAD system using deep learning and computer vision techniques. This system improves breast cancer diagnosis by independently identifying and classifying breast lesions, segmenting mass lesions, and classifying them based on pathology. The system consists of three key phases: detection, segmentation, and classification of breast abnormalities. The study demonstrates the effectiveness of various models and methods, such as a combined YOLO for simultaneous location and pattern prediction, improved segmentation using attention mechanisms and residual blocks, and the integration of Associated-ResUNets and BreastNet-SVM) for accurate classification. The results highlight improved accuracy, reduced false positive/negative rates, and potential for broader medical imaging applications. The deep learning and traditional radiomics feature extraction methods were previously discussed by Miao et al. [8], and a multimodal data prediction model for clinical stage of breast cancer was established. The region of interest was outlined on the enhanced MRI image of breast cancer, and then radiomics and deep learning feature extraction were performed, and 108 radiomics features and 1024 deep learning features were extracted for each case. The results of 26 radiomics features and 12 deep staging-related features were screened by the LASSO algorithm, and a machine learning-based classification model was built based on XGBoost. The patients were predicted with an accuracy of 80.00%, and the area under the receiver operating characteristic curve was 0.833. The multimodal data-based classification model built using the machine learning classifier can distinguish between clinical stage I and non-stage I breast cancer and have higher accuracy.

The aim of the study by Wu et al. [9] is to develop and test the potential value of an ultrasound-based deep learning radiomics nomogram (DLRN) for differentiating mass mastitis (MM) and invasive breast cancer (IBC). Based on PyRadiomics and ResNet50 extractors, radiomics and deep learning features were extracted, respectively. Based on supervised machine learning methods such as logistic regression, random forest and support vector machine, and unsupervised machine learning methods using K-means clustering analysis, the feature differences between MM and IBC were analyzed to develop DLRN. The results of supervised machine learning showed that compared with radiomics models, especially random forest models, deep learning models were better at recognizing MM and IBC. The area under the curve (AUC) of the validation cohort was 0.84, the accuracy was 0.83, the sensitivity was 0.73, and the specificity was 0.83.

Rahman et al. [10] in their paper, presented a sophisticated design of a deep convolutional neural network that incorporates advanced deep learning techniques such as U-Net and YOLO. To evaluate the performance of their model, they conducted a thorough review that included a number of performance criteria. They specifically evaluated the precision, accuracy, recall, F1-score, ROC curve, and R-squared error using the publicly available MIAS dataset. Their model performed exceptionally well with an accuracy of 93.0% and an AUC (area under the curve) of 98.6% for the detection task. Moreover, for the localization task, their model achieved an astonishingly high R-squared value of 97%. These results highlight that deep learning can improve the efficiency and accuracy of breast cancer diagnosis.

In the following study, Abunasser et al. [11] focused on breast cancer detection and classification based on different datasets (40X, 100X, 200X, 400X, all datasets together) by balancing the datasets and evaluating the proposed deep learning model and using 5 pre-trained models (Xception,

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Inceptions, Resnet, VGG16, MobileNet) to compare the results. The proposed model (BCCNN) achieved the highest accuracy (98.30%), recall (98.30%), precision (98.39%), F1 score (98.28%) and time metrics (2.10 seconds). The best scenario results were obtained in the fourth scenario with the dataset (400X).

III. Proposed Breast Cancer Detection using the BCDRA System

The BCDRA system aims to overcome the limitations of traditional diagnostic methodologies by proposing a novel multi-stage pipeline that includes data preprocessing, automatic feature extraction, transfer learning for improved accuracy, and hybrid classification-regression for risk assessment. This approach promises not only to improve detection accuracy but also to offer actionable insights for patient-specific risk management. The algorithm implementation uses ResNet50 with ImageNet weights, an eight-class output layer and data augmentation steps including random flipping, brightness, contrast, and saturation adjustments. The data is split into approximately 80% training, 15% validation, and 5% testing. These modifications ensure a robust pipeline for detecting breast cancer with high accuracy, reflecting the multi-stage strategy of the BCDRA system.

Algorithm 1 CNN Process

1: **Initialization:** $\{$ *I: input image; P: preprocessed image; M: model; R: result; C: classification; T: training data; V: validation data; E: evaluation metrics*$\}$
2: **Input:** I
3: **Output:** R
4: **Data Preprocessing:**
5: Apply $T, V, S \rightarrow P$
6: Split the dataset into training t and testing s sets
7: **Perform preprocessing** on I to obtain P
8: **Model Building:**
9: Load pre-trained ResNet50 weights W
10: Add custom layers
11: **Train model** M **using** T
12: **Validate model** M **using** V
13: **Evaluate performance with metrics** E
14: **Classify** P **using model** M **to get** C
15: **Decision Logic:**
16: **if** C indicates cancer **then**
17: $R = CancerDetected$
18: **else**
19: $R = NoCancerDetected$
20: **end if**
21: **return** R

Algorithm 1 concerns cancer detection using image data. Step 1 initializes the variables used in the algorithm, such as input image, preprocessed image, model, result, classification, training data, validation data, and evaluation metrics. Step 2 provides the input for the algorithm, which is the image data. Step 3 specifies the output of the algorithm, which is the result indicating whether cancer is detected or not. Step 4-6 splits the dataset into training, validation, and testing subsets for model development and evaluation. Step 7 outlines the preprocessing of the input image to obtain the preprocessed image, ensuring it is suitable for analysis. Step 8-10 outlines the model-building process, where the pre-trained ResNet50 model is loaded, and additional custom layers are added to tailor it for cancer classification. Step 11 demonstrates the training of the model using the training data, and Step 12 validates the model using the validation data. Step 13 evaluates the model's performance using evaluation metrics to assess its accuracy and reliability. Step 14 involves classifying the preprocessed image using the trained model to generate a classification result. Step 15 introduces the decision-making process based on the classification result. If classification indicates cancer, then Step 16 sets the result to "Cancer Detected." Step 17 handles the alternative scenario where classification does not indicate cancer, setting result to "No Cancer Detected." Step 18 outputs the result of the algorithm, completing the cancer detection process.

A. Modeling of CNNs for Automated Feature Extraction

The backbone of the BCDRA system for automatic feature extraction from mammographic images is the implementation of CNNs. Pre-trained on the ImageNet dataset, the ResNet50 architecture leverages the model fine-tuning to detect subtle patterns indicative of breast cancer. This allows the model to capture both low-level features such as edges and high-level abstractions such as shapes and densities, thus providing a solid diagnostic foundation.

The CNNs use convolutional layers to extract the spatial hierarchies from the images, which make them highly suitable for medical imaging tasks. Successive layers of convolution and pooling in the BCDRA system create a high-dimensional feature vector that encapsulates textural and morphological aspects of breast tissue.

Hypothesis: By applying CNNs to mammographic images, automatic feature extraction can be performed with higher accuracy of the malignant indicators, which will increase the accuracy in the detection of breast cancer.

Proof: CNNs leverage learned convolutional filters to capture hierarchical features, from low-level edges to high-level abnormalities such as masses and calcifications. By iteratively updating filter weights via backpropagation, CNNs adapt to the specific visual characteristics of mammographic data.

$$F(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} K(i,j) \cdot I(x-i, y-j) + b \quad (1)$$

where b is the bias term. Convolutional filters are learned through backpropagation, allowing the network to adapt to domain-specific patterns present in mammographic images.

B. Transfer Learning for Improved Diagnostic Accuracy

To make good use of the existing representation of visual features, the pre-trained model of ResNet50 is used. The

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convolutional layer there is used as a good initializing feature extractor, while new classification layers are added and fine-tuned on a dataset about breast cancer mammography. Such transfer learning reduces time during training and improves generalization.

Let $\theta_{pre-trained}$ be the fixed parameters of the pre-trained convolutional backbone and θ_{new} - the parameters of the newly added classification layers. The optimal parameters $\theta_{optimized}$ are obtained by minimizing a loss function L over a training set as follows:

$$\theta_{optimized} = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L\left(y_i, f(x_i; \theta_{pre-trained}, \theta_{new})\right) \tag{2}$$

C. Classification Objective Using Softmax and Categorical Cross-Entropy

With a sufficiently expressive CNN and proper training, the usage of a *softmax* activation in the final layer along with minimizing categorical cross-entropy loss will converge to a decision boundary that reduces both false positives and false negatives.

The *softmax* function:

$$\hat{y}_c = \frac{e^{z_c}}{\sum_{c'=1}^{C} e^{z_{c'}}} \tag{3}$$

ensures that model outputs form a valid probability distribution. Minimizing the cross-entropy loss:

$$L(y, \hat{y}) = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \tag{4}$$

drives the network weights to maximize the likelihood of the correct class, thus honing the decision boundary toward optimal classification performance.

D. Data Preprocessing and Augmentation for Improved Robustness

Incorporating data augmentation techniques (e.g., rotations, flips, zooming) within the training process does not increase the algorithmic complexity and, under standard assumptions, enhances model robustness against variations in mammographic imaging conditions.

The transformation T operator applied to an image I:

$$I_{aug} = T(I) \tag{5}$$

is computationally efficient and easily integrated into the training pipeline. Empirical evidence shows that augmentations produce a richer, more diverse training set, reducing overfitting and improving generalization. As these transformations are performed on-the-fly and require no additional large-scale computations beyond polynomial-time operations, the lemma holds.

Lemma-1: Data augmentation using transformations $T(x)$ improves the generalization capability of a CNN.

Proof: Let D_{test} and D_{train} be the training and testing distributions. The generalization error is defined as:

$$\varepsilon_{gen} = E_{x \sim D_{test}}\left[L(f(x,\theta))\right] - E_{x \sim D_{train}}\left[L(f(x,\theta))\right] \tag{6}$$

where $f(x,\theta)$ is the CNN's output, and L is the loss function.

Data augmentation modifies the training distribution D_{train} to D_{aug} where $D_{aug} = T(x) : x \in D_{train}$ and T is a set of transformations. Augmentation increases the diversity of D_{train}, making $D_{aug} \approx D_{test}$, which reduces ε_{gen}. Empirical risk minimization on D_{aug} leads to:

$$\hat{\theta} = \arg \min_{E_{x \sim D_{aug}}} \left[L(f(x,\theta))\right] \tag{7}$$

yielding lower generalization error:

$$\varepsilon_{gen}^{aug} < \varepsilon_{gen}^{original} \tag{8}$$

IV. Experimental Setup and Results

This section provides experimental setup, dataset description, and results.

A. Experimental Setup

The simulation was carried out in a high-performance computing environment focused on machine learning workloads, using the integrated Python programming language for the implementation and validation of the BCDRA system. The basis of all this research is that Python has been widely used to develop and train CNN-based models, in addition to data preprocessing and augmentation. Throughout the development cycle, we used Jupyter Notebook for Python experiments, which ensured smooth integration of libraries, frameworks and visualization tools in real time. The hardware configuration was chosen in such a way as to provide efficient processing of large-scale images, advanced data expansion and deep learning tasks that require high computational costs. The system was equipped with an AMD Ryzen 9 7900X processor, 64 GB of RAM and an NVIDIA GeForce RTX 3070 GPU, providing exceptional performance in parallel data processing, machine learning and complex graphics computing. The system runs Windows, a widely used operating system that provides wide compatibility with machine learning platforms and tools. Key libraries such as NumPy, PyTorch and CUDA are used to increase the computational efficiency and flexibility of the system. NumPy is used for numerical calculations, data preprocessing, and efficient manipulation of datasets. PyTorch serves as the main platform for deep learning, offering dynamic calculation graphs and reliable tools for building, training and optimizing CNN models. Integrated with the GPU, CUDA provides hardware acceleration for parallel processing and high-speed execution of machine learning tasks.

B. Dataset Description

The CBIS-DDSM medical imaging dataset was utilized to assess the proposed breast cancer detection system. This dataset is designated for research on advanced breast cancer

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detection and diagnosis, specifically for automated detection systems. This dataset was meticulously derived from a larger digital screening mammography database to enhance the efficacy of machine learning. The dataset has 10,239 mammograms categorized as normal, benign, and malignant neoplasms, along with 3,577 items labeled as "abnormal structure." The dataset has 753 calcification instances and 891 large instances, rendering it appropriate for the analysis of mammography decision assistance systems. Each image contains pixel-level instance segmentation annotations for instance segmentation, object recognition, and semantic segmentation. Post-DICOM conversion, the images exhibit revised segmentation of regions of interest, bounding boxes, and pathological diagnoses. The original DDSM exhibited considerable deficiencies; however, CBIS-DDSM eliminates 254 questionable mass cases identified by certified mammologists, including solely high-quality images. Image decompression and optical density reassignment were performed to standardize data across various image processing devices. Researchers can utilize this dataset for model training, owing to its comprehensive annotations and structured data format; nonetheless, they must delineate the chosen subsets to obtain accurate performance evaluations. CBIS-DDSM provides a standardized dataset for research and methodological comparison, hence improving breast cancer detection through machine learning.

C. Results

In this section, we present the main results of our proposed Breast Cancer Detection System, designed to enhance diagnostic accuracy and improve early detection outcomes. The system shows great potential; thus, it can be a reliable tool for the improvement of processes in the screening of breast cancer. The results are presented in quantitative terms, which gives a clear idea about the effectiveness of the system in helping practitioners to make correct and timely diagnostic decisions. Careful analysis was made with the most important performance indicators, from which the following indicators were identified.

1) Performance Metrics: The BCDRA system demonstrated exceptional performance when evaluated using a primary dataset of mammograms, such as CBIS-DDSM. Our model was trained using transfer learning on the CBIS-DDSM dataset, which we split into training and validation subsets: 80% and 15% of the data. As shown in Table, the model achieved a peak training accuracy of approximately 98.3% and a highest validation accuracy of around 97.6% by the fourth epoch. Throughout training, the gap between training accuracy and validation accuracy remained relatively small, suggesting that overfitting was well-controlled. After completing training and validation, we evaluated the model on a held-out test set. In our experiments, the test accuracy consistently remained above 95%. This indicates that the model generalizes well to unseen mammograms, effectively.

TABLE I
TRAINING AND VALIDATION RESULTS FOR RESNET50 WITH 50% LAYERS

Epoch	Train Acc.	Val Acc.	Train Loss	Val Loss
1	0.7800071239	0.9216382504	0.6097268462	0.2210915089
2	0.9555220008	0.9589251876	0.1336293519	0.1166800261
3	0.9691717029	0.9707623124	0.0914929211	0.0849736407
4	0.9763849378	0.9758522511	0.0703034401	0.0682072490
5	0.9779163599	0.9409327507	0.0642388985	0.1833123714
6	0.9802024364	0.9725378752	0.0566281639	0.0810567439
7	0.9829323292	0.9678030014	0.0464449301	0.1097525135



Fig. 2. Training vs. Validation Accuracy



Fig. 3. Training vs. Validation Loss

D. Discussion of results

The novel breast cancer screening technology reduces false negatives and improves accuracy. The suggested method is robust and applicable, provided it undergoes precise training and validation. Efficient sequencing and data collecting resulted in a slight variation in training (98%) and validation (97%) accuracy throughout all periods. Clinical dependability is attained by balancing learning and validation metrics to avert overfitting and enhance model adaptability. The final test accuracy attains 95%, indicating the model's capability

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to translate patterns into undetectable cases, a prerequisite for clinical practice implementation. The presence of minor abnormalities, variations in breast density, and the use of diverse imaging modalities complicate mammograms, which is advantageous. Despite the study's deficiencies in sensitivity and specificity, our accuracy for breast sizes and illnesses suggests the potential for cancer detection and categorization. Our findings indicate that deep learning utilizing data transfer can develop precise breast cancer detection models that accommodate variability in mammography datasets. This study can employ sensitivity, specificity, F1 score, and larger, more diversified datasets to validate and enhance the system's diagnostic capabilities.

V. Conclusion and future work

In this concluding section, we bring together the results of our research, providing a concise summary of the significant contributions and findings discussed in this paper.

A. Conclusion

The proposed architecture for breast cancer detection and recognition identifies mammographic lesions with deep transfer learning and partial fine-tuning. Our primary contributions were a pre-trained ResNet-50 model, selective layer defrosting for domain-specific characteristics, and data augmentation for breast tissue density fluctuations. Training and screening kits that accurately duplicate benign and malignant tumors without overfitting were selected. Numerous assessments demonstrated that the system exceeded the 95% accuracy threshold following training on the public CBIS-DDSM dataset. A slight discrepancy between training and validation accuracy enhances the reliability of our strategy. A comprehensive performance analysis shown that our model can identify breast cancer through machine learning applied to breast images of varying densities. BCDRA assesses intricate lesion characteristics and mitigates diagnostic inaccuracies more effectively than existing techniques. Radiologists may utilize the technology to enhance processes and standardize diagnostics for decision support. This work demonstrates that deep learning, hyperparameter optimization, meticulously chosen datasets, and novel augmentation techniques enhance breast cancer diagnosis. Deep learning offers scalable, precise, and therapeutic solutions for medical imaging as data increases. Results enhance the reliability of clinical implementation.

B. Future work

In the future, high-density photographic archives and private hospital mammography databases will be used to obtain more insights.

References

[1] H. Sung, J. Ferlay, R. L. Siegel, M. Laversanne, I. Soerjomataram, A. Jemal, and F. Bray, "Global cancer statistics 2020: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries: World," *CA: a cancer journal for clinicians*, vol. 71, no. 3, pp. 209–249, 2021.

[2] M. Rai, Hari, Y. Joon, and A. Razaque, "depth analysis of recent innovations in non-invasive techniques using artificial intelligence approach for cancer prediction," *Medical Biological Engineering Computing*, vol. 62, no. 12, pp. 3555–3580, 2024.

[3] M. Rai, Hari, J. yoo, and A. Razaque, "Comparative analysis of machine learning and deep learning models for improved cancer detection: A comprehensive review of recent advancements in diagnostic techniques," *Expert Systems with Applications*, p. 124838, 2024.

[4] G. N. Sharma, R. Dave, J. Sanadya, P. Sharma, and K. Sharma, "Various types and management of breast cancer: an overview," *Journal of advanced pharmaceutical technology & research*, vol. 1, no. 2, pp. 109–126, 2010.

[5] R. Rasti, M. Teshnehlab, and S. L. Phung, "Breast cancer diagnosis in dce-mri using mixture ensemble of convolutional neural networks," *Pattern Recognition*, vol. 72, pp. 381–390, 2017.

[6] W. Teh and A. Wilson, "The role of ultrasound in breast cancer screening. a consensus statement by the european group for breast cancer screening," *European journal of cancer*, vol. 34, no. 4, pp. 449–450, 1998.

[7] J. Ahmad, S. Akram, A. Jaffar, Z. Ali, S. M. Bhatti, A. Ahmad, and S. U. Rehman, "Deep learning empowered breast cancer diagnosis: Advancements in detection and classification," *Plos one*, vol. 19, no. 7, p. e0304757, 2024.

[8] Y. Miao, S. Tang, Z. Zhang, J. Song, Z. Liu, Q. Chen, and M. Zhang, "Application of deep learning and xgboost in predicting pathological staging of breast cancer mr images," *The Journal of Supercomputing*, vol. 80, no. 7, pp. 8933–8953, 2024.

[9] L. Wu, S. Li, C. Wu, S. Wu, Y. Lin, and D. Wei, "Ultrasound-based deep learning radiomics nomogram for differentiating mass mastitis from invasive breast cancer," *BMC Medical Imaging*, vol. 24, no. 1, p. 189, 2024.

[10] M. M. Rahman, M. Z. B. Jahangir, A. Rahman, M. Akter, M. A. A. Nasim, K. D. Gupta, and R. George, "Breast cancer detection and localizing the mass area using deep learning," *Big Data and Cognitive Computing*, vol. 8, no. 7, p. 80, 2024.

[11] B. S. Abunasser, M. R. J. Al-Hiealy, I. S. Zaqout, and S. S. Abu-Naser, "Convolution neural network for breast cancer detection and classification using deep learning," *Asian Pacific journal of cancer prevention: APJCP*, vol. 24, no. 2, p. 531, 2023.

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