Salud, Ciencia y Tecnología. 2025; 5:2207
doi: 10.56294/saludcyt20252207

ORIGINAL

Integrative Feature Learning from Mammographic Images Using a Hybridized Diagnostic Model

Aprendizaje integrado de características a partir de imágenes mamográficas mediante un modelo de diagnóstico hibridado

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Cite as: Latha DU, Bhavani KG, Chethan BK, Shruthi N, Dharini KR. Integrative Feature Learning from Mammographic Images Using a Hybridized Diagnostic Model. Salud, Ciencia y Tecnología. 2025; 5:2207. https://doi.org/10.56294/saludcyt20252207

Submitted: 01-05-2025 **Revised:** 02-08-2025 **Accepted:** 08-10-2025 **Published:** 09-10-2025

Editor: Prof. Dr. William Castillo-González

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ABSTRACT

Traditional Conventional machine learning approaches to breast cancer diagnosis tend to rely on manual feature extraction, which is fraught with variability and time-consuming. These constraints limit the scalability and consistency of diagnostic platforms. As the need for precise and efficient diagnostic technologies escalates, the need for automated frameworks that can effectively interpret mammographic data and facilitate clinical decision-making arises. This paper introduces the Feature-driven Breast Cancer Classification Model (F-BCC-ML), which is intended to optimize diagnostic precision and efficiency in the detection of breast cancer. The goal is to create a hybridized model that can automate feature extraction and classification from mammogram images and eliminate the dependency on manual techniques to improve clinical results. The F-BCC-ML model combines an Adaptive Classifier Engine (ACE) with a strong preprocessing and segmentation pipeline. First, preprocessing of mammogram images is done for noise reduction using the Improved Bilateral Filtering Technique (IBFT), which maintains important anatomical information. Segmentation is achieved through SegNet, a deep learning architecture optimized for semantic segmentation. Feature extraction merges texture descriptors Weber Local Descriptor-harmonized Local Gabor XOR Pattern (GTE) and Grid Feature Encoding (GFE) with color and deep features from region-segmented regions. The features are subsequently classified as normal or cancerous via the ACE architecture in combination with a Deep Vision Network (DVN). The F-BCC-ML model showcases strong clinical promise through the automation of the diagnostic process and feature representation improvement.

Keywords: Breast Cancer Classification; Mammogram Images; Deep Learning; GTE; Improved Bilateral Filtering Technique; Grid Feature Encoding.

ABSTRACT

Los enfoques tradicionales de aprendizaje automático para el diagnóstico del cáncer de mama suelen basarse en la extracción manual de características, que presenta una gran variabilidad y requiere mucho tiempo. Estas limitaciones limitan la escalabilidad y la consistencia de las plataformas de diagnóstico. A medida que aumenta la necesidad de tecnologías de diagnóstico precisas y eficientes, surge la necesidad de marcos automatizados que puedan interpretar eficazmente los datos mamográficos y facilitar la toma de decisiones clínicas. Este artículo presenta el Modelo de Clasificación del Cáncer de Mama Basado en Características (F-BCC-ML), cuyo objetivo es optimizar la precisión y la eficiencia diagnósticas en la detección del cáncer de mama. El objetivo es crear un modelo híbrido que pueda automatizar la extracción y clasificación de características de las imágenes de mamografía y eliminar la dependencia de las técnicas manuales para mejorar los resultados clínicos. El modelo F-BCC-ML combina un Motor de Clasificación Adaptativa (ACE) con un potente proceso de preprocesamiento y segmentación. En primer lugar, se realiza el preprocesamiento de las imágenes de mamografía para la reducción de ruido mediante la Técnica de Filtrado Bilateral Mejorada (IBFT), que conserva información anatómica importante. La segmentación se realiza mediante SegNet, una arquitectura de aprendizaje profundo optimizada para la segmentación semántica. La extracción de características combina los descriptores de textura Weber Local Descriptor-Harmonized Local Gabor XOR Pattern (GTE) y Grid Feature Encoding (GFE) con características de color y profundas de regiones segmentadas por regiones. Posteriormente, las características se clasifican como normales o cancerosas mediante la arquitectura ACE en combinación con una Red de Visión Profunda (DVN). El modelo F-BCC-ML presenta un gran potencial clínico gracias a la automatización del proceso de diagnóstico y la mejora de la representación de características.

Palabras clave: Clasificación del Cáncer de Mama; Imágenes de Mamografías; Aprendizaje Profundo; GTE; Técnica de Filtrado Bilateral Mejorada; Codificación de Características de Cuadrícula.

INTRODUCTION

Breast cancer (BC), a malignant tumor originating from epithelial cells of the breast, remains a critical threat to women's health and a major challenge for global healthcare systems.(1) Accounting for approximately 25 % of all cancer cases worldwide, BC ranks as the second most prevalent cancer among women, following lung cancer.(2) According to the World Health Organization (WHO), worldwide cancer burden is expected to increase considerably with a projected 19,3 million new cases in 2025.(3) In just 2018 alone, BC occurred in more than 2,1 million people and caused 627000 deaths worldwide.(4) Early detection is pivotal in improving treatment outcomes and survival rates. Although BC can affect individuals of any gender and age, it is predominantly diagnosed in middle-aged and older women.(5) Major risk factors include gender, age, family history, obesity, and genetic mutations. While other cancers such as cervical, lung, and thyroid also pose significant risks, BC is particularly notable for its high incidence and complex treatment protocols. Prompt diagnosis significantly enhances the likelihood of five-year survival, especially when treatment begins in the early stages.(6) In developed nations, more than 70 % of breast cancer (BC) cases are identified in the early (I and II) stages, whereas in low- and middle-income countries, the proportion of early BC detection ranges from a mere 20 % to 50 %. While histological image interpretation, which involves analyzing tissue sections for pathological features, still constitutes a gold standard for tumor characterization and plays an important role in treatment pathways,(7) imaging modalities such as mammography, magnetic resonance imaging (MRI), and ultrasonography are also key in the detection of BC. Mammography is still the most preferred modality for early detection, especially in asymptomatic women, but the shortage of radiologists and interpretative errors continue to be critical challenges.(8) To address these limitations, computer-aided diagnostic (CAD) systems have gained prominence in assisting radiologists with tumor detection. In recent years, deep learning (DL) techniques have revolutionized CAD systems by enabling automatic extraction and analysis of both low- and high-level features from mammographic images.(9) Despite significant progress, challenges remain in improving classification accuracy and diagnostic reliability. To overcome these challenges, the use of computer-aided diagnostic (CAD) systems has become widespread with the help of radiologists for tumor localization. With the rapid advancement of technology, deep learning (DL) methods have led to further progress in CAD by facilitating the automatic extraction and interpretation of low- and high-level features directly from mammographic images.(10) Despite this advancement, several issues continue to persist regarding enhancing categorization accuracy and diagnostic confidence. This work introduces a comprehensive framework for breast cancer categorization, with three key contributions. First, it presents the IBFT technique to effectively suppress impulsive and additive noise in input images, enhancing image quality. Second, it proposes the GTE method for extracting local intensity gradients and edge features, complemented by GFE, color descriptors, and deep features from models such as AlexNet, VGG-16, and ResNet. Finally, it introduces the ACE model, which eliminates the vanishing gradient problem, improves scalability, and integrates the DVN model for robust and accurate classification.

METHOD

In this work, the hybrid classification scheme ACE+DVN is replaced with the hybrid ResNet50+SVM model, which combines ResNet50 for deep feature representation and SVM for classification.(11) ResNet50, which is a 50-layer deep residual network, is known for its great performance in the field of image classification. In the current study, it is employed for high-level feature extraction on segmented mammogram images. All the extracted features are then applied to the SVM classifier, which is very powerful for a binary classification problem like normal vs. abnormal (cancerous) tissues. This hybrid ResNet50+SVM scheme is expected to improve accuracy while remaining computationally attractive.[12] As shown in figure 1, the various steps involved in breast cancer detection using mammogram images are shown. The procedure starts with the input of the mammogram image, which plays the role of raw material. The first step is related to image preprocessing, where the image is filtered by using the improved bilateral filtering technique (IBFT). It is used to reduce noise and preserve important structural details in the image that are important for detecting tumors or anomalies in breast tissue. After the preprocessing stage, image segmentation is performed using SegNet, a DL-based framework implemented for semantic segmentation. After completing image segmentation, the next step comprises feature extraction, where a set of features are extracted from the image for classification. These features consist of gradient texture encoding (GTE) for texture characterization, grid feature encoding (GFE), deep features, and color features from the segmented image.[13,14] The presented hybrid ResNet50+SVM model for mammogram classification is based on a multi-stage pipeline consisting of five different stages for enhancing accuracy and efficiency in breast cancer detection. Initially, raw mammogram images are denoised using the Improved Bilateral Filtering Technique (IBFT), which preserves the boundaries and structural details of the tumor. Then, the image segmentation of suspicious masses or calcifications is performed by the SegNet encoder-decoder framework. Next, the handcrafted features (Gradient Texture Encoding, Grid Feature Encoding, and color features) along with ResNet50 Deep Features are fused. The 50-layer residual network ResNet50 provides high-level hierarchical representations of the tissue pattern, while the handcrafted descriptors retain the texture and spatial characteristics. Then, the combined features are fed into the Support Vector Machine (SVM) classifier, which is quite effective in binary classification. Thus, integrating Preprocessing, Segmentation, Handcrafted Descriptors, Deep Learning, and Machine Learning Classification provides higher accuracy, robustness, and computational efficiency than the standalone methods.

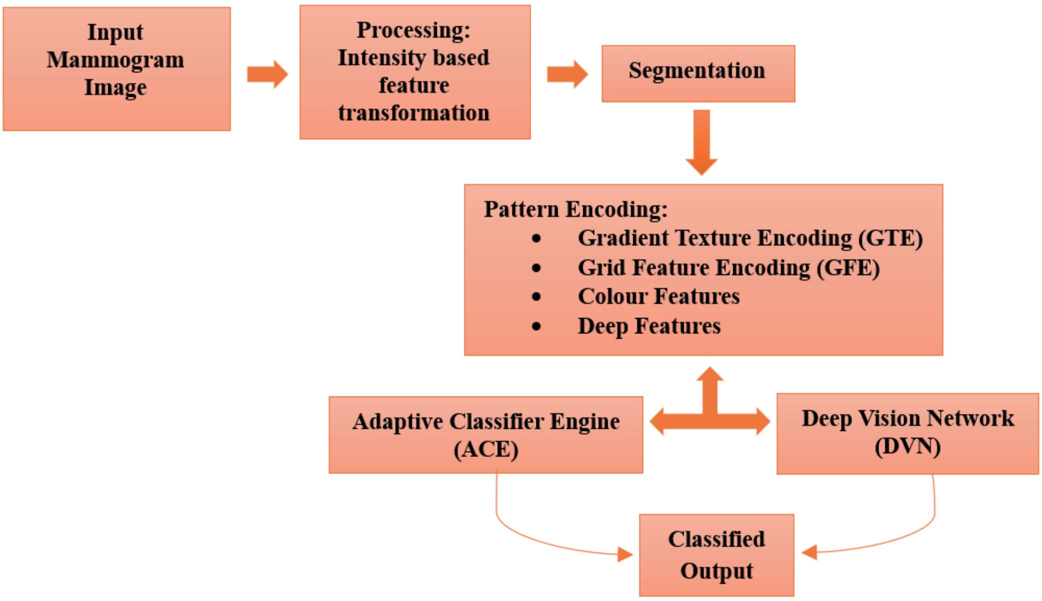


Figure 1. Outline of F-BCC-ML

Preprocessing via IBFT

In the context of mammogram image analysis for breast cancer (BC) detection, intensity variations often carry critical diagnostic information. However, raw intensity values can be affected by noise, illumination inconsistencies, and acquisition artifacts.[15] To address these challenges, we propose a novel Intensity-Based Feature Transformation (IBFT) method that enhances the discriminative power of intensity features while preserving structural integrity.

Let the input mammogram image be denoted as I(x,y)I(x,y), where (x,y)(x,y) represents the spatial coordinates. The transformation process involves three key stages:

Gradient-Weighted Enhancement: the normalized intensity is modulated by the local gradient magnitude G(x,y)G(x,y), emphasizing edges and transitions:

$$Ig(x,y) = In(x,y) \cdot (1+\alpha \cdot G(x,y)) \; Ig(x,y)=In(x,y) \cdot (1+\alpha \cdot G(x,y)) \qquad (1)$$

Where α is a tunable parameter controlling the influence of gradients.

Entropy-Based Suppression: to reduce the impact of noisy or homogeneous regions, the transformed intensity is further weighted by the inverse of local entropy H(x,y)H(x,y):

IIBFT (x, y) = Ig(x,y) / (1+β · H(x,y))

Where β controls the entropy suppression strength.

Segmentation via SegNet

The segmentation process in image analysis, especially for mammogram-based BC detection, involves separating the image into distinct regions that focus on areas of interest, such as potential masses or abnormal tissue.[16] This work uses a SegNet scheme to isolate the specified region from the preprocessed image, . This step aims to identify and extract the critical features necessary for diagnosis, allowing for more effective analysis in subsequent stages.

The SegNet architecture is a DL model adopted for semantic segmentation, in which the goal is to classify each pixel of an image. SegNet is a fully convolutional network, meaning it does not use any fully connected layers. It comprises into two main components: "the encoder and the decoder". The encoder compresses the image's spatial resolution, and the decoder upsamples the feature maps through the pool indices from the encoder, followed by convolution with a learnable filter bank for refinement. The output is then passed into a softmax classifier for pixel-wise labeling.[17] A major strength of SegNet is its capability to detect and classify fine details at the pixel level, making it particularly effective for identifying small or subtle objects within images that might be overlooked by other models. Thus, the segmented image is denoted as .

Feature extraction

Feature extraction is an essential step in the Breast cancer classification task, where the goal is to transform a segmented image, into a set of significant features that can be adopted for further analysis. The feature extraction process involves recognizing key attributes of the image that are most appropriate to the task at hand.

Classification

The classification step involves the sclassification of the disease based on the features. This process uses extracted meaningful features, as the input to a hybrid classifier like Improved LeNet and DVN to make predictions.[18] As shown in figure 2, the Improved LeNet and DVN individually trains and the outcomes of each classifier are averaged to obtain the final classified output.

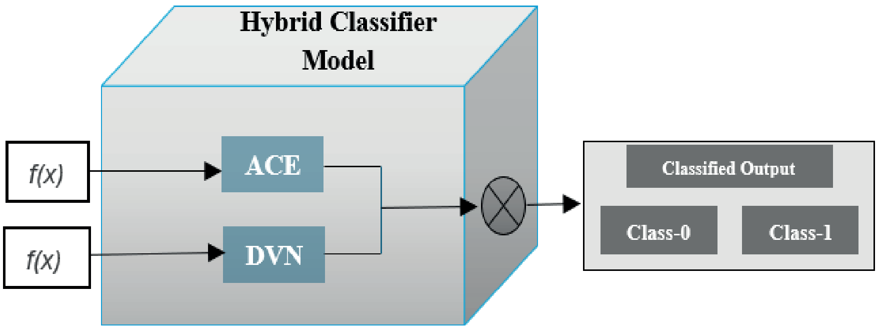


Figure 2. Workflow of the Classification phase via ACE model

The proposed ACE model updates its loss function, activation function and dropout rate. The standard form of LeNet architecture uses ReLU activation function as in (2), which suffers from vanishing gradient issue. To avoid this, a modified ReLU activation function is proposed as in (3).

$f(x) = \{x \text{ if } x \geq 0 \text{ else } 0$ (2)

$f(x) = \{x \text{ if } x>0 \text{ else } 1-e^{\delta x}$ (3)

Where, β indicates a coefficient factor that can be expressed as β = d.tan(g.M); here, d = 1,7159; g = 2/3; and M = (d-g).

Also, the dropout rate of standard LeNet model is (0,2, 0,5). To acquire better scalability and computational time, the dropout rate is modified as in (4).

$rate=u / \pi(x2+u2)$ (4)

Where, u = 0,2 and x = 1/(2xu).

Moreover, the loss function of the standard LeNet model is Categorical Cross Entropy (CCE) function, which possesses slow convergence rate. To address this, a new Calibrated KL Divergence Loss function (CKLDL) is proposed. The proposed CKLDL is computed as in (5).

$CKLDL=KL - Divergence\ (C||D) + a.diff$ (5)

Where, L- Divergence $(C/D) = \sum C(x) \log (C(x)/D(x))$; $\alpha = 0{,}5$ and diff = sum $(y_{true} - y_{pred})$

As depicted in figure 3, the suggested ACE architecture begins with the input layer, which is comprised of the feature set, f_{set}. The first stage of the network is a 2D conv layer utilizing 5x5 filters, which is then followed by BN, used to normalize the activations and enhance the training process.[19] Thereafter, a modified ReLU activation function is used to inject non-linearity and enable the network to learn complicated patterns. Following this, max pooling, with a 2x2 filter, is used to reduce the spatial dimensions of the feature maps, along with dropout, which deactivates a random proportion of neurons to help prevent overfitting.[20] This procedure is repeated, with another 2D conv layer, BN, modified ReLU activation, max pooling, and dropout. The output of the convolutional and pooling layers is then flattened into a one-dimensional vector.

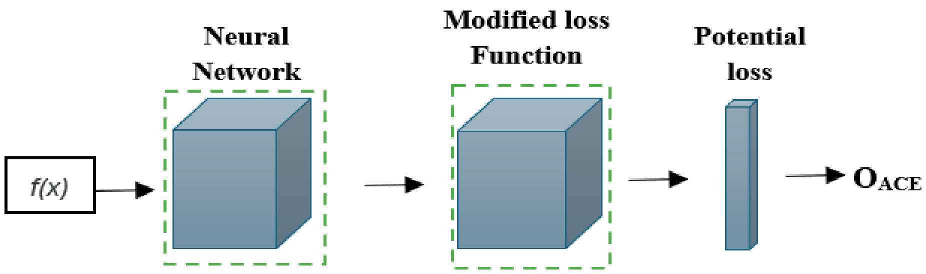
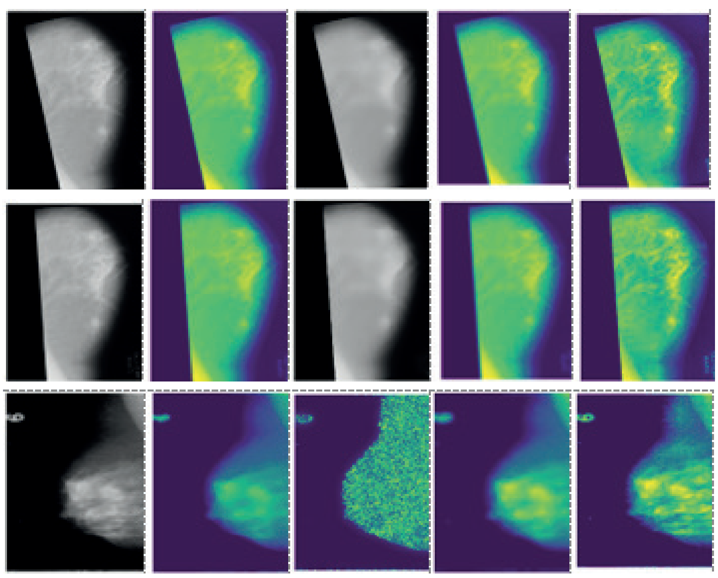


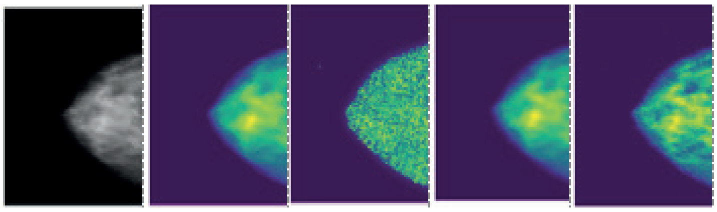
Figure 3. Structure of Modified Loss and Activation function assisted ACE Model

The flattened features are passed through a dense layer with 120 neurons, followed by BN, a modified ReLU activation as well as dropout to ensure robust learning. The next fully connected layer has 84 neurons, with BN, activation, and dropout again applied to refine the feature representation. The structure of the modified Loss and activation function is shown in figure 3. The network outputs a single neuron representing the classification result as OACE. Thereby, the proposed approach completely reduces the vanishing gradient issue and acquires better scalability with minimal computation time.[21]

Pre-processing Analysis

Figure 4 shows the original images together with their corresponding pre-processed results for Gaussian, Median, Conventional Bilateral, and IBFT. In this context, the IBFT provided exceptional pre-processed results compared to the traditional approaches.





(a) (b) (c) (d) (e)

Figure 4. Pre-processed outcomes a) Sample Images b) Median c) Conventional Bilateral d) Gaussian and e) IBFT

Comparative Evaluation on PSNR and SSIM

PSNR and SSIM measures are utilized to examine the quality of images. The PSNR and SSIM study on IBFT analysis is contrasted with Gaussian, Conventional Bilateral, and Median is exposed in table 1. The IBFT approach recorded maximum PSNR of 34,496 dB and SSIM of 0,938, whereas the Conventional Bilateral, Gaussian and Median methods scored reduced PSNR and SSIM values.[22] The introduction of log function in IBFT filtering, which can successfully overwhelm the impulsive and additive noise concurrently.

Table 1. PSNR and SSIM Analysis on IBFT

Method	PSNR (dB)	SSIM
Conventional Bilateral	27,930	0,544
Gaussian	16,813	0,556
Median	26,570	0,740
IBFT	34,496	0,938

RESULTS

The comparative analysis points out the ACE+DVN method as a fundamentally better technique for breast cancer classification when compared to a variety of traditional deep learning methods. Its performance stands out with higher sensitivity and lower false negative rates, which are essential in sound medical diagnostics. The incorporation of sophisticated feature extraction methods, like WLD in LGXOR, helps it to detect subtle texture and edge details in mammogram images, which is a critical aspect in detecting cancerous patterns. Additionally, the model proves to be robust against different proportions of training data, holding high classification efficacy and generalizability. These results highlight the promise of ACE+DVN as a superior and scalable solution within clinical decision support systems, especially when precision and early detection are of great importance. In this comparative assessment, the ACE+DVN approach for Breast Cancer Classification is meticulously assessed against conventional approaches, including EfficientNet, LinkNet, DCNN, LeNet, SqueezeNet, VGG-16, ResNet, LWCNN and edRVFL. As portrayed in figure 5, the assessment emphasizes Positive, Negative and Neutral measures, which assist as a significant indicator of the model's efficiency. To attain efficient breast cancer classification, the model must exhibit greater positive and neutral measures.[23]

DISCUSSION

From figure 5(a), it is obvious that the ACE+DVN scheme reaches greater accuracy values across all training data. More particularly, at 90 % training data, the MLAL+DCNN strategy achieves an accuracy of 0,974, this is maximal than the accuracies of EfficientNet (0,831), LinkNet (0,851), DCNN (0,791), LeNet (0,900), VGG-16(0,892), ResNet (0,951) LWCNN (0,863) and edRVFL (0,773), respectively. When trained with 90 % of data, DCNN achieved a sensitivity of 0,725, while edRVFL closely followed at 0,751. LinkNet and EfficientNet establish a sensitivity of 0,795, signifying a modest enhancement over DCNN and edRVFL. LWCNN and LeNet exhibited a sensitivity of 0,845 and 0,925. In comparison, the ACE+DVN approach excelled with a sensitivity of 0,985, significantly surpassing all other traditional methods. Integrating WLD in LGXOR emphasizes local intensity gradients and edge features, which can be useful for capturing edge information within textures and leads to better texture detection.For 80 % of training data, the ACE+DVN scheme attains an MCC of 0,873, outperforming existing methodologies like EfficientNet, LinkNet, DCNN, LeNet, VGG-16, ResNet, SqueezeNet, LWCNN and edRVFL. In the analysis of 80 % of training data, LeNet and edRVFL stand out with FNRs of 0,151 and 0,245, resulting in higher error values. LWCNN, LinkNet and SqueezeNet exhibit a higher FNR of 0,176, suggesting less consistent performance. DCNN and Efficient display an increase in FNR to 0,201, signifying reduced efficiency. The ACE+DVN approach surpasses all traditional methods with a lower FNR of 0,074, emphasizing its superior ability in breast cancer classification. Utilizing Modified ReLU activation in the LeNet model reduces the vanishing gradient problem and the Dropout rate will get better scalability and less computational time.

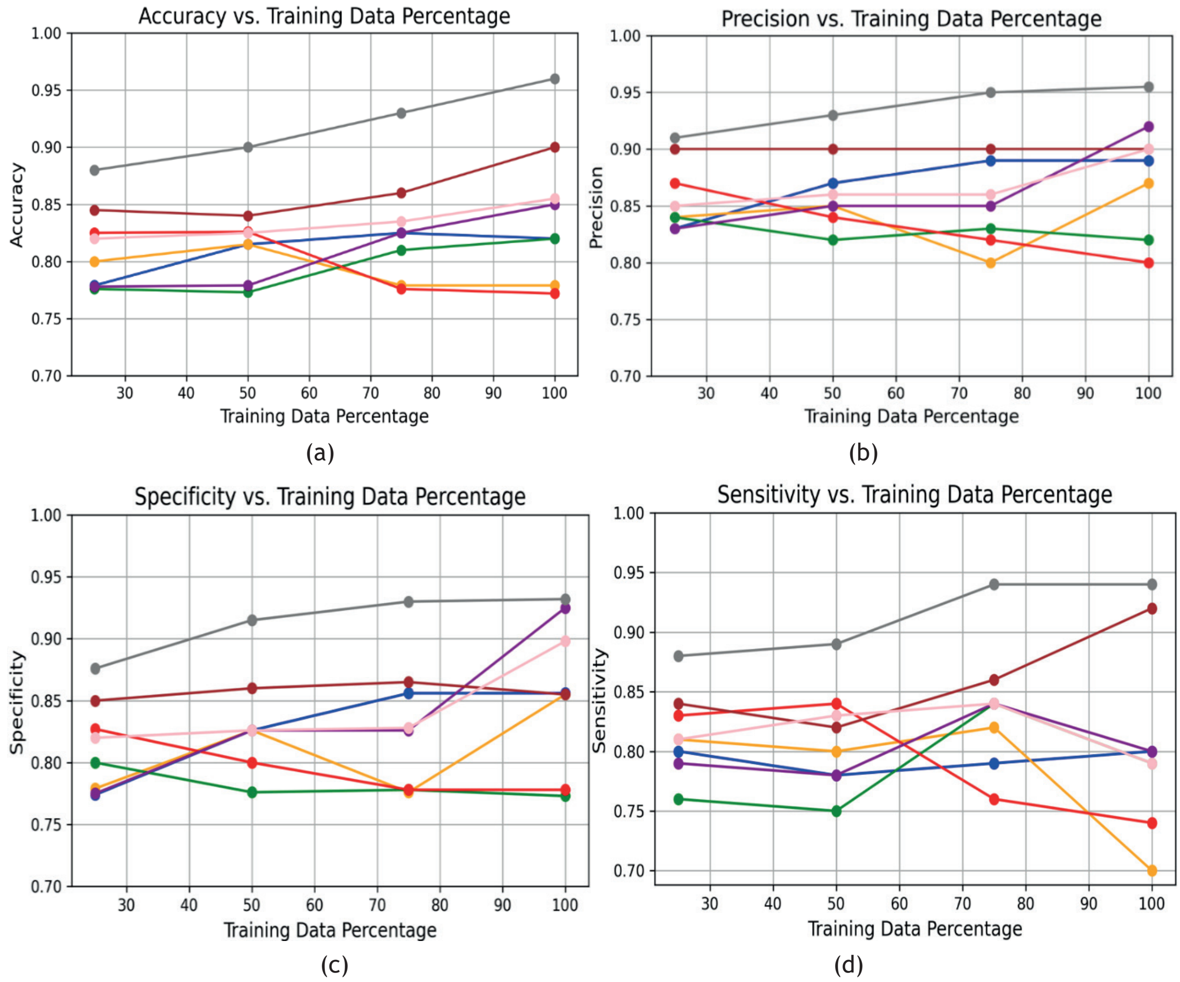


Figure 5. Evaluation on MLAL+DCNN Vs. Traditional Approaches regarding Positive Measures a) Accuracy b) Precision c) Sensitivity and d) Specificity

The statistical evaluation on ACE+DVN strategy in comparison to existing approaches, including EfficientNet, LinkNet, DCNN, LeNet, SqueezeNet, LWCNN and edRVFL for Breast Cancer Classification is illustrated in the results. For Mean Statistical Metric, the ACE+DVN approach acquired the highest accuracy rate of 0,920, whereas the conventional methodologies scored lesser accuracies with EfficientNet at 0,815, LinkNet at 0,816, DCNN at 0,798, LeNet at 0,861, SqueezeNet at 0,799, LWCNN at 0,833 and edRVFL at 0,799, respectively. In comparison, EfficientNet, LinkNet, DCNN, LeNet, SqueezeNet, LWCNN[23] and edRVFL generated lesser accuracy ratings. The Improved WLD-LGXP helps to extract robust features indicating the texture of breast tissue, which is crucial for recognizing cancerous patterns in mammogram images.

CONCLUSIONS

The F-BCC-ML is a new hybrid approach for feature-based breast cancer image classification from mammograms. The technique integrates a rich feature extraction strategy that fuses WLD-LGXP, MBP, colour features, and deep features of pretrained models like AlexNet, VGG-16, and ResNet with Improved Bilateral Filtering Technique (IBFT) for noise reduction and SegNet for accurate image segmentation. To improve classification performance and efficiently handle problems like disappearing gradients, these features are classified using an ACE+DVN combined with a DCNN. The suggested model obtained an excellent accuracy of 97,4 % at 90 % training data, which surpasses the performances of existing approaches like Efficient Net, Link Net, DCNN, LeNet, LWCNN, and edRVFL. This reveals the efficacy and reliability of F-BCC-ML in effectively assisting radiologists in the accurate and non-invasive diagnosis of breast cancer. Dataset bias and class imbalance are forms of internal threats that can adversely affect the learning performance of the model and lead to overfitting and under-representation of patterns. The generalization ability of the model is prone to threats in the external environment because results may differ significantly when applied to datasets from other hospitals with different imaging modalities or different types of patients. Despite strong performance and very high accuracy, the proposed F-BCC-ML model has several limitations. Using different feature extraction approaches increases the complexity of the process, which may hinder real-time implementation and deployment in a low-resource environment.

Furthermore, the model's effectiveness depends on SegNet's segmentation quality, and it lacks explainability, which is essential for clinical adoption. Future studies will assess the model's resilience using several publicly available mammography datasets, improve interpretability by implementing explainable AI techniques, refine the model for real-time applications, and investigate integrating multi-modal data—like genetic and patient history—to increase diagnostic accuracy.

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FINANCING

The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST

None.

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