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A hybrid deep learning approach for breast cancer detection using AlexNet-ResNet with CNN features

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Abstract

Breast cancer detection is a serious challenge in medical imaging, and use of deep learning techniques has shown promising results in improving accuracy and efficiency. This research introduces a hybrid deep learning strategy for breast cancer identification, utilizing the combination of AlexNet-ResNet architectures with convolutional neural network (CNN) features. The proposed model extracts intricate features from medical images and uses skip connections to handle deeper neural networks. The work introduces a hybrid deep learning approach for breast cancer detectionby proposing a hybrid model, called AlexNet-ResNet. Hybrid approach improves the network's generalization ability and provides a better understanding of key features contributing to breast cancer diagnosis. The AlexNet architecture possesses a remarkable depth of 8 layers, allowing it to excel in feature extraction when compared to the other models. On the other hand, ResNet architecture is a smart approach that not only considerably diminishes training time, but also elevates accuracy.The performance of the presented strategy was estimated by employing multiple metrics, such as specificity, accuracy, and sensitivity. Findings show that the AlexNet-ResNet approachgained impressive scores of 95.2% accuracy, 97.9% sensitivity, and 93.9% specificity. The proposed method could enhance the effectiveness of breast cancer screening programs and support personalized treatment planning.

Keywords: Deep Learning, Breast cancer detection, Disease detection, Convolutional Neural Networks, AlexNet, ResNet.

World Health Organization	WHO
ductal carcinoma in situ	DCIS
invasive ductal carcinoma	IDC
Deep Learning assisted Efficient Adaboost Algorithm	DLA-EABA
Deep Learning	DL
whole-slide images	WSI
benign adenosis	BA
benign fibroadenoma	BF
benign phyllodes tumor	BPT
benign tubular adenoma	BTA
malignant ductal carcinoma	MDC
malignant lobular carcinoma	MLC
malignant mucinous carcinoma	MMC
malignant papillary carcinoma	MPC
computer-aided detection	CAD
extreme learning machine	ELM
generative adversarial network	GAN
digital database for screening mammography	DDSM
regions of interest	ROI
true positive rate	TPR
False positive rate	FPR

Brightness preserving dynamic histogram equalization	BPDHE

1. Introduction

WHO reports that cancer is a prevalent and deadly disease that impacts countless individuals globally. In particular, female breast cancer is more prevalent in underdeveloped nations compared to those that are more developed. This destructive disease typically originates in the breast tissue, often within the lining of the Milk Ducts or Breast Lobules, and has capability to spread to further part of body [7]. Given its status as the second most common disease worldwide, early detection and treatment play a crucial role in reducing mortality rates [2]. Fortunately, medical imaging offers a means of detecting and treating breast cancer, with non-invasive methods available to provide a view of the human body [8], [9]. It is crucial to recognize that imaging techniques alone are not sufficient to confirm the presence of cancer. Microscopic examination is necessary to definitively detect cancer cells [15]. Additionally, there is a possibility of cancerous cells spreading through the surgical incision or needle insertion site during biopsy [12]. To accurately diagnose breast cancer using a mammogram, it is common practice to preprocess the images by eliminating the pectoral muscle. This allows for a more targeted evaluation of the breast profile region and the detection of any irregularities [1].

Breast cancer, is a complex and potentially deadly condition that can manifest in two common forms: DCIS and IDC [3]. While DCIS is only found in 2% of breast cancer cases, IDC poses a much greater threat with a prevalence of 80% among breast cancer patients and a 10% rate of death per 100 individuals [5]. The insidious nature of IDC lies in its ability to develop in various types of breast cells, making it difficult to diagnose and detect. These cells, also known as tumor cells, are characterized by their irregular shapes and can be either benign or malignant [13]. Malignant tumors have a tendency to spread to surrounding tissue cells, inhibiting healthy cell growth. On the other hand, benign tumors are non-cancerous and do not pose a threat to neighboring tissue cells. Even experienced pathologists find it challenging to distinguish between different tissue structures in breast cancer cases, and minor changes may require specific medical procedures. A variety of therapies, like radiation, medication, and surgery, can be used to treat breast cancer [4].

Over the past ten years, attention to the research dedicated to breast cancer, with significant advancements being made [2]. A particularly notable development has been the implementation of DL techniques to tackle intricate challenges and enhance the outcomes of previous studies [10]. The effectiveness of DL technology in medical settings has been well-documented, with the potential to provide quicker and more precise analysis compared to human experts [6]. Among the various applications of ML/DL, the detection of invasive breast cancer stands out as a widely used area. This type of ML follows a similar process to how our own brain neurons comprehend information. DL networks consist of artificial neurons prearranged in layers, where neuron is linked to individual neuron in next layer through weighted connections. However, relying solely on a single DL model, such as CNN, LSTM, or RNN, has often led to underwhelming results for researchers [11]. To improve the accuracy of categorization, it is suggested to incorporate hybrid DL models [14].

The main aspiration of presented strategy is as below:

- To examine a novel hybrid DL strategy for breast cancer detection, AlexNet- ResNet so that the proposed approach incurs the advantages, like AlexNet has the ability to handle large scale image recognition tasks efficiently and its early success in popularizing DL. ResNet, on the other hand, overcame the problem of vanishing gradients by introducing skip connections that allowed for better gradient flow throughout the neural network, making it easier to train very deep network.
- To estimate efficacy of presented strategy, metrics, like specificity, sensitivity, and accuracy are utilized.

Work's arrangement is as bellow: Section 2 showsoverallpreview of traditionalliterature related to breast cancer identification models. Section 3 introduces presented AlexNet-ResNet model for breast cancer detection. In Section 4, work delves into findings and discussion of AlexNet-ResNet model. Segment 5 examines the conclusion of projected work.

2. Literature Survey

The following section describes traditional research works developed to breast cancer identification.

Jing Zheng *et al.,* [1] completed a rigorous mathematical assessment of the DLA-EABA for breast cancer identification. Employing state-of-the-art computational techniques, the study not only tapped into conventional computer vision methods but also dived into the probability of using deep CNNs. These powerful tools were used for tumor classification, with the added application of transfer learning to precisely characterize breast nodules across multiple imaging modalities, such as mammography, digital breast tomosynthesis, ultrasound, and MRI. The study's innovative approach included a fusion of machine learning methods, feature selection, and extraction strategies, culminating in the utilization of segmentation and classification strategies to pinpoint the mainly effective method. Saad Awadh Alanazi *et al.,* [2] are dedicated to improving the identification of breast cancer through the use of a CNN approach. By analyzing aggressive ductal carcinoma tissue zones in WSIs, the team aimed to automate the detection process. Multiple CNN architectures were tested and compared against ML algorithms, with quantitative performance testing validating their findings. The results were promising, with an accuracy rate of 87%, surpassing the 78% accuracy achieved by ML algorithms. This breakthrough has the potential to decrease human error in the diagnostic process and could potentially lead to more accurate and timely diagnoses.

Xiaomei Wang *et al.,* [3] explored the potential of a hybrid DL CNN-GRU model in identifying breast cancer IDC (+,−). This ground-breaking study utilized WSIs from the widely used PCam Kaggle dataset and incorporated various CNN and GRU architecture layers to accurately identify the presence of IDC (+,−) cancer. To evaluate their model, the authors conducted rigorous validation tests and measured various performance parameters. They found that the hybrid model outperformed pathologist judgment and effectively tackled the issue of misclassification, achieving impressive results such as 86.21% accuracy, 85.50% precision, 85.60% sensitivity, 84.71% specificity, 88% F1-score, and an AUC of 0.89. This study marks a significant step towards automated and accurate detection of breast cancer, providing promising potential for future advancements in diagnosing this disease. Basem S Abunasser *et al.,* [4] examined the BCCNN, a powerful DL tool to accurately identifying and categorizing various types of breast cancer. This groundbreaking model specifically targets eight categories: MPC, MMC, BTA, BPT, MLC, MDC, BF, and BA. To fully assess the effectiveness of the BCCNN, the study conducted a thorough comparison with five different pre-trained models, all utilizing the dataset independently.

Abhishek Das *et al.,* [5] delved into the potential of a DL model in analyzing one-dimensional data transformed into images. They explored the process of converting one-dimensional data into images and devised a stacked ensemble DL approach to enhance classification accuracy, surpassing that of individual models. The team utilized this approach to identify breast cancer in both gene expression datasets and breast histopathology images. Drawing upon the fact that gene expression data is one-dimensional, study utilized the t Distributed Stochastic Neighbor embedding technique and the Convex Hull algorithm to successfully convert the data into images. Unlike most methods that use the datasets directly for classification andtraining, the approach utilized both the dataset and decomposed forms of same to enhance performance. Hanan Aljuaid *et al.,* [6] introduced an innovative computer-aided approach for diagnosing breast cancer. This method goes beyond the traditional binary classification and also incorporates multi-class cases. By leveraging a powerful combination of deep neural networks (specifically ShuffleNet, Inception-V3Net18, and ResNet) and utilizing transfer learning on the vast BreakHis dataset, the team achieved outstanding results.

Wang Zhiqiong *et al.,* [7] explored a breast CAD method that utilized feature fusion with CNN deep features. This innovative approach to mass detection involved using a combination of unsupervised ELM clustering and CNN deep features. Furthermore, the researchers constructed a feature set by fusing deep features with density features, morphological, and texture. This fused feature set was then used to develop an ELM classifier capable of accurately distinguishing between benign and malignant breast masses. Results from experiments showcased the effectiveness of this methodology in both mass identification and breast cancer classification. Guan Shuyue, and Murray Loew [8] harnessed the power of a GAN to produce artificial mammographic images sourced from the DDSM. The GAN was trained on two distinct ROIs extracted from the DDSM images: abnormal (cancer/tumor) and normal. The resulting synthetic images were then compared to those generated through traditional affine transformation methods like rotation, shifting, and scaling using a categorization of six separate ROI groups. These groups included three simple groups: real (original), and affine augmented GAN synthetic images, along with three mixture groups that combined two of three simple groups. Each group was used to train a CNN classifier from scratch. The findings indicated that adding GAN-generated ROIs in data of training improved classification accuracy by preventing overfitting.

2.1Challenges

The major challenges of conventional methods in breast cancer detection are illustrated in this subsection. Accuracy of the DLA-EABA model has to be improved to gain better success rates [1]. The main limitation of the study by using CNN [2] to ensure the utmost accuracy in identifying breast cancer, it is vital to carry out the examination using primary data. Similarly, the future study in hybrid DL CNN-GRU [3] is also to increase accuracy of result connected to breast cancer detection.

3. Proposed AlexNet-ResNet based breast cancer detection

The study presented a hybrid DL model, known as AlexNet-ResNet, for breast cancer identification. The AlexNet-ResNet model is proposed by the combination of AlexNet and ResNet architectures, designed to improve the accuracy of DL models for image classification. By combining these two architectures, the AlexNet-ResNet model improves on the accuracy and robustness of neural networks, allowing for more accurate classification of complex images. The model achieves this through its capability to haul out more detailed and intricate features from images, while also addressing the problem of vanishing gradients, which can limit the depth of neural networks. The AlexNet-ResNet model has productively employed to a range of image classification tasks, inclusive of breast cancer identification. By improving the accuracy and robustness of current DL models, the AlexNet-ResNet model represents a significant step forward in fields of machine learning and computer vision. Figure 1 shows the framework structure of the presented AlexNet-ResNet model used for the breast cancer detection.

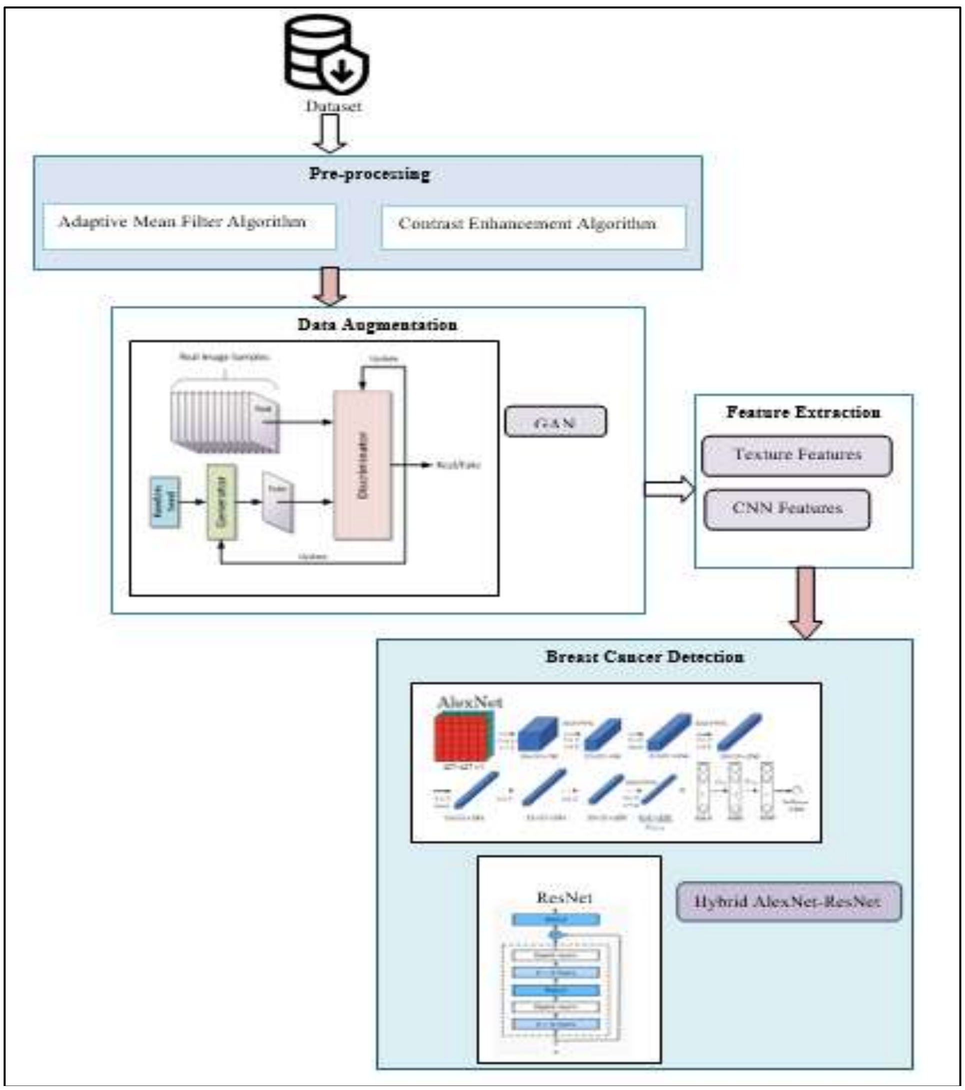


Figure 1: Framework of the proposed breast cancer detection using AlexNet-ResNet

3.1Preprocessing

Preprocessing is a crucial step in examination of data and machine learning models, involving techniques for cleaning, transforming, and preparing data for subsequent tasks. It helps to enhance the quality of the data and improve the accuracy of the resulting models. Here, an adaptive mean filter is employed to minimizeimage noise. This filter works by rearranging each pixel in the image with the mean of the pixel values in a local neighborhood around the pixel. Meanwhile contrast enhancement is a technique used to improve the visibility and clarity of an image. The adaptive mean filter can be useful to image to reject noise before contrast enhancement is applied. This helps to lessen effect of noise on resulting image and improve the quality of contrast enhancement. By incorporating these preprocessing techniques into the pipeline of the machine learning model, approach's accuracy can incremented.

3.1.1 Adaptive Mean Filter

Adaptive mean filters [17] are a proposed solution for reducing blurring caused by speckle noise in images. Unlike traditional averaging filters, adaptive mean filters balance among straightforward averaging in all-pass filtering and homogeneous regions in which edges are present. These filters adjust to the unique properties of image, removing speckles from various parts of image in a selective manner. Local image statistics, including variance, spatial correlation, and mean, are employed in effect to identify and preserve features and edges. Speckle noise is eliminated by reinstated it with a local mean value. Compared to mean filters, adaptive mean filters are more effective at reducing speckles while maintaining the edges. Examples of these filters include Lee [19], Kuan [18], and Frost [20], all of which are related to the multiplicative speckle model

$$i(T) = r(T)u_t(T) \quad (1)$$

Coordinates of current pixel are represented by $T = (X, Y)$, whereas $r(T)$ is used to state the ideal image's intensity devoid of speckle. On the other hand, $i(T)$ signifies the intensity of the observed image, while $u_t(T)$ refers to the speckle with a mean value of $\overline{u}_t$ and a variance of $\sigma^2_{u_t}$.

3.1.2 Contrast Enhancement

The process of contrast enhancement [21] consists of 5 steps.

1. Enhance histogram's appearance with a Gaussian filter for a smoother effect:

To identify local maximums of a digital image histogram, it is necessary to smooth the histogram first. This is because the histogram is typically fluctuating and may have missing probability for certain brightness levels. First, the missing brightness levels are filled up by performing linear interpolation. Next, a one-dimensional Gaussian filter is applied to smooth the histogram.

2. The identification local maximum location on the smoothed histogram:

During the splitting procedure of original histogram, only smoothed histogram is utilized. Histogram is divided into smaller sub-histograms, with local maximum values serving as the separation points instead of local minimums. This method is preferred because it helps preserve overall image brightness.

3. Transform each partition into a new dynamic range:

Through the procedure of dynamic repartitioning, new partitions are generating as desirable within a prearranged interval to accommodate incoming data. While these partitions may initially be empty, they are necessary for maintaining the smooth flow of the data sequence.

4. Equalize each partition independently:

The input image histogram is dispersed into two parts according to the image's mean. These disconnectedfragments are then equalized before being assigned to new dynamic ranges. The resulting histogram equalization procedure is initialized individually in each partition.

5. Normalize the image brightness:

The BPDHE algorithm moves on to calculating the average brightness of both the original input image and the equalized image. This is a crucial step in maintaining the integrity of the processed image's brightness, which is achieved through the use of brightness normalization.

*3.2*Data Augmentation using *GAN*

GAN [8], a neural-network-based generative strategy, effectively learns probability distribution of real data and generates simulated data examples with a similar allocation. Formally, in D-dimensional space, for $x_g \in r^D, y_g = p_{data}(x_g)$ is a mapping from x_g to real data y_g. GAN generates a neural network, known as generator G_1 to simulate mapping. If sample y arrives from p_{data}, it is a real one; if sample Z arrives from

G_1, it is a synthetic one. Another neural network, discriminator d, is employed to identifyeither a sample is synthetic or real. Ideally, $d(y_g)=1, d(Z)=0$. Two neural networks G_1 and d create the GAN.

Study can find G_1 and d by solving the two-player minimax game, with value function $v(G_1, d)$:

$$\min_{G_1} \max_{d} v(G_1, d) = E\{\log d[p_{data}(x_g)\} + E \log\{1 - d[G_1, (x_g)]\} \quad (8)$$

The objective of GAN is to determine the probability allocation of real data by solving min-max issues with a global optimal solution (Nash equilibrium) for $G_1(x_g) = p_{data}(x_g)$. When discriminator d can no longer differentiate between real and synthetic samples, system reaches equilibrium, with $d(y_g) = d(Z) = 0.5$ d=t=0.5. Synthetic samples can be produced by varying input x_g of G_1. In this work, input x_g for G_1 contained 100 elements drawn from a Gaussian distribution $\sim n(0,1)$. Effectiveness of a well-established GAN lies in its ability to produce synthetic data samples that appear true and indistinguishable from real data.

3.3Feature Extraction

3.3.1 CNN Features

The convolution-pooling operations in CNN [27] make it highly efficient in feature extraction. It is capable of automatically extracting crucial image characteristics without any need for human intervention. For feature extraction, an architecture consisting of a 10-layer CNN is utilized. The input to the CNN is the augmented images. Following multiple convolution and max-pooling layers, the final fully-connected layer consists of 20 neurons representing deep features. These features are identified as $1 = [c1, c2, \ldots, c20]$, where 2 × 2 × 5 has been used to denote their count.

3.3.2 Texture Features

Texture features [7] provide valuable insights into the malignant and benign traits of breast masses, and can aid in the timely detection of breast cancer. One commonly used texture feature is the gray-level co-occurrence matrix, pioneered by Haralick. This matrix describes the distribution of grayscale values across all pixels in the image, according to second-order joint conditional prospect. Here, the texture features, such as contrast coefficient, correlation, and entropy are extracted from the gray-level co-occurrence matrix.

i) Contrast coefficient:

$$a = bj + e \quad (9)$$

where, b is the contrast, e is the brightness and j is the input

ii) Correlation:

$$z = \frac{\sum (k_s - \bar{k})(q_s - \bar{q})}{\sqrt{\sum (k_s - \bar{k})^2 \sum (q_s - \bar{q})^2}} \quad (10)$$

where, k_s and q_s denote the image intensity values in a sample and $\bar{k}$ and $\bar{q}$ denote their mean values.

iii) Entropy:

$$A = -\sum J(E) \log_2 [J(E)] \quad (11)$$

When calculating the entropy of an image I, frequency of occurrence of pixel intensity i, denoted as $J(E)$, is commonly estimated from the image histogram. Entropy, on the other hand, $0 \log 0 = 0$ is known as a measure of the uncertainty or complexity present in an image. Thus, the resulting model for texture features can be expressed as,

$F_{t_3} = [T_{t_1}, T_{t_2}, T_{t_3}]$.

3.4Breast Cancer Detection

This section elaborates the proposed technique, AlexNet-ResNet, developed for the detection of breast cancer. Classification using hybrid DL techniques is found to exhibit superior performance than the DL technique employed for the image classification. Hence, the architectures of AlexNet and ResNet are combined to develop AlexNet-ResNet, as detailed below,

3.4.1 AlexNet

AlexNet [25], in the field of medicine, has been experimented with for detecting various diseases, such as breast cancer. For breast cancer detection using AlexNet, a dataset would need to be collected with labeled images of normal and cancerous breast tissues. The dataset can then be fed into AlexNet, which consumes a sequence of convolutional layers pursued by fully connected layers. The network learns features from the images during the training process, which can then be used to classify new, unlabeled images. Once the model is trained, it would be evaluated on a separate set of testing images to assess its accuracy in detecting breast cancer. This process helps to determine the effectiveness of the model in identifying cancerous tissue and comparing it with other classification methods. Overall, AlexNet can be a useful tool in breast cancer detection with the potential to improve accuracy and support early diagnoses.

The convolutional layers effortlessly extract features while the pooling layer effectively reduces them. Given an image R of height h and width w, and a convolutional kernel n of height B and width C, the convolution operation is expressed bellow:

$$V(h,w) = (R*n)(h,w) = \sum_B \sum_C R(h-B, w-C)n(B,C) \tag{12}$$

The approach is intended to learn from image features through convolution, with the added benefit of shared parameters for reduced complexity. Additionally, pooling layers are utilized to streamline the process of extracting features.

3.4.2 ResNet

ResNet [23] is a prominent DL architecture that comes in various layers, such as 50, 101, and 152. The model employs a residual representation framework for learning. The prior layer's output is fed as input to the following layer lacking any amendments. Thus, the ResNet model possesses characteristics, such as recognition and localization. ResNet consists of two kinds of building blocks, namely Convolutional and Identity blocks. A group of residual models constitute each building block to form ResNet. Furthermore, the residual entities are arranged in the form of convolution, batch normalization, and layers pooling.

$$Y_n = H(Q_n) + f(Q_n.W_n) \tag{13}$$

$$X_{n+1} = f(Y_n) \tag{14}$$

where, Q_n is input, Q_{n+1} is output of *n*-th unit, and f is residual function of *n* th unit.

$$H(Q_n) = Q_n \tag{15}$$

$H(Q_n)$ is simply the identity mapping of the ReLu function. A key advantage of ResNet is that problem of disappearance of gradients does not arise during backpropagation. This is due to the presence of shortcut networks which are equivalent to standard convolutional layers. These shortcut networks enable input values to skip over several weight layers and be directly added to outputs. This approach ensures that gradients can flow back through the network, which improves learning efficacy.The architecture of the proposed breast cancer detection using AlexNet-ResNet is represented in figure 2.

The proposed AlexNet-ResNet employs map layer that incorporates output with features to form other layers,

$$X_3 = \sum_{m=1}^{M} \sum_{l=1}^{L=1} S_{t+1} * X_2 * w \tag{16}$$

$$X_2 = \sum_{m=1}^{M=1} \sum_{l=1}^{L=1} H(Q_n) * I * X_1 \tag{17}$$

Applying fractional calculus [26], S_{t+1} can be represented as,

where, $S_{t+1} = S_t + \frac{S_{t-1}}{2} + \frac{S_{t-2}}{3} + \ldots + \frac{S_{t-n}}{n}$ (18)

$$S_{t+1} = \sum_{m=1}^{M=1} \sum_{l=1}^{L=1} f_1 \times w_1 + \frac{1}{2} \sum_{m=1}^{M} \sum_{l=1}^{L} f_2 \times w_2 + \ldots + \frac{1}{n} \sum_{m=1}^{M=1} \sum_{l=1}^{L=1} f_n \times w_n \tag{19}$$

where, f_i is the i th feature from feature extracted vector and w_i denotes weight in range (0-1).

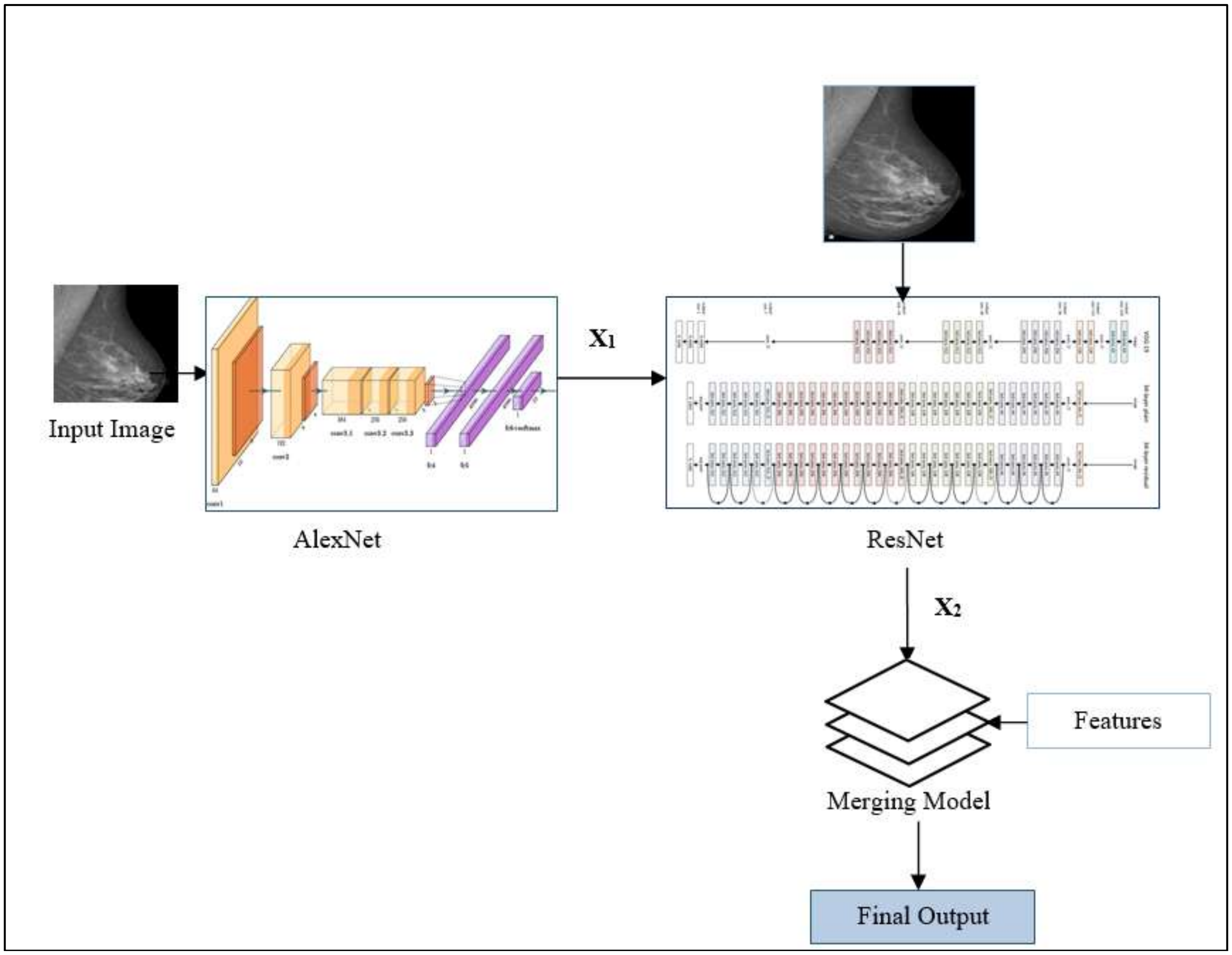


Figure 2: Architecture of proposed AlexNet-ResNet based breast cancer detection

4. Results and discussion

The findings of the assessment and examination of the presented strategy were illustrated. To productivelyemploy the approach for identifying breast cancer, combination of two DL strategies was utilized and coded in Python. Thorough examinations were performed using the CBIS-DDSM: Breast Cancer Image Dataset [18], and the approach's effectiveness was calculated utilizing several metrics, containing specificity, accuracy, and sensitivity.

4.1Dataset Description

CBIS-DDSM [18] is a dataset of breast cancer images, which stands for "Curated Breast Imaging Subset of DDSM". It is a public dataset that includes more than 14,000 mammography exams, with over 42,000 images of both benign and malignant breast lesions. The dataset provides an extensive resource for researchers and practitioners working on breast cancer detection and diagnosis, with images of different modalities, containing full-field digital mammography and digital breast tomosynthesis. The dataset also includes rich meta-data annotations, such as breast density, lesion size, and biopsy results that can aid in advancement of computer-aided detection and diagnosis feature for breast cancer. CBIS-DDSM dataset has been widely used in various studies related to breast cancer screening, diagnosis, and treatment.

4.2 Performance Metrics

In subsection, study illustrates the matrices employed to consider performance of strategy.

a) Accuracy: It calculates the correct prediction percentage done by the presented approach. It is obtained by separatingtotalamount of precise prediction with overall count of the predictions made.

b) Sensitivity: It measures capability of proposed AlexNet-ResNet approach to precisely forecast the positive cases. It is gained by separating overall count of true positives with total amount of positive cases.
c) Specificity: Specificity considers efficacy of presented AlexNet-ResNet strategy to detect negative cases. It measured by separating overall count of true negatives with total amount of negative cases.
d) RoC: ROC curve is an evaluation that exhibits exquisite binary classification analysis such as AlexNet-ResNet performs at diverse classification approaches. It is considered by evaluating TPR with FPR. It is employed to evaluate the total performance of the presented strategy across a wide range of values.

4.3Experimental Results

The findings of presented AlexNet-ResNet for breast cancer identification are in figure 3. In Figure 3, image in figure 3 (a) depicts original image, figure 3 (b) portrays the de-noised image and figure 3 (c) illustrates the contrast enhancement image.

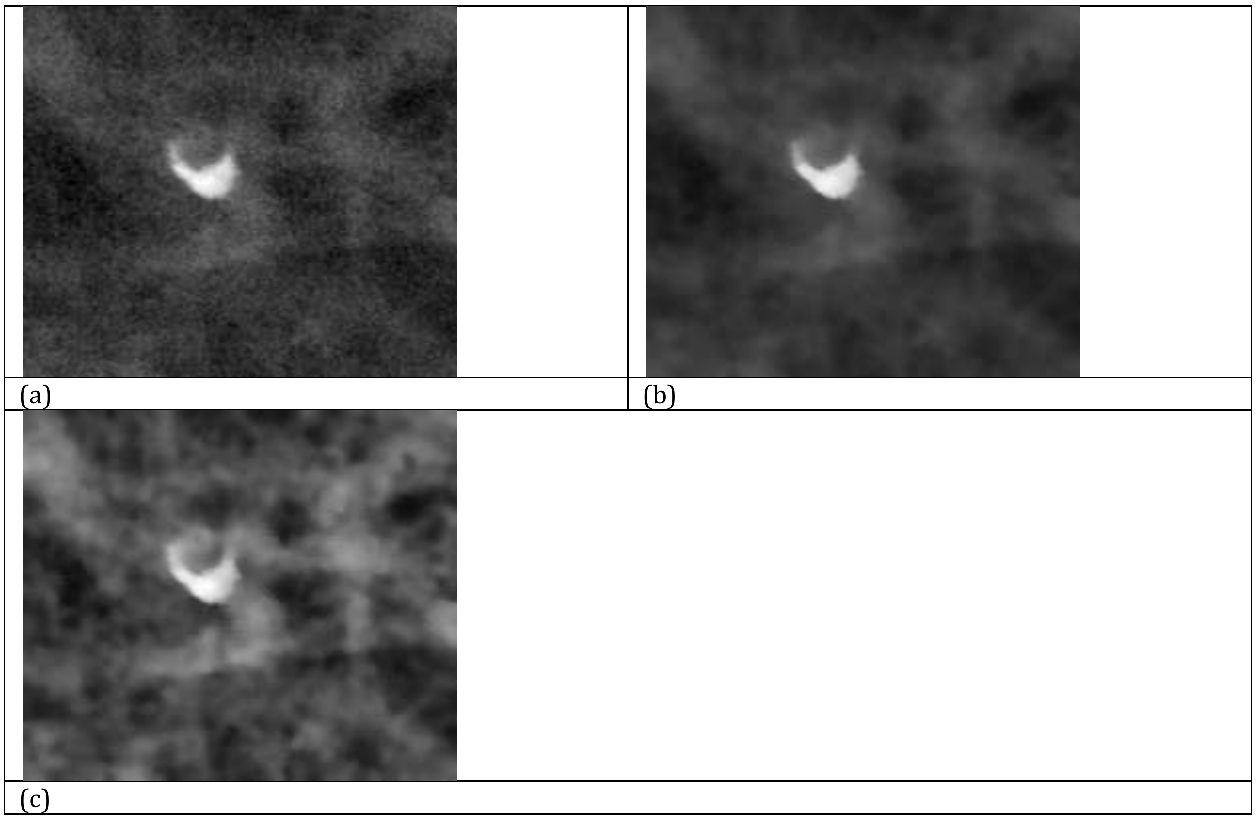
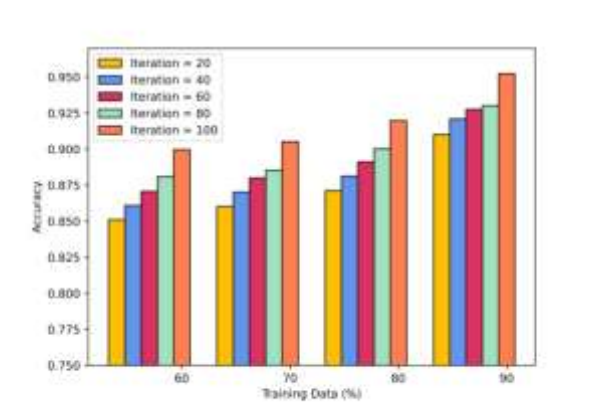


Figure 3:Experimental outcomes(a) original image, (b) de-noised image and (c) contrast enhancement image.

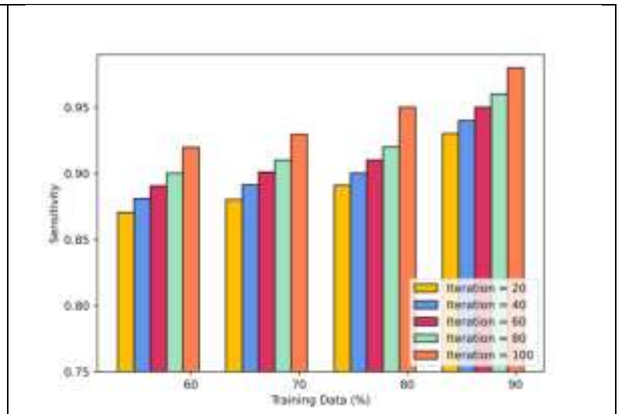
4.4Performance Analysis

4.4.1 Varying Training data

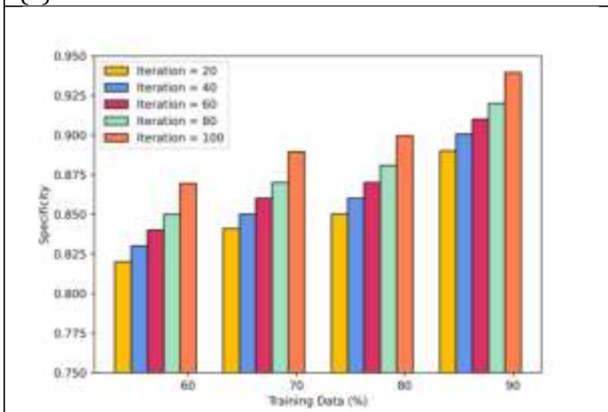
Figure 4 illustrates performance examination of projected strategy in terms of specificity, sensitivity, and accuracy, according to examination of training data. Accuracy analysis is presented in Figure 4 (a), where AlexNet-ResNet strategy accomplished an accuracy of 0.8711 at the 80th iteration for 20% training data. Sensitivity of the model is depicted in Figure 4 (b), whereasexaminedstrategy attained a sensitivity rate of 0.9101 at 60th iteration for 80% training data. Specificity of presented strategy is derived in Figure 4 (c), where the AlexNet-ResNet method gained a specificity rate of 0.9395 at 100th iteration for 90% training data.



(a)



(b)

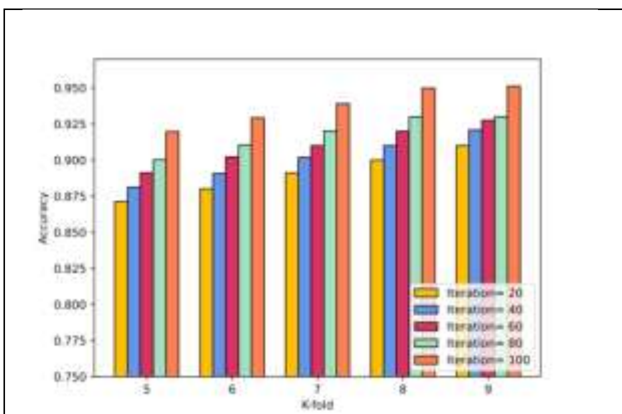


(c)

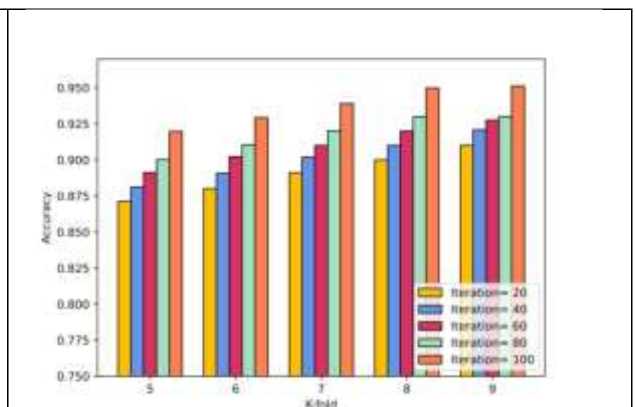
Figure 4: The performance evaluation of presented AlexNet-ResNet method on the basis of training data, (a) accuracy (b) sensitivity (c) specificity.

4.4.2 Varying K-fold

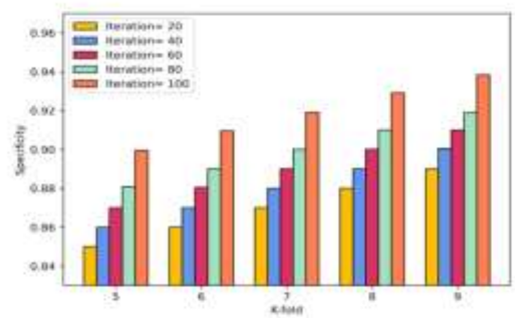
Figure 5 shows findings of the performance examination for developed strategy, utilizing the k-fold approach. The sensitivity, specificity, and accuracy metrics are examined. In figure 5 (a), presents accuracy analysis revealing that depicted AlexNet-ResNet model attained an accuracy of 0.951 at 100th iteration and k-fold of 9. Moving on to figure 5(b), sensitivity of presented strategy is defined, with a sensitivity rate of 0.930 at 60th iteration in the 7 k-fold. Finally, figure 5(c) portrays specificity of strategy, showing a rate of 0.919 at the 100th iteration in the 7 k-fold.



(a)



(b)



(c)

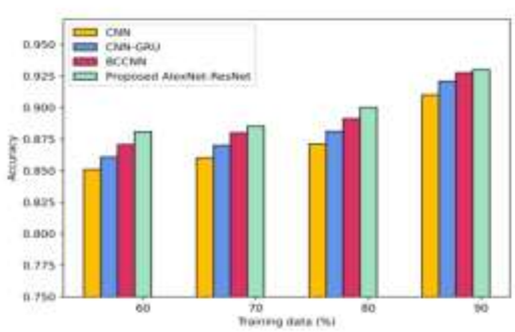
Figure 5: Performance assessment of developed strategy for the K-fold, (a) accuracy (b) sensitivity (c) specificity.

4.5Comparative Analysis

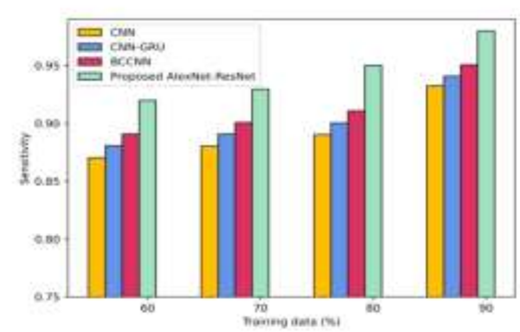
Based on examination, presented AlexNet-ResNet model is compared during the other traditional strategies, like CNN [2], CNN-GRU [3], BCCNN [4].

4.5.1 Training Data

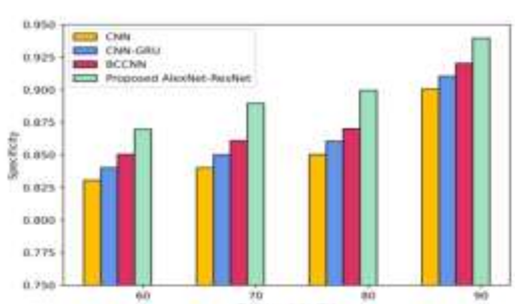
Figure 6 shows the comparative examination of presented approach when compared to other traditional methods. In figure 6(a), presented strategy gained impressive accuracy score of 0.899 when trained on a sample of 60%. In comparison, the CNN, CNN-GRU, and BCCNN methodsgained lower accuracy of 0.858, 0.862, and 0.887. Moving on to figure 6(b), shows a comparative analysis in terms of sensitivity, where the proposed AlexNet-ResNet strategy obtains a sensitivity value of 0.979 when trained on 90% of the training data. In distinguish, the CNN and BCCNN gained sensitivity of 0.932 and 0.9506. Figure 6(c), presents comparative examinationfor specificity demonstrates that presented AlexNet-ResNet model achieved specificity score of 0.889 with a 70% training data. In comparison, both CNN-GRU and BCCNN exhibited lower specificity values of 0.850 and 0.861. [27]



(a)



(b)

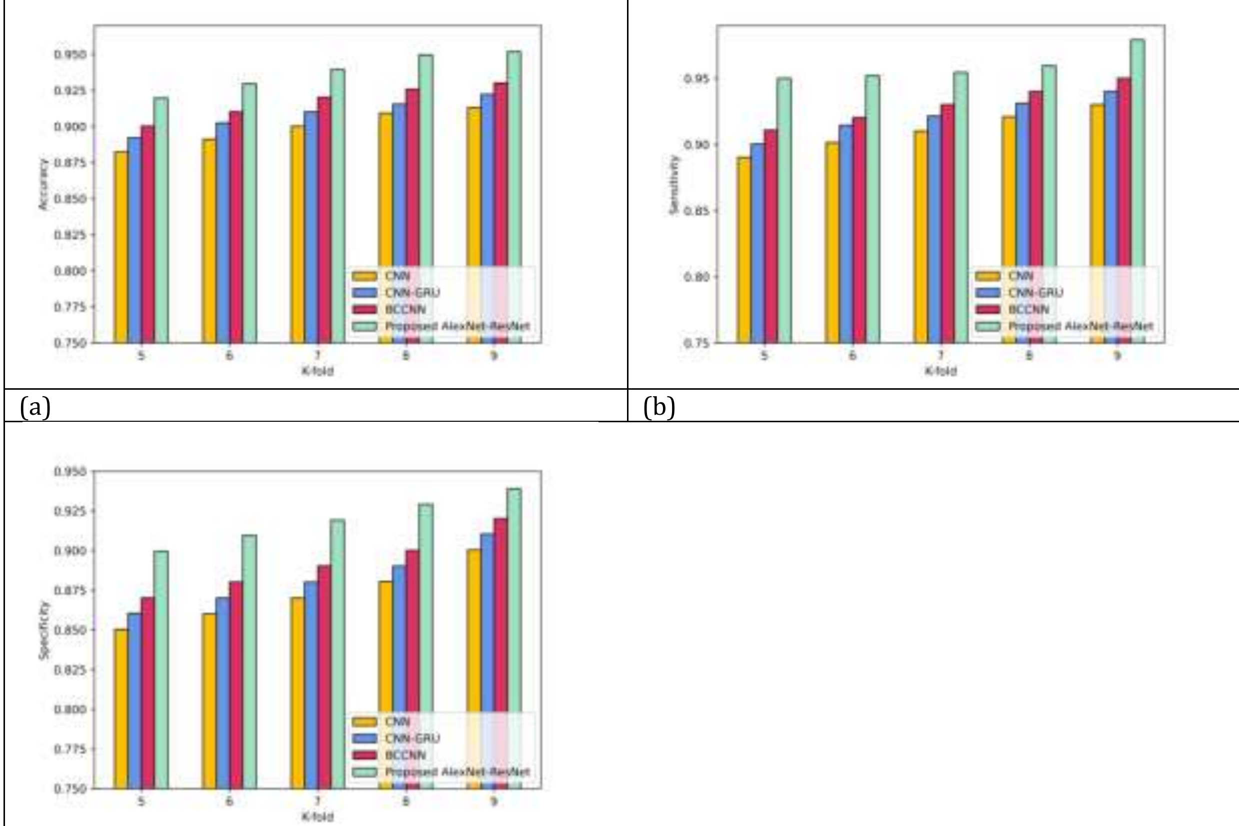


(c)

Figure 6: Comparative assessment of strategies in accordance with training data a) accuracy b) sensitivity c) specificity

4.5.2 K-fold

Figure 7 displays a comparison of effectiveness of the presented AlexNet-ResNet approach with traditional methods. Findings reveal that developed strategy surpasses the CNN, CNN-GRU, and BCCNN models in terms of sensitivity, specificity, and accuracy. Figure 7(a), presented approach demonstrates a remarkable accuracy score of 0.929 for a k-fold of 6, outperforming the other approaches. The findings in Figure 7(b) shows that the AlexNet-ResNet model proves to be more efficient in terms of sensitivity, as attained score of 0.954 for a k-fold of 7, which is elevated than sensitivity values of CNN-GRU (0.921) and BCCNN (0.930) models. Figure 7(c) portrays that presented strategy accomplished a superior specificity value of 0.939 for a k-fold of 9, while CNN and CNN-GRU models gained values of 0.900 and 0.910. [28]



(a) (b) (c)

Figure 7: Comparative evaluation of strategies in base of k fold (a) accuracy (b) sensitivity (c) specificity

Table 1 portrays comparative assessment of presented AlexNet-ResNet approach. AleNet-ResNet gained an accuracy of 3.86% when contrasted with CNN and attained 3.15% of accuracy when contrasted to BCCNN model. The developed strategy gained a specificity of 2.05% when compared to the conventional BCCNN. When contrasted to the CNN-GRU, AlexNet-ResNet attained a sensitivity of 4% more. Findings demonstrate that AlexNet-ResNet method outperformed other traditional approaches, suggesting it's prospective as an influential strategy for increasing the accuracy, [29] sensitivity, and specificity in image classifying responsibilities.

Table 1: Comparative discussion of presented method

Metrics	CNN	CNN-GRU	BCCNN	Proposed AlexNet-ResNet
Accuracy	0.9155	0.9223	0.9302	**0.9523**
Sensitivity	0.9323	0.9407	0.9506	**0.9799**
Specificity	0.9005	0.9104	0.9202	**0.9395**

5. Conclusion

Research presented a novel hybrid DL approach for breast cancer identification using AlexNet-ResNet with features of CNN. The presented approach was tested and trained on a CBIS-DDSM dataset of medical images, creating promising outcomes that surpasses accessible strategies. The presented hybrid strategy leverages the potency of both ResNet and AlexNet architectures to hold deeper neural networks to extort approach features from medical images. Moreover, the assimilation of CNN features permits the approach to enhance the generality aptitude, provide a superior perceptive to breast cancer identification. The presented hybrid DL strategy provides a capable explanation for breast cancer diagnosis, screening, and personalized treatment planning. The findings show the prospective of DL procedures in enhancing healthcare outcomes and encouraging future research efforts in the field of medical image classification. The approach attained an accuracy of 95.23%, sensitivity of 97.9%, and specificity of 93.99% representing high potential of DL in enhancing reliability and accuracy of breast cancer diagnosis.

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