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BREAST CANCER CLASSIFICATION ON ENHANCED SEGMENTED MAMMOGRAMS USING OPTIMIZED CONVOLUTIONAL NEURAL NETWORKS

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Abstract: Breast cancer ranks as the second most common malignancy among women and the second-most common reason for cancer deaths worldwide. Digital Mammogram screening can offer low-cost early diagnosis and reduce the breast cancer fatality rate among victims. This research aims to build a model that automatically assists in classifying malignant and benign lesions depicted on digital mammograms without any human interventions. The Mammographic Image Analysis Society (mini-MIAS) image dataset, which contains 322 mammograms, is employed in the present study. This research focuses on the Background Preserved and Feature-Oriented Contrast Improvement (BPFO-CI) method for contrast enhancement that uses the Weighted Cumulative Distribution Function. The Region of Interest (RoI) is then extracted from the improved mammograms using the Thresholding Segmentation method. Then extracted RoIs are used as input for classification using optimal Convolutional Neural Networks (CNN). Data augmentation is applied to the pre-processed dataset. The suggested pre-processed CNN model's performance is compared to various classification algorithms in pertaining to accuracy and confusion matrix. The simulation results confirm the importance and effectiveness of the suggested model in comparison to other well-known conventional approaches. As a result, this classification method is predicted to aid in the diagnosis of breast cancer.

Keywords: Breast Cancer; Digital Mammogram; Convolutional Neural Networks (CNN); Feature-Oriented Contrast Improvement (BPFO-CI); Thresholding Segmentation

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1. Introduction

Breast cancer is ranked as the most dangerous disease currently afflicting Indian women in terms of its severity and survival rate. In recent years, in it reported that younger age groups have greater percentage prevalence than the worldwide average (Kanimozhi et al., 2020). Screening at the early stage is the best solution to prevent and protect the victims from this dreadful disease. The American Cancer Society (ACS) provides some guidelines for screening, such as Annual and periodic screening is a must for women from the age of 40; doctors should administer Clinical Breast Exam (CBE) for every three years for women in the age of 20s-30s and every 12 months at 40 years and above; Screening should start ten years earlier than the index case for the women with family history in a first-degree relative (Kanimozhi & Shanmugavadivu, 2021). Early detection and diagnosis of breast cancer incorporated with screening are essential to reduce the death rate.

Mammography screening is currently considered the best medical imaging method in opposition to other particular modalities (Computed Tomography, Magnetic Resonance Imaging), which uses low-dose X-rays that serve as an advantageous tool for early detection of breast cancer. Mammography assimilates two types of views: Cranio Caudal (CC) view (Left (LCC), Right (RCC)), which shows top to bottom view, and Medio Lateral Oblique (MLO) view (Left (LMLO), Right (RMLO)) which displays the side view. The radiologists infer their opinion about masses, calcifications, architectural distortion, and asymmetries (Moreira et al., 2012).

Histogram Equalization (HE) is a common technique for a pre-processing process to enhance the contrast/ brightness of mammograms. HE calculates the occurrence of mammogram intensity within the dynamic range of the input mammogram. It has proven setbacks such as increased noise and enhanced foreground and background imbalance in the mammography (Sundaram et al., 2011), despite its computational advantages. Furthermore, HE cannot retain the average brightness of the input mammography in the enhanced mammogram, indicating a lack of edge and details preservation.

Bi-histogram partition-based techniques namely Brightness Preserving Bi-Histogram Equalization (BBHE) and Dualistic Sub-Mammogram Histogram Equalization (DSIHE), Mean Brightness Preserving Histogram Equalization (MBPHE), Recursive Mean Separate HE Method (RMSHE), and Minimum Mean Brightness Error Bi-HE Method (MMBEBHE) tend to alter the contrast and conserve brightness, in addition to their own merits and demerits (Wang et al., 1999; Kaur et al., 2011; Reddy, 2013; Gowri & Amudha, 2014; Gupta & Tiwari, 2017; Omer & Elfadil, 2017; Charate & Jamge, 2017; Singh & Bovis, 2005).

Adaptive Histogram Equalization is another HE version (AHE). It enhances contrast by extending contrast within the mammography kernel's range, but it falls short of preserving the mammogram's mean brightness. As a result, while computing intensity transformation/equalization, Contrast Limited AHE and its variants aim to eliminate the additional high frequencies grey levels (Pisano et al., 1998; Anand & Gayathri, 2015; Carneiro et al., 2019; Jenifer et al., 2016). However, their mammogram performances were insignificant because of their computational measures. These methods reduce the grey levels of tissues or obscure the breast tissues. For mammography improvement, this reported research study has employed the Background Preserved and Feature-Oriented Contrast Improvement (BPFO-CI) approach, which has outperformed other existing methods (Dhamodharan & Shanmugavadivu, 2021).

Threshold-based techniques are predominantly used in mammography pre-processing. Thresholding is a technique for transforming a higher-scale image into a binary image that separates the pixels in the foreground from those in the background, based on a given value, known as threshold value (Gonzalez, 2009). The global and local thresholding are the two types of thresholding techniques. The first option is to apply a single threshold value to the whole image. The second category is the pixel threshold value, which decides whether the pixel is in the background or foreground, based on the information around it. Thresholding is preferred for its simple and straightforward principle. Several thresholding approaches have been developed and are now in use in various applications, including medical image processing (Al-Amri & Kalyankar, 2010).

Computer-Aided Diagnostics are based on mammography images with precisely designed hand-crafted features, and classification can be done through machine learning (Ribli et al., 2018). Deep learning is becoming an increasingly important tool for making decisions. The developed models are trained using neural networks on a large number of datasets. Training a deep convolutional network since its introduction remains a challenge and requires a diverse large dataset for training (Hepsağ et al., 2017).

The remaining of this paper is shaped as describes here: Reviewing the related works which used thresholding-based segmentation and Deep Learning methods on several mammography databases is provided in section 2. Section 3 contains the dataset and methodology used in this article. Then the results and discussions are given in section 4. Conclusion and future works are gathered in section 5.

2. Related Works

This section provides a summary of the related scientific works on breast cancer segmentation and classification that have been published.

For identifying breast boundaries in mammograms, Ergin et al. recommended a thresholding strategy. To remove microscopic background artefacts like labels, in their described procedures, the images are filtered using median filtering, augmented by thresholding and morphological processes. The portion of the breast is then split by identifying the object with the most relative pixels. The findings of their suggested approaches were verified using visual inspection of segmentation precision, but no statistical performance indicators were supplied (Ergin et al., 2016). Palkar and Agrawal developed a global threshold method for erasing breast boundaries that used a fixed threshold of 32 and median-filtered images. The findings were further supported by a visual evaluation of segmentation accuracy (Palkar & Agrawal, 2016), which was performed without any extensive statistical analysis.

Ibrahim et al. devised a strategy that relied on a predefined threshold value of 18 to verify their findings rather than statistical performance metrics (Ibrahim et al., 2016). Qayyum and Basit employed Otsu's thresholding approach to extract the breast boundaries. To remove minor background elements like markings, prior to thresholding and morphological processing, median filtering is used to initially filter the images. The entity with the most related pixels determines the breast area (Qayyum and Basit, 2016).

Salama et al. proposed a technique that utilizes a 55% median filtering of the pictures before thresholding but no precise statistical performance indicators (Salama et al., 2018). Esener et al. used adaptive median filtering of the pictures before thresholding using Otsu's thresholding approach, but without incorporating any specific statistical performance measurements (Esener et al., 2018). Without any precise statistical performance indicators, Ancy and Nair developed an approach that uses a similar strategy but adds a contrast enhancement phase using Gamma correction before thresholding (Ancy and Nair, 2018).

Giger proposed that networks with multiple layers were applied to assess complicated patterns within the raw image input data by using deep learning, a subcategory of machine learning. It has been accomplished using deep convolutional neural networks (CNNs) that contain several layers and activation functions to tune the networks. The significance is that it trained the machines to train automatically from image data (Giger, 2018).

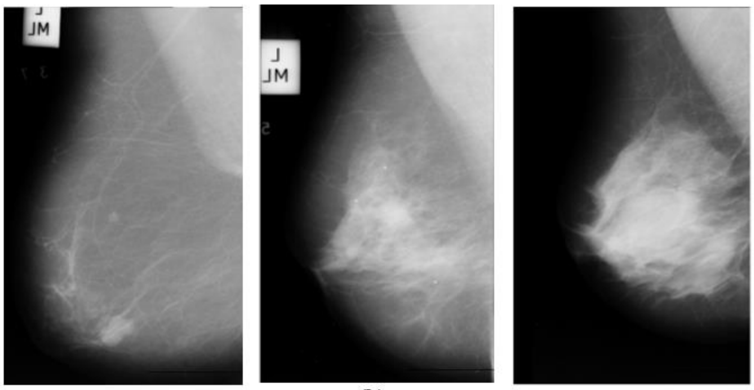
Qiu et al. have developed a CAD method for classifying masses between benign and malignant using Deep Learning. They used an image dataset of about 560 RoI images, out of which 280 were benign mass, and 280 were malignant mass. To evaluate the classification performance, 420 RoI were sent for training and 140 for testing. The training and testing accuracy were moderately produced by varying the epoch value. This method improved the CAD system to facilitate Deep learning techniques by providing standalone classifiers without large datasets (Qiu et al., 2016).

Charan et al. presented a new breast cancer detection method for mammograms using Convolutional Neural Networks (CNN). They used a mini-MIAS image dataset and the parameters, Minimum Batch Size, Maximum Epoch, and Learning Rate, were tuned to get the optimum result for training. The training datasets and the second one was on pre-processed RoI datasets. The accuracy of pre-processed images yielded better results than raw images because the parameters were already learned and fixed. The overall accuracy of 65% was obtained on RoI datasets, whereas it was 60% on raw datasets (Charan, 2018).

3. Methodology

3.1 Experimental Dataset

The "mini-Mammography Image Analysis Society" data collection (mini-MIAS) was used in this analytical study. It is a smaller collection of mammograms that comprises greyscale Portable Gray Map (PGM) format of 322 images with related ground truth data (Suckling, 1994) and images that are all reduced to a regular size of 1024 x 1024 pixels. There are three categories of mammograms in the dataset: glandular dense, fatty, and fatty glandular, each of which is further categorized into normal, benign, and malignant instances (Vishrutha and Ravishankar, 2015; Yen et al., 1995). **Figure 1** shows the sample mini-MIAS dataset images.



(a) (b) (c)

Figure 1 Sample images from mini-MIAS dataset: (a) fatty, (b) dense glandular, (c) fatty glandular

3.2 Background Preserved and Feature-Oriented - Contrast Improvement (BPFO - CI)

The BPFO - CI is used to improve the mammography by adding features to the background and foreground. The BPFO - CI calculates the background preserving grey-level threshold first and then traces symmetric dynamic grey level breakpoint. This is the difference between the background-holding threshold's grey level and the maximum grey level value of the input image. The input mammogram's grayscale dynamic range is separated into three sections: a background-preserving area and two symmetric areas. The mean is used to split the first symmetry range, while the median is used to divide the second symmetry range. The input mammogram's whole grayscale dynamic range is separated into five parts.

In order to accomplish background preservation, BPFO - CI assigns 0 to all grey levels below the background preservation limit. Then, for each of the remaining grayscale regions, PDF is calculated. The CDF is calculated using a weighted intensity adjustment factor derived from each subdivided intensity range in the proposed technique. This weighted Intensity Adjustment Factor guides (IAF) the CDF calculation. The IAF for each intensity range is the difference between the start and finish grey levels, with the exception of the last grey level range. In the last area, the difference between the maximum and the starting grey level value is utilised to compute the IAF. The WCF's grayscale regions are merged into a single WCF. Finally, improved mammography was obtained using WCF grayscale intensity mapping.

3.3 Yen Method

This approach can be considered as a version of Kapur's method. The value of the computed threshold is chosen to maximize the sum of background and foreground attributes. 'Correlation' is the name given to the creators of this approach. The greatest correlation criterion is another name for this strategy (Nithya & Shanmugavadivu, 2021). The correlation between foreground $(C_F)$and background (C_B) is denoted as follows:

$$K(T) = \underset{k\epsilon\{0,\ldots,L-1\}}{argmax}[(C_B + C_F)] \quad (1)$$

where,

$$C_B = \log_2\left[\sum_{i=0}^{k}\left(\frac{\omega_B}{p_i}\right)^2\right] C_F = \log_2\left[\sum_{j=k+1}^{L-1}\left(\frac{\omega_F}{p_i}\right)^2\right] \quad (2)$$

This method is used on mini-MIAS enhanced mammograms as the thresholding-based segmentation technique.

3.4 Convolutional Neural Networks

To attain improved accuracy, CNN requires a large dataset for training. Due to the scarcity of big datasets, training and testing were conducted using the most widely available dataset available on the internet.

Out of 322 pre-processed images in the mini-MIAS dataset consists of 209 normal images, 62 benign, and 51 malignant images. With these three classes, split as 70% training, and 30% testing images, as represented in **Table 1.**

Table 1 Partition of mini-MIAS dataset into training and testing set in the proposed work

Classes	**Pre-processed mini-MIAS images (322)**	
	Training Samples (70%)	**Testing Samples (30%)**
Normal	146	63
Benign	44	18
Malignant	36	15

After subjecting the images for training and testing from the dataset, deep learning-based CNN was built to classify normal, benign, and malignant.

The proposed CNN structure for the classification of breast cancer used Keras with TensorFlow as an open-source framework. **Figure 2.** illustrates the CNN architecture of the proposed classification work. It includes the Convolution layer, ReLU (Rectified Linear Unit) layer, Pooling layer, and fully connected layer. The input units are the pre-processed segmented images that can be fed into the convolution layer. The convolution layer is integrated with an activation function that produces one or more feature maps. The pooling layer further complements dimensionality reduction on the feature map(s) computed by the convolution layer. The pooling outcome is flattened into a vector and fed into fully connected neural networks that result in classification or prediction. **Figure 3**. depicts the overall workflow of the proposed work.

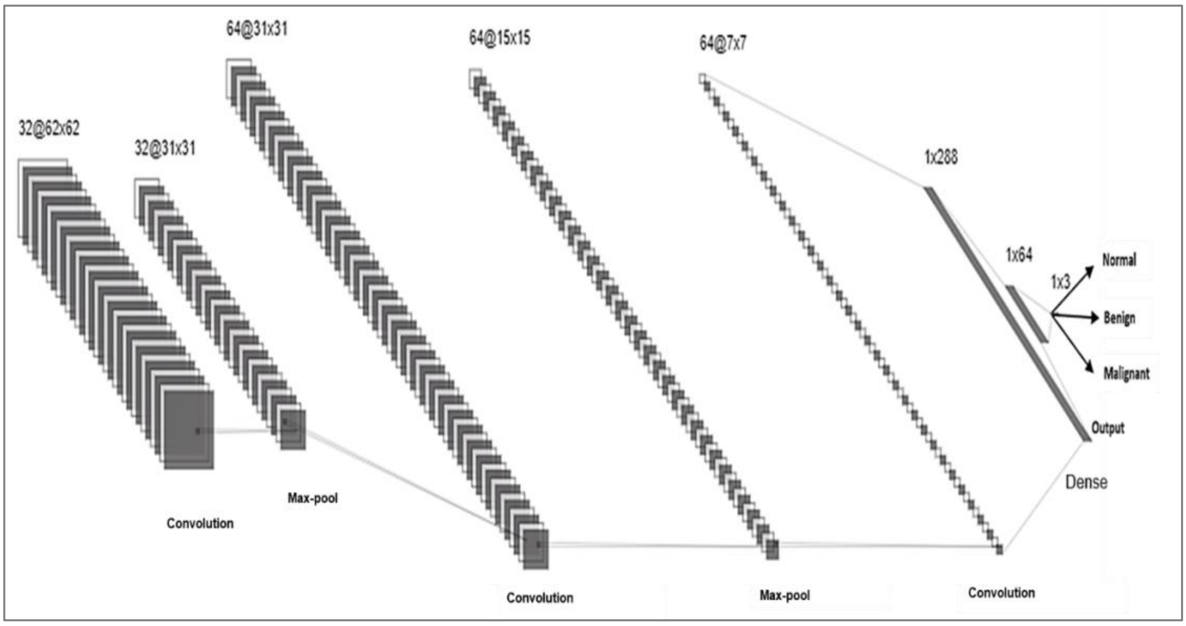


Figure 2 Illustration of proposed CNN architecture

4. Results and Discussion

This section displays the proposed research work's performance analysis. To accomplish successful abnormality region/object detection, segmentation, and classification, a mammogram has various artifacts that must be eliminated. Tags, pectoral muscles, and other non-breast areas are among the artifacts.

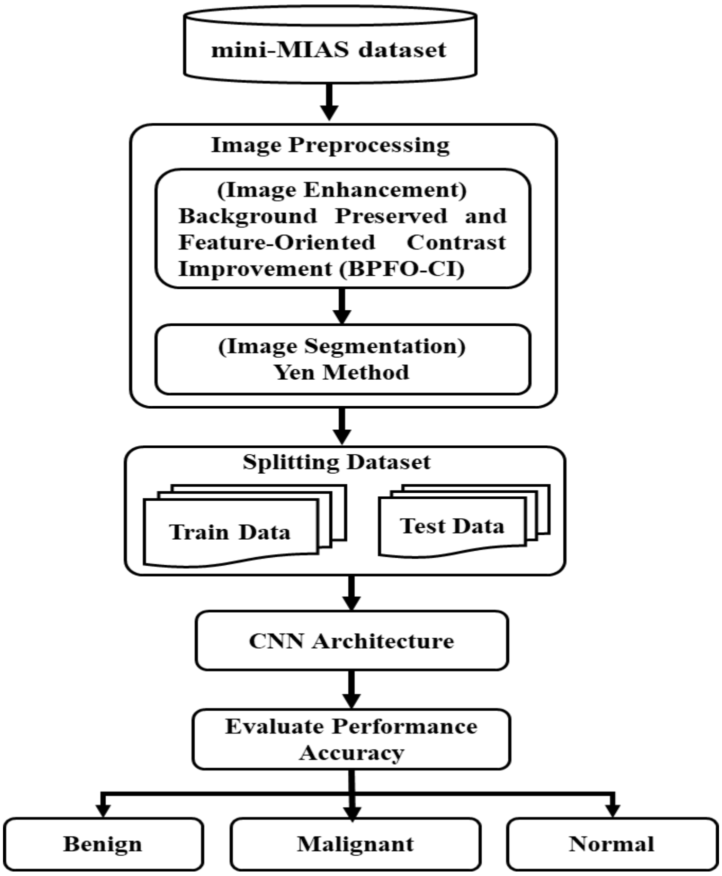
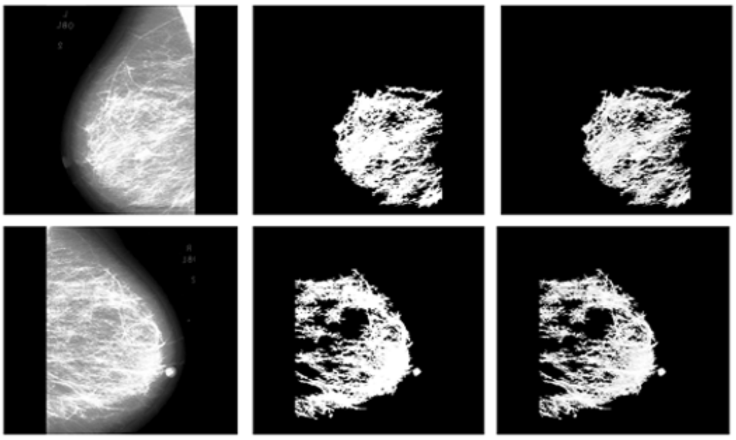


Figure 3 Overall workflow of the proposed work

4.1 Thresholding-based Segmentation

The thresholding-based Yen method is chosen for extraction of the artifacts. In this method, the original mammogram images are converted to binary images. In binary images, linked component labelling is used to detect connected parts. Its pixel-by-pixel scans an image (from left to right and top to bottom) and divides pixels into discrete connected-components based on pixel connection; that is, all the related pixels in a linked component have comparable pixel intensity values and are related in some way. This approach helps to remove the artifacts and to extract the breast region(s). Then, appropriate pixel mask is used on the original mammogram image's output image. Finally, the binary masks of the original mammogram and corresponding binary images is produced. The sample result of the yen thresholding method is proven in **Figure 4**.

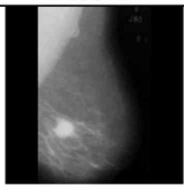
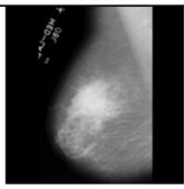
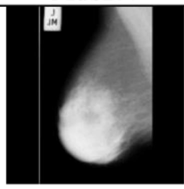
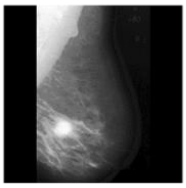
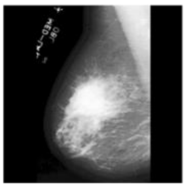
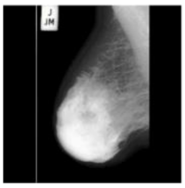
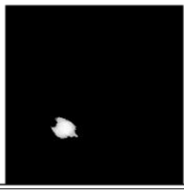
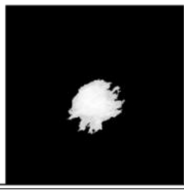
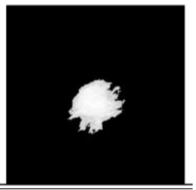


(a) (b) (c)

Figure 4 (a) Original enhanced image T2, (b) yen threshold image, (c) mask image

Table 2 depicts the outcomes of the BPFO-CI enhancement method and subsequent Segmentation process. The first row consists of the original mammogram of the MIAS dataset; the second and third-row rows contain BPFO-CI and Yen segmentation results of the respective original mammograms. From **Table 2**, the pre-processing method has produced the suspicious region of breast cancer in a mammogram for the classification process. It is confirmed to increase the classification process performance.

Table 2 Enhanced segmented mammogram images

MAMMOGRAM	Mdb028	Mdb081	Mdb257
Original			
BPFO-CI (Contrast Enhanced)			
(Thresholding based Segmentation)			

At first, the CNN architecture is created using the sequential model. The segmented mini-MIAS dataset used in this study contains 322 images with a regular range of 1024 x 1024 pixels. Four convolution layers were used with the grayscale images of stride=1. Four pooling layers were used to perform down sampling in order to minimize the computation as well as to improve the network robustness. ReLU is the most used activation function in order to classify those images based on CNN. This study evaluated the categorical classification problem, and thus Softmax activation function is used in the output node. After creating the layers, it is compiled with the categorical_crossentropy loss function, which is used to calculate the difference of the value between actual and predicted outputs, Adam as optimizer with a learning rate of 0.01 and accuracy as the metrics to measure the performance of the model are used. **Figure 5**. illustrates the summary of the sequential CNN model.

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_13 (Conv2D)          (None, 62, 62, 32)        896

 activation_5 (Activation)   (None, 62, 62, 32)        0

 max_pooling2d_5 (MaxPooling  (None, 31, 31, 32)       0
 2D)

 conv2d_14 (Conv2D)          (None, 31, 31, 64)        18496

 activation_6 (Activation)   (None, 31, 31, 64)        0

 max_pooling2d_6 (MaxPooling  (None, 15, 15, 64)       0
 2D)

 dropout_4 (Dropout)         (None, 15, 15, 64)        0

 conv2d_15 (Conv2D)          (None, 15, 15, 64)        36928

 activation_7 (Activation)   (None, 15, 15, 64)        0

 max_pooling2d_7 (MaxPooling  (None, 7, 7, 64)         0
 2D)

 conv2d_16 (Conv2D)          (None, 7, 7, 32)          18464

 activation_8 (Activation)   (None, 7, 7, 32)          0

 max_pooling2d_8 (MaxPooling  (None, 3, 3, 32)         0
 2D)

 dropout_5 (Dropout)         (None, 3, 3, 32)          0

 flatten_3 (Flatten)         (None, 288)               0

 dense_5 (Dense)             (None, 3)                 867

=================================================================
Total params: 75,651
Trainable params: 75,651
Non-trainable params: 0
```

Figure 5 Summary of the sequential CNN model

The training and testing data were sent through an image data generator for the image augmentation technique. Then, it used a batch size of 32 and trained on the whole dataset using 50 epochs. To prevent overfitting, a dropout layer is used between the convolutional layers. Early stopping is also used to monitor the overfitting issue.

CNN-based proposed Breast Cancer classification method on enhanced Segmented Mammograms has produced a satisfactory result. The accuracy of the classification in both training and testing samples is obtained by varying the epochs. The accuracy of the model obtained as 66% with 50 epochs and 32 as batch size for the given architecture is described in the classification report in **Figure 6**.

Classification Report

	precision	recall	f1-score	support
Benign	0.63	0.57	0.58	18
Malignant	0.54	0.49	0.50	15
Normal	0.66	1.00	0.79	63
accuracy			0.66	96
macro avg	0.22	0.33	0.26	96
weighted avg	0.43	0.66	0.52	96

Figure 6 Classification report of the proposed CNN model

The macro avg (average) and weighted avg represents the calculated metrics for each label and find their unweighted mean and their weighted average against Support, respectively. This developed model will be able to identify between normal, benign, and malignant instances based on the accuracy data. The results obtained using the proposed work proved to have a good classification accuracy of 66% for the mini-MIAS dataset.

5. Conclusion

This article reports the mechanics of developing the CNN model and categorising the mammogram images as normal, benign, or malignant, based on the improved segmented mammography images. First, the screened mammography images are processed using the BPFO-CI enhancement method and Yen segmentation method. The segmented images were fed into CNN for training and testing. By altering the epochs, the performance measures Precision, Recall, F1-Score, Support, and Accuracy were calculated. When tested with the dataset, this CNN-based CAD scheme demonstrated a variety of computational improvements over conventional CAD methods. A small collection of images was used to test the proposed research work. A new comprehensive analysis has to be carried out with a large dataset by incorporating pre-trained model, with the primary objective of achieving maximum accuracy of classification. This research work has amble scope to further develop a novel optimizer with optimal update rules for robust prediction rate and improved accuracy in breast cancer prognosis.

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