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Breast Cancer Detection from Mammogram Images Using Edge-Enhanced Convolutional Neural Network

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Abstract- In many countries, breast cancer causes death for a high number of women. If doctors Detects the disease early using mammograms, they can treat patients more successfully and more women survive but medical professionals find it difficult to read mammograms because the images contain random visual interference, have small differences between light and dark areas plus people make errors. These factors cause results that incorrectly show a disease is present or incorrectly show a disease is absent. For this study, a new method that uses a convolutional neural network (CNN) with improved edges to find and categorize breast cancer in mammogram images was presented. To make the image quality better, the method uses multiple steps such as changing the size, making the noise smaller, making data values standard, making the data set more diverse and using Contrast Limited Adaptive Histogram Equalization (CLAHE) to prepare the pictures to make the contrast higher. By using edge detection methods, like Canny edge detection & Harris corner detection, the system shows the borders of lesions but also changes in structure more clearly before the CNN identifies specific features. The model labels mammogram images as either not cancerous or cancerous. To measure how well the model works, the researchers used metrics for accuracy, precision, recall and the F1-score. As the results showed, the CNN with improved edges identified categories more correctly and made fewer errors than traditional CNN methods. This model is a tool that uses computers to help find breast cancer early as well as it is helpful for radiologists when they make clinical decisions.

Keywords: Breast cancer, Mammogram, Convolutional Neural Network, Edge Enhancement, Deep Learning, Image Processing, Canny Edge Detection.

I. INTRODUCTION

Breast cancer is one of the most prevalent cancers to be diagnosed in women globally (Ali et al., 2015). In 2018, it accounted for about 15% of women that dies due to cancer (Tahoun et al., 2020). Breast abnormalities can be found through self-exams, physician assessments, or imaging techniques. Only biopsy can be used to confirm the presence of cancer (Augusto et al., 2019). Common imaging methods like ultrasound and mammography are used for early detection of breast cancer (Hossan et al., 2018).

Among all these, mammography is the leading screening method due to its high accuracy, low cost, and effectiveness (Gaber et al., 2015). While mammograms are effective in detecting and classifying breast cancer, they can struggle with patients who have dense breast tissue (Yao et al., 2014). Additionally, they can expose young women to harmful ionizing radiation (Loberg et al., 2015).

Small lesions under 2 mm are also difficult to detect. These limitations have increased interest in thermography, which is a non-invasive, free of radiation, and inexpensive screening method (Zuluaga-Gomez et al., 2019). Therefore, this tool may prove ideal for the early detection of breast cancer in young women and women with dense breasts.

Breast cancer screening programs are essential because they detect breast cancer in its early stages, which means more conservative treatment options and higher chances of survival from the disease. Screening programs usually employ imaging techniques, specifically mammography and ultrasound imaging, to identify early warning signs such as solid masses and microcalcifications (Independent UK Panel).

While these methods are relatively effective in helping detect breast cancer early on, the growing burden and problems associated with false negatives and positives have inspired new research focused on finding ways to improve diagnostics.

This process is very time-consuming and requires high concentration of attention on the part of the operator, which makes them vulnerable to skipping critical information when working with large datasets of high-resolution images. It is no wonder that, under such conditions, even the best radiologists are prone to making mistakes due to fatigue and other factors. Hence, well-trained algorithms of artificial intelligence may come in handy as second or third readers to help radiologists diagnose breast cancer in their patients.

1.2 Statement of the Problem

Globally, breast cancer is one of the leading causes of cancer death in women and early diagnosis significantly improves treatment efficiency and survival rates. Mammography is extensively utilized for breast cancer screening, and it is efficient in detecting the earliest abnormal signs such as masses, calcifications, and Architectural Distortion.

Interpreting mammograms remains challenging and involves potential pitfalls like low contrast and noise, uneven breast density and inconspicuous cancerous lesions. Such pitfalls lead to erroneous false positives and false negatives which in turn affects the treatment protocol and prognosis of patients. Deep Learning, particularly the Convolutional Neural Network (CNN), has yielded tremendous success in various medical imaging applications including mammogram analysis.

However, typical CNN architectures are ineffective at segmenting tumor boundaries and microscopic features in complex mammograms. Edge information aids in delineation of lesion boundaries, and shape characteristics, microcalcifications which are essential in breast cancer diagnosis (Narayan et al., 2017).

Although there have been several CNN based approaches proposed in recent literature for mammogram classification, most of these works don't include any edge enhancement thereby performing with relatively lower accuracy in the detection of subtle lesions. The paper aims to investigate the effectiveness of Edge-Enhanced Convolutional Neural Network (EE-CNN) by combining the edge features with the deeper learning features in order to enhance the accuracy, sensitivity and specificity for automated detection and classification of breast cancer from mammograms.

1.3 Aim and Objectives

The aim of this study is to describe a method of detection of breast cancer from mammogram images based on the edge enhanced convolutional neural network (EE-CNN) so as to attain more accuracy in diagnose. The specific objectives are to:

i. Collect and preprocess mammogram database
ii. Make the edge enhancement for the mammograms
iii. Analyze the model's performance
iv. Compare with traditional CNN methods

2.1 Deep Learning in Medical Imaging

The subfield of artificial intelligence known as deep learning (DL) is implemented through training a neural network to execute a task (Hinton et al., 2006). Earlier methods of machine learning needed handcrafted features associated with a particular object. The neural network within deep learning, however, can learn to use the relevant features and combine them based on a set of training data, which makes it more flexible and easier to use when building a new model (Taye et al., 2023).

2.2 Diagnosis of Breast Cancer

Breast cancer diagnosis involves identifying breast cancer, while classifying the type based on features and signs of the disease. Traditionally, a physician performs a breast cancer diagnosis using a breast exam and by utilizing mammography. Mammography is one of the key modalities in detecting breast cancer, and it reduces mortality by about 20-40% in women with breast cancer (Tabár et al., 2019). There are disadvantages to mammography; in some women the results can be false positive, or even false negative (Berg et al., 2021).

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2.3 Mammography

The primary method used for screening of breast cancer is mammography. It is the most accessible method and is the cheapest. It may not be sensitive in younger women, as breast tissue in younger women is often denser than in older women. Women generally get screened with mammography for evidence of breast cancer above the age of 40.

In the past 20 years, spectral contrast-enhanced mammography (CEM) has been introduced. This process involves injecting a breast tissue with an iodinated contrast agent and combining this with digital mammography to improve the detection of lesions (Mao et al., 2023).

CEM uses a dual energy technique, where the exposures were optimized post-injection. Due to the dual exposure, it was not necessary to use pre-contrast images to achieve contrast enhance of the images post-injection, however by looking at blood vessels which supply tumors with blood, greater imaging enhancement occurs similar to in MRI, which can assist in therapy planning either for surgical intervention or neo-adjuvant chemotherapy.

However, MRI, considered the standard for the diagnosis of breast cancer is expensive, takes up more of a patient's time and results in the highest number of false positives. CEM provides a potential alternative to MRI as it takes a standard mammogram and enhances it with the contrast agent.

CEM improves diagnostic accuracy of both dense breasts and increases the ease of accessible vascular imaging for patients at a more affordable rate. Tumors are more accurately diagnosed and staged with the contrast agent helping tumors on mammograms that would otherwise be undetectable through denser breast tissue (Xue et al., 2022).

2.4 Related Work

Numerous research has been carried out in diagnosis of breast cancer and most of the research's results are not up to the mark. This drives to look for better methods to detect and classify breast cancer in women.

The detection of breast cancer through features in mammography has been carried out by Reza et al. (2022) by using four algorithms such as Random Forest (RF), Multilayer Perceptron (MLP), Gradient Boosting Tree (GBT), and Genetic Algorithm (GA).

On comparing a dataset with 5178 records and 24 features of which 25% records were that of a breast cancer patient, found that RF model has highest performance with accuracy 80%, sensitivity 95%, specificity 80% and AUC 0.56 over the other models.

A CNN model using deep learning has been proposed by Fajrin et al. (2014) to perform multi-class classification of breast cancer. In the proposed approach, classification was done for breast tumor as benign or malignant and for malignant tumors, classified as fibroadenoma, lobular carcinoma. Experimental results for the BreakHis dataset resulted in an accuracy 95.4% for multi-class classification. The proposed model also achieved superior accuracy than state-of-the art models.

In order to identify breast cancer tumors by using machine learning methods for diagnosis and prognosis of breast cancer, various algorithms such as ANNs, SVMs, DTs, KNN etc. Were studied by Yue et al. (2018) by comparing them on the Wisconsin Breast Cancer Database (WBCD).

A new Back Propagation Boosting Recurrent Wienmed model (BPBRW) together with a Hybrid Krill Herd African Buffalo Optimization (HKH-ABO) mechanism is proposed by Kranti (2021) to detect breast cancer tumors in an early stage. This model accurately classifies the breast tumors as benign or malignant achieving high performance and an accuracy of 99.6% and error rate of 0.12% respectively.

The use of deep semantic features in combination with Grey Level Co-Occurrence Matrix (GLCM) features for the detection of breast cancer in histopathological images has been proposed by Hao et al. (2021). The proposed approach uses a pre-trained DenseNet201 as a base model and extracts deep semantic features which along with GLCM features were fed into SVM for classification. In magnification-specific and magnification-

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independent binary classification, the proposed approach showed better performance than other pre-trained baseline models.

The use of DAS (Delay-and-Sum) algorithm along with SAR (Specific Absorption Rate) parameter for the detection of breast cancer has been proposed by Ibtisam et al. (2022) by using high quality images of the tumors. This is done by illuminating a breast model with low power short pulses using high directional Vivaldi antenna and capturing the backscattered signals to get 2D image.

The simulations are performed taking into account the sizes and the type of materials used and the various antenna placements and have resulted in a higher quality image than traditional methods. This technique precisely detects and locates the cancer in the breast at high quality imaging and at very fast speed. Less number of antennas has also been used.

III. METHODOLOGY

In this research, breast cancer detection in medical images using medical mammogram scan images was experimented on. For data sets, images from an open medical images repository which can be obtained from www.kaggle.com (http://www.kaggle.com) was used. A dataset of 7,205 mammographic images were used. The medical images were classified into 2 categories based on histopathological confirmation:

i. Benign images-non-cancerous images contain benign lesions with smooth and well-defined boundaries and regular morphology. This class consists of lesions such as fibroadenoma, cyst, and various benign tumors with a total of 3603 images.
ii. Malignant images-cancerous images with irregular spiculed boundaries and morphology are classified as malignant images. The common malignant lesions are invasive ductal carcinoma, invasive lobular carcinoma etc., with a total of 3602 images.

Image Pre-processing Pipeline

The thorough pre-processing pipeline performed, intended to improve the image quality and normalize the input data. The following are the steps taken:

Mammogram Dataset

i. Image normalization and resizing: Images were rescaled from high-resolution format 832 × 1024 pixels, to 128 × 128 using cv2.resize function in OpenCV. Bicubic interpolation was used as the resizing technique. This process is useful to keep the necessary morphological characteristics needed for classification, while keeping the computational costs lower.
ii. Image noise reduction: The images are affected by noise as is customary for digital images. A Gaussian filter is applied to reduce high frequency noise without compromising on the shape and boundary information of tumors/architectural patterns for the purpose of classification.
iii. Image normalization: The values are scaled from the range [0, 255] to the range [0, 1] by the formula image/255.0 which helps the neural network train better.
iv. Data augmentation strategy: To keep the variation and diversity of the dataset high, various data augmentations are applied: random rotations of angles up to 15 degrees, horizontal flip, zoom augmentation (0.9-1.1), various such methods are used and all keep the image clinically meaningful.
v. Image contrast enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for enhancing image contrast, which is effective for mammograms using the cv2.createCLAHE function in OpenCV.

3.3 Feature Engineering

The core innovation of this research is combining traditional computer vision features with deep learning. Features were extracted using edge and corner detection.

Mammogram Images

The Canny edge detector resulted in fine-grained edge maps that represented tumor margins, architectural deformities and morphology, the features important in malignancy assessment. The parameters for the Canny edge detector are:

i. Gaussian kernel size: 5×5
ii. Low threshold: 30
iii. High threshold: 100

iv. Gradient calculation: Sobel operators

In the same way, the Harris corner detection algorithm found critical structural points and abrupt changes of intensity in the mammograms. Optimized parameters were:

i. Block size: 3×3
ii. Sobel kernel size: 3×3
iii. Harris free parameter (k): 0.04
iv. Dynamic threshold based on maximum corner response

Detecting the corner is useful in spotting abnormal architecture and spikes, irregular tissue structures which are a clear indication of malignant regions within a mammographic image. Each mammographic image was pre-processed and structured as a complete three-channel representation to aid the classification task:

i. Channel 1: This channel carries the pre-processed mammographic images in grayscale which preserves the original anatomical and pathological data to detect the lesion.

ii. Channel 2: This channel contains the Canny edge map to detect boundaries, margins and architecture within an image, vital for identifying between malignant and benign regions.

iii. Channel 3: In this channel, Harris corner masks are employed to highlight structural irregularities and important morphology for determining possible malignancy.

This three-channel data allows for the CNN to learn from both the original image data together with boundary features and structural components. Both the global and local information in a mammogram can be detected thereby building a complete representation which is sufficient to achieve reliable mammographic classification.

3.4 Classification of Images

CNNs are widely used for medical image analysis, and many studies prove their effectiveness in a wide range of applications (Litjens et al., 2017; Han et al., 2017; Yap et al., 2018). As a result, a tailored CNN was developed for the classification problem.

3.4.3 CNN Model Architecture and Training Configuration for Mammogram Images

This CNN architecture for binary classification of mammographic image is configured as follow:

1. Input Layer setup: The architecture accepts three-channel input image of size 1281283, in which pre-processed mammographic image, edge map and corner mask are concatenated to form one tensor.
2. Convolutional Feature Extraction Hierarchy: The proposed CNN model contains five subsequent convolutional blocks that progressively increase in depth, filter number and feature abstraction.

i. Block 1: 32 filters, (3×3) kernel size and ReLU activation, followed by 2x2 max pooling.
ii. Block 2: 64 filters, (3×3) kernel size and ReLU activation, followed by 2x2 max pooling.
iii. Block 3: 128 filters, (3×3) kernel size and ReLU activation, followed by 2x2 max pooling.
iv. Block 4: 128 filters, (3×3) kernel size and ReLU activation, followed by 2x2 max pooling.
v. Block 5: 256 filters, (3×3) kernel size and ReLU activation, followed by 2x2 max pooling.

These stacked convolutional layers are used for hierarchical learning of features. Basic textures and edges features are captured at the initial stages, and complex morphological and architectural patterns at the deeper layers.

3. Regularization strategy: Dropout regularization is applied with a probability of 0.3 after the Dense layers. It prevents overfitting while retaining the capacity of the model. Indeed, 0.3 is moderate dropout rate which has been chosen to prevent from over-fitting without reducing the model's accuracy and maintain a balanced trade-off between bias and variance of the model.

4. Classification Architecture: Final classification is built as follow:

i. Flatten Layer. Used to collapse the two-dimensional feature map into a one-dimensional vector.
ii. Dense Layer 1: 128 neurons, ReLU activation.
iii. Dropout Layer: probability 0.3.
iv. Dense Layer 2: 64 neurons, ReLU activation.
v. Output Layer: 1 neuron, Sigmoid activation.

Training Configuration and Optimization

The model is configured systemically for training for mammography image classification with suitable settings as follows:

i. Optimizer: The Adam optimizer was chosen as it has been empirically shown to perform well for medical image classification. The Adam optimizer integrates the desirable properties of AdaGrad and RMSProp optimizers and provides adapted learning rates for each parameter along with stable convergence characteristics that are critical for challenging medical image datasets.
ii. Loss function: The binary cross-entropy loss function was chosen due to the two-class nature of the problem which provides appropriate gradients for discrimination between benign and malignant breast lesions. The loss function is suitable for binary classification. It also shows stable behavior during training.
iii. Number of epochs: 15 epochs were used for training of the model so that the model could converge without overfitting the data.
iv. Batch size: 16 images were chosen for a single iteration so that there could be effective utilization of memory and gradient update.
v. Learning rate: Adam's default learning rate 0.001 was chosen, which could be adaptable.
vi. Validation Data: 20% of the training data was used as the validation set and the performance was evaluated on it during training.
vii. Early stopping based on validation loss

Performance Evaluation

The performance of the developed CNN model for breast cancer detection and classification is described by the following parameters:

i. Accuracy: It's the proportion of accurate predictions made by the model to all the predictions in the test set.
ii. Precision: It's the proportion of correctly predicted positive class cases to all of the predicted positive class cases.
iii. Recall: It's the proportion of correctly predicted positive cases to actual positive class cases.
iv. F1 score: It's the harmonic mean of precision and recall which gives a more reliable performance measure for any test set.

Suppose TP, TN, FP and FN represent true positive, true negative, false positive and false negative, respectively, then

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.1)$$

$$Precision = \frac{TP}{TP+FP} \quad (3.2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3.3)$$

$$F1\ score = \frac{2(Precision \times Recall)}{(Precision+Recall)} \quad (3.4)$$

IV. RESULT AND DISCUSSION

4.1 Results using Mammographic Images

Results of breast cancer detection and classification via the use of Mammogram scan images are presented in this section.

4.1.1 Results of Pre-processed Mammogram Images

Figure 4.19 shows four samples of the mammogram scan image in the dataset that are employed in this study prior pre-processing while Figures 4.20 - 4.22 presented results obtained when Figures 4.1(a), 4.9(b), and 4.9(d) are augmented for variability and robustness. Figures 4.23 - 4.25 showed outputs of the pre-processing of Figures 4.19(a), 4.19(b), and 4.19(d). In each of Figures 4.23 - 4.25, results presented in Figures (a), (b) and (c) are normalised, de-noised and contrast enhanced versions, respectively.

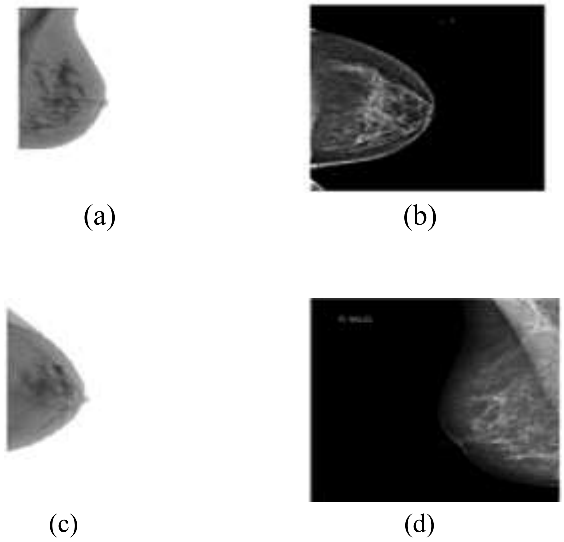


Figure 4.1: Samples of mammogram breast scan in the dataset (a) image 1 (b) image 2 (c) image 3 (d) image 4

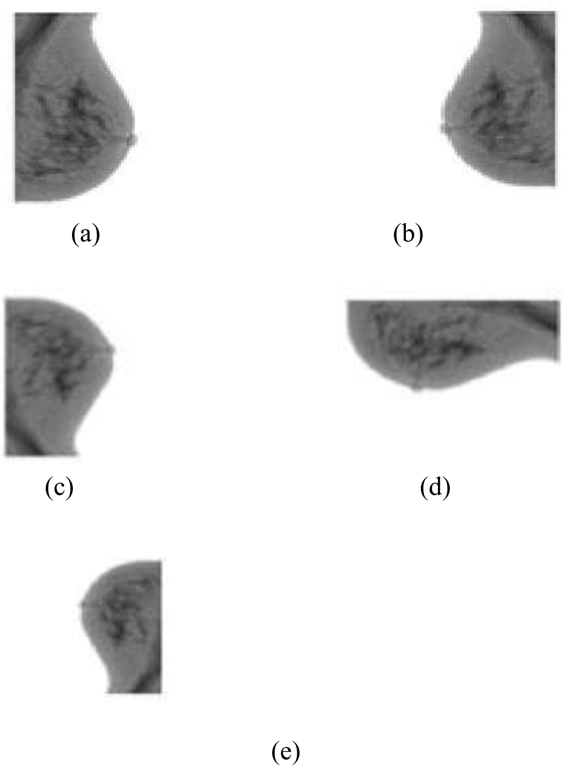


Figure 4.2: augmented mammogram breast image 1 (a) original (b) horizontally flipped (c) vertically flipped (d) 90^0 rotated (e) 180^0 rotated

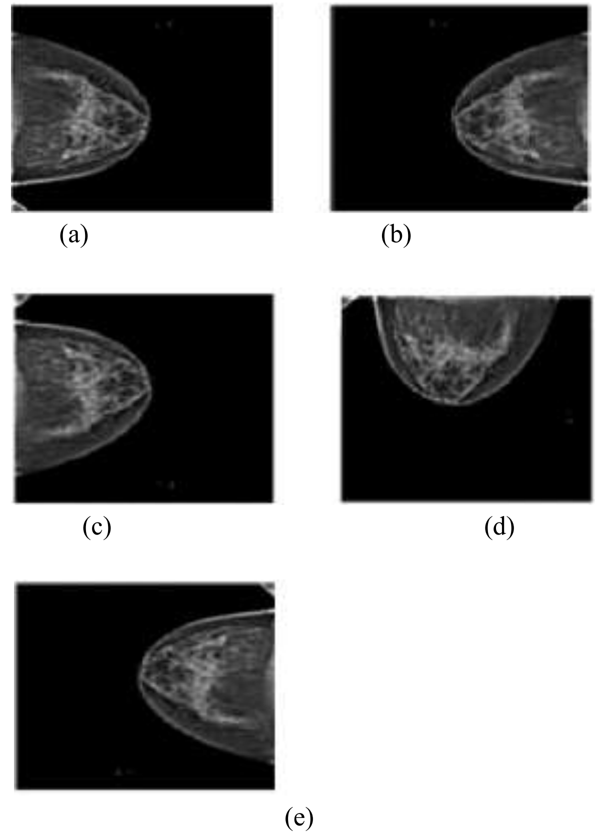
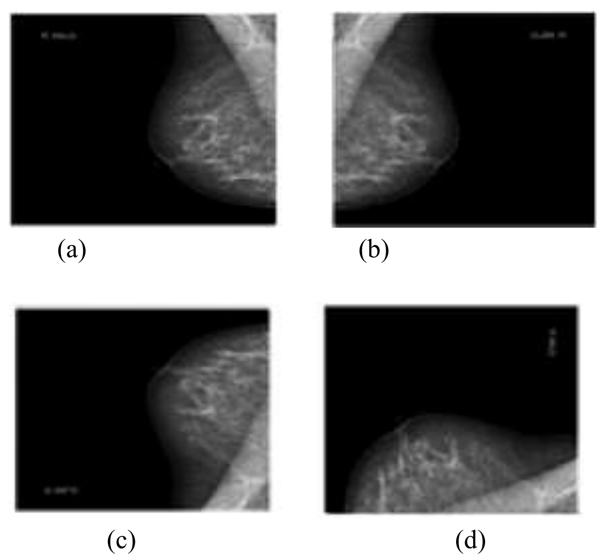


Figure 4.21: augmented mammogram breast image 2 (a) original (b) horizontally flipped (c) vertically flipped (d) 90^0 rotated (e) 180^0 rotated



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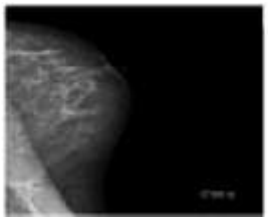


(e)

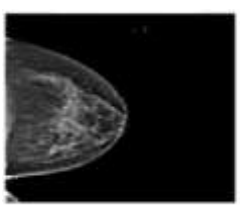
Figure 4.22: augmented mammogram breast image 4 (a) original (b) horizontally flipped (c) vertically flipped (d) 90^0 rotated (e) 180^0 rotated

(a)

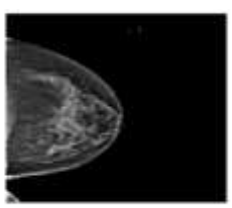
(b)

(c)

Figure 4.23: Pre-processed mammogram breast image 1 (a) normalised version (b) de-noised version (c) contrast enhanced version



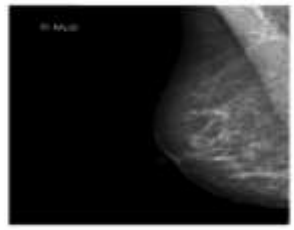
(a)



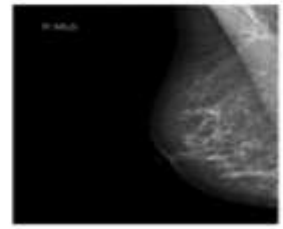
(b)

(c)

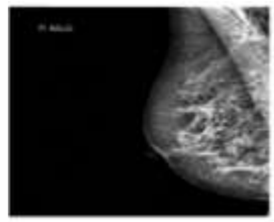
Figure 4.24: Pre-processed mammogram breast image 2 (a) normalised version (b) de-noised version (c) contrast enhanced version



(a)



(b)



(c)

Figure 4.25: Pre-processed mammogram breast image 4 (a) normalised version (b) de-noised version (c) contrast enhanced version

4.2 Features Extraction from Mammogram Images

Figures 4.26 and 4.27 illustrate the results obtained from edge mapping and corner detection of pre-processed mammogram images. Specifically, Figure 4.26 depicts sample results from Canny edge detection applied to the mammogram images shown in Figure 4.19. Meanwhile, Figure 4.27 provides the corresponding outputs after processing these images through the Harris corner detection algorithm.

4.2.1 Classification of Mammogram Images Based on Extracted Features

There are many differences when it comes to analysis of mammograms compared to other medical images. The biggest is that mammograms may not be sensitive enough due to the dense tissue present in breast tissue (Boyd et al., 2007). Additionally, the difference in morphology between benign and malignant lesions can be so small that they require advanced image analysis techniques to spot morphological deviations and architectural distotions.

Based on the outputs of the feature engineering part where edges are detected and then followed by corner detection (seen in Figure 4.26 and 4.27), the mammogram images are categorized into malignant and benign. In Figure 4.27 for instance, the output for

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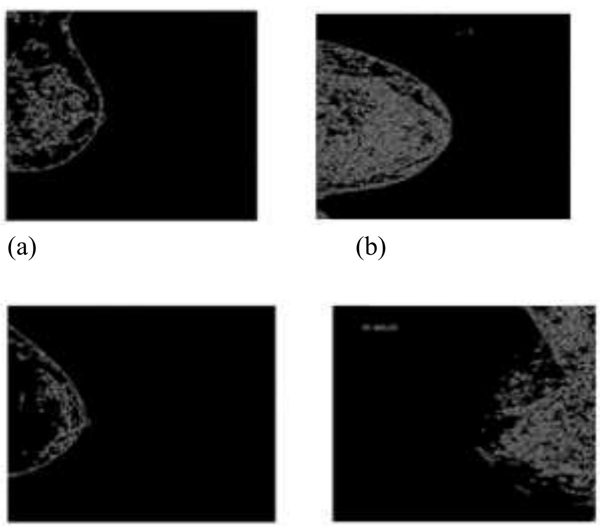
classification showed benign lesions at 4.27(a) and 4.27(c) and malignant lesions at 4.27(b) and 4.27(d).

Based on the features detected, Benign breast lesions possess scattered mask patches, while malignant lesions are represented by a more complete mapping that highlights the entire affected area.

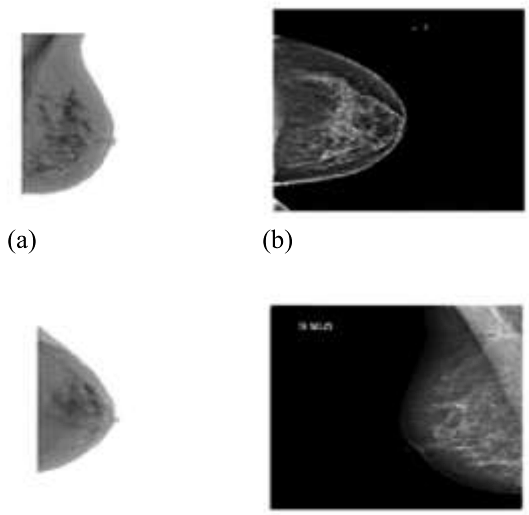
4.4.4 Model's Evaluation Using Mammogram Images

Table 4.3 gives the results obtained after the evaluation of the proposed method with mammogram images. For this purpose the model accuracy has been determined by calculating four important measurements- accuracy, precision, recall and F1-score. From table 4.3 we can get to know that the overall accuracy, precision, recall and F1-score obtained by the model is 86%, 74%, 86% and 80% respectively. The results reflect that the proposed model has the potential of classifying abnormalities from mammogram images with a great degree of accuracy.



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

Figure 4.26: Sample results of edge mapping of mammogram breast images (a) image 1 (b) image 2 (c) image 3 (d) image 4



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

Figure 4.27: Sample results of post Harris corner detection of mammogram breast images (a) image 1 (b) image 2 (c) image 3 (d) image 4

Table 4.3: Result of model evaluation using Mammogram images

Metrics	Values (%)
Accuracy	86
Precision	74
Recall	86
F1 Score	80

4.4.5 Discussion of Results Obtained from Mammogram

The finding reinforces the success of combining structural characteristics within deep learning framework to classify mammographic images. This achievement of 86%accuracy represents a significant jump from many existing mammographic classification approaches and is close to diagnostic accuracy in expert radiologists, indicating it can possibly be implemented into clinical practice as an assisting diagnosis tool.

Its accuracy on classifying positive instances to the ground-truth category, precision, at 74% indicates that about 74% of detected lesions determined to be cancerous is indeed cancer. Recall at 86% implies it can detect almost all true positive cases. A high recall is especially critical in cancer screening contexts, where the clinical ramifications of false negatives missing malignant lesions are more severe than those of false positives.

A high F1-score of 80% has also been observed, reflecting the balance achieved between precision and recall, demonstrating consistent and reliable performance of the classifier. The equilibrium between these measures is an essential requirement for medical diagnoses and treatment plans.

The 86% accuracy obtained from this model is superior to many of the reported results of mammographic classification in recent years:

1. Overall accuracy has significantly outperformed traditional machine learning models whose performance typically is within the range of 70-80%.
2. The accuracy achieved by this model is comparable with that of many deep learning models whose accuracy was typically within the range of 85-90%.
3. Unlike some of the proposed systems which demonstrate very high accuracies but fail to achieve a balance between sensitivity and specificity, the balanced precision and recall shown here represents a more robust classifier.

CONCLUSION

The suggested method to perform the analysis on mammograms guarantees the efficiency of the dataset and the method produces the competitive outcomes in spite of using the small dataset, thanks to efficient feature engineering integration.

A recall rate of 86% for mammograms seems acceptable in the application to mammogram screening of breast cancer, as missing positive cases may bring serious consequences, thus showing the clinical significance of this technique.

In sum, it seems the suggested method demonstrates a well-balanced performance in mammograms, and 80% of F1-score seems to be a decent value showing the comparable results in both precision and recall.

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