

Breast Cancer Detection in Magnetic Resonance Images using Edge-Enhanced Convolutional Neural Network

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ABSTRACT

Early detection of breast cancer plays a crucial role in its diagnosis and treatment. This research presents an edge-enhanced Convolutional Neural Network (CNN) model for breast cancer detection and classification using Magnetic Resonance Imaging (MRI) scans. A dataset of 1480 breast MRI scans (comprising of healthy and diseased MRI breast scans) was sourced from Kaggle, an open repository for medical images. The images were pre-processed via resizing, de-noising, normalization, and contrast enhanced using contrast limited adaptive histogram equalization (CLAHE) to obtain uniform and standard images. Pre-processed images were then split into training, testing and validation sets in the ratio 60:20:20. To enhance the structural descriptors, the grayscale MRI images were further processed by means of Canny edge- and Harris corner- detection algorithms, leading to generation of additional two versions of each of the images: Canny edge map and Harris corner mask. These two versions together with the grayscale version constitute the three inputs that were fed into the CNN model. The CNN model uses three convolutional blocks with rectified linear unit activation, max-pooling, dropout regularization, a sigmoid output, binary cross-entropy loss with Adam optimizer for 15 epochs and batch size of 16. The model achieves an accuracy, precision, recall, and F1-score of 97%, 99%, 95%, and 97%, respectively. The results indicate that incorporating explicit edge and structural information into the CNN input can enhance the aid detection of breast cancer in MRI images

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INTRODUCTION

Cancer can almost develop in every part of human body, where cells have the uncontrolled growth (Nenclares and Harrington, 2020). Cancer accounts for about 9.6% of deaths globally, which makes it to be regarded as the most common disease worldwide (Siege et al., 2020). Breast cancer is categorized as one of the most significant diseases contributing to the highest mortality rates among women, particularly in developing countries (Sung *et al.*, 2021). Although breast cancer is more likely to develop in women than in men, but they can be affected by breast cancer as well (Abdelwahab, 2017). The major anatomy of women's breast is consisted of the milk duct, lobules and adipose tissues (Nahid and Kong., 2017). Breast cancer can develop in the ducts that deliver milk to the nipple or in the glands of lobules that develops and produces breast milk.

Medical imaging plays a central role in breast cancer detection and diagnosis, with mammography, ultrasound, and magnetic resonance imaging (MRI) providing complementary information. Among these modalities, breast MRI provides high soft-tissue contrast and can provide detailed information concerning breast lesions. MRI is particularly useful in situations in which conventional imaging methods may be insufficient and is widely used in breast cancer diagnosis, staging, treatment response assessment, and surveillance (Tang *et al.*, 2023). In addition, MRI is an important breast-imaging modality because it provides high contrast between different soft tissues. Breast MRI may include conventional anatomical sequences and dynamic contrast-enhanced sequences. In deep-learning studies, researchers have used T1-weighted, T2-weighted, diffusion-weighted, multipara

metric and dynamic contrast-enhanced MRI (Abdullah *et al.*, 2025).

While breast MRI provides detailed information about breast tissue and lesions, interpretation can be difficult because of variations in lesion appearance and the similarity that may exist between some benign and malignant lesions. Conventional computer-aided methods based on manually engineered features may not adequately represent the complex characteristics of breast lesions. Hence, the need for a more accurate and robust approach.

Many researchers have expended efforts in the quest of finding solution to the problem of aiding radiologist judgement in respect of detection and diagnosis of breast cancer using MRI scans. In the area of computer-aided medical imaging, hierarchical unsupervised learning of imaging features from a deep convolutional neural network (CNN) was proposed by Zhang *et al.* (2016), allowing the acquisition of increasingly complex image features directly from the raw image by learning to discover the relevant features rather than eliciting them beforehand. Mohamed *et al.* (2022) proposed a U-Net based breast cancer detection system. The U-Net was employed in the isolation of breast area from the rest of the body part. Thereafter, a two-class deep learning model was used to classify breast tissues into normal or otherwise using thermal images of the breast. The proposed system was evaluated using DMR-IR dataset and achieved accuracy of 99.33%, sensitivity of 100% and specificity of 98.67%. These and many more deep-learning approaches have improved automated breast-image analysis, but conventional CNNs primarily learn features from the intensity information presented to the network. Important structural information, particularly lesion boundaries and margins, may not be explicitly emphasized.

Research has demonstrated that edge information can contribute to breast cancer detection in MRI scans. Tang *et al.* (2023) showed that the integration of Sobel-derived edge information with multimodal MRI inputs improved the classification of benign and malignant breast masses. However, further investigation is required into a clearly defined edge-enhanced CNN framework that integrates original MRI information and explicit edge representations for breast cancer classification. This study addresses the problem by proposing an edge enhanced-CNN model for detection presence or otherwise of breast cancer in MRI images, through incorporation of edge information into CNN model for improved representation of breast lesions and facilitation of automated classification.

MATERIALS AND METHODS

The study utilized a dataset comprising 1,480 MRI scans that was sourced from Kaggle.com. The dataset was categorized into two distinct classes:

- i. Healthy MRI scans: images showing normal breast tissue without pathological findings;
- ii. Diseased MRI scans: images containing malignant or suspicious lesions.

A comprehensive pre-processing pipeline was implemented to enhance image quality and standardize input data. Such pre-processing procedures on the images are image resizing, noise reduction, normalization, data augmentation, and contrast enhancement. Adopted procedures are briefly highlighted as follows:

- i. Image resizing - images are standardized from their original resolution of 540×250 pixels to 128×128 pixels using OpenCV's `cv2.resize()` function. This standardization ensures consistent input dimensions for the neural network while maintaining computational efficiency without compromising loss of image details.
- ii. Noise reduction - Non-Local Means de-noising was applied using OpenCV's `fastNlMeansDenoisingColored()` function to reduce noise while preserving important structural details in tumour regions. This technique is particularly effective for medical images where fine details are crucial for accurate diagnosis.
- iii. Normalization - pixel intensity normalization is performed by scaling values from the original range [0, 255] to [0, 1] using the transformation `image/255.0`. This normalization stabilizes training and prevents large pixel values from dominating the learning process.
- iv. Data augmentation - To enhance dataset diversity and improve model generalization, several augmentation techniques are applied which include rotation at random angular rotations to simulate different imaging orientations, horizontal flipping to mirror transformations and increase data variety, zooming to realize scale variations and simulate different imaging perspectives.
- v. Contrast enhancement - CLAHE was implemented using OpenCV's `cv2.createCLAHE()` function to enhance local contrast while preventing over-brightening, thereby improving tumour visibility.

The final output pre-processed images constitute the grayscale image versions of the original 1481 images in the dataset. What is done next is the creation of edge maps in each of the pre-processed images via the use of Canny edge detection algorithm.

Rather than implementation of Canny edge detection algorithm from the scratch for the creation of edge maps that highlight tumour boundaries and tissue interfaces, in the images, the OpenCV `Canny()` function in the python library was used. The OpenCV `Canny()` generates the required binary edge maps that emphasize structural boundaries that are crucial for tumour identification.

Post edge mapping leads to identification of areas where sharp changes in intensity occur in images. Harris corner detection was implemented to identify sharp intensity changes and key structural points within the images. The OpenCV `cornerHarris()` function generated corner masks that capture geometric irregularities often associated with pathological tissue.

At the end of corner masking stage, each of the MRI scans is transformed into a three-channel representation, which are:

- i. Channel 1: pre-processed MRI grayscale image;
- ii. Channel 2: Canny edge map for pre-processed MRI grayscale image; and
- iii. Channel 3: Harris corner masks for pre-processed MRI grayscale image.

It is these three-channel representations that is split into ration 60:20:20 for training, testing, and validation sets, respectively that are fed into CNN model. This multi-channel approach enables the CNN to simultaneously learn from the original image data and the engineered features.

The architecture of a custom CNN designed specifically for this binary classification task consists of 4 layers, which are input, convolution, regularization and classification layers. The model accepts three-channel input images of dimensions $128 \times 128 \times 3$, incorporating the preprocessed image, edge map, and corner mask representations of each of the images. Three sequential convolutional blocks were implemented, which are:

- i. Block 1: 32 filters with ReLU activation;
- ii. Block 2: 64 filters with ReLU activation; and
- iii. Block 3: 128 filters with ReLU activation.

Each block includes max pooling layers for dimensional reduction and computational efficiency.

Next is the regularization layer where dropout layers with 0.5 probability are integrated after dense layers to prevent overfitting and improve generalization capability of the CNN model. Lastly but not the least is the classification layer, which includes:

- i. Flatten layer for dimension reduction;
- ii. Dense layer with 128 neurons and ReLU activation; and
- iii. Output layer with sigmoid activation for binary classification.

The model was trained using the following parameters:

- i. Optimizer: Adam (Adaptive Moment Estimation) for adaptive learning rate optimization;
 - ii. Loss Function: Binary cross-entropy for binary classification tasks;
 - iii. Epochs: 15 training cycles; and
- Batch Size: 16 images per batch for optimal memory utilization and training stability

RESULTS AND DISCUSSION

Figure 1 showed four samples of the MRI scan image in the dataset utilised in this research before pre-processing while Figures 2-3 presented results obtained when the first and third images in Figure 1 are augmented. Figure 4 showed outputs of the pre-processing stage for image 1 and image 3 displayed in Figure 1. Shown in Figure 5 are obtained results from application of Canny edge detection and Harris corner detection on three of sample images depicted in Figure 1.

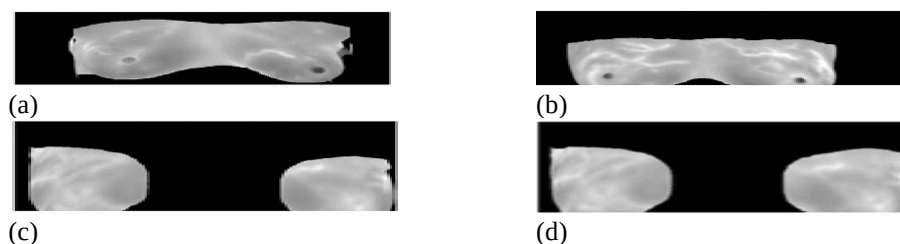


Figure 1: Samples of Images in MRI Dataset (a) MRI Image 1 (b) MRI Image 2 (c) MRI Image 3 (d) MRI Image 4

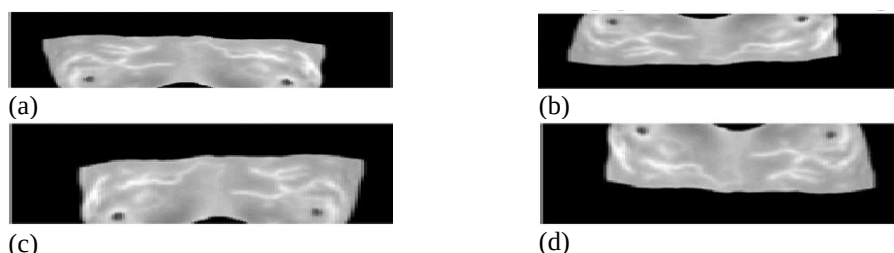


Figure 2: Augmentation of Sample MRI Image 1 (a) Original Image (b) Vertically Flipped Version (c) Horizontally Flipped Version (d) 180° Rotated Version

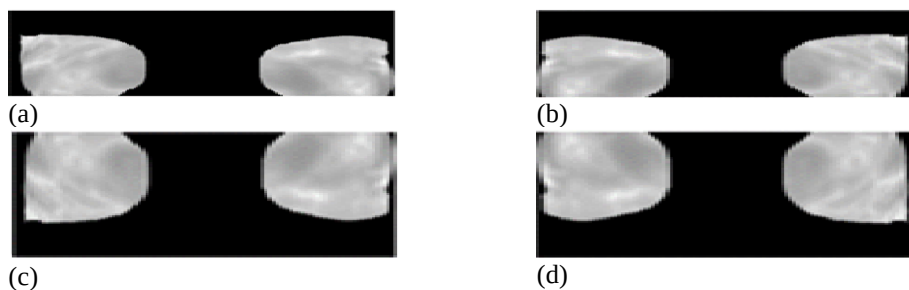


Figure 3: Augmentation of MRI Image 2: (a) Original Image (b) Vertically Flipped Version (c) Horizontally Flipped Version (d) 180° Rotated Version

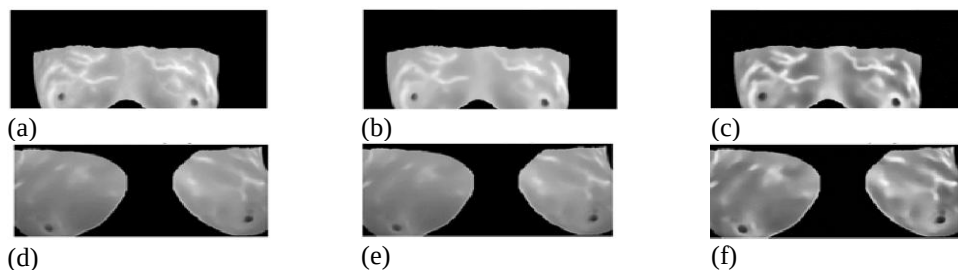


Figure 4: Pre-processed MRI Images (a) Normalized Version of Image 1 (b) De-noised Version of Image 1 (c) Contrast Enhanced Version Image 1 (d) Normalized Version of Image 2 (e) De-noised Version of Image 2 (f) Contrast Enhanced Version Image 2

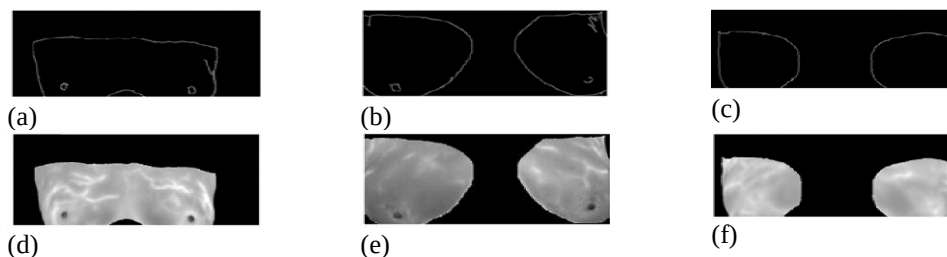


Figure 5: Results of Feature Extraction Stage of MRI Images (a) Map of the Edge of Image 1 (b) Map of the Edge of Image 2 (c) Map of the Edge of Image 3 (d) Corner Detection of Image 1 (e) Corner Detection of Image 2 (f) Corner Detection of Image 3

Classification of MRI Images Based on Extracted Features

Judging from results obtained from feature engineering stage (which involves edge mapping/detection and corner detection), as exemplified in Figure 5, the developed edge-enhanced CNN enables classification of processed MRI images into healthy and diseased groups. As illustrations, images 1 and 2 in Figure 1 are both healthy while image 3 is diseased. This position is reinforced by the results of feature extraction stage shown in Figure 5. The presence of small dot-like structure in each of images

1 and 2 indicate the location of nipples unlike what obtains in image 3 that is completely plain without any dot, which signals presence of tumour growth.

Evaluation of the Performance of the Developed Model with MRI Images

Table 1 presents results of the evaluation of the developed method in this study. Four metrics adopted for the model's evaluation are accuracy, precision, recall and F1-score.

Table 1: Result of Model Evaluation

Metrics	Values (%)
Accuracy	97
Precision	99
Recall	95
F1 Score	97

It can be seen from Table 1 that the developed model has overall accuracy of 97%, precision of 99%, recall of 95% and F1-score of 97%. These values are pointer to satisfactory performance of the developed model for detection and classification of breast cancer in MRI images. The high precision (99%) indicates that the model has minimal false positive rates, which is crucial in medical diagnosis where false alarms can lead to unnecessary anxiety and procedures. The recall rate of

95% shows that the model is able to identify most of the diseased cases, but there is still some room for improvement in terms of reducing false negatives. The study has successfully shown the possibility of combining traditional computer vision algorithms with deep learning in medical image classification.

Table 2 showed results of comparison of edge-enhanced CNN with three existing works in the literature.

Table 2: Comparison of Obtained Results with Existing Works

Authors	Method used	Dataset size	Accuracy (%)	Remark
This work	Edge-enhanced CNN	1480	97	
Zhang <i>et al.</i> (2021)	Standard CNN architecture	1200	94.2	edge-enhanced approach shows 2.8% improvement, demonstrating the value of feature engineering
Kumar and Singh (2021)	Transfer learning with ResNet-50	1800	91.5	Our method shows 5.5% advantage, highlighting the effectiveness of multi-channel input design
Chen <i>et al.</i> (2019)	Traditional CNN with data augmentation	2100	89.3	Our approach shows significant 7.7% improvement, emphasizing the importance of structural feature integration

CONCLUSION

Edge-enhanced CNN model for breast cancer detection was shown to outperform typical CNN architectures in classifying breast cancer from MRI images with 97% accuracy and robust precision-recall measures. Adding channels containing either the Canny edge image or the Harris corner image was found to help enhance the classification results. The method offered in this paper lays down the base to design more advanced computer-aided diagnostic systems that could support clinicians with early detection of breast cancer. Because of the high results, this approach could potentially be translated into the clinical setting and help to improve patient's outcome by mean of breast cancer early diagnosis.

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