Breast Cancer Detection via Advanced Deep Learning Networks

Md. Tahidul Islam *Computer Science and Engineering Pabna University of Science and Technology* Pabna, Bangladesh.
billahmasum124@yahoo.com

Md Abdur Rahim *Computer Science and Engineering Pabna University of Science and Technology (PUST)*, Pabna, Bangladesh. rahim@pust.ac.bd

Abu Saleh Musa Miah
Computer science and engineering The University of Aizu Aizuwakamatsu, Japan
abusalehcse.ru@gmail.com

Md. Imran Hossain
Information and Communication Engineering Pabna University of Science and Technology (PUST) Pabna, Bangladesh.
imran05ice@pust.ac.bd

Md. Shafiul Azam
Computer Science and Engineering Pabna University of Science and Technology (PUST) Pabna, Bangladesh.
shahincseru@gmail.com

Abstract—**Breast cancer happens when healthy breast cells grow abnormally, creating lumps or masses. It is the second leading cause of cancer deaths among women worldwide and the top cause among Hispanic women. Detecting breast cancer early, often using mammography (a type of X-ray), greatly improves treatment success and survival rates. Current methods for analyzing mammograms rely on traditional machine learning, which struggles to process complex and high-dimensional data. This often leads to lower accuracy when identifying benign and malignant cases. To address these challenges, this study proposes a deep learning-based approach combining Convolutional Neural Networks (CNNs) with transfer learning techniques to enhance the accuracy and reliability of breast cancer detection. The novelty of the work lies in employing advanced pre-processing methods and optimizing key parameters, such as kernel sizes, hidden layers, and learning rates tailored for mammographic data. Benchmark datasets, including the MIAS database, were used for training and validation, with models like VGG16 and DenseNet achieving accuracies of 96% and 98%, respectively. These results demonstrate the potential of the proposed method to overcome the limitations of existing approaches, offering robust and efficient diagnostic solutions for early breast cancer detection.**

Index Terms—**breast cancer, deep learning, convolutional neural networks, mammograms.**

I. INTRODUCTION

Breast cancer is one of the most prevalent cancers in women, second only to skin cancer. It occurs when breast cells grow and divide uncontrollably, forming a mass of tissue. Symptoms may include a lump in the breast, changes in breast shape, or changes in the skin of the breast. Women over 50 are at increased risk of developing breast cancer [1]. There are various types of breast cancer, including ductal carcinoma in situ (DCS), invasive ductal carcinoma (IDC), inflammatory breast cancer (IBC), and metastatic breast cancer (MBC).DCS is a noninvasive form of cancer characterized by abnormal cells confined to the lining of the breast milk ducts. IDC, on the other hand, is an invasive malignancy that spreads from the milk ducts to surrounding breast tissue. IBC is a rare but aggressive type of breast cancer that affects the skin and lymphatic vessels of the breast. MBC occurs when breast cancer spreads beyond the breast to other parts of the body. Several risk factors, including age, sex, family history, genetic predisposition, smoking, alcohol consumption, obesity, radiation exposure, and hormone replacement therapy, have been shown to increase the likelihood of developing breast cancer [2].

Early detection and appropriate treatment significantly improve outcomes and quality of life. Medical professionals recommend routine screenings to detect breast abnormalities, with mammograms being a key diagnostic tool. A mammogram is an X-ray image that is used to examine the breast for signs of abnormal growth or changes. This paper analyzes mammography images to enable more accurate and automated breast cancer predictions. Numerous studies have shown that screening for mammography reduces breast cancer mortality by facilitating early detection [3-5]. Breast cancer detection frequently employs intermediate X-ray photon energy mammography. A diagnostic mammogram is recommended for further evaluation if abnormalities are detected during screening. For example, [6] utilized a neural network-based approach to diagnose breast cancer from digital mammograms, achieving 88.23% accuracy for all abnormalities and 79.31% accuracy in distinguishing benign from malignant regions.

In this study, we enhance recognition accuracy by employing various image-processing and augmentation techniques. Specifically, we utilize convolutional neural networks (CNNs) and transfer learning methods for mammography-based breast cancer diagnosis. Experiments were conducted on the MIAS dataset to evaluate the proposed approach. Key contributions of this work include improving the accuracy, efficiency, and generalization of breast cancer detection models.

This paper is organized as follows: Section 2 reviews related works on breast cancer detection, while Section 3 provides

an overview of the dataset used. Section 4 outlines the key stages of the proposed methodology. Section 5 discusses the evaluation results, and Section 6 concludes the paper.

A. Related Works

Extensive research has been conducted to breast cancer detection and tumor diagnosis. Various deep learning and machine learning algorithms have been developed to facilitate cancer diagnosis and prediction. Among these, convolutional neural networks (CNNs) have emerged as highly effective and advanced tools, demonstrating exceptional performance in analyzing and interpreting medical imaging data for breast cancer diagnosis. In [7], the authors propose a method to extend classifiers from patch-based recognition to whole-image analysis. Their approach leverages the sliding window technique, a widely used method for classifying or segmenting large, complex images. This technique involves detecting small patches across the image and generating a probabilistic output grid, enabling more comprehensive image analysis. In [8], the Authors surveyed convolutional neural networks (CNNs) in mammography, comparing traditional Computer-Assisted Detection (CAD) with advanced CNN models for tasks like breast density, asymmetry, and mass detection. The study reviews datasets, FDA-approved models, and quantitative results, offering insights into challenges, opportunities, and future directions to enhance breast cancer screening accuracy. An automated, data-driven model for breast cancer detection in mammograms was developed using a YOLO-based approach in [9]. In [10], the authors compared and evaluated YOLOv5 models of different sizes (nano, small, medium, and large) using the CBIS-DDSM and INbreast datasets. However, the study left some crucial aspects unaddressed, particularly the issue of model explainability, which is essential for ensuring the reliability and transparency of models, especially in medical applications. In [11], the authors proposed a novel approach for breast cancer detection in mammography images, utilizing feature extraction and reduction techniques. This method achieved an accuracy of up to 94.5%, highlighting its potential effectiveness in improving detection performance.

II. DATASET DESCRIPTION

The Mammographic Image Analysis Society (MIAS) [12] image database used in the proposed technique. The Mammographic Imaging and Analysis Society (MIAS) in the United Kingdom records and stores mammography. There are 322 occurrences in this database, each with a 1024 x 1024-pixel image. The resolution of film mammography is 50-micron pixels, whereas the resolution of a scanned image is no more than 200-micron pixels. There are six different abnormalities in the database, and each one is categorized as benign (B) or malignant (M). In addition, there are three different types of background tissue: dense glandular tissue, fatty glandular tissue, and fatty tissue. Table I shows the some class of abnormality. Figure 1 shows the sample images from the MIAS dataset.

TABLE I
CLASS OF ABNORMALITY PRESENT

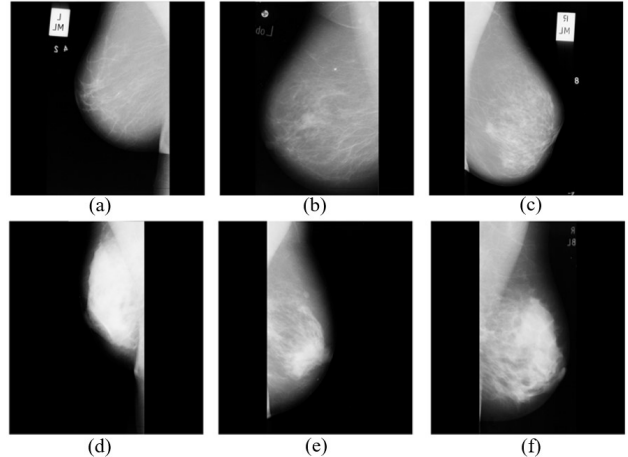| Class	Descriptions
CALC	Calcification
CIRC	Well-defined/circumscribed masses
SPIC	Spiculated masses
MISC	Other, ill-defined masses
ARCH	Architectural distortion
ASYM	Asymmetry
NORM	Normal

Fig. 1. Sample data of mini-MIAS dataset. a) NORM image, b) CIRC image, c) MISC image, d) SPIC image, e) ASYM image, and f) CALC image.

III. PROPOSED METHODOLOGY

Figure 2 presents the flow diagram of the mammography image analysis pipeline developed for breast cancer detection. The MIAS database was utilized as the primary dataset, annotating anomalous regions as ground truth for extracting Regions of Interest (ROIs). The proposed methodology consists of several key stages: image preprocessing, feature extraction, training data generation, testing data preparation, classifier training, and performance evaluation. Convolutional Neural Network (CNN) were employed for breast cancer detection. The VGG16 and DenseNet architectures, known for their effectiveness in medical imaging, were systematically trained and validated. Advanced feature extraction and classifier optimization techniques were implemented to enhance detection accuracy and improve the generalization capabilities of the models.

A. Data Preprocessing and augmentation

The MIAS mammographic dataset, consisting of 332 grayscale images, required significant preprocessing to address noise, off-centre irregularities, and resolution constraints due to hardware limitations. Images were resized to optimize classifier performance and computation speed. A sliding window approach was employed for noise reduction and patch-based classification, enhancing overall detection accuracy. To enhance the dataset, image augmentation techniques were applied, including rotating each sub-sample by 90, 180, and
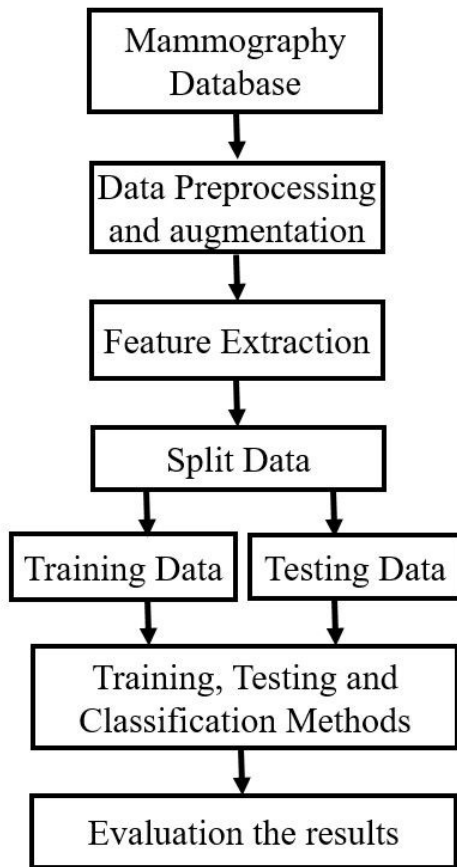
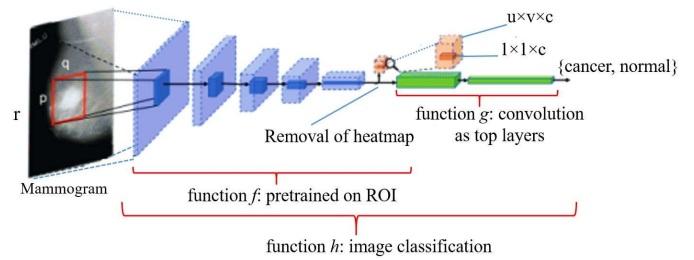Fig. 2. Basic block diagram of breast cancer detection system.

Fig. 3. Feature Extraction Map.

in the layers organized in width, height, and depth. The input images are resized to 256×256 pixels, then convolved to extract features, which are subsequently strengthened. Max pooling, with a tile size of 2×2, selects the largest value from each tile to reduce data while preserving important features. The CNN architecture enables efficient feature extraction and classification, as depicted in Figure 4. This study compares the effectiveness of rectified linear units (ReLUs) with saturated activation functions, such as tanh and sigmoid, in CNNs. ReLUs, which use non-saturating functions like f(x) = max(0, x), significantly reduced training time and improved initial learning speed.
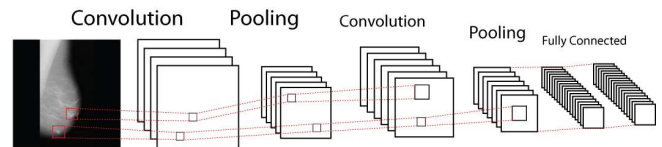

Fig. 4. CNN architecture.

IV. RESULT AND DISCUSSION

In this study, we conducted an analysis of the MIAS dataset to detect abnormalities in breast tissue. Three convolutional neural network (CNN) models—VGG16, DenseNet121, and a custom architecture—were trained and compared for performance and accuracy. The Softmax activation function was used to classify abnormalities. Each model included convolutional layers with max pooling and a dropout rate of 0.25. The input layer used a 32-filter (3×3) convolution, followed by an additional layer with 64 filters (3×3) and a max pooling size of 2×2. The fully connected layer, utilizing Softmax, output probabilities to classify samples as benign or malignant. Model selection was based on achieving the lowest validation loss or highest validation accuracy. Table II shows the classification results based on the VGG16 model.

TABLE II
VGG16 MODEL CLASSIFICATION REPORT FOR MALIGNANT AND BENIGN

Class name	Precision	Recall	F1-score	Accuracy
Class-1	92.0	100.0	96.0	-
Class-2	100.0	91.0	95.0	-
Average	96.0	95.0	96.0	96.0

270 degrees, along with horizontal mirroring. This increased the sample size and improved generalization, enabling more effective classifier training.

B. Feature Extraction

For feature extraction, we subsampled abnormal data by identifying the Region of Interest (ROI) in each image, using the known x and y coordinates of the abnormality center. These cropped regions were scaled to a consistent 48×48 dimension. For normal mammograms, a random region was selected from the center, and a 48×48 patch was extracted. Poorly cropped sub-samples, such as those with excessive black space, were filtered out. Sub-sampling reduced training time by simplifying the image size, and provided a dataset suitable for training a CNN to classify benign, malignant, and normal cases. The feature extraction map is presented in Figure 3.

C. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are highly effective for image processing and analysis, comprising three main layers: the Convolutional Layer, Pooling Layer, and Fully Connected Layer, culminating in the classification output. In this study, max pooling was used to enhance translation invariance and reduce feature map size. CNNs process image data represented as a three-dimensional matrix, with neurons

DenseNets represent a significant advancement in deep convolutional networks by addressing challenges faced as CNNs grow deeper. These challenges include the vanishing gradient problem, where information and gradients dissipate as they propagate through layers. For malignant classification cases, DenseNets achieved a recall rate of 97% and an accuracy of 98%, as shown in Table III. These results were obtained using the GPU runtime on Google Colab. The DenseNet confusion matrix, presented in Table 6, indicates 32 true positives and 29 true negatives, highlighting the model's robust classification performance. Table II presents the classification results based on the DenseNet model.

TABLE III
DENSENET MODEL CLASSIFICATION ACCURACY

Class	Precision	Recall	F1-score	Accuracy (%)
Class 1	97.0	100.0	98.0	-
Class 2	100.0	97.0	98.0	-
Average	98.0	98.0	98.0	98.00

V. CONCLUSION

This paper presents an in-depth study on breast cancer classification using Convolutional Neural Networks (CNNs), addressing the complexities of optimizing neural network parameters within the constraints of limited mammography datasets and domain-specific challenges. The research underscores the importance of domain expertise in accurately interpreting medical data and tailoring models to the nuances of mammography. Data augmentation techniques significantly enhanced the learning and predictive capabilities of the models, with a class-balanced approach ensuring more accurate and fair classification. Among the tested architectures, VGG16 and DenseNet achieved commendable performance, particularly excelling in malignant classification, which is critical for early diagnosis and treatment. However, computational constraints limited extensive parameter tuning and cross-validation. This highlights the necessity of more advanced computational resources and deeper explorations of model configurations to further improve classification accuracy and reliability in future studies.

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