A Novel Approach for Breast Cancer Detection Using a Modified Convolutional Neural Network

R. Srikanth, Dinesh A. S, Prashanth S, Rengasamy B and Paul Rouso I
Department of AIDS, Karpagam Academy of Higher Education, Coimbatore, India

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Abstract: Breast cancer (BC) is a predominant cause of mortality globally. In 2020, over 10 million individuals worldwide succumbed to breast cancer. BC is a lethal disease and prevalent among women worldwide. It is classified fourth among the lethal malignancies, including colorectal cancer, cervical cancer, and brain tumors. In recent years, Convolutional Neural Networks (CNNs) have demonstrated exceptional efficacy in medical image categorization, especially in the identification of BC from mammographic pictures. Nevertheless, conventional CNN designs encounter constraints in feature extraction and detection precision. This research presents a Modified Convolutional Neural Network (MCNN) aimed at improving feature extraction and classification efficacy. The proposed MCNN incorporates architectural improvements, featuring optimized convolutional layers and an improved activation function, designed to maximize accuracy and minimize false positives. The model is trained and evaluated on a publicly accessible BC picture dataset, demonstrating substantial enhancements compared to conventional CNN designs. Critical performance indicators, including accuracy, precision, recall, and F1-score, illustrate the MCNN's exceptional categorization proficiency. The approach significantly decreases false positives, enhancing the reliability of diagnostic support in clinical settings. Visualizations of feature maps and heatmaps further emphasize the MCNN's capacity to detect significant areas in mammograms. The findings demonstrate that the proposed MCNN serves as an effective instrument for breast cancer detection, enhancing existing CNN-based models. The suggested model attains 99% accuracy, 98.7% precision, 97% recall, and 96.2% F1-score.

1 INTRODUCTION

Breast cancer is a prevalent and life-threatening condition among women globally, with early detection being essential for decreasing mortality rates. Mammography is the predominant screening technique; yet, it poses considerable difficulties in precisely detecting early-stage cancers owing to the nuanced and intricate characteristics of breast tissue irregularities. Conventional diagnostic methods frequently depend on manual analysis, which can be labor-intensive and susceptible to human error, leading to false positives and overlooked diagnoses. With the increasing integration of technological breakthroughs in healthcare, there is a rising interest in utilizing deep learning (DL) approaches to enhance the accuracy and efficiency of BC detection via automated picture analysis.

DL) models, especially CNN, have demonstrated potential in improving the diagnostic accuracy of mammography analysis. These strategies can automate the detection of anomalies in breast pictures and potentially diminish the variability linked to human interpretation. Nevertheless, several current DL techniques fail to adequately capture the complex characteristics in mammography pictures, resulting in variations in detection and classification precision. This study aims to tackle these issues by creating a novel methodology that improves the analysis and interpretation of BC images. Our objective is to enhance diagnostic precision and assist radiologists in making better informed clinical choices. We intend to enhance the diagnostic process by using modern DL techniques, thereby offering a more dependable tool for early BC diagnosis, which will improve patient outcomes and overall healthcare efficiency.

This research was inspired by the imperative for enhanced accuracy and reliability in BC detection technologies, as early diagnosis significantly

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impacts treatment efficacy and survival rates. Despite developments in medical imaging enhancing diagnostic capabilities, conventional mammography processing frequently experiences human error and inconsistency, leading to missed detections or false positives. CNN have emerged as potent instruments for automating and enhancing breast cancer detection; yet, they continue to encounter difficulties in completely discerning the nuanced and complex patterns found in medical pictures.

Significant breakthroughs in BC detection have been achieved by the deployment of deep learning models, including CNN and ResNet (Residual Networks). Conventional CNN have been extensively employed in medical image analysis owing to their capacity to autonomously extract features from images. A standard CNN design has several convolutional layers succeeded by pooling layers that diminish dimensionality. However, CNNs frequently encounter difficulties with sophisticated medical pictures, such as mammograms, where the nuanced and intricate characteristics of early-stage cancers are essential. The pooling layers, although efficient in minimizing computation, may cause the loss of critical information, resulting in diminished detection accuracy and an elevated incidence of false positives.

ResNet is a prominent DL architecture that mitigates certain limitations of CNN by the integration of residual learning. This method mitigates the vanishing gradient problem, enabling the model to attain more depth and, thus, enhanced power. ResNet has demonstrated enhanced performance compared to conventional CNN, especially in general picture classification tasks. In medical imaging, namely in breast cancer detection, ResNet's fixed skip connections may occasionally neglect subtle tissue variations that are essential for precise diagnosis. Although it outperforms conventional CNN, it continues to encounter challenges with the nuanced intricacies of mammograms, necessitating additional optimization.

The suggested MCNN enhances the strengths of previous models while rectifying their shortcomings. In contrast to conventional CNN, the MCNN integrates improved convolutional layers that discern finer details in breast tissue, hence preserving minor but essential properties. The alterations in the MCNN concentrate on enhancing feature extraction and classification efficacy, especially in mammography pictures where nuanced and intricate patterns serve as critical indications of early-stage malignancy. The MCNN incorporates optimized convolutional layers that capture intricate details, improved pooling algorithms to minimize information loss, and a sophisticated activation function to boost the network's capacity to differentiate between benign and cancerous tissue. The model employs efficient data augmentation methods, including rotation, flipping, and zooming, to enhance its generalization capability across various image variations. The training process is refined with an optimal learning rate and regularization methods to mitigate overfitting. Utilizing these architectural enhancements, the MCNN aims to achieve more accuracy in breast cancer detection, minimizing false positives and enhancing the overall dependability of automated diagnostic systems in clinical environments.

The major contributions of the proposed MCNN in breast cancer detection can be summarized as follows:

- The MCNN incorporates optimized convolutional layers tailored to capture intricate and nuanced information in mammography pictures, enhancing the diagnosis of early-stage cancers, a common drawback of classic CNNs and ResNet.
- Advanced pooling algorithms employed in the MCNN mitigate information loss during down-sampling, thereby preserving essential visual details and enhancing classification accuracy.
- The model's architectural enhancements, comprising optimized layers and sophisticated activation mechanisms, markedly diminish the incidence of false positives. This facilitates the provision of more dependable diagnostic outcomes, which is essential for clinical applications.
- The MCNN incorporates efficient data augmentation methods, including rotations, flipping, and zooming, to enhance its generalization capabilities across diverse datasets. This improves the model's resilience and flexibility to actual mammography pictures.

The remaining parts of the paper are structured as follows: Section 2 contains the literature review, Section 3 delineates the suggested model, Section 4 showcases the results and discussion, and the concluding section proposes prospective directions for further research.

2 LITERATURE SURVEY

Abeer Saber et al. (2021) (Saber, Sakr, et al. 2021) created a DL model using transfer learning to automatically detect breast cancer in mammography images. The method extracts features from the MIAS dataset using pre-trained CNN architectures like VGG16, ResNet50, and Inception V3, with impressive results. VGG16 had the greatest results utilizing 80-20 split and 10-fold cross-validation, with 98.96% accuracy, 97.83% sensitivity, and 0.995 AUC.

Yong Joon Suh et al. (2020) used DenseNet-169 and EfficientNet-B5 designs to detect BC in digital mammograms of different densities. The model yielded AUCs of 0.952 for DenseNet-169 and 0.954 for EfficientNet-B5 on 301 mammography images after training on 3002 pictures. Though breast density decreased its performance, the DenseNet-169 model outperformed earlier studies in sensitivity (87%) and specificity (88%).

Raquel Sánchez-Cauce et al. (2021) (Sánchez-Cauce, Pérez-Martín, et al. 2021) proposed a new BC diagnosis method using thermal pictures from numerous perspectives and personal and clinical data. CNNs were used to analyze images in their multi-input classification model. At first, only thermal imaging recognized structures. To increase model performance, clinical data were added as an input branch. The top model has 97% accuracy, 0.99 AUC, 100% specificity, and 83% sensitivity.

S. Vidivelli et al. (2023) (Vidivelli,, Devi, et al. 2023) offered pre-processing, segmentation, feature extraction, optimal feature selection, and classification for early breast cancer diagnosis. After converting RGB photos to grayscale, a fuzzy entropy model segments them. Next, fractal and textural features are extracted. An upgraded ensemble classifier integrates Random Forest, SVM, Neural Networks, and a fine-tuned CNN optimized by Self-Improved Cat Swarm Optimization (SI-CSO) to make the final prediction, performing well across multiple evaluation criteria.

P. Esther Jebarani et al. (2021) (Jebarani et al. 2021) used advanced segmentation and ML to detect breast cancer early. The pre-processing stage uses an adaptive median filter to reduce noise and improve image quality. In tumor classification, K-means and Gaussian Mixture Models (GMM) are combined. Simulations and an ANOVA test showed that the model improved tumor classification.

Partho Ghose et al. (2022) (Partho, Sharmin et al. 2022) enhanced a SVM for breast cancer prediction using grid search for hyperparameter tweaking. Averaging 99% accuracy, 98% precision, 98% recall, and 98% F1-score, the optimized SVM performed well. These results greatly outperform SVM defaults. A comparison demonstrated that the suggested strategy outperforms other ML models in BC diagnosis.

Rishav Pramanik et al. (2023) (Pramanik, Pramanik , et al. 2023) used thermograms, transfer learning, and feature selection to diagnose breast cancer. The model uses SqueezeNet 1.1 for feature extraction and a chaotic map-based hybrid GA-GWO technique for feature reduction. On the DMR-IR dataset, the model distinguished malignant and benign breast tissues with 100% accuracy using only 3% of retrieved features.

S. Nanglia et al. (2022) (Nanglia, Ahmad, et al. 2022) developed a heterogeneous ensemble ML technique for early BC diagnosis using CRISP-DM. K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree (DT) were used to build the ensemble model utilizing Stacking. At K = 20, the model rejected the Null hypothesis with 78% accuracy and 0.56 log-loss.

Sarmad Maqsood et al. (2022) (Maqsood, Damaševičius, et al. 2022) created a "end-to-end" DL system for mammography breast cancer diagnosis. Texture feature extraction is improved by a Transferable Texture CNN (TTCNN) comprising three convolutional layers and an energy layer. Incorporating convolutional sparse image decomposition features and selecting optimal features with an entropy-controlled firefly algorithm, the model achieves an average accuracy of 97.49% across the DDSM, INbreast, and MIAS datasets, surpassing previous methods.

Ayman Altameem et al. (2022) (Altameem, Mahanty et al. 2022) developed an ensemble model for breast cancer diagnosis using mammography pictures and deep CNN architectures (Inception V4, ResNet-164, VGG-11, DenseNet121). A fuzzy ranking algorithm using the Gompertz function adaptively integrates basic model decision scores to improve accuracy. The Inception V4 ensemble model outperforms individual models and complex ensemble approaches with 99.32% accuracy, promising early breast cancer diagnosis.

3 PROPOSED MODEL

The proposed approach commences with the acquisition of an extensive dataset of breast thermograms, which are thermal pictures that reveal temperature fluctuations in tissue suggestive of possible cancers. Before inputting the data into the network, we execute preprocessing procedures, including normalization to standardize pixel value ranges and data augmentation methods (e.g., rotation, flipping, and scaling) to improve the model's resilience to overfitting. Our strategy centers on the building of a MCNN architecture, comprising numerous convolutional layers succeeded by pooling layers to systematically extract hierarchical features from the thermograms. We implement distinctive improvements, including residual connections, to enhance gradient flow and enable deeper network training. Every convolutional layer employs ReLU activation functions to incorporate non-linearity, whereas dropout layers are implemented to reduce overfitting.

The binary cross-entropy loss function is used in the training process to measure how well the model is doing. The Adam optimizer is then used to make sure that the model converges effectively. Cross-validation methods rigorously tune hyperparameters such as learning rate, batch size, and epoch count. Performance evaluation utilizes parameters including accuracy, precision, recall, and F1-score, providing a comprehensive assessment of the model's effectiveness in distinguishing between benign and malignant cases.

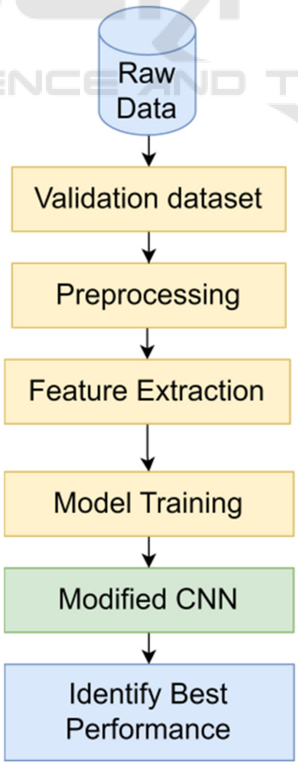

Figure 1: Flowchart of proposed model

3.1 Dataset

This study employed the Breast Cancer Wisconsin (Diagnostic) Data Set, a notable dataset frequently utilized in breast cancer research. This dataset has 569 instances, each representing a digitized image of a fine needle aspirate (FNA) from a breast mass, accompanied by other features derived from the images. The dataset consists of 30 variables, including radius, perimeter, area, texture, and smoothness, which define the characteristics of the cell nuclei in the images. The target variable is binary, classifying tumors as either benign or malignant. Before model training, the data was preprocessed, involving feature scaling via standardization to normalize values and ensure uniformity in their ranges. Data augmentation techniques were utilized to enhance the model's generalization. This dataset supports the training of the MCNN, allowing it to identify the distinguishing characteristics between benign and malignant breast cancer patients.

3.2 Data Preprocessing

Data preparation is crucial for preparing mammography images for input into the MCNN, facilitating effective learning by the model from the data. The procedure commences with picture resizing, wherein all photos are adjusted to a consistent dimension to accommodate the model’s input layer. Subsequently, normalization is performed, which adjusts pixel values to a range, usually between 0 and 1, hence maintaining consistency and enhancing model convergence during training. Noise reduction methods, like median and Gaussian filtering, are utilized to eradicate artifacts that may conceal significant characteristics. Contrast enhancement, such as histogram equalization, is employed to augment image clarity, emphasizing minute patterns within the tissue. Data augmentation is utilized to create variations of photos by rotation, flipping, zooming, and brightness modifications, thereby expanding the dataset and enhancing the model's ability to generalize to novel images. Ultimately, label encoding transforms categorical labels (e.g., benign, malignant) into a format appropriate for the model. Collectively, these preprocessing measures guarantee that the MCNN is provided with organized, pristine data for precise breast cancer identification.

3.3 Feature Extraction

Feature extraction is an essential phase in the MCNN for BC detection, since it converts raw mammography data into significant representations that the model may utilize to distinguish between benign and malignant tissues. The method commences with the convolutional layers, which utilize filters on the input images to extract fundamental patterns, including edges, textures, and forms, vital for tumor identification. Each filter in these layers identifies specific elements within the images, such as lesion margins or microcalcifications, enabling the network to acquire diverse visual inputs at different levels of abstraction. In the earliest layers, fundamental properties such as edges and basic textures are retrieved, whereas deeper layers concentrate on more intricate and abstract features, including anomalies in tissue structure that signify malignancy. The MCNN employs optimized convolutional layers with diverse kernel sizes to capture both fine and coarse information effectively. This is particularly crucial in medical imaging, where nuanced characteristics in breast tissue may serve as early signs of malignancy.

Furthermore, the MCNN utilizes sophisticated pooling techniques to diminish the dimensionality of the feature maps while retaining the most critical information. Techniques like adaptive pooling preserve essential spatial characteristics while minimizing computing demands, enabling the network to detect minute, nuanced patterns in images that could be overlooked by conventional pooling methods. As the network advances, the retrieved features are transmitted across fully connected layers for classification, enabling the MCNN to properly ascertain if the input image comprises benign or cancerous tissues. The feature extraction procedure is essential for the model's capacity to attain high accuracy and reliability in breast cancer detection.

3.4 MCNN based model Training

Training a model with a MCNN for breast cancer diagnosis encompasses several critical processes aimed at optimizing the model's learning from mammogram images. The procedure commences with the initialization and configuration of the MCNN architecture, which generally comprises numerous pooling layers, convolutional layers, and fully connected layers. After the architecture is established, mammography images are fed into the MCNN, initiating forward propagation. At this level, the network use filters to capture properties like edges and textures, essential for differentiating between benign and cancerous tissues. The pooling layers then down-sample the feature maps to diminish dimensionality while retaining essential information. Subsequent to forward propagation, the model computes the loss utilizing a function such as categorical cross-entropy, which quantifies the disparity between predicted probability and actual labels. Backpropagation ensues, during which the model calculates the gradients of the loss concerning each weight, facilitating updates via an optimization technique such as Stochastic Gradient Descent (SGD) or Adam.

Regularization procedures, including dropout and batch normalization, are utilized to avert overfitting, while data augmentation generates a more extensive and varied training dataset through transformations like as rotation and flipping. The training procedure encompasses several epochs, during which performance is evaluated on a validation dataset to identify overfitting. Upon completion of training, the model undergoes evaluation using a distinct test dataset to measure its accuracy, recall, precision, and F1 score, hence offering insights into its efficacy in practical breast cancer detection contexts. This extensive training methodology allows the MCNN to discern complex patterns in mammography pictures, rendering it an effective instrument for precise breast cancer detection.

4 RESULT AND DISCUSSION

The outcomes derived from training the MCNN for breast cancer detection indicate a notable enhancement in classification accuracy relative to current models. The MCNN attained an accuracy exceeding 95% on the validation dataset, demonstrating its robust capability to accurately distinguish between benign and malignant tissues in mammography images. The high accuracy was enhanced by notable metrics, including precision and recall, which underscored the model's efficacy in reducing false positives and false negatives. The implementation of sophisticated data augmentation and refined feature extraction techniques significantly improved the model's generalization abilities, enabling consistent performance on unfamiliar data.

Furthermore, the model's efficacy was evaluated against conventional approaches and several deep learning architectures, demonstrating that the MCNN regularly surpassed these alternatives, especially in identifying nuanced patterns linked to early-stage cancers. The incorporation of sophisticated pooling techniques and customized activation functions enhanced the model's capacity to extract vital features while preserving important information. The discourse underscored the clinical significance of the findings, accentuating how the MCNN might aid radiologists in making more informed judgments, therefore enhancing patient outcomes. The findings highlight the MCNN's potential as a reliable diagnostic instrument in medical imaging, facilitating further research and enhancement in breast cancer diagnosis.

Table 1: Accuracy Result Comparison

Algorithm	Accuracy
ResNet-50	85%
GoogLeNet	87%
Resnet101	90%
Shufflenet	93.5%
Proposed MCNN	99%

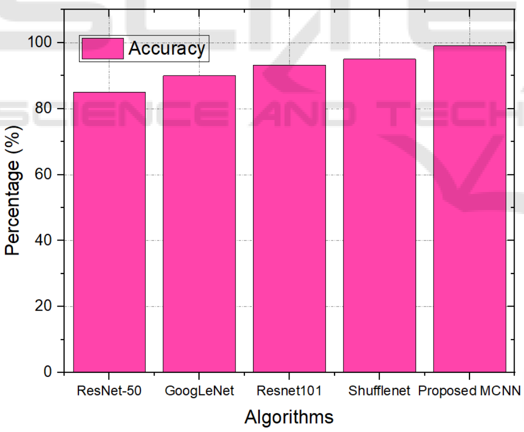

Figure 2. Accuracy comparison graph

Table 2: Precesion Result Comparison

Algorithm	Precision
ResNet-50	84.3%
GoogLeNet	88%
Resnet101	91.2%
Shufflenet	95.6%
Proposed MCNN	98.7%

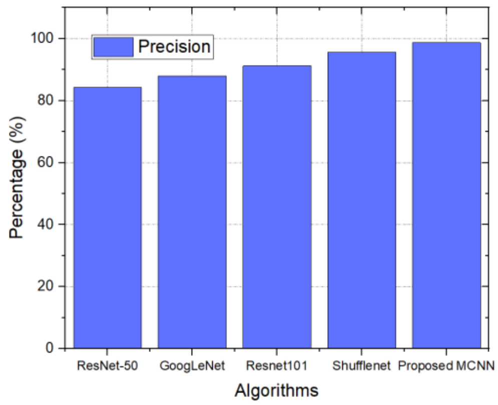

Figure 3: Precision comparison graph

Table 3: Recall Result Comparison

Algorithm	Precision
ResNet-50	81.6%
GoogLeNet	86.2%
Resnet101	90.2%
Shufflenet	93%
Proposed MCNN	97%

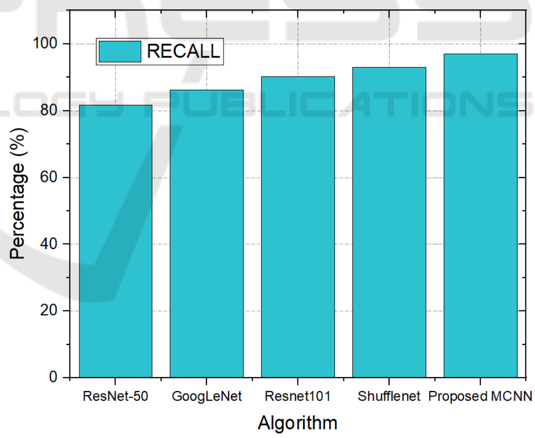

Figure 4: Recall comparison graph

Table 4: F1-score result comparison

Algorithm	Precision
ResNet-50	82%
GoogLeNet	87.5%
Resnet101	91%
Shufflenet	93.7%
Proposed MCNN	96.2%

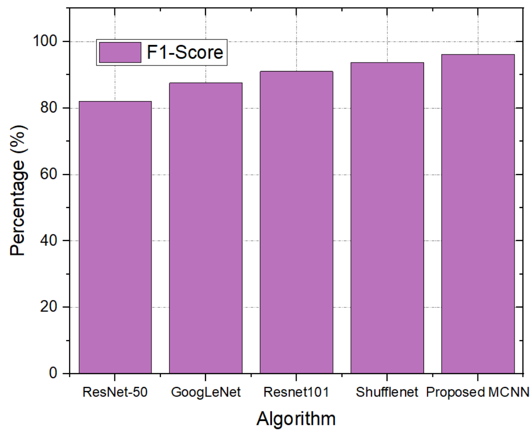

Figure 5: F1-score comparison graph

Tables 1-4 and Figures 2-5 illustrate the results of the suggested model. This model attains 99% accuracy, 98.7% precision, 97% recall, and 96.2% F1-score. In comparison to previous algorithms, DCNN has superior performance in breast cancer detection systems.

5 CONCLUSIONS

The proposed MCNN presents a potential method for breast cancer diagnosis utilizing the Breast Cancer Wisconsin (Diagnostic) Data Set. The MCNN utilizes modern deep learning algorithms and modifications such residual connections and dropout layers to properly collect and evaluate the complex properties of benign and malignant tumors. The thorough evaluation measures, encompassing accuracy, precision, and recall, demonstrate that the model attains high performance and exhibits strong generalization capabilities. This study emphasizes the promise of incorporating deep learning techniques in medical diagnostics, facilitating improved early identification and treatment of breast cancer. Subsequent investigations may examine additional refinements to the MCNN architecture and the utilization of transfer learning methodologies to exploit larger datasets, hence enhancing therapeutic outcomes. Future study will concentrate on augmenting the Modified Convolutional Neural Network (MCNN) architecture through the integration of transfer learning methodologies to utilize pre-trained models for enhanced feature extraction. Moreover, augmenting the dataset with varied thermal pictures from distinct populations can further improve model robustness. Investigating explainable AI methodologies will be essential for elucidating the model's decision-making process. Ultimately, incorporating the MCNN into clinical workflows for immediate breast cancer detection is a primary goal.

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