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# Automated Mammogram-Based Breast Cancer Detection with Deep Learning and Advanced Image Enhancement

Hazheen Sarbast Mahmood [1,2], Shakir Fattah Kak [2]

[1]Duhok Polytechnic University,[2]Akre University for Applied Sciences, Technical College of Informatics, Department of Information Technology, Akre, Duhok , Kurdistan Region, Iraq,

email: hazheen.sarbast@auas.edu.krd

[2]Akre University for Applied Sciences, Technical College of Informatics, Department of Information Technology, Akre, Duhok, Kurdistan Region, Iraq,

email: shakir.fattah@auas.edu.krd

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**ABSTRACT**

Breast cancer is a significant worldwide health issue, and early detection is key to enhancing survival. Although mammography is the accepted screening method, human interpretation is susceptible to errors, resulting in misdiagnosis. Convolutional neural networks (CNNs), in particular, have shown promise in deep learning for automating breast cancer detection, increasing accuracy, and reducing human variability. In this research, a deep learning model for automatically classifying breast cancer from mammograms is proposed and evaluated. The suggested model's performance on the CBIS-DDSM dataset is compared to transfer learning using pre-trained models like MobileNetV2, DenseNet121, and EfficientNetV2L in terms of classification accuracy and generalizability. Moreover, the study investigates how data augmentation and preprocessing affect the models. Accuracy, sensitivity, specificity and computational efficiency were used to measure performance. The proposed technique achieved the highest performance, with 98.21% accuracy, 99.04% Sensitivity and 97.33% Specificity in the 80%-10%-10% data split and 99.02% accuracy in the 85%-5%-10% split. Affirming the effectiveness of deep learning in enhancing the accuracy, 99.24% Sensitivity and 98.80% Specificity of breast cancer detection. This study systematically contrasts CNN models for mammogram classification, optimizes preprocessing methods, and evaluates computational efficiency. It fills a research gap by balancing accuracy against computational tractability and proves proposed model higher diagnostic potential for AI-augmented mammography. The research verifies that deep learning models drastically enhance breast cancer detection based on mammograms, with proposed model being the most balanced between accuracy and efficiency.

**Keywords:** Breast Cancer Detection, Mammogram Analysis, Deep Learning, Convolutional Neural Networks (CNNs), Medical Image Processing,

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## INTRODUCTION

Breast cancer accounts for a significant portion of cancer deaths in women, making it one of the most dangerous diseases in the world. According to the World Health Organization (WHO) in 2012, breast cancer is the most frequent disease worldwide and makes up over 25% of all malignancies in women [1]. Early diagnosis is essential in enhancing survival, as treatment is best when cancer is detected early. Mammography is generally accepted as the norm for breast cancer screening, helping radiologists detect abnormalities like masses and micro calcifications [2]. Conventional mammogram interpretation, though, is very dependent on the skill of radiologists, tending to produce high false- positive and false-negative rates, differences in tumor appearance, and variability in evaluation among different experts [3]. These challenges underscore the importance of automated, AI-based solutions that have the potential to improve diagnostic accuracy, efficiency, and consistency. Deep learning, more specifically CNNs, has been shown to show high promise for medical image analysis, providing superior performance compared to conventional diagnostic methods [4]. CNN-based approaches do away with the requirement for manual feature extraction by learning in a direct way from raw image data, facilitating more accurate, efficient, and objective tumor classification [5]. Although numerous AI- based methods have been investigated to detect breast cancer, the best CNN architecture to use for classifying mammography is still a research question. In this article, the efficiency of three deep learning models (EfficientNetB0, MobileNetV2, and DenseNet121) in detection of breast cancer automatically is checked using the Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) dataset [6]. Of screening options [7], mammography is the gold standard because it is non-invasive, has high resolution, and is cost-effective [8]. However, some challenges include manual mammogram interpretation, such as inter observer variability, tiredness, high false negative and false positive rates [9]. The challenges might prevent diagnosis, or lead to worthless biopsies and distressing patient visits [10]. In order to overcome such limitations, Computer Aided Diagnosis (CAD) systems have appeared as important support tools for the radiologists [11], to provide uniform and unbiased assessments [12]. Artificial intelligence (AI), specifically deep learning, has been added into CAD systems to extract the features, classify and interpret images from pixel level images automatically. Deep learning, particularly CNNs, has greatly enhanced the accuracy of image-based classification problems over the last few years. As opposed to traditional machine learning [13], which needs hand-crafted feature engineering, CNNs can automatically learn hierarchical and complex features without human intervention, and thus are particularly well-suited for medical image analysis [14]. The models have shown outstanding performance in areas like diabetic retinopathy, pneumonia, and skin lesion classification, and have exhibited growing promise in mammographic image analysis [15]. This study addresses this gap by proposing a novel CNN-based model and evaluating its performance against state-of-the-art architectures, including proposed model, EfficientNetV2L, MobileNetV2, and DenseNet121, using the CBIS-DDSM. The models are evaluated in terms of classification accuracy and computational efficiency with the aim of identifying the most efficient and feasible model for early and accurate breast cancer detection. The rest of this research is organized as follows. In section II, the literature review is presented. In section III, The proposed model methodology. In section IV, dataset descriptions discussed. In section V, Dataset Image Features Extracting used in this paper is presented. Experimental results are given in section VI. Finally, conclusion in section VII.

## LITERATURE REVIEW

This section summarizes major studies on deep learning-based breast cancer detection with an emphasis on analysis of mammography, optimization of CNN models, and computational efficiency.

An Efficient Net-based convolutional network was employed in a study by D. G. Petrini et al. [16] to diagnose breast cancer using two-view mammography. It was trained and tested using the CBIS-DDSM dataset. The model's cross-validation AUC of 0.9344 demonstrated its great accuracy. It was constrained, nevertheless, by the amount of the dataset and the inability to compare models under various test scenarios D. Li et al.) [17] presented an classifying breast cancer in mammograms using

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deep learning. It employed the INbreast and CBIS-DDSM datasets with a CNN-based model incorporating a novel adaptive feature descriptor selection (AFDS) method, achieving high accuracy. The method outperformed state-of-the-art models in both datasets. Limitations included noise in mask maps and the triangle threshold strategy producing larger maps for extreme lesion cases. In research published by ( Z. Sani et al. ) [18] A novel G-CNN, enhanced by DCT, outperformed traditional CNN models for breast cancer classification using mammography images, achieving 94.84% accuracy, but faced limitations like complexity and large dataset requirements. The research by ( S. Chakravarthy et al. ) [19] discusses utilizing a Fusion of Hybrid Deep Features (FHDF) approach for breast cancer classification using CNNs (VGG16, VGG19, ResNet50, DenseNet121). It applied digital mammogram images from MIAS, CBIS-DDSM, and INbreast datasets, achieving maximum accuracies of 98.70%, 97.73%, and 98.83%, respectively. Despite its effectiveness in early tumor detection and classification, it struggled with computational complexity and slightly less precision in recognizing malignant cases. The study presented by (Gengtian et al.) [20] a the CBIS-DDSM dataset was utilized to assess the EfficientNet model's accuracy in classifying breast cancer using mammogram images. The model achieved an accuracy of 0.75 and an AUC of 0.83, demonstrating its effectiveness in early breast cancer detection, despite potential improvements through image quality enhancement and architectural modifications.

## I. The Proposed Model Methodology

Deep learning model-based breast cancer detection depends on high-quality mammogram databases, effective preprocessing methods, fine-tuned deep learning architectures, and clear-cut evaluation metrics. The goal of this study is to validate the research hypotheses, particularly the computational efficiency of CNN models, the impact of data augmentation and preprocessing on model performance, and the value of deep learning in improving classification accuracy. The approach in this section explains dataset selection, data preprocessing methods, selection of the deep learning model, training setups, and measurement metrics.

This study employs multiple interconnected implementation layers to build a novel CNN layering architecture model. For the overall architecture of the breast cancer detection process, the suggested model has three primary stages. Groups of pictures stored in mammography databases undergo preprocessing processes initially. Stage one involves scaling the images, stage two involves extracting features, and stage three involves feeding the information into a classification algorithm. The findings, as shown in Figure 1, are categorized using the SoftMax Classifier.

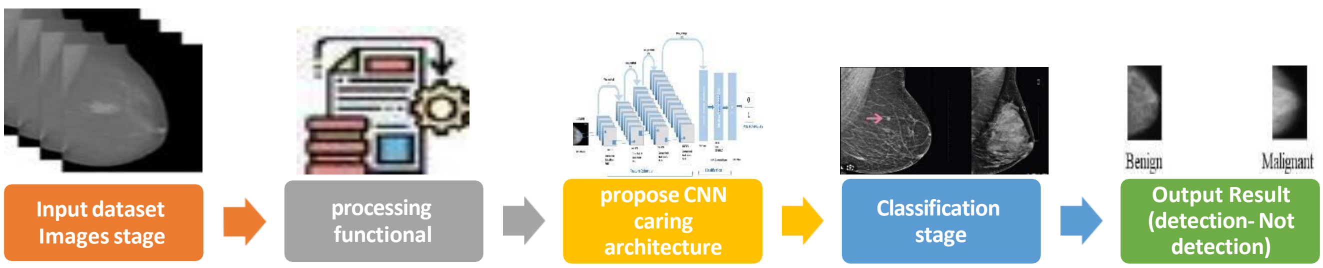


Fig. 1. The phases of Mammogram Analysis for Breast Cancer Detection with CNN algorithm

Improving breast cancer detection is the goal of the four-stage CNN methodology that has been proposed. Input Data Layer, Four Convolutional Layers, Four Batch Normalization Layers, Four Activation Layers, Four Max Pooling Layers, a Global Average Pooling Layer, Two Dense Fully Connected Layers, One SoftMax Layer, and One Classification as output Layer are all components of

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the suggested CNN model's architecture. To get the highest possible output accuracy, the CNN suggested model's layer parameters were fine-tuned. In the initial step known as pre-processing, the ROI is cropped and resized. Second, we take the mammography images and pull out the important features. The final step is to use the Softmax classification module to sort the extracted feature sets. In the end, the CBIS-DDSM dataset is used to assess the CNN recognition system's performance using a number of relevant matrices, including accuracy, sensitivity, and others. Breast cancer detection will be made more accurate and reliable with this approach. Here, we test a CNN model for breast cancer detection by adjusting the parameters of the CNN layers to see how well the network generalises, with an emphasis on batch normalization layers and the use of multiple normalization layers.

The following are the three primary components of the suggested algorithm:

1- Input layer: The input images are resized to 224X224X3 to standardize their dimensions for processing.

2- CNN Architecture: A multilayer CNN structure is built consisting of 18 layers, including convolutional, max pooling, batch normalization, ReLU, and dropout layers:
   - Convolutional Layers: Conv2D(32, (3,3), activation='relu', padding='same')
   - Batch Normalization: Batch Normalization ()
   - Max Pooling: MaxPooling2D((2,2))
   - This structure is repeated multiple times with increasing filter sizes (32, 64, 128, 256) for more complex feature extraction.

3- Classification: The last step is to use a Softmax classifier to categorise the extracted data and make a prediction about the mammogram's benign or malignant status. The suggested CNN model was tested on the CBIS-DDSM dataset to detect breast cancer. The results reveal that the model can effectively generalise to identify different types of breast cancer (see Fig. 2).

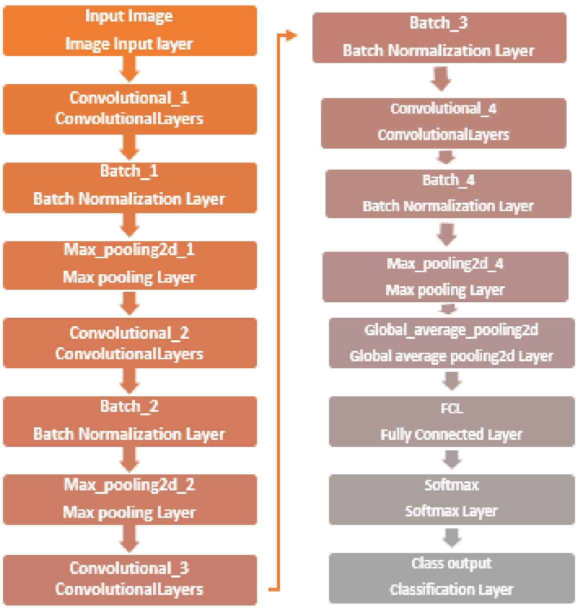


Fig 2: CNN layering architecture model

In order to improve the model's generalizability and reduce overfitting, various augmentation techniques were used, including horizontal flipping, brightness adjustment, contrast and saturation, and more. These adjustments were made to improve the model's ability to adapt to distortions that may

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occur due to differences in equipment or settings between different mammogram images. The CNN architecture is shown in Figure 2. For example, some images may be brighter, darker, or more saturated in color than others.to meet the input requirements of the CNN model. About 80%–85% of the dataset is reserved for training purposes, while 10%–10% is for validation and 10%–5% is for testing. Model learning takes place on the training set, hyper parameter tweaking on the validation set, and final performance evaluation on the test set. The CNN architecture as shown in Figure 3. The system implemented using Python and Keras platform.

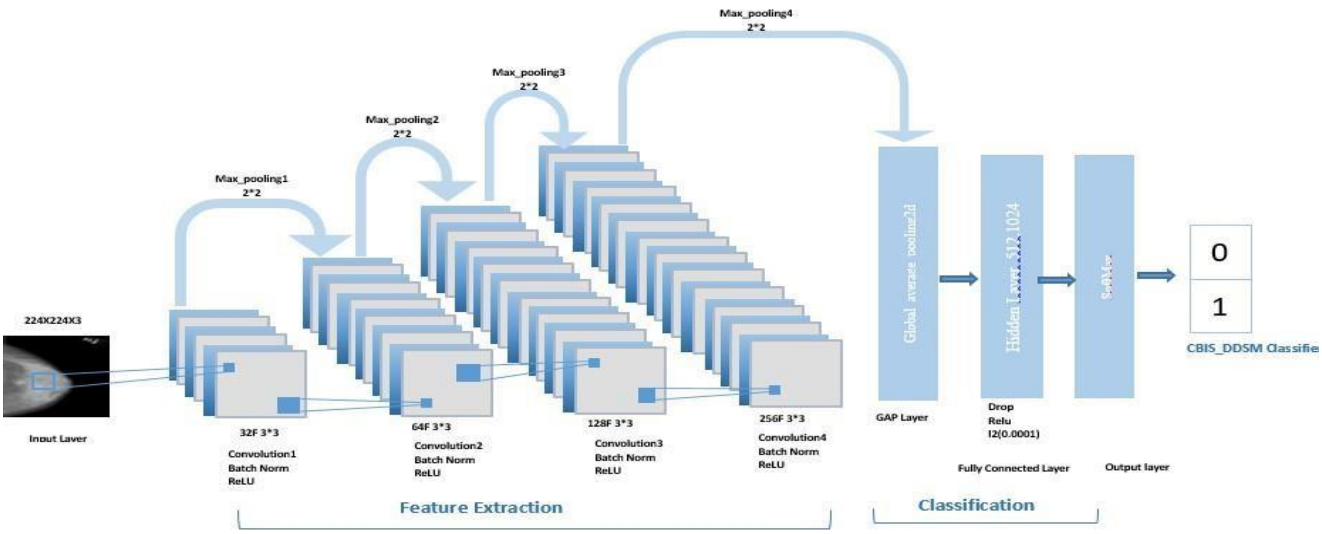


**Fig 3:** Architecture of the proposed model Implementation.

At this stage, several changes were made to the learning rate, batch size, epoch number, convolutional kernel assignments, Maxpooling parameters, and others. Using the test's prediction correction in comparison to the training dataset, the CNN model was evaluated.

## II. Dataset Description

The proposed model CNN architecture is evaluated in this work using the CBIS-DDSM dataset for breast cancer diagnosis. It functions as a well-known database for mammography analysis and is utilised in this work. The following features of the CBIS DDSM database are displayed in Table 1.

Table 1. The CBIS-DDSM Dataset Overview and Structure [6].

| Properties | Explanation |
|---|---|
| Purpose | Training automatic breast cancer detection systems |
| Total Images | 10,237 |
| Classes | Benign and Malignant |
| Image Types | Full Mammograms, Cropped Mammograms, ROI Masks |
| Original Format | DICOM |
| Converted Format | JPEG (for compatibility with deep learning frameworks) |
| Metadata | Anonymized patient information, lesion shape, tumor type, pathology labels |
| Special Features | ROI masks for tumor localization, pre-cropped regions of interest (ROI) |
| Dataset Source | Selected Breast Imaging Data from the Digital Mammography Screening Database |

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The database contains three fundamental categories of mammographic images:

- **Full Mammograms:** Give a total scan of the breast tissue, taking detailed structural features.
- **Cropped Mammograms:** Have localized tumor areas, such that the model only considers important tumor-related features for classification.
- **ROI Masks:** Mask tumor areas, enabling accurate extraction of pathological information to improve classification accuracy.

Figure 4 shows an example of full mammograms from the CBIS-DDSM dataset.

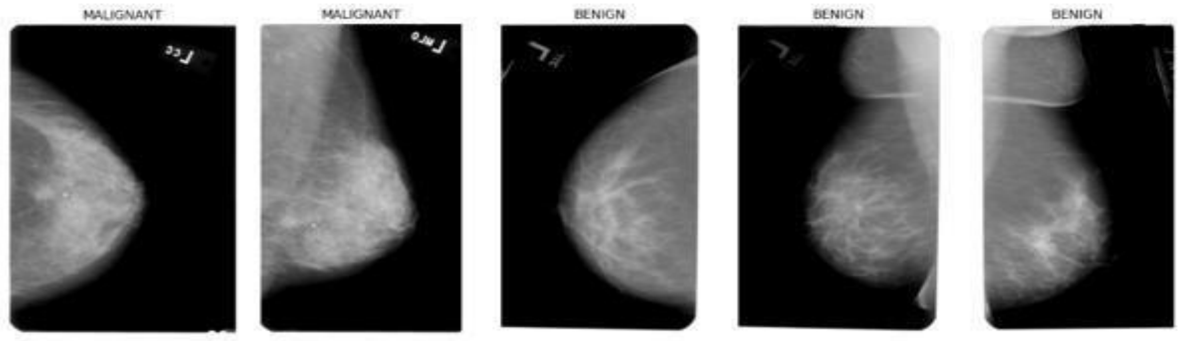


Fig 4: Full Mammograms from CBIS-DDSM Dataset

Figure 5 shows cropped mammograms with regions of interest (ROI) marked.

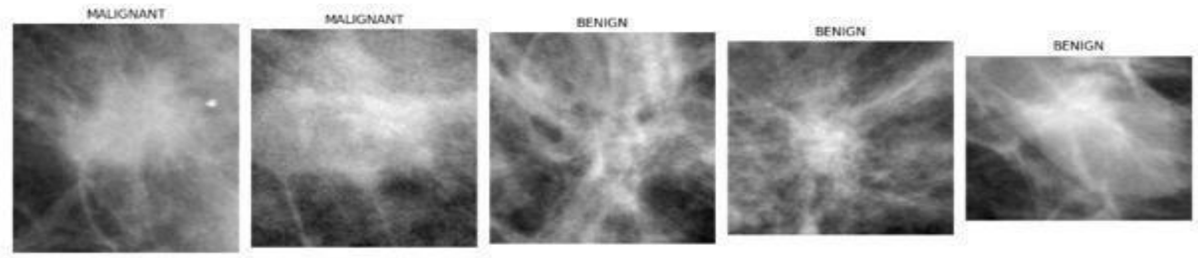


Fig 5: Cropped Mammograms Highlighting Regions of Interest (ROI)

Figure 6 demonstrates segmented tumor areas with ROI masks.

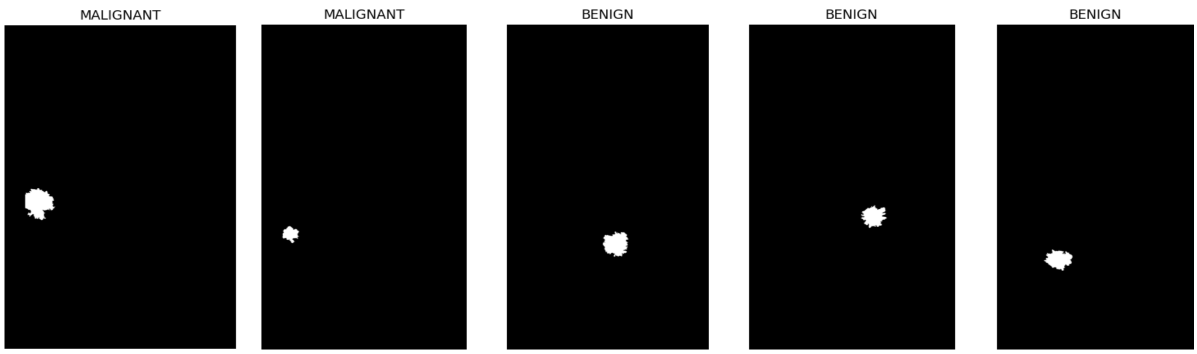


Fig 6: Segmented Tumor Regions Using ROI Masks

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### III. Dataset Image Features Extracting

In order to produce a collection of significant features for machine learning models, feature extraction entails choosing and modifying the most important information from raw data. In this CNN model, convolution operations detect image features through matrix multiplication using filters, while batch normalization normalizes outcomes to enhance model stability. Activation functions, particularly ReLU, play a key role in determining outputs and improving generalization. To optimize performance, MaxPooling2D is applied to reduce spatial dimensions while preserving crucial features, reducing computational costs, and mitigating overfitting—making it a fundamental technique in deep learning for high-resolution image analysis.

## EXPERIMENTAL RESULTS

This section presents the experimental outcomes assessing the effectiveness of the proposed model for classifying mammograms. The results, shown in Table 2 and Fig.7, were derived from the proposed technique in addition to the use of four preprocessing algorithms and the proposed CNN model, evaluated across two testing stages. The first experimental setup utilized an 80% training, 10% testing, and 10% validation split of the CBIS-DDSM dataset.

Table 2: Performance of Different Techniques on the CBIS-DDSM Dataset (80% Training, 10% Testing, 10% Validation Split)

| Model | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| MobileNetV2 | 83.52% | 86.35% | 80.49% |
| DenseNet121 | 89.46% | 99.62% | 78.60% |
| EfficientNetV2L | 97.92% | 97.31% | 98.56% |
| Proposed model | 98.21% | 99.04% | 97.33% |

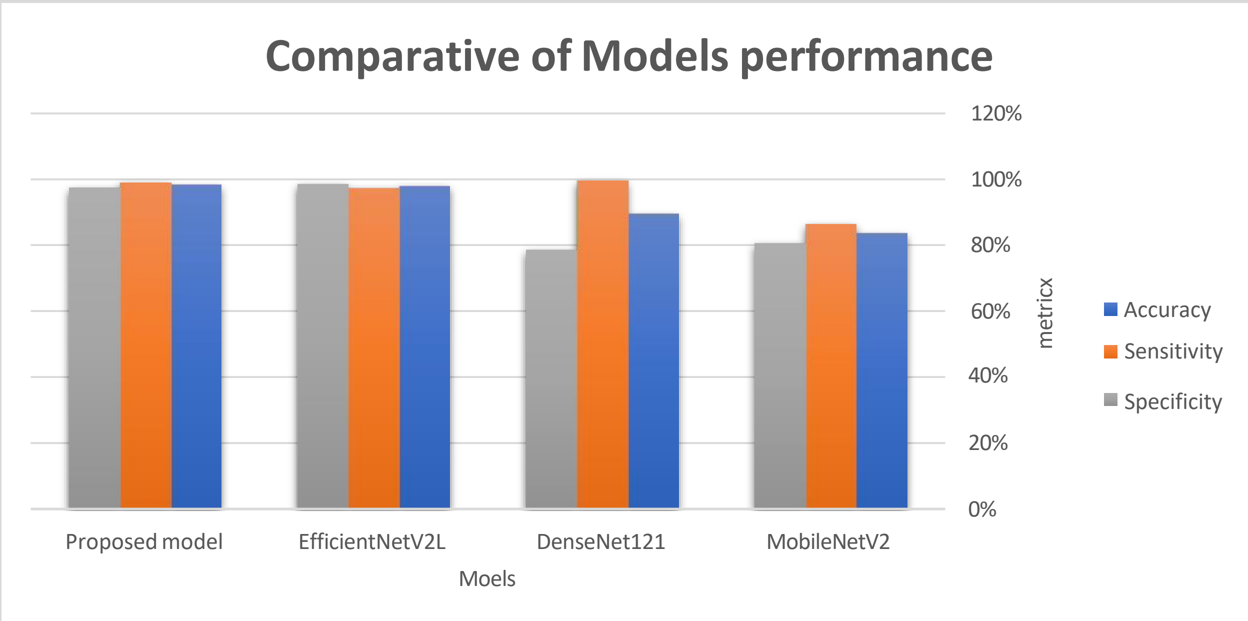


**Fig 7:** Performance of breast cancer classification models on CBIS-DDSM (80% training, 10% testing, 10% validation)

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The suggested model performed better than the other breast cancer classification models on the majority of assessment criteria, such as accuracy, sensitivity, and specificity, when the data is divided into 80% training, 10% testing, and 10% validation, as shown in Figure 7. These metrics provide a comprehensive evaluation of the models' classification effectiveness: specificity reveals how well the model can distinguish between healthy and cancerous instances, sensitivity measures how well the model can distinguish between cancerous and non-cancerous cases, and accuracy shows how many predictions were right.

In Table 3 and Fig.8 presents the second set of experiments applied a different split of the dataset: 85% training, 5% testing, and 10% validation. This new configuration aims to further test the robustness of the models.

Table 3: Performance of Different Techniques on the CBIS-DDSM Dataset (85% Training, 5% Testing, 10% Validation Split).

| Model | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| MobileNetV2 | 86.50% | 91.54% | 80.75% |
| DenseNet121 | 95.50% | 97.06% | 93.72% |
| EfficientNetV2L | 98.44% | 98.87% | 97.98% |
| Proposed model | 99.02% | 99.24% | 98.80% |

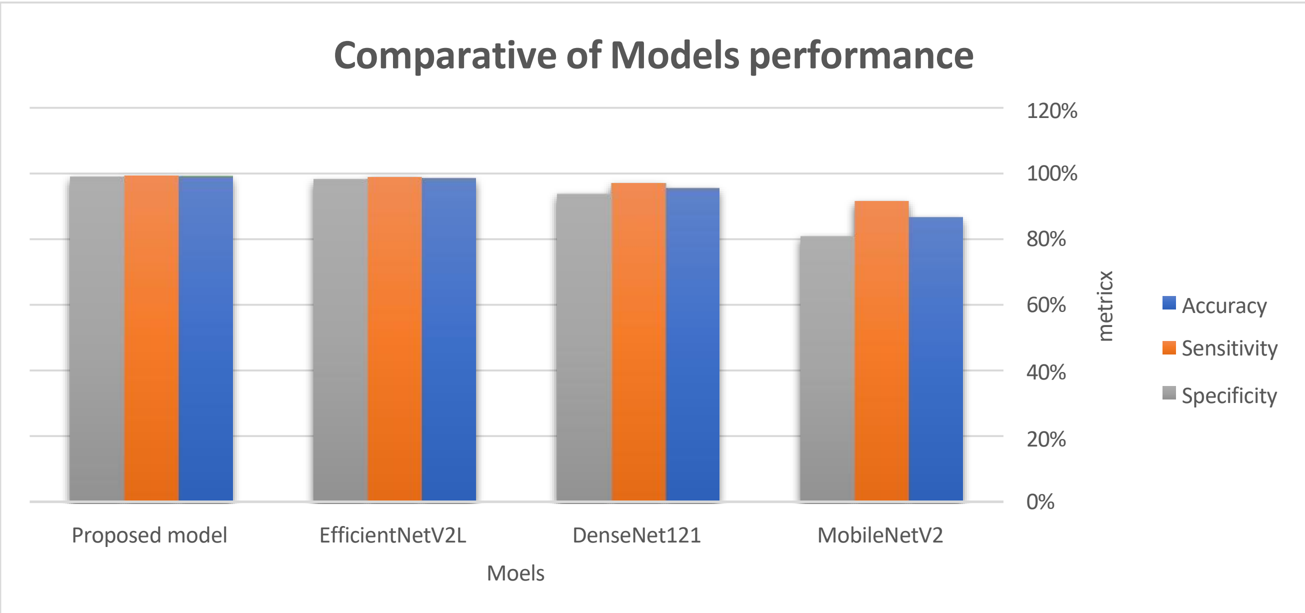


Fig 8: Performance of breast cancer classification models on CBIS-DDSM (85% training, 5% testing, 10% validation)

Fig. 8 illustrates the performance of different models when the dataset is split into 85% training, 5% testing, and 10% validation. In this setup, the proposed technique consistently outperformed most other models across all metrics, demonstrating its high efficiency in breast cancer classification.

The Table 4 shows a comparative evaluation of this study with existing work in the area of deep learning-based breast cancer detection from mammograms. The comparison is based on the dataset utilized,

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models tested, most important findings, and the limitations of each study to bring out the contributions and improvements made in this study.

Table 4: Comparative Analysis of This Study with Previous Research

| Ref | Types of Images | Dataset | Base Model | Accuracy% |
|---|---|---|---|---|
| [16] | Mammography | CBIS-DDSM | EfficientNet | 85.13% |
| [17] | Mammograms | INbreast, | CNN + AFDS | 92.4%<br>97.2% |
| | | CBIS-DDSM | | 79.7%<br>86.2% |
| [18] | Mammography | CBIS-DDSM | G-CNN with SE(2) + DCT | 94.84% |
| [19] | Mammography | MIAS, | CNNs FHDF | 98.70% |
| | | CBIS-DDSM, | | 97.73% |
| | | INbreast | | 98.83% |
| [ 20 ] | Mammography | CBIS-DDSM | EfficientNet-based deep learning model | Achieved 0.75 accuracy and 0.83 AUC |
| This Study | Mammography | CBIS-DDSM | Proposed technique | 98.21%<br>99.02% |

The study achieved the best level of accuracy when compared to other studies that utilised similar datasets and technology, as seen in the table above. A multitude of factors, such as the datasets' size and quality, the preprocessing techniques used, and the parameters of the machine learning algorithms, could influence the reliability of the results obtained from these studies. Nevertheless, the results of the comparison indicate that the study outperforms other research that has used similar datasets and technologies in terms of accuracy.

## CONCLUSION

This study offers a thorough examination of automated breast cancer identification using mammograms, utilizing advanced deep learning frameworks with refined picture enhancement methods. The research assessed the efficacy of three leading CNN models—MobileNetV2, DenseNet121, and EfficientNetV2L—using the CBIS-DDSM dataset, alongside a specifically constructed model for the binary classification of breast cancers. The incorporation of preprocessing approaches, such as data augmentation and normalization, markedly improved model accuracy and generalization, ensuring resilience across diverse input conditions. Under an 85% training, 5% testing, and 10% validation split, the suggested model achieved superior results—99.02% accuracy, 99.24% sensitivity, and 98.80% specificity—demonstrating significant gains in diagnostic performance, according to the experimental results. These results show how well the suggested strategy supports accurate and timely breast cancer diagnosis. The combination of a well-crafted classification pipeline, optimized CNN architectures, and a big, high-quality dataset is responsible for the model's success. All things considered, this study highlights the revolutionary possibilities of deep learning in medical imaging and makes significant contributions to the creation of intelligent diagnostic systems. Future developments in the use of scalable, affordable, and real-time diagnostic tools in clinical practice are also made possible by the encouraging outcomes.

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