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Breast Mammogram Classification using Deep Learning

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Abstract:
Breast cancer remains the most common cancer among women worldwide. Early and accurate detection is vital for increasing survival rates and ensuring effective treatment planning. Despite significant progress, conventional diagnostic techniques often lack consistency and precision, leading to misdiagnosis and limited clinical reliability. To address these shortcomings, this study explores advanced deep learning approaches for multi-class classification of mammogram images into benign, malignant, and normal categories. The investigation utilized three publicly available datasets—INbreast, MIAS, and DDSM—and implemented five transfer learning models (VGG16, InceptionV3, ResNet50, and EfficientNetB0) alongside two custom Convolutional Neural Network (CNN) architectures enhanced with attention mechanisms. Among all models, the custom CNN integrated with attention achieved the highest test accuracy of 98.69%, along with F1-scores of 0.98 for both benign and malignant classifications. The transfer learning models VGG16 (93.00%) and InceptionV3 (93.90%) also yielded competitive results. Incorporating the attention mechanism significantly enhanced the network's ability to differentiate between subtle variations in mammographic features, particularly those distinguishing benign from malignant lesions. Overall, the findings establish a reliable and high-performing framework for automated breast cancer detection, highlighting the critical role of attention-based deep learning in improving diagnostic accuracy.

Keywords: Deep Learning, Transfer Learning, Attention Mechanism.

1 Introduction

Breast cancer is the most frequently diagnosed cancer among women worldwide, accounting for an estimated 2.3 million new cases in 2022 [16]. Notably, nearly half of these cases occurred in women with no previously identified risk factors. The disease may develop any time after puberty, and its likelihood increases with age. On average, a woman somewhere in the world is diagnosed with breast cancer every 14 seconds [6]. The condition exhibits substantial variability in presentation, including differences in tissue morphology, tumor progression, and genetic makeup [53].

The risk of recurrence varies significantly depending on the cancer's type and stage, influencing both treatment effectiveness and long-term recovery [41, 26]. Survival rates are closely tied to the stage at which cancer is detected and the patient's geographic location. For instance, in India, over half of the diagnosed cases are detected at advanced stages (Stage III or IV), leading to an approximate survival rate of 60%, compared to nearly 80% in the United States [7]. In metastatic cases, where the cancer has spread to other parts of the body, treatment primarily focuses on prolonging life and enhancing quality of life [7].

Women identified as high-risk may consider preventive measures such as hormone-blocking therapy or prophylactic mastectomy to reduce the likelihood of developing breast cancer [4]. Growing awareness has led to more individualized and less invasive treatment strategies that emphasize overall well-being and long-term health benefits [20]. Drugs such as tamoxifen and raloxifene are commonly used to reduce breast cancer risk; however, they carry potential adverse effects, including blood clots and an increased susceptibility to other forms of cancer [53].

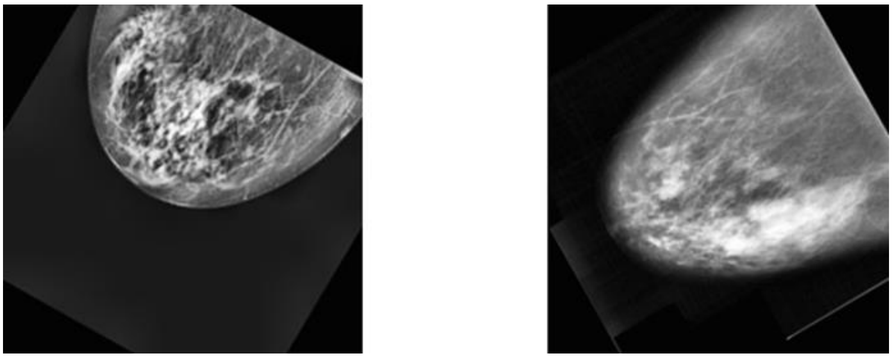

Figure 1: (a) Benign and (b) Malignant

Early detection can help with effective treatment. Medical imaging techniques such as mammography, ultrasound, MRI, and other imaging techniques play a vital role in identifying the type and stage of cancer, with monitoring of patient progress [29, 31]. Advances in treatment strategies, such as surgery, radiation, hormone therapy, targeted drug therapy, and chemotherapy have significantly improved survival rates and reduced re-occurrence [41]. With improved early detection, researchers are focusing on improving quality of life during and after treatment [26]. Many patients undergo a combination of treatments depending on their conditions. Easy options like cryotherapy and focused ultrasound are currently being tested for small tumors but still have limitations [31].

Research consistently shows that most breast cancer treatments significantly reduce the risk of recurrence [14]. Countries with strong screening programs re- port higher survival rates, especially when cancer is detected early [49]. A combination of treatments—surgery, radiation, and medication—has been effective in reducing recurrence rates and improving patient outcomes [42]. However, some treatments may cause complications such as cardiovascular problems, anemia, or mental health problems [17]. Aggressive tumors that grow and spread rapidly can also decrease survival rates [22].

To achieve optimal results with minimal side effects, treatment choices must be carefully made in each patient [30]. Despite the effectiveness of some treatments, patients may avoid them due to concerns about side effects or impacts on quality of life [37]. Ideally, treatments should target only the breast to minimize systemic effects [26].

Existing breast cancer detection techniques lack robustness, reliability, and effectiveness. For this reason, the use of their diagnostics is less, showing reduced clinical effectiveness. In this study, we used advanced deep learning models such as VGG16, InceptionV3, ResNet50, EfficientNetB0 and two custom CNN models with attention mechanisms for the multi-class classification of mammography images into benign, malignant, and normal categories.

This paper is divided into four sections. First, discuss the introduction to breast cancer, second review of the literature of recent advances in breast cancer detection using ML and DL algorithms, third is research methodology, and finally analysis of the results with conclusion

2 Literature Review

Artificial intelligence has emerged as a powerful tool in breast cancer diagnosis and classification, driven by progress in deep learning and medical imaging technologies. Researchers have shown that AI can help reduce missed diagnoses and diagnostic delays, particularly in regions with limited healthcare infrastructure [52]. Deep learning models are increasingly used to interpret mammograms, ultrasounds, MRIs, and other medical scans, identifying and categorizing breast tumors with growing precision [12]. Despite its promise, the adoption of AI in clinical practice remains limited due to a shortage of large, validated datasets and insufficient real-world testing [11].

Convolutional Neural Networks (CNNs) have become central to breast cancer image analysis, especially in ultrasound and mammogram interpretation. For instance, CNN architectures such as VGG, ResNet, and Inception were applied to the BUSI ultrasound dataset, achieving accuracies between 85% and 88%, though performance was constrained by small sample sizes [19]. Other studies combining CNNs with tumor segmentation improved accuracy beyond 90% [18]. Reported performances include 93.8% accuracy using deep learning [44] and 98.29% with an EfficientNetB7 model enhanced through data augmentation [33]. In histopathological imaging, a hybrid model known as GradeDiffIM exceeded 97% accuracy across multiple tumor grades [36]. AI applications have also extended to non-image data, such as infrared thermography for recurrence prediction, though these approaches achieved lower accuracy levels [25]. Structured data models, such as DHH-GRU, demonstrated 98.05% accuracy in predicting cancer outcomes [39].

For mammographic imaging, CNN-based Computer-Aided Diagnosis (CAD) systems have produced strong results. One study reported accuracies of 95.3% and 96.52% on the MIAS and INbreast datasets, respectively [15]. Optimization-based CNN models achieved accuracies up to 96.5% [23], while hybrid architectures surpassed 97% [1]. A feature-fusion strategy integrating outputs from several CNNs reached 98.83% accuracy [2]. Hybrid and optimized deep learning approaches continue to refine these results: Quantum SpinalNet achieved 90.3% accuracy [43]; wavelet-enhanced models produced an AUC of 0.92 [24]; and optimization combined with a Support Vector Machine yielded 99.25% accuracy [8]. EfficientNet-B4 with improved contrast reached 98.45%, while a dual-CNN ensemble achieved comparable performance [10, 34].

Pre-trained CNNs remain widely applied across various modalities. A 3D mammogram system achieved 96.6% accuracy [50], while VGG16 produced 96.94% [32], and ResNet50 combined with visualization tools attained an AUC of 0.983 [21]. A dual-view mammogram model, analyzing two perspectives simultaneously, achieved 95.86% accuracy [9]. StethoNet demonstrated consistent performance across diverse datasets [27].

Multiple datasets have supported these advances, including MIAS [46], INbreast [38], and CBIS-DDSM [28]. More recent datasets—KAU-BCMD [5], DMID [40], and KAUH-BCMD [3]—provide richer annotations and patient-level metadata. The KAUH-BCMD dataset, for example, includes 7,205 images from 5,000 patients, preprocessed using rescaling and contrast enhancement. Using this dataset, a Residual Depth-wise Network (RDN) achieved 97.82% accuracy, 96.55% precision, and 99.19% recall [3].

In ultrasound imaging, the BCDNet model—built on a pre-trained VGG16 and advanced optimization—attained 94.5% accuracy, outperforming other architectures [13]. This suggests that combining ultrasound with mammogram imaging could further enhance diagnostic accuracy. Another study simulated radiologist workflows by integrating multiple mammogram views and patient data, achieving improved reliability [45]. Transformer-based and graph neural network models have also shown strong performance when analyzing multi-view mammograms, with ensemble versions delivering the best outcomes [35]. A large-scale study on Asian women employed a multi-view CNN system to analyze over 24,000 mammograms, achieving an exceptional AUC of 0.995 [48]. This system notably helped radiologists reduce diagnostic errors, particularly in dense breast tissues. Another study that integrated traditional handcrafted features with deep learning methods achieved 97.14% accuracy on the MIAS dataset by effectively addressing challenges such as image noise and overlapping tissue structures [51].

3 Research Methodology

In this study, the research methodology emphasizes the development of reliable deep learning models to classify mammogram images into benign, malignant, and normal categories using the INbreast, MIAS, and DDSM datasets. The process involves data collection, preprocessing, model construction, training, and performance evaluation with various CNN-based architectures. The datasets are collected from kaggle, consisting of 26,602 images, with the distribution of 10,866 images (40.8%), 13,710 images (51.5%) and 2,026 images (7.6%) for benign, malignant and normal tumor types respectively.

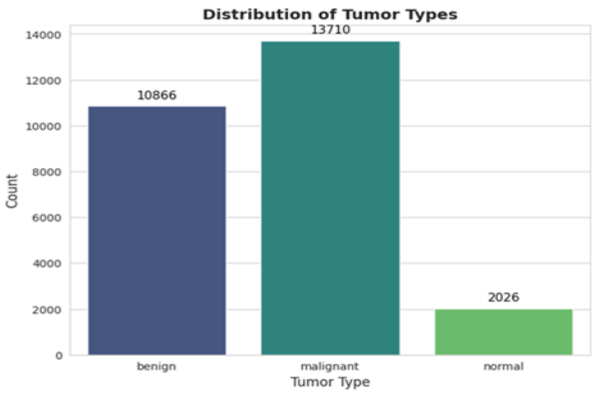

Figure 2: Distribution of Tumor Types

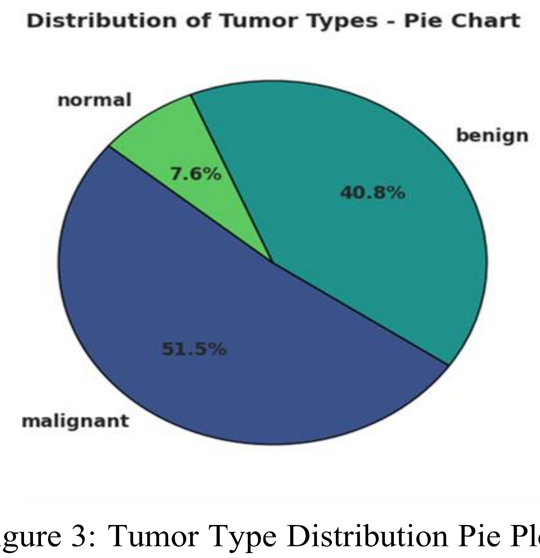

Figure 3: Tumor Type Distribution Pie Plot

3.1 Data Preprocessing

The Contrast Limited Adaptive Histogram Equalization (CLAHE) method was applied to improve the visual quality and contrast of the mammography images while data preprocessing. Categorical labels (benign, malignant, normal) were numerically encoded to facilitate model training. To address class imbalance, the dataset was upsampled using resampling to ensure that each class contained 13,710 images, resulting in a balanced dataset of 41,130 images. This balanced dataset was further divided into training (80%), validation (10%), and test (10%) sets using stratified sampling to maintain class distribution:

- Training set: 32,904 images
- Validation set: 4,113 images
- Test set: 4,113 images

The images were resized to 224x224 pixels and normalized to maintain uniformity in the data. No additional data augmentation was applied to the training set to maintain the original image characteristics.

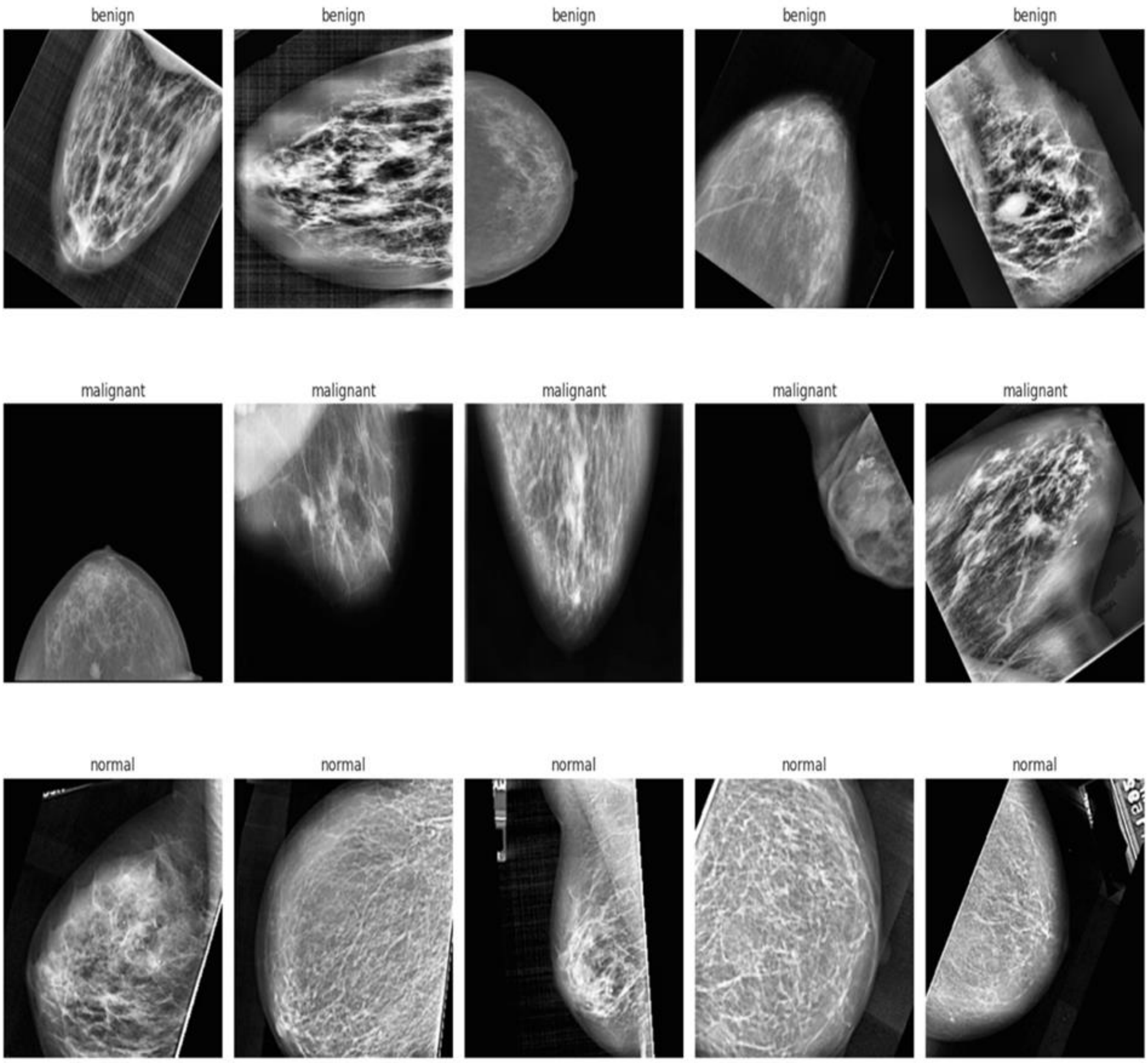

Figure 4: Classification of Breast Cancer Subtypes

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3.2 Model Development

Five deep learning models were designed and evaluated for classifying mammography images. These models included both transfer learning architectures and a custom CNN model integrated with an attention mechanism.

3.2.1 Transfer Learning Models

In transfer learning, the following models were used.

- **VGG16:** A pre-trained VGG16 model initialized with ImageNet weights was utilized, where the top layers were modified to include a global average pooling layer, a dense layer with 512 units and ReLU activation, followed by a dropout layer (rate 0.5) and a softmax output layer for classification.
- **InceptionV3:** A pre-trained InceptionV3 model with ImageNet weights, following the same architecture modifications as VGG16.
- **ResNet50:** A pre-trained ResNet50 model with ImageNet weights, with similar modifications.
- **EfficientNetB0:** A pre-trained EfficientNetB0 model with ImageNet weights, with the same modifications.

All pre-trained models were frozen by making their parameters as non-trainable, and the Adam optimizer, with learning rate = 0.001, was used with sparse categorical cross-entropy loss.

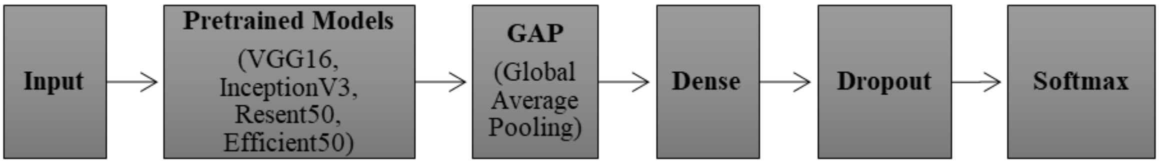

Figure 5: Transfer learning using Pretrained Models

3.2.2 Custom CNN Models with Attention Mechanisms

A custom CNN based architecture with CBAM (Convolutional Block Attention Module) layers was built to improve feature extraction through channel and spatial attention mechanisms. The model consisted of:

- Three convolutional blocks (32, 64, 128 filters, 3x3 kernels, ReLU activation, same padding).
- MaxPooling layers (2x2) after each convolutional layer.
- CBAM layers after each pooling layer to focus on relevant features.
- A global average pooling layer, a dense layer (512 units, ReLU activation), a dropout layer (0.5), and a softmax output layer.

Similarly to transfer learning models, Adam optimizer with a learning rate of 0.001 is used with sparse categorical cross-entropy as loss.

Further, a new custom CNN based architecture was built with a simpler attention mechanism using global average pooling, 1x1 convolution, and upsampling to generate attention maps. The architecture included:

- Three convolutional blocks (32, 64, 128 filters, 3x3 kernels, ReLU activation, same padding).
- MaxPooling layers (2x2) after each convolutional layer.
- Attention modules after each pooling layer to refine feature maps.
- A flatten layer, a dense layer (256 units, ReLU activation), a dropout layer (0.5), and a softmax output layer.

The model was compiled using the Adam optimizer with a learning rate of 0.001, and the loss function was defined as sparse categorical cross-entropy.

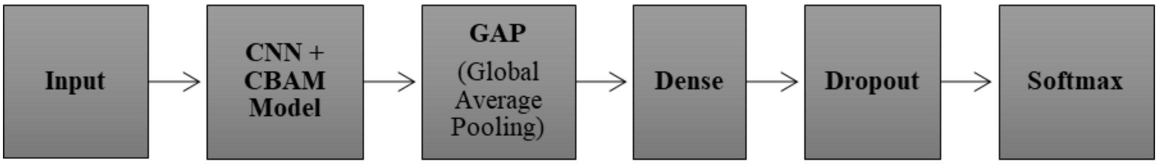

Figure 6: Custom CNN with CBAM Model

3.3 Model Training

All models were trained for 10 epochs with a batch size of 16. The training was performed on a system with two NVIDIA Tesla T4 GPUs, utilizing TensorFlow's GPU support for accelerated computation. ImageDataGenerator was used to feed images in batches to the models, with shuffling enabled for training and validation sets to ensure randomization. Training and validation accuracy and loss were monitored for each epoch to assess model performance and convergence.

3.4 Model Evaluation

The models were evaluated on the test set using accuracy, precision, recall, and F1-score, derived from the classification report and confusion matrix. For evaluation, following steps were performed:

- The test accuracy was computed using the evaluation method on the test set.
- Predictions were generated using the predict method, and class labels were obtained by applying argmax to softmax outputs.
- The confusion matrix is plotted to visualize the classification performance between classes.
- The classification report provided detailed metrics for each class.

4 Results Analysis

This section outlines the evaluation outcomes of six deep learning models developed for classifying mammography images into benign, malignant, and normal categories. Among these, the CNN model integrated with an attention mechanism achieved the highest test accuracy of 98.69%., showing an almost perfect classification across all classes. This is be- cause of its ability to focus on important features present in the images due to the attention mechanism. InceptionV3 and VGG16 also performed well, with accuracies of 93.90% and 93.00% respectively, showing balanced precision and recall.

However, both got occasionally confused with the benign and malignant classes. CNN with CBAM achieved 88.96% accuracy, performing well on normal cases but with lower recall for benign ones. ResNet50 showed moderate accuracy (83.18%) and struggled to differentiate between benign and malignant images effectively. EfficientNetB0 performed the worst, with an accuracy of only 33.33%, as it did not learn meaningful patterns and classified almost all samples as malignant. In general, models that used attention mechanisms and deeper architectures showed superior results in accurately classifying mammography images.

The table-1 summarizes the performance of all models on the test set, including accuracy and F1-scores for each class.

Table 1: Comparative performance of models on the test set

Model	Accuracy	Benign F1	Malignant F1	Normal F1
VGG16	93.00%	0.89	0.90	1.00
InceptionV3	93.90%	0.90	0.91	1.00
ResNet50	83.18%	0.74	0.78	0.96
EfficientNetB0	33.33%	0.00	0.50	0.00
CNN with CBAM	88.96%	0.81	0.85	1.00
CNN with Attention	98.69%	0.98	0.98	1.00

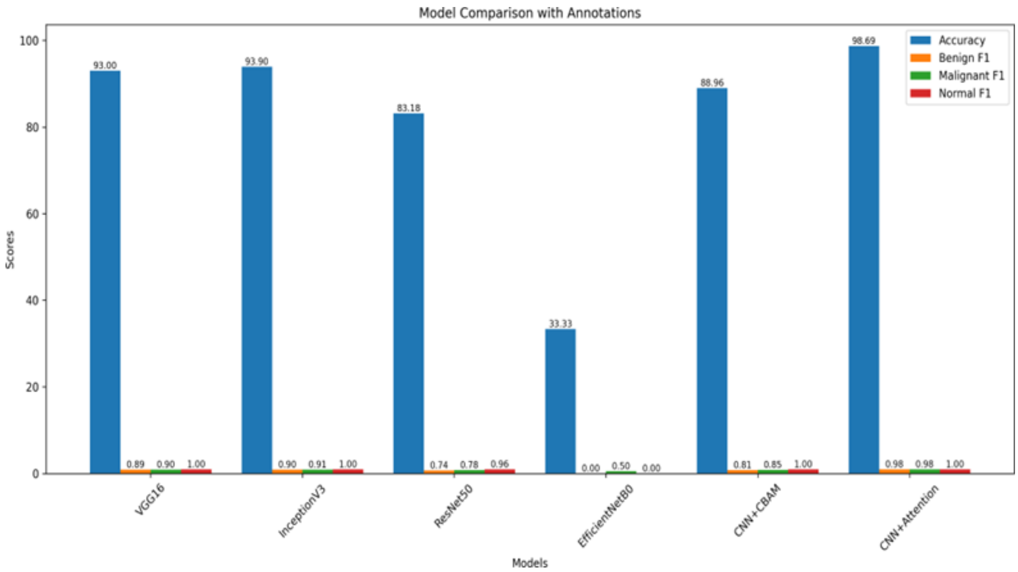

Figure 7: Accuracy Comparison of all Model’s

4.1 Training Dynamics

Accuracy and Loss Curves:

- VGG16 and InceptionV3: Showed a steady improvement in accuracy and decreased loss, with minimal overfitting.
- ResNet50: Showed slower convergence and higher validation loss, indicating potential under fitting or suboptimal feature extraction.
- EfficientNetB0: Resulted in 33.33% accuracy and constant loss (~1.098), suggesting

that the model did not learn discriminative features.

- CNN with CBAM: Improved steadily but showed slight overfitting.
- CNN with Attention: Exhibited rapid convergence, with validation accuracy reaching 98.71% and minimal gap between training and validation metrics, indicating excellent generalization.

According to the confusion matrix, CNN with Attention had the fewest misclassifications, followed by InceptionV3 and VGG16. ResNet50 and CNN with CBAM showed more errors in benign-malignant differentiation, while EfficientNetB0 misclassified all benign and normal cases.

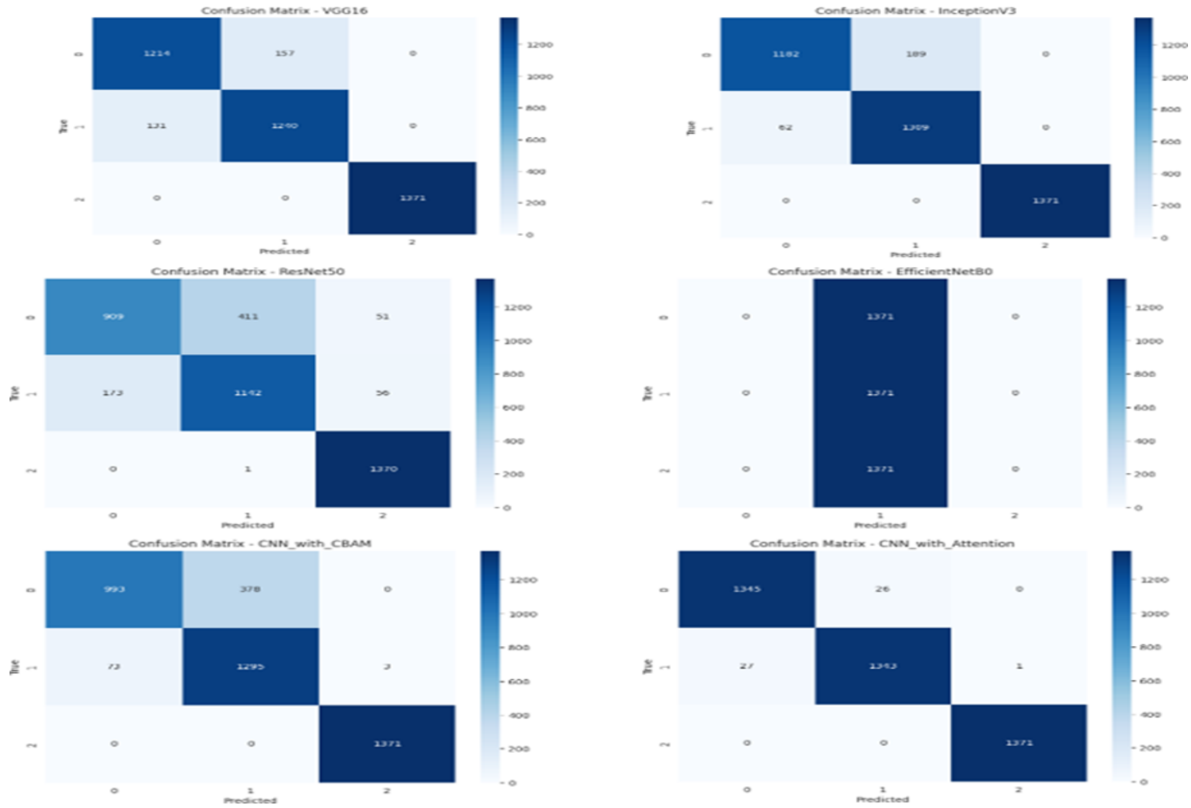

Figure 8: Confusion Matrix of all models

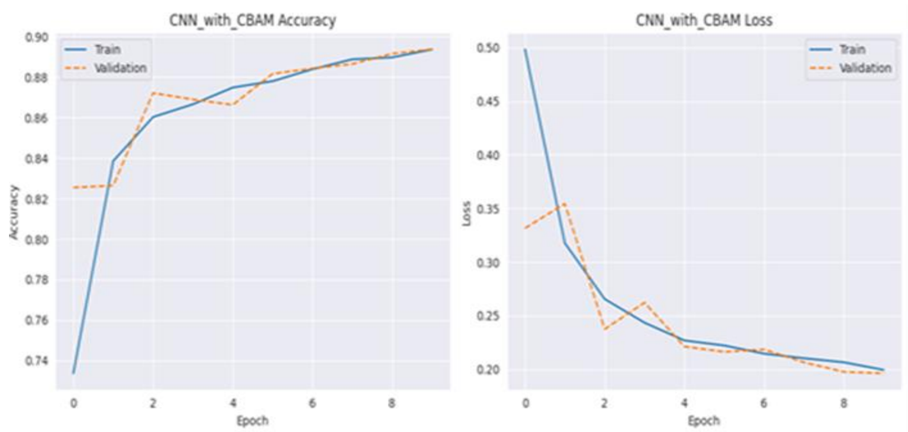

Figure 9: Training and Validation Accuracy and Loss Curves for CNN with CBAM Model

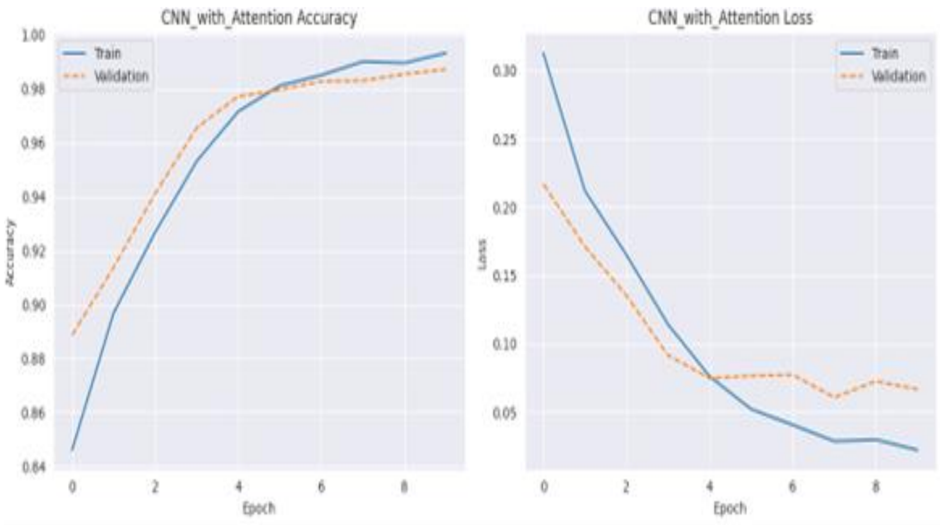

Figure 10: Training and Validation Accuracy and Loss Curves (Custom CNN with Attention Model

5 Conclusion

In this study, mammographic image data were systematically collected, preprocessed, and analyzed using a range of deep learning models. Among them, the Convolutional Neural Network (CNN) integrated with an attention mechanism achieved the best performance, recording a test accuracy of 98.69%, thereby demonstrating the effectiveness of attention-based learning in medical image classification. Transfer learning models such as VGG16 and InceptionV3 also produced strong results, while ResNet50 and EfficientNetB0 exhibited comparatively lower performance.

The proposed research framework establishes a reliable and reproducible approach for mammogram classification. It can be further refined through extended training, optimized hyperparameter selection, and advanced data augmentation strategies to enhance generalization and stability. Moreover, the adaptability of this framework makes it suitable for broader applications in medical imaging, supporting the design of precise and efficient diagnostic systems for early breast cancer detection.

6 Future Work

Building upon the identified limitations, future research should focus on enhancing model optimization and interpretability. Extending the training epochs from 10 to 20–30, coupled with techniques such as early stopping and learning rate scheduling, could substantially improve the performance of underachieving models like EfficientNetB0 and ResNet50, potentially increasing their accuracy by 10–20%. Incorporating advanced data augmentation methods—including rotation, flipping, zooming, and GAN-based synthetic image generation—would strengthen model robustness and generalization across diverse imaging conditions. Furthermore, exploring hybrid architectures that integrate CNN with Attention and Transformer-based components could enhance the model's capability to capture both local and global contextual features, thereby improving multi-class classification performance. Another key direction involves the integration of explainable AI (XAI) techniques such as Grad-CAM visualizations for all trained models. These tools can provide greater transparency in decision-making, offering visual insights into the regions of interest influencing model predictions. Such interpretability is critical for gaining clinical trust, supporting regulatory validation, and promoting real-world clinical deployment of AI-driven diagnostic systems.

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