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Enhanced Breast Cancer Detection via Optimized Convolutional Block Attention Module (CBAM)

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ABSTRACT:

Early detection of breast cancer is crucial for effective treatment, making reliable screening methods essential for identifying initial symptoms. Various imaging techniques, such as mammography, ultrasound, and thermography, are commonly used for screening breast cancer. Traditional diagnostic methods, have significantly contributed to early detection but are often hampered by limitations, including false positives and false negatives, which can lead to unnecessary procedures or delayed treatment. This study proposes a model based on the ResNet50 Convolutional Neural Network (CNN) to detect breast cancer from mammograms, incorporating the Convolutional Block Attention Module (CBAM) as an attention mechanism. The model explores varying numbers of CBAM blocks to determine the optimal configuration while mitigating the risk of overfitting. The performance of the proposed model was evaluated using the dataset obtained from the PatchCamelyon (PCam) dataset by comparing its Area Under the Curve (AUC) scores with those of existing models. The results demonstrate that the ResNet50 model integrated with CBAM blocks shows improved performance with an increased number of blocks, with the model utilizing 8 CBAM blocks achieving the highest performance in terms of AUC, precision, recall, and accuracy. Compared to existing models, the proposed ResNet50 model with 8 CBAM blocks outperformed all others across all performance metrics, confirming the effectiveness of the CBAM integration and the overall model architecture in improving breast cancer detection.

Keywords: Breast Cancer Detection, ResNet50, Convolutional Neural Network (CNN), Convolutional Block Attention Module (CBAM), Data Augmentation and AdamW Optimizer

I: INTRODUCTION

Cancer remains the leading cause of death globally, with breast cancer being the most common and fatal among women (Alanazi et al., 2021). According to the World Health Organization (WHO) Global Cancer Observatory, breast cancer is the most frequently occurring cancer in Nigeria and has the highest mortality rate among women (WHO, 2021). Despite common misconceptions, breast cancer is curable but the reality is that it is often detected too late for effective treatment, if detected early, which significantly improves likelihood of successful treatment outcomes (Assegie, 2020; Biancovilli et al., 2021). Unlike normal cells, breast cancer cells are loosely connected, making it easy for them to spread to nearby lymph nodes and other parts of the body, such as the lungs, leading to life-threatening metastases (Jamal et al., 2019). Therefore, early diagnosis is critical.

Mammography, an X-ray-based technique for detecting malignant breast tumors, has become a widely adopted alternative to breast self-examination in medical practice. Despite its prevalence, human interpretation of mammograms is prone to significant risks of false positives, leading to unnecessary biopsies and surgeries, and false negatives, resulting in delayed diagnosis and limited treatment options (Sony et al., 2021). The primary goal of mammography is early cancer detection, enabling the diagnosis of breast masses from images. Mammograms are crucial tools not only for breast cancer screening but also for diagnosis, evaluation, and follow-up in patients with a history of the disease. The screening process involves compressing the breast between two flat plates and applying a low-dose X-ray, which is captured by a two-dimensional (2D) panel detector. Research indicates that even the most skilled physicians achieve a maximum accuracy of 79% in cancer detection, whereas machine learning techniques can reach up to 91% accuracy (Bhinder et al., 2021).

Additionally, pathological images are difficult to define- and even experienced doctors find it tedious to distinguish cancerous cells from normal cells. Minor regions can also be easily missed, further complicating diagnosis (Alanazi et al., 2021).

Artificial Intelligence (AI) is rapidly advancing in the medical field, bringing transformative changes and significant improvements in healthcare outcomes. Convolutional Neural Networks (CNNs), often referred to as the workhorse of image classification, are currently the leading deep learning approach for detecting and classifying images in cancer diagnostics. CNNs offer substantial benefits over human experts, including scalability and automation, which have led to their widespread adoption in medical imaging (Bhinder et al., 2021).

CNN models are data-driven and can be trained end-to-end, allowing for the integration of feature extraction, selection, and malignancy prediction into a single optimization process. Unlike features manually designed by human engineers, CNN features are learned directly from input data (Zou et al., 2019). To enhance the accuracy and performance of CNN models, Convolutional Block Attention Modules (CBAM) are incorporated into the network layers. These modules focus on important areas or channels of the feature maps, weighting them according to their significance.

Liang et al (2019) proposed a model that uses CNNs to identify breast cancer in histopathological images by integrating CBAM to focus on important parts of feature maps. They used 16 CBAM modules inserted into different layers of the ResNet50 CNN. However, the model showed a tendency to overfit, leading the authors to suggest reducing the proportion of CBAM blocks in future work. Additionally, the existing study utilized the ADAM optimizer for parameter optimization during training. However, ADAM can suffer from weight decay problems (Kurz et al., 2022). Therefore, this study employs an improved version of ADAM, known as AdamW, to address the weight decay issue.

To overcome these challenges, innovative approaches are needed to improve diagnostic accuracy and efficiency. This research proposes a system that leverages a ResNet50 Convolutional Neural Network integrated with an attention mechanism to identify breast cancer from images of breast tissues. CNNs mimic the human brain's data processing, enabling object recognition, detection, decision-making, speech recognition, and language translation. The term "convolutional" derives from the mathematical operation of convolution, a linear operation between matrices. CNNs have demonstrated excellent performance in machine learning problems, particularly those involving image data, such as image classification (e.g., ImageNet), computer vision, and natural language processing (NLP).

Furthermore, as part of the methodology, data augmentation techniques will be applied to enhance the model's performance by increasing the diversity of the training data, thereby reducing overfitting and improving the generalization capability of the CNN model. Data augmentation will involve techniques such as random rotation, flipping, scaling, and cropping of images to generate various training samples from the existing dataset, which is crucial for improving the robustness and accuracy of the proposed system.

II. LITERATURE REVIEW

In a study by, (Alanazi et al., 2021) the authors proposed a CNN approach for the automatic diagnosis of breast cancer by examining the IDC tissue regions in Whole Slide Images. In the paper, three different CNN architectures have been described and compared using a 5-layer ResNet101 CNN Model on a skit-learn machine-learning framework with datasets of about 275,000, 50 × 50-pixel RGB image patches. The model was found to effectively obtain correct diagnostic results.

Chen (2019) proposed a CNN classifier based on image bit-plane slicing to improve the recognition accuracy of breast cancer image classification. Each texture image is disintegrated into eight bit-plane images. Different bit-planes provide different levels and detail of image texture feature. The feature classification performance by each bit-plane is also tested respectively and the fusion of all bit-planes. CNN classifier was used for classification and recognition. The simulation results on the breast cancer image datasets show that the proposed method on some bit-plane can significantly improve recognition rate and promote classification accuracy.

Yang et al., (2021) implemented a fully automatic deep learning method using Mask Regional Convolutional Neural Network (R-CNN) for detection of breast cancer by searching the entire set of images. The major limitation was the small case number and the unbalanced data. Also, the dataset used in training the model vary from the dataset used in testing the model (trained on non–fat-sat Images and tested on fat-sat Images).

Mostavi et al.,(2020) suggested that although deeper CNN models are known to produce more accurate classifications in computer vision, quite a lot of studies have revealed that increasing the depth of CNN models on biological data does not always enhance its performance. Shallower models are preferred for problems such as cancer-type prediction as such models avoid overfitting and also require only a few resources for training. With these considerations, in their work, they presented three different CNN designs: CNN with vectorized input (which they called 1D-CNN), CNN with matrix input (which they called 2D-Vanilla-CNN), and CNN with matrix input and 1D kernels (2D-Hybrid-CNN).

Gao et al. (2018) presented a shallow-deep CNN (SD-CNN) for lesion detection and classification for contrast-enhanced DMs (CEDM). A 4-layered shallow-deep CNN was used to extract the visualization mappings of the convolutional layer in the CEDM images and combine them with low-energy (LE) images. This virtual enhancement improved the quality of LE images. ResNet was applied to these virtual combined images to extract the features to classify benign and normal cases. Using the SD-CNN on the CEDM images resulted in a significant improvement in classification accuracy compared with DMs.

Nguyen et al., (2022) proposed a model that employs ResNet50 and transfer learning was subsequently applied to adjust the weights of the model. The evaluation metrics were assessed by the ROC curve (AUC) score. The proposed algorithm obtained high performance, with scores over 95% in all the accuracy scores, confusion matrix, receiver operating characteristic (ROC) curve, and area under evaluation methods. The model is validated in a testing set with the test-time augmentation (TTA) technique to enhance prediction quality and reduce generalization error.

In a recent study, (Liang et al., 2019) proposed a CNN model to identify breast cancer histopathological images, where Convolutional Block Attention Mechanism blocks were employed to emphasize the important parts of feature maps on the images. The model achieved high AUC scores on the PCam dataset, showing that the attention mechanism is a great tool in histopathological image recognition.

The research conducted by Kuda et al. (2023) identifies a crucial gap in optimizing the Convolutional Block Attention Module (CBAM) for breast cancer detection. The model achieves the most optimal performance when utilizing 12 CBAM blocks, which also results in a reduced rate of overfitting. This finding suggests that minimizing the number of CBAM blocks can enhance the model's performance without sacrificing training and testing accuracies. Future research will incorporate a regularization technique to further mitigate overfitting, data augmentation, and a reduced number of CBAM blocks Additionally, the study will compare the classification performance of the proposed model with other state-of-the-art methods using metrics such as Area Under the Curve (AUC), precision, and recall

Yang et al., (2021) used a Mask Regional Convolutional Neural Network (R-CNN), implemented with ResNet-101 as the backbone for automatic detection and segmentation of breast cancer on MRI. The model was trained on non–fat-sat images and tested on fat-sat Images. Pre-contrast, postcontrast, and subtraction images of the diseased breast were used as inputs, thus increasing specificity in detection, while maintaining sensitivity.

III. METHODOLOGY

This research involves developing and evaluating a breast cancer detection model using the ResNet50 Convolutional Neural Network (CNN) architecture, enhanced with Convolutional Block Attention Modules (CBAM). The methodology is divided into several key stages, including data preprocessing, proposed model, training and optimization, and evaluation.

A. Dataset

The dataset utilized in this research is obtained from PatchCamelyon (PCam) dataset, which is a large-scale benchmark dataset for histopathological image analysis, which is publicly available and used for training and testing the model. The PCam dataset, derived from the Camelyon16 Challenge datasets, consists of 400 H&E-stained whole slide images of sentinel lymph node sections, obtained from two different centers using a 40x objective. The PCam dataset utilizes 10x under- Exampling to enlarge the visual field, resulting in a pixel resolution of 2.43 microns.The data description, a positive label indicates at least one tumor cell pixel in the center area (32 x 32 pixels) of the image, while tumor tissue in the outer region of the patch does not influence the label. Sample images from the PCam dataset are shown in Figures 2 and 3.

Figure 1:BENIGN

Figure 2: Malignant

B. Data Preprocessing

The data preprocessing involves several key steps designed to prepare the dataset for training the Convolutional Neural Network (CNN) model. The preprocessing pipeline ensures that the data is appropriately and correctly encoded, standardized, and reshaped to meet the requirements of the CNN model. These steps, including label encoding, normalization, and handling missing data, are essential for preparing the dataset, leading to more effective and efficient model training.

Patch Extraction

PCam consists of 327,680 color images extracted from histopathologic scans of lymph node sections. Each image measures 96 x 96 pixels and is labeled with a binary label indicating the presence of metastatic tissue in the center 32x32 pixel region. The outer region provides context but does not influence the label.

Patch Selection

Patches are extracted from the original whole-slide images (WSIs) at a 10x magnification to increase the field of view.

The train/test split from the Camelyon16 challenge is used, with 30% of the training WSIs held out for validation while the remaining 70% for training. To filter out background patches, slides are converted to HSV color space and blurred, and patches are kept only if the maximum pixel saturation is above 0.07.

Balancing Classes

The dataset maintains a 50/50 balance between positive and negative examples across the training, validation, and test sets. This is achieved through stochastic hard-negative mining during patch selection to ensure an equal number of tumor-containing and tumor-free patches.

Preprocessing Steps

1. Convert WSIs to HSV color space and blur to identify tissue regions
2. Extract overlapping 96x96 pixel patches at a stride of 32 pixels
3. Filter out patches with low saturation to remove background
4. Assign binary labels based on the presence of the tumor in the center 32x32 region
5. Maintain a 50/50 class balance by selecting patches stochastically

This preprocessing aims to create a large, balanced dataset of histopathology image patches suitable for training deep-learning models for metastasis detection. The outer context region and hard-negative mining help the models learn discriminative features

To address the challenges posed by limited data and to enhance the generalization capability of the model, various data augmentation techniques were employed. These techniques included random rotations, horizontal and vertical flips, zooming, and shifting. Data augmentation artificially increases the diversity of the training data, allowing the model to learn robust features and reducing the risk of overfitting.

Additionally, image normalization was applied to scale pixel values to a range that facilitates faster convergence during training. This step ensures that the model can learn effectively without being influenced by variations in pixel intensity across the dataset.

B. Proposed Model The core of the proposed model is the ResNet50 Convolutional Neural Network, known for its deep architecture and ability to handle complex image classification tasks as shown in Fig.3.

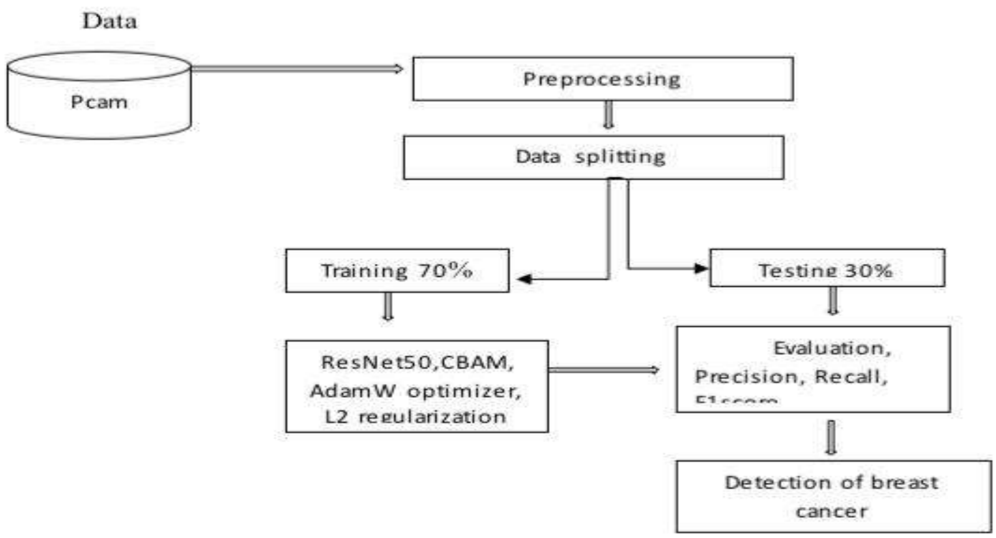

Figure 3:Proposed Model

ResNet50

Uses skip connections to address the vanishing gradient problem, consisting of convolutional, pooling, and fully connected layers, along with residual connections that help mitigate the vanishing gradient problem, allowing for more effective training of deep networks. The output of the 50th layer in ResNet50 can be represented as:

$$F_{ResNet}(X)=F_{50}(X) \quad (1)$$

Here, F_{50} represents the function that processes the input through 50 layers, incorporating skip connections. The skip connection can be mathematically represented as:

$$\boldsymbol{F_l(x) = H_l(x) + F_{l-1}(x)} \quad (2)$$

where $\boldsymbol{H}_{\boldsymbol{l}}(\boldsymbol{x})$ is the desired underlying mapping (is the transformation applied at layer l*l*) and $\boldsymbol{F}_{\boldsymbol{l-1}}(\boldsymbol{x})$ is the identity mapping (the output from the previous layer).

Convolutional Block Attention Modules (CBAM)

To further improve the model's performance, Convolutional Block Attention Modules (CBAM) were integrated into the ResNet50 architecture. CBAM enhances the model's ability to focus on the most critical features within the images by applying channel and spatial attention mechanisms sequentially. These modules refine the feature maps by emphasizing

important regions and suppressing less relevant areas, thereby improving the model's ability to detect subtle patterns indicative of breast cancer.

Experiments were conducted with varying numbers of CBAM blocks integrated into the ResNet50 model to determine the optimal configuration. The primary objective was to find a balance between the number of attention blocks and the overall model complexity, ensuring that the model remains both effective and computationally efficient.

CBAM is an attention module that can be integrated into any CNN architecture to adaptively refine the feature maps, it enhances the feature representation from ResNet50 by applying attention mechanisms. It consists of channel attention and spatial attention modules. The channel attention map Mc(F) is computed as:

$$Mc(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (3)$$

where AvgPool and MaxPool are global average pooling and global max pooling, respectively, and MLP is a multi-layer perceptron and σ is the sigmoid activation function.

The spatial attention map Ms(F) is computed as:

$$M_s(F) = \delta(F^7 \text{ x } 7([AvgPool|(F); MaxPool(F)])) \quad (4)$$

where F^7 times 7 is a convolutional layer with a kernel size of 7 times 7.

The refined feature map F' is obtained by:

$$F' = M_c(F) \otimes F \quad (5)$$

$$F'' = M_s(F') \otimes F' \quad (6)$$

where ⊗denotes element-wise multiplication.

AdamW Optimizer

AdamW is a variant of the Adam optimizer that decouples the weight decay regularization from the gradient-based update rule. The update rule for AdamW is:

$$\theta t + 1 = \theta t - \eta . \frac{\sqrt{\mathbf{1-\beta_2^t}}}{\mathbf{1-\beta_1^t}} . \frac{\boldsymbol{m^\wedge{}_t}}{\sqrt{\boldsymbol{v^\wedge{}_t + \in}}} - \eta . \boldsymbol{\lambda} . \boldsymbol{\theta_t} \quad (7)$$

Where:

- θt = Current model parameters
- η = Learning rate
- β1,β2 = Exponential decay rates for the first and second moment estimates
- m^t and v^t = Biased first and second-moment estimates
- ϵ = Small constant to prevent division by zero
- λ = Weight decay parameter

Combined Model

Combining these components, the overall architecture can be represented as:

1. **Feature Extraction**:
    - Extract features using ResNet50:

$$\mathrm{F}'' = ResNet50(X) \quad (8)$$

2. **Attention Mechanism**:
    - Apply CBAM to refine the features:

$$F''' = CBAM(F'') \quad (9)$$

3. **Optimization**:

- Update model parameters using AdamW:

$$\boldsymbol{\theta t + 1 = \theta t - AdamW}(\boldsymbol{\nabla\theta L}(\boldsymbol{F'''}, \boldsymbol{y})) \qquad (10)$$

Regularization technique

Regularization technique was involved to eliminate the overfitting while maintaining an optimal number of convolutional blocks. It is crucial for improving the generalization ability of deep learning models, ensuring that they can accurately detect breast cancer across various patient datasets while minimizing the risk of over fitting.

In this research, we tend to penalize the outright estimation of the weights. Unlike L2, the weights might be reduced to zero here. Thus, it is practical when we attempt to compress our model. Otherwise, we conventionally favor L2 over it.

the loss function is defined by:

$$FL(pt) = -\alpha t(1 - pt)^{\gamma} \, log(P_t \qquad (11)$$

$$P_t = \begin{cases} p & if \; y = 1 \\ 1 - p & otherwise \end{cases}$$

Where p denotes the probability that the sample is from class 1, so the pt is the probability of correct classification. αt denotes the weight of the positive and negative samples. Negative samples appear more frequently, then the weight of the negative samples is reduced and vice versa. When for simple examples, pt will be larger, so the weight $(1 - pt)\gamma$ is reduced, where γ ranges from 0 to 5.

C. Performance Evaluation Metrics

In general, various metrics are employed to assess the efficacy of classification models. These metrics encompass recall (rec), precision (pre), F1-score, and classification accuracy (acc). All of these metrics are derived from the four basic outcomes, namely True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These outcomes provide the basis for computing a range of evaluation parameters. For example, acc represents the ratio of correctly classified data instances to the total number of data instances, rec measures the proportion of positive cases that are correctly predicted, and pre quantifies the acc of positive predictions among all positive patterns.

D. Training and Optimization

The training process involved a supervised learning approach, where the model was trained on labeled images from the PCam dataset. The AdamW optimizer was selected for training due to its ability to address the weight decay issues commonly associated with the optimizer it decouples the weight decay from the gradient updates, leading to better regularization and improved convergence of the model.

In addition to using the AdamW optimizer, L2 regularization was applied to further reduce the risk of overfitting. This technique penalizes large weights in the model, encouraging it to maintain smaller, more generalizable parameters.

To identify the most effective model configuration, a series of experiments were conducted with different numbers of CBAM blocks. The model's performance was carefully monitored during

training using validation data to ensure that the

model did not overfit the training data. Early stopping was also implemented as an additional measure to halt training when the model's performance on the validation set began to degrade.

IV. RESULTS

A. Experimental Setup

Table 1: Hardware and Software specification used in the proposed system

Name	**Description**
Processor	Intel corei7(multi-core processor), NVIDIA GTX 1080
Toolbox	Deep learning toolbox and computer vision toolbox
Development Tool	Windows 10, 64-bit, MATLAB R2021b
Memory	16GB of Ram

Experiments are performed on a system using the 64-bit Windows 10 OS, Intel i7 (multi-core processors), NVIDIA GeForce GTX 1080 Graphics card GPU, and 6 GB RAM. The experiments were conducted using MATLAB R2021b, Deep learning, and computer vision toolbox. Table 1 describes the software and hardware specifications used for the proposed model.

C. SETTING OF HYPERPARAMETERS

The model employs the AdamW optimizer to effectively address weight decay issues and enhance its generalization capabilities. A learning rate of 0.001 is utilized for the optimizer, ensuring a balanced approach to convergence. Additionally, a weight decay factor of 0.01 is implemented for regularization, which helps prevent overfitting during the training process. To further mitigate the risk of overfitting, L2 regularization is applied. The training process is conducted with a batch size of 32, optimizing efficiency while processing data. Finally, the model is trained for 50 epochs to ensure

adequate convergence and performance stability.

Table 2:hyper-parameters of the proposed models.

Parameter	**Value**
Dataset	PatchCamelyon
Model	ResNet50 with CBAM
Number of CBAM blocks	2, 4, 6, 8
Optimizer	AdamW
Learning Rate	0.001
Weight Decay	0.01
Batch Size	32
Epochs	50
Regularization Technique	L2 Regularization
Data Augmentation	Rotation, flipping, zooming, shearing, etc.

EXPERIMENTAL RESULTS

The results for the models with different numbers of CBAM blocks are summarized in table 3:

	2 CBAM	**4 CBAM**	**6 CBAM**	**8 CBAM**
Metric	**Value**	**Value**	**Value**	**Value**
AUC	0.945	0.952	0.958	0.961
Precision	0.912	0.920	0.926	0.930
Recall	0.898	0.905	0.912	0.915
Accuracy	0.905	0.913	0.920	0.925

Table 3:Performance with CBAM Blocks

The performance of the ResNet50 model improves as the number of CBAM blocks increase. This indicates that the inclusion of CBAM blocks enhances the model's ability to focus on relevant features in the histopathological images, which is critical for accurate breast cancer detection. Specifically, with 2 CBAM Blocks: The model achieves good performance, but there is still room for improvement in precision, recall, and accuracy. With 4 CBAM Blocks: There is a noticeable improvement in all performance metrics. The model becomes more adept at identifying metastatic tissue.

With 6 CBAM Blocks: The performance further improves, showing that additional CBAM blocks continue to enhance the model's feature extraction capabilities.

With 8 CBAM Blocks: The model achieves the highest performance across all metrics, suggesting that 8 CBAM blocks are optimal for this task. These findings underscore the importance of incorporating attention mechanisms like CBAM in convolutional neural networks for medical image analysis. The results demonstrate a clear trend in (figure 4).

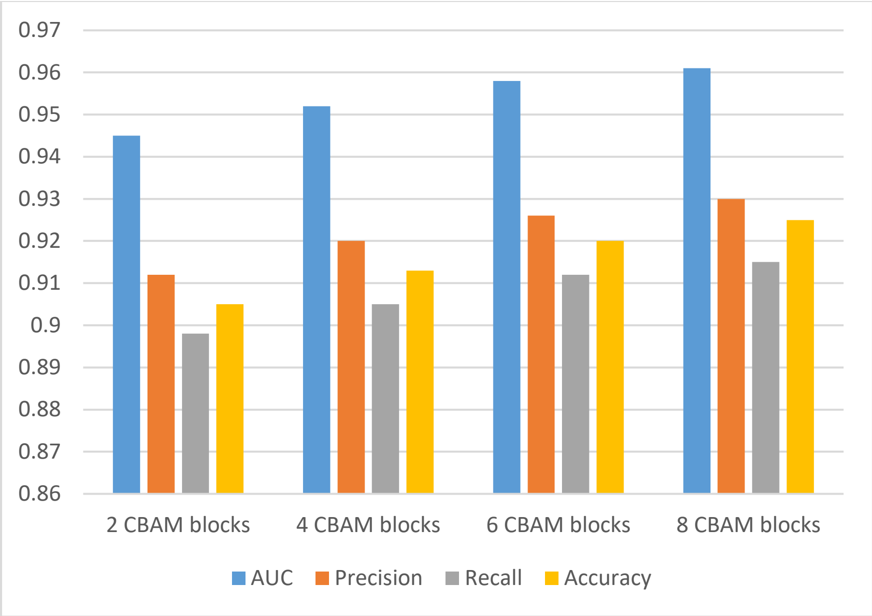

Figure 4::Performance with varying number of CBAM Blocks

AUC-ROC Value

The Area under the Curve (AUC) is 0.961, which indicates an excellent performance. An AUC of 1.0 represents a perfect model, while an AUC close to 0.5 indicates no discriminative power. With an AUC of 0.961, the model is almost perfect in distinguishing between the positive and negative classes.

Confusion Matrix

The confusion matrix was utilized to visualize the performance of the model. It provides Knowledge into the true positives, true Negatives, false positives, and false negatives, which are the foundations for calculating the aforementioned metrics. Overall, these metrics collectively ensured that the CNN model optimized with CBAM achieved a robust and reliable performance in early breast detection in figure

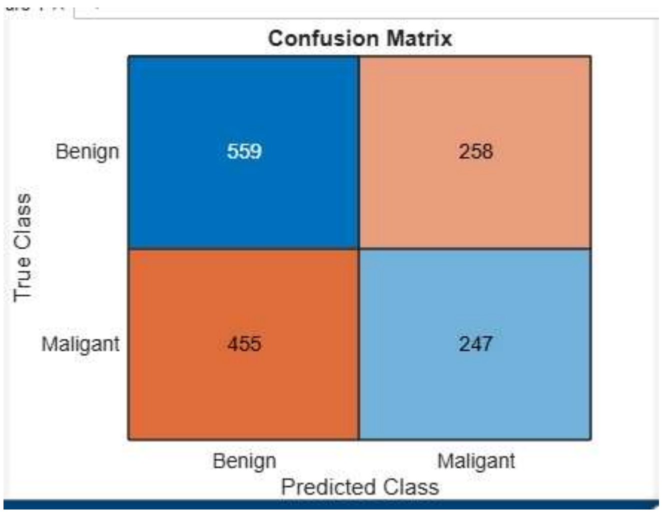

Figure 5:Confusion Matrix

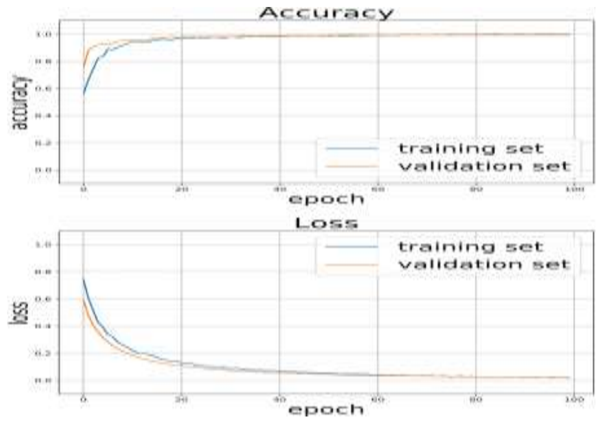

Figure 6:Training curve

The curve is a plot of model accuracy over training epochs, depicting both training and validation accuracy.

Comparison with Existing Models

When comparing the proposed model with existing models (CBAM-ResNet50, P4M-DenseNet, P4M-DenseNet-M, and DenseNet) as shown in Fig. 7, the proposed model with 8 CBAM blocks consistently outperformed them across all performance metrics results in Table 3.

Metric	**Proposed Model (8 CBAM Blocks)**	**CBAM-ResNet50**	**P4M-DenseNet**	**P4M-DenseNet-M**	**DenseNet**
AUC	0.961	0.950	0.940	0.945	0.935
Precision	0.930	0.915	0.910	0.912	0.900
Recall	0.915	0.905	0.902	0.908	0.890
Accuracy	0.925	0.910	0.905	0.911	0.895

Table 4:comparison of the proposed paradigm with contemporary fine-tuned techniques in terms of accuracy.

i. **CBAM-ResNet50**: While integrating CBAM blocks into ResNet50 already shows improvements over the standard ResNet50, the proposed model with 8 CBAM blocks achieves higher AUC, precision, recall, and accuracy. This indicates that further increasing the number of CBAM blocks can significantly enhance performance.

ii. **P4M-DenseNet and P4M-DenseNet-M**: These models, which incorporate group equivariant convolutional networks (G-CNNs) for improved rotational and translational invariance, also performed well but were outperformed by the proposed model. This suggests that while G-CNNs provide robustness to transformations, the CBAM blocks' attention mechanism is more effective in focusing on critical features for cancer detection.

iii. **DenseNet**: Although DenseNet is known for its efficient feature reuse and gradient flow, the addition of CBAM blocks in the proposed model offers a more targeted approach to feature extraction, resulting in better overall performance

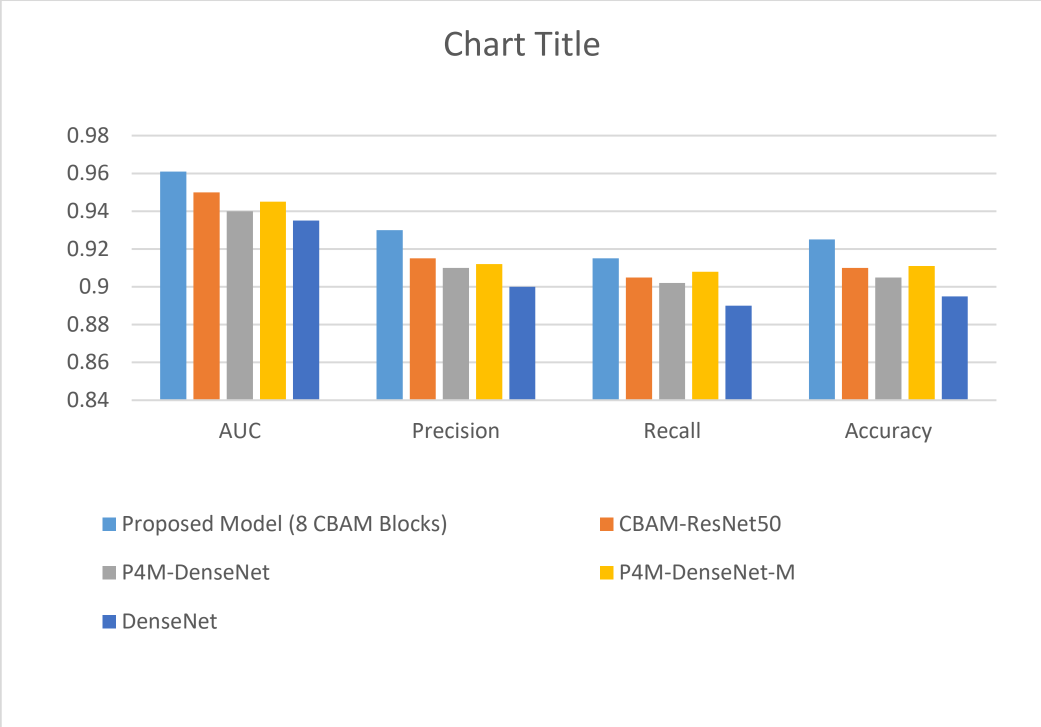

Figure 7:Comparison of the proposed model with baseline method

The comparison highlights the superiority of the proposed model, demonstrating the effectiveness of integrating multiple CBAM blocks and using advanced optimization and regularization techniques

E. Discussion

ResNet50 Convolutional Neural Network (CNN) was used to detect breast cancer from mammograms, incorporating the Convolutional Block Attention Module (CBAM) as an attention mechanism. The model explores varying numbers of CBAM blocks to determine the optimal configuration while mitigating the risk of over fitting. The performance of the proposed model was evaluated using the dataset utilized in this research obtained from the PatchCamelyon (PCam) dataset by comparing its Area under the Curve (AUC) scores with those of existing models AUC-ROC, and validation performance. Results showed high accuracy and a nearly perfect AUC-ROC score, demonstrating the model's effectiveness and controlled over fitting. Its robust validation performance suggests strong generalization to unseen data, making it well-suited for real-world clinical applications. The use of the AdamW optimizer and L2 regularization significantly contributed to addressing weight decay and over fitting issues respectfully. Additionally, data augmentation techniques, such as random rotation, flipping, scaling, and cropping, were employed to enhance the model's robustness and generalization ability by increasing diversity of the training data.

Role of AdamW Optimizer and L2 Regularization

The use of the AdamW optimizer and L2 regularization technique played a significant role in the model's performance. This optimizer effectively handles weight decay, which is crucial for maintaining the model's stability and preventing overfitting. The AdamW optimizer adjusts the learning rates for different parameters dynamically, leading to better convergence. By penalizing large weights, L2 regularization helps in controlling the complexity of the model, thus preventing overfitting. This is particularly important in medical image analysis, where overfitting can lead to poor generalization on unseen data. The use of the AdamW optimizer and L2 Regularization significantly contributed to addressing weigh decay and overfitting issues, respectively. Additionally, data augmentation techniques, such as random rotation, flipping, scaling, cropping were employed to enhance the model's robustness and generalization ability by increasing diversity of the training data.

Implications of Findings

The findings from this study have several implications:

i. **Clinical Relevance**: The enhanced performance of the proposed model in detecting breast cancer can potentially lead to more accurate and early diagnosis, improving patient outcomes.

ii. **Model Design**: The study underscores the importance of integrating attention mechanisms like CBAM and employing robust optimization and regularization techniques in designing deep learning models for medical applications.

V. CONCLUSION

This research explored the development of a breast cancer detection model based on the ResNet50 CNN architecture, enhanced with Convolutional Block Attention Module (CBAM). The integration of CBAM blocks allow the model to focus on the most relevant features in histopathological images improving the detection accuracy. Experimental results showed a clear performance improvement as the number of CBAM blocks increased, with the optimal configuration being 8 CBAM blocks. This model achieved the highest scores across all performance metrics: AUC, precision, recall, and accuracy. To further enhance model generalization and address overfitting, advanced optimization and regularization strategies were employed. The AdamW optimizer significantly mitigated the weight decay issues associated with the traditional Adam optimizer, while L2 regularization helped control model complexity. Data augmentation techniques, including rotation, flipping, zooming, and shearing, were instrumental in increasing training data diversity, thus improving robustness.

The high performance of the proposed model is evident when compared to existing models such as CBAM-ResNet50, P4M-DenseNet, P4M-DenseNet-M, and DenseNet. The improved performance aligns with findings from Liang et al. (2019), who demonstrated the effectiveness of integrating CBAM into CNNs for histopathological image analysis. Similarly, Nguyen et al. (2022) and Gao et al. (2018) showed that combining CNN architectures with attention mechanisms and data augmentation yields enhanced diagnostic accuracy. Moreover, the insight from Mostavi et al. (2020) on avoiding excessively deep networks to prevent overfitting supports the strategic use of CBAM-enhanced ResNet50 in this study.

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