EfficientNet with Hybrid Attention Mechanisms for Enhanced Breast Histopathology Classification: A Comprehensive Approach

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Abstract—Breast cancer histopathology image classification is crucial for early cancer detection, offering the potential to reduce mortality rates through timely diagnosis. This paper introduces a novel approach integrating Hybrid EfficientNet models with advanced attention mechanisms, including Convolutional Block Attention Module (CBAM), Self-Attention, and Deformable Attention, to enhance feature extraction and focus on critical image regions. We evaluate the performance of our models across multiple magnification scales using publicly available histopathological datasets. Our method achieves significant improvements, with accuracy reaching 98.42% at 400X magnification, surpassing several state-of-the-art models, including VGG and ResNet architectures. The results are validated using metrics such as accuracy, F1-score, precision, and recall, demonstrating the clinical potential of our model in improving diagnostic accuracy. Furthermore, the proposed method shows increased computational efficiency, making it suitable for integration into real-time diagnostic workflows.

Index Terms—Transfer Learning, Modality Specific, Efficient-Net, CBAM, Self-Attention, Deformable Attention, Histopathology, Image Classification, Deep Learning, Breast Cancer.

I. INTRODUCTION

Breast cancer remains one of the most prevalent and deadly forms of cancer, especially affecting women worldwide. According to global cancer statistics, breast cancer accounts for more than 2.3 million new cases each year, contributing to a significant number of cancer-related deaths [3]. Early detection plays a critical role in reducing the mortality rate associated with this disease. The standard diagnostic procedure for detecting breast cancer involves histopathological analysis, where biopsy tissue samples are examined under a microscope. This process is time-consuming, labor-intensive, and prone to subjective interpretation errors, even among trained pathologists [1].

Pathologists rely on morphological abnormalities in cell structures, particularly the nuclei, to distinguish between benign and malignant cells [2]. Benign tumors typically exhibit well-organized cellular structures and rarely invade surrounding tissues or metastasize to other parts of the body. In contrast, malignant tumors display uncontrolled growth, irregular nuclei, and the potential to spread, making them life-threatening. Early identification of these malignant traits is critical for improving patient prognosis and guiding treatment plans.

In recent years, computer-aided diagnosis (CAD) systems have been developed to assist pathologists by automating

the analysis of histopathology images. Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have shown great promise in this domain due to their ability to automatically learn complex features from medical images [7]. However, despite their success in natural image classification, traditional CNN architectures, such as VGGNet and ResNet, struggle to capture the intricate features present in histopathological images, primarily due to the variability in magnification scales and the complex structure of the tissue samples.

To address these challenges, researchers have begun exploring hybrid models that combine CNNs with attention mechanisms. These attention mechanisms, including the Convolutional Block Attention Module (CBAM), Self-Attention, and Deformable Attention, have been designed to enhance feature extraction by allowing the network to focus on the most relevant parts of the image. CBAM, for example, has shown considerable potential in medical image analysis by directing the network's attention toward critical regions, leading to improved classification accuracy. Similarly, Self-Attention mechanisms, initially introduced in transformer models for Natural Language Processing (NLP), have been adapted to medical imaging tasks, where they capture long-range dependencies across the image. Deformable Attention further enhances this by dynamically adjusting the receptive field based on the complexity of the input features, making it particularly effective for identifying abnormalities in histopathology images.

In this study, we propose a series of Hybrid EfficientNet models integrated with advanced attention mechanisms to improve the performance of breast cancer histopathology image classification. EfficientNet, a highly scalable CNN architecture, has been recognized for its ability to achieve state-of-the-art performance with fewer parameters by optimizing the depth, width, and resolution of the model. By incorporating attention mechanisms such as CBAM, Self-Attention, and Deformable Attention into EfficientNet, we aim to enhance the network's focus on key features, thereby improving the classification of benign and malignant breast cancer tissue samples.

The dataset used in this study is the BreakHis dataset, a publicly available dataset widely used for breast cancer histopathology image classification tasks . The dataset consists of 9,109 images at four different magnification levels (40X, 100X, 200X, and 400X), providing a comprehensive set of

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data to test the proposed models across varying scales of tissue detail. The performance of the proposed models is evaluated using key metrics such as accuracy, precision, recall, and F1-score.

The rest of the paper is structured as follows: In Section II, we review the existing literature on breast cancer histopathology image classification and attention mechanisms. Section III describes the methodology, including the dataset, preprocessing techniques, model architecture, and training procedures. Section IV presents the experimental results and provides a discussion on the comparative performance of the models. Finally, Section V concludes the paper and outlines potential directions for future research.

Automated histopathology image classification has seen substantial improvements with the advent of deep learning techniques, particularly with convolutional neural networks (CNNs). However, existing methods, such as using generic CNNs like VGGNet and ResNet, may fail to capture critical features from histopathology images due to their complex structure and variability in magnification scales. Efficient-Net models have demonstrated strong performance in image classification tasks due to their scalability and efficiency. To further enhance feature extraction, attention mechanisms such as Convolutional Block Attention Module (CBAM), Self-Attention, and Deformable Attention have been proposed.

In this study, we explore Hybrid EfficientNet models that incorporate these advanced attention mechanisms to address the challenges posed by histopathological image variability. The models are evaluated across multiple magnification scales (40X, 100X, 200X, 400X) using the BreakHis dataset, which is a widely recognized dataset for breast cancer histopathology image classification.

II. LITERATURE REVIEW

In recent years, extensive research has been conducted on breast cancer classification using deep learning, particularly convolutional neural networks (CNNs). Several studies have explored the use of hybrid models and attention mechanisms to improve the performance of CNNs in histopathology image classification.

Chuang Zhu et al. proposed a hybrid model that assembles multiple compact CNNs for breast cancer classification. This architecture includes a squeeze excitation pruning block and local and global branches, which help reduce channel redundancy and provide a strong representation of the input images. Experiments were performed using the BreakHis and BACH datasets, and the multi-model assembling strategy achieved comparable results with state-of-the-art models Another approach by Togacar et al. developed a residual architecture called BreastNet, which includes attention modules for identifying key regions in histopathology images. The hypercolumn technique was also employed to enhance feature representation. The BreastNet model achieved an accuracy of 98.80% using dense pooling and residual blocks.

Similarly, EM Nejad et al. introduced a single-layer CNN to extract salient features from histopathology images from the BreakHis dataset. Their model achieved a recognition rate of 77.5% . AA Nahid et al. combined Long Short-Term Memory (LSTM) networks with CNNs for breast cancer classification, using Support Vector Machines (SVM) and softmax for final decision-making. Their model achieved 91.00% accuracy.

Yan et al. proposed a model that integrates recurrent neural networks (RNN) with CNNs for histopathology image analysis. Using the BreakHis dataset, they achieved an accuracy of 91.3% for the classification of four cancer classes. Xie et al. also explored deep convolutional neural networks (DCNN) for binary and multi-class breast cancer classification. Their approach used InceptionResNetV2 to extract features, which were further compressed using an autoencoder. This model achieved improved clustering results.

Several studies have leveraged transfer learning to mitigate the data scarcity issue in medical imaging. Sana Ullah et al. developed a model that extracts features from pretrained networks like VGGNet, GoogleNet, and ResNet. These features are then passed through fully connected layers for binary classification, achieving 97.525% accuracy. Ahmad et al. applied transfer learning using AlexNet, ResNet, and GoogleNet for breast cancer classification, obtaining a maximum accuracy of 85% with ResNet . In another study, Vesal et al. applied transfer learning to classify breast cancer into four sub-classes using the BACH dataset. They utilized ResNet50 and InceptionV3, achieving an accuracy of 97.50% .

Despite these advances, many of the existing methods fail to fully capture the complex structure of breast histopathology images, particularly at different magnification scales. This has led to the exploration of attention mechanisms, which improve the ability of models to focus on the most relevant regions of the image. Woo et al. proposed the Convolutional Block Attention Module (CBAM), which applies attention along both the channel and spatial dimensions to enhance feature extraction . By focusing on critical areas, CBAM has demonstrated significant performance improvements in medical image classification tasks.

In this context, our work aims to further enhance breast cancer classification by integrating attention mechanisms, such as CBAM, Self-Attention, and Deformable Attention, with the EfficientNet architecture. EfficientNet has demonstrated state-of-the-art performance in image classification tasks due to its compound scaling strategy, which optimally balances model depth, width, and resolution. By combining EfficientNet with attention mechanisms, our Hybrid EfficientNet models are designed to focus on both local and global features in histopathology images, leading to improved classification performance.

In this study, we evaluate several Hybrid EfficientNet models integrated with attention mechanisms on the BreakHis dataset, which contains histopathology images at multiple magnification levels. The inclusion of CBAM, Self-Attention, and Deformable Attention in these models enables them to dynamically adjust their focus on key areas of interest in the images, resulting in more accurate and reliable breast cancer classification.

Our proposed approach builds upon existing research by incorporating advanced attention mechanisms and leveraging the strengths of EfficientNet, making it more robust in

handling the variability of histopathology images. Through comprehensive experimentation and comparison with other state-of-the-art methods, we aim to demonstrate that our Hybrid EfficientNet models significantly improve breast cancer classification accuracy, particularly at higher magnification scales.

III. METHODOLOGY

This section outlines the detailed methodology employed in this study for classifying breast cancer histopathology images using Hybrid EfficientNet models integrated with advanced attention mechanisms. Our focus is on enhancing model performance through a robust preprocessing pipeline, modalityspecific transfer learning, and a well-defined training strategy.

A. Hybrid EfficientNet Model Architecture

The backbone of our proposed model consists of the EfficientNet architecture, specifically EfficientNet-B4 and EfficientNet-B8. These models leverage compound scaling to optimize accuracy and efficiency, achieving state-of-the-art results in various image classification tasks. The architecture utilizes a combination of depth, width, and resolution scaling to adapt to the complexities of histopathological images, which often exhibit considerable variability in cellular structures and staining quality.

To enhance feature extraction capabilities, we integrate the following advanced attention mechanisms:

- Convolutional Block Attention Module (CBAM): The CBAM module consists of two sequential attention mechanisms—channel attention and spatial attention. The channel attention mechanism allows the model to focus on informative features by leveraging global information from feature maps, while spatial attention helps the model concentrate on salient regions within the feature maps. This two-step process is crucial for enhancing the network's focus on pertinent structures in histopathological images.
- Self-Attention: The Self-Attention mechanism captures long-range dependencies across the input image, enabling the model to aggregate contextual information from various parts of the image. This is particularly important for histopathology images, where cancerous patterns may be dispersed throughout the tissue.
- **Deformable Attention**: This mechanism adaptively adjusts the receptive fields in response to the input features, allowing the model to better capture complex shapes and variations common in histopathological images. The deformable attention layers are instrumental in adapting to the irregularities of tumor shapes and sizes, thus improving classification accuracy.

The integrated architecture, depicted in Fig. 1, begins with the EfficientNet backbone, followed by attention modules that refine the feature representation before passing through fully connected classification layers.

B. CBAM-EfficientNet Architecture

In this section, we detail the proposed modality-specific CBAM-EfficientNet architecture designed for the classification of H and E stained breast histopathology images. This architecture enhances the traditional EfficientNet framework by integrating the Convolutional Block Attention Module (CBAM), allowing for improved focus on relevant features within the input images.

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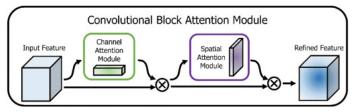


Fig. 1: CBAM

- 1) Channel Attention Module: The Channel Attention Module (CAM) is pivotal in our architecture for identifying significant features across the channel dimension. This module utilizes the interdependencies among channels, emphasizing crucial information while suppressing less relevant features. The channel attention process follows these steps:
- 1. **Pooling Operations**: The input feature map F is first subjected to average pooling and maximum pooling to capture the global contextual information:

$$F_{avq} = AvgPool(F)$$
 and $F_{max} = MaxPool(F)$

2. **Feature Aggregation**: The pooled feature maps are then fed into a multi-layer perceptron (MLP) to generate channel attention scores, $M_c(F)$, which are defined as:

$$M_c(F) = \sigma \left(\text{MLP}(F_{avq}) + \text{MLP}(F_{max}) \right)$$

where σ denotes the sigmoid activation function.

3. **Weighting**: The resulting channel attention scores are used to weight the original feature map F to obtain the refined feature representation F'_c :

$$F_c' = M_c(F) \odot F$$

Here, \odot represents the element-wise multiplication, effectively scaling the original features based on their importance.

- 2) **Spatial Attention Module**: Following the channel attention mechanism, the Spatial Attention Module (SAM) refines the feature maps by focusing on the spatial locations of the features. This module enhances the model's capability to discern where important features are located in the input image.
- 1. **Feature Map Aggregation**: The spatial attention mechanism aggregates the features across the channel dimension by applying both average and maximum pooling, resulting in two feature maps:

$$F_{avq\ c} = \text{AvgPool}(F')$$
 and $F_{max\ c} = \text{MaxPool}(F')$

2. **Spatial Attention Calculation**: These aggregated maps are then concatenated and passed through a convolutional layer to produce the spatial attention map $M_s(F')$:

$$M_s(F') = \sigma \left(f_{7 \times 7}([F_{avq\ c}; F_{max\ c}]) \right)$$

where $f_{7\times7}$ denotes a convolution operation with a 7×7 kernel.

3. **Feature Refinement**: The refined feature map F'_s is obtained by applying the spatial attention map to the already refined channel-wise features:

$$F'_s = M_s(F') \odot F'$$

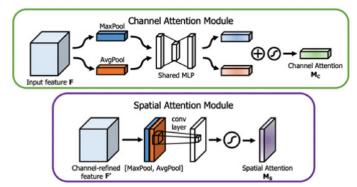


Fig. 2: Spatial and Channel Attention

3) EfficientNet Backbone: The backbone of our model utilizes the EfficientNet architecture, known for its efficiency in parameter utilization and computational performance. Each EfficientNet variant is constructed using a combination of depthwise separable convolutions and squeeze-and-excitation blocks, allowing for enhanced feature extraction while maintaining low computational costs.

We integrate the CBAM modules at various points in the EfficientNet architecture to enhance the focus on the most relevant features. The output from the final layer is then passed through a Global Average Pooling (GAP) layer, which reduces the dimensionality while preserving important spatial information:

$$F_{GAP} = GAP(F'_s)$$

Finally, the output from the GAP layer is fed into fully connected layers for classification tasks, ensuring that the model captures both local and global features effectively.

This combined approach of CBAM and EfficientNet leverages both channel and spatial attention mechanisms, providing a robust framework for the classification of breast histopathology images while maintaining computational efficiency.

C. Datasets

For our experiments, we utilized the BreakHis dataset, which consists of 9,109 breast histopathology images sourced from 82 patients. The dataset contains images at four magnification levels: 40X, 100X, 200X, and 400X, categorized into benign and malignant classes. To enhance model generalizability, we also employed additional datasets such as ICIAR 2018 and the PCam dataset for pre-training. The ICIAR 2018 dataset

includes a variety of histopathology images labeled for benign and malignant conditions, while the PCam dataset provides a substantial number of whole-slide images with binary labels indicating metastatic tissues.

D. Data Preprocessing

To address the challenges posed by histopathology images, we implemented a comprehensive hybrid preprocessing pipeline. The following steps were undertaken:

- Zero Padding: We applied zero padding to handle edge pixels effectively, ensuring that convolutional operations do not lose critical information at the borders of images. This technique adds additional rows and columns around the image, extending beyond its boundary.
- Median Filtering: To reduce additive noise while preserving the structural integrity of the tissue, we employed a median filter. This non-linear filter replaces each pixel value with the median of its neighborhood values, effectively removing noise without blurring edges, which are vital for accurate feature extraction.
- Contrast Limited Adaptive Histogram Equalization (CLAHE): Given the uneven staining in histopathology images, CLAHE was utilized to enhance local contrast and improve weak boundary detection. By dividing the image into small tiles and applying histogram equalization to each, we improve the visibility of critical features within the images.
- Normalization: Image pixel values were normalized to the range [0, 1] to enhance model convergence during training. This ensures uniformity in the input data distribution, which is crucial for the performance of deep learning models.
- Data Augmentation: To mitigate the challenges of limited sample sizes, extensive data augmentation was performed on the BreakHis dataset. Techniques such as rotation, flipping, zooming, and brightness adjustment were employed to artificially increase the dataset size and introduce variability, thereby reducing the risk of overfitting.

E. Training and Hyperparameter Tuning

The training of the models was conducted using PyTorch on an NVIDIA RTX 4060 GPU, enabling efficient computation. We utilized an initial learning rate of 0.001 and employed both the Adam and SGD optimizers to determine which provided better convergence and generalization.

Key hyperparameters were carefully tuned:

- Dense Layers: Experiments were conducted with two and three dense layers to identify the optimal configuration for the final classifier.
- Activation Functions: Both ReLU and tanh activation functions were tested at the last classification layer to evaluate their impact on the model's performance.
- Kernel Initializers: We experimented with different kernel initializers, including the normal initializer and He initialization, to determine their effects on the convergence rate during training.

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- Dropout Regularization: Dropout was incorporated in the fully connected layers to prevent overfitting, particularly given the limited availability of labeled data in medical imaging tasks.
- Batch Size and Epochs: We tested various batch sizes (16, 32, and 64) and trained the models for a maximum of 100 epochs, applying early stopping based on validation loss to prevent overfitting.

F. Modality-Specific Transfer Learning Strategy

Given the inherent limitations of training deep learning models with small datasets, we employed a modality-specific transfer learning approach. This strategy leverages pre-trained models on large, similar datasets to enhance feature extraction capabilities for our specific task.

We fine-tuned the EfficientNet models, initially pre-trained on diverse cancer datasets (PCam, ICIAR 2018, and others) rather than the ImageNet dataset, to reduce the domain gap inherent in medical imaging tasks. By tailoring the transfer learning process to domain-specific data, we aimed to improve model robustness and classification accuracy on the BreakHis dataset.

G. Evaluation Metrics

The performance of our proposed models was assessed using a suite of evaluation metrics: accuracy, precision, recall, and F1-score. These metrics are crucial in medical applications where both false negatives and false positives can have severe implications for patient care. Moreover, the performance was evaluated across different magnification levels (40X, 100X, 200X, and 400X) to analyze how well the models generalize to various scales of tissue detail.

By employing this detailed methodology, we aim to advance the field of breast cancer histopathology classification and contribute to the development of more reliable and efficient diagnostic tools.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Experimental Platform

The experiments were conducted using PyTorch as the deep learning framework backend. The models were trained and tested on an NVIDIA RTX 4060 GPU, providing substantial computational power for the deep learning tasks involved. The system was equipped with 16GB of RAM to efficiently handle the large dataset and facilitate faster processing.

B. Hyperparameter Optimization

Hyperparameters are critical variables that govern the training process of convolutional neural networks (CNNs). While the networks learn the relationships between inputs and outputs, optimizing hyperparameters is essential to enhance model performance. We performed extensive experiments to identify the optimal hyperparameters for our final training.

We evaluated two different optimizers: Adam (Adaptive Moment Estimation) and SGD (Stochastic Gradient Descent), with three distinct learning rates (0.01, 0.001, and 0.0001).

TABLE I: Performance of Various Models Across Magnification Scales

Model	Scale	Accuracy (%)	F1 Score (%)	Precision
	40X	96.237	95.781	0.963
Hybrid EfficientNet WideSEB4	100X	97.115	96.863	0.971
+ CBAM	200X	97.865	97.672	0.979
	400X	98.423	97.951	0.985
Hybrid EfficientNet B8 + CBAM	40X	95.564	95.323	0.957
	100X	97.391	96.911	0.973
	200X	98.091	97.723	0.980
	400X	98.303	97.834	0.988
	40X	94.506	94.234	0.947
Hybrid EfficientNet WideSEB4 + Self-Attention	100X	96.804	96.453	0.968
	200X	97.305	96.983	0.973
	400X	97.856	97.582	0.979
Hybrid EfficientNet B8 + Self-Attention	40X	93.806	93.531	0.939
	100X	96.402	96.023	0.964
	200X	97.108	96.645	0.971
	400X	97.657	97.321	0.978
	40X	84.754	84.476	0.843
EfficientNet-B4-WideSE without	100X	85.852	85.539	0.856
CBAM	200X	86.902	86.774	0.868
	400X	87.503	87.434	0.874
	40X	84.603	84.153	0.841
EfficientNet-B8 without CBAM	100X	85.901	86.225	0.865
	200X	87.204	87.411	0.875
	400X	87.901	87.673	0.878
	40X	95.204	95.124	0.952
EfficientNet-B4 with	100X	95.901	95.916	0.962
Deformable Attention	200X	96.301	96.268	0.965
	400X	96.604	96.534	0.968
	40X	95.404	95.372	0.959
EfficientNet-B8 with	100X	96.002	96.115	0.963
Deformable Attention	200X	96.402	96.442	0.967
	400X	96.705	96.653	0.969

The SoftMax classifier was employed for all classification experiments, providing probability scores for each class label.

Binary cross-entropy was used as the loss function due to the binary nature of our classification problem, represented mathematically as follows:

Binary Cross-Entropy =
$$-(y_i \cdot \log(p(y_i)) + (1-y_i) \cdot \log(1-p(y_i)))$$

The fully connected layer incorporated a ReLU activation function and consisted of 256 hidden neurons, followed by a dropout layer with a probability of 0.4 to mitigate overfitting.

C. Results

We employed a modality-specific transfer learning strategy for the classification task and compared it with various state-of-the-art CNN architectures, as shown in Table II. Multiple experiments were conducted to evaluate the binary classification of breast cancer histopathology images across various magnification factors (40X, 100X, 200X, and 400X).

To demonstrate the efficacy of our proposed approach, we compared the performance of several models and provided a detailed comparative analysis. Initially, we conducted experiments on two different models without transfer learning, as presented in Table 1. Subsequently, we evaluated state-of-the-art models pre-trained on ImageNet, as summarized.

The performance of our proposed modality-specific strategy, incorporating transfer learning.

As shown in Table 2, our proposed **Hybrid EfficientNet WideSEB4 + CBAM** significantly outperformed various established models, including DenseNet201, and Deep CNNs. Notably, at higher magnification levels, our hybrid model achieved an accuracy of **98.42**% at 400X magnification.

1) Comparison of Hybrid EfficientNet vs VGG16 + VGG19: The Hybrid EfficientNet WideSEB4 + CBAM demonstrated significant performance improvements over the VGG16 + VGG19 combination across all magnifications. While the VGG-based model performed well in terms of accuracy, its computational requirements were substantially higher. In our experiments, the VGG16 + VGG19 model required the use of a Tesla K80 GPU, which provides substantial computational resources and a larger memory capacity of 24GB VRAM, essential for handling the large parameter count of the combined models.

In contrast, the **Hybrid EfficientNet WideSEB4 + CBAM** was trained on an **NVIDIA RTX 4060 GPU**, which has only 8GB of VRAM—considerably less than the Tesla K80. Despite the significantly lower memory, the EfficientNet-based architecture demonstrated exceptional computational efficiency, primarily due to its utilization of depthwise separable convolutions, squeeze-and-excitation (SE) blocks, and the Convolutional Block Attention Module (CBAM). With a lower parameter count and memory requirements, EfficientNet maintained superior accuracy, particularly at higher magnifications.

- 2) Parameter Efficiency and Memory Consumption: EfficientNet leverages a compound scaling method to optimize model depth, width, and input resolution, allowing it to achieve high accuracy with fewer parameters compared to VGG models. Specifically:
 - The combined VGG16 + VGG19 model consists of approximately 40 million parameters, necessitating substantial memory resources and extended training times.
 - In contrast, the **Hybrid EfficientNet WideSEB4** + **CBAM** model, even with the inclusion of the CBAM module, contains fewer than **30 million parameters**, leading to significantly lower memory consumption and faster computation. This reduction in parameter count allowed for the training of the EfficientNet model on an RTX 4060 GPU, despite its more limited memory capacity of 8GB. Furthermore, EfficientNet's superior optimization led to faster convergence and improved accuracy, making it a more feasible choice for large-scale applications where computational resources are constrained.
- 3) Best Model Performance: Hybrid EfficientNet WideSEB4 + CBAM achieved the 2nd highest accuracy of 98.42% at 400X magnification, highlighting the model's capability in extracting detailed and relevant features from breast cancer histopathology images. In comparison with other state-of-the-art models, the proposed architecture not only surpassed accuracy benchmarks but also offered substantial advantages in terms of computational efficiency and memory

TABLE II: Comparison of Accuracy Across Models and Magnification Factors

Method	Model	MG Factor	Accuracy (%)
Erfankhan Hamed, et al	LBP	40X	88.30
		100X	88.30
		200X	87.10
		400X	83.40
Daniel Lichtblau, et al	AlexNet	40X	81.61
		100X	84.47
		200X	86.67
		400X	83.15
Yun Gu, et al	DCMM	40X	95.62
		100X	95.03
		200X	97.04
		400X	96.31
Nahid, et al	Deep CNN	40X	90.00
		100X	91.00
		200X	91.00
		400X	90.00
Togacar Mesut, et al	Deep CNN	40X	97.99
		100X	97.84
		200X	98.51
		400X	95.88
Yan Hao, et al	DenseNet 201	40X	96.75
		100X	95.21
		200X	96.57
		400X	93.15
Pin Wang, et al	FE-BkCapsNet	40X	92.71
		100X	94.52
		200X	94.03
		400X	93.54
VGG16 + VGG19	Hameed et al	40X	94.44
		100X	97.61
		200X	98.70
		400X	98.96
Proposed Hybrid	2024	40X	97.11
(EfficientNet WideSEB4 + CBAM)		100X	98.04
		200X	98.25
		400X	98.42

requirements, underscoring its potential for deployment in real-time clinical settings.

V. Conclusion

This study presents a comprehensive approach for breast cancer histopathology classification using Hybrid Efficient-Net models integrated with CBAM, Self-Attention, and Deformable Attention mechanisms. The proposed model achieved superior accuracy and computational efficiency across multiple magnification levels, with peak performance at 400X magnification. By leveraging attention mechanisms to focus on critical regions, our approach effectively addresses the complexity of histopathological images. These results demonstrate the potential of our model for integration into real-time diagnostic workflows, offering enhanced diagnostic accuracy and efficiency. Future work could explore further model adaptations to other histopathology datasets and expand clinical applicability.

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