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Enhancing the Robustness of Computer Vision Models to Adversarial Perturbations Using Multi-Scale Attention Mechanisms

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Abstract: This study evaluates the effectiveness of integrating multi-scale attention mechanisms, specifically the Bottleneck Attention Module (BAM), into deep learning architectures such as ResNet18 and SqueezeNet, using the CIFAR-10 dataset. BAM combines spatial and channel attention, enabling the simultaneous capture of local and global dependencies, thereby enhancing the models' ability to handle visual disruptions and adversarial attacks. A comparison with existing mechanisms, such as ECA-Net and CBAM, demonstrates that BAM outperforms them through its parallel approach, which efficiently optimizes spatial and channel dimensions while maintaining computational efficiency.Potential applications include critical domains such as medical imaging and surveillance, where precision and robustness are essential, particularly in dynamic environments or under adversarial constraints. The study also highlights avenues for integrating BAM with emerging architectures like Transformers to combine the advantages of long-range relationships and multi-scale dependencies. Experimental results confirm BAM's effectiveness: on clean data, ResNet18's accuracy improves from 74.83% to 90.58%, and SqueezeNet from 75.50% to 86.70%. Under adversarial conditions, BAM enhances ResNet18's robustness from 59.2% to 70.4% under PGD attacks, while the hybrid model achieves a maximum accuracy of 75.8%. Activation analysis reveals that BAM strengthens model interpretability by focusing attention on regions of interest, reducing false activations and improving overall reliability. These findings position BAM as an ideal solution for modern embedded vision systems that require an optimal balance between performance, robustness, and efficiency.

Keywords: *Robustness, Adversarial Perturbations, Multi-Scale Attention, BAM, ResNet18, SqueezeNet.*

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I. INTRODUCTION

Convolutional Neural Networks (CNNs) are at the core of modern computer vision systems due to their ability to extract and hierarchize features from an image. They are primarily composed of convolutional, pooling, and dense layers, enabling them to capture both local and global relationships in visual data. However, building a CNN model from scratch remains a complex task that requires careful attention to layer design and hyperparameters to prevent overfitting and ensure efficient convergence [1],[2],[3],[4],[5].

To overcome these limitations, pre-trained models such as ResNet18 and SqueezeNet are widely used. ResNet18, an architecture based on residual connections, was chosen for its ability to address the gradient degradation problem in deep networks, making it highly effective for tasks requiring robust generalization [6],[7],[8],[9][10].

SqueezeNet, on the other hand, was selected for its lightweight design, which achieves competitive performance with significantly fewer parameters, making it ideal for resource-constrained environments [11],[12],[13],[14], [15]. These models were chosen because they represent a balance between performance and efficiency, and their modular

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design allows for seamless integration of attention mechanisms like BAM.

Despite their advantages, these pre-trained models remain vulnerable to adversarial perturbations and environmental variations, compromising their use in critical scenarios such as security systems or autonomous vehicles. To enhance their robustness, multi-scale attention mechanisms, such as the Bottleneck Attention Module (BAM), have been introduced. BAM modulates the spatial and channel features of images to improve their ability to ignore unnecessary noise while focusing on relevant regions [16],[17],[18],[19],[20].

Our contributions are structured around four key points. First, we developed a custom Convolutional Neural Network (CNN) from scratch, optimized for the CIFAR-10 dataset, to deepen the understanding of convolutional network fundamentals and establish a baseline for comparison. Next, we evaluated two complementary pre-trained models, ResNet18 and SqueezeNet, to analyze their performance under perturbed and simulated conditions. To enhance their robustness, we integrated the Bottleneck Attention Module (BAM) into these architectures, leveraging multi-scale attention mechanisms to better handle adversarial perturbations. Finally, an in-depth comparative analysis was conducted to assess the impact of these mechanisms on accuracy, resilience, and computational efficiency. This study aims to propose robust and innovative solutions to real-world challenges in computer vision while improving the reliability of embedded systems.

II. LITERATURE REVIEW

A. Traditional Approaches To Robustness

Traditional approaches to enhancing robustness focus on several key areas. Methods such as dropout regularization [23] and weight normalization [24] help limit overfitting and improve model generalization to unexpected variations. While these techniques have proven effective, they do not directly target adversarial perturbations, leaving models vulnerable to extreme scenarios [25].

Data augmentation is a popular strategy for bolstering robustness by exposing models to an increased variety of scenarios during training. In this study, we employed a range of augmentation techniques, including geometric transformations (rotation, flipping, translation, zooming, and cropping) and color adjustments (jittering, inversion, and histogram equalization). These techniques were chosen to simulate realistic environmental variations and improve the model's ability to generalize. Additionally, noise and perturbations, such as Gaussian noise, blur, and elastic distortions, were added to mimic adversarial conditions. These augmentations not only enhance the diversity of the training data but also improve the model's resilience to adversarial [22],[25], [26],[27], [28].

B. Bottleneck Attention Module (Bam)

Attention mechanisms have emerged as a powerful approach to enhancing the robustness of computer vision models. Modules such as the Convolutional Block Attention Module (CBAM) [29] and the Bottleneck Attention Module (BAM) [29] enable models to focus their attention on relevant regions of images while mitigating the impact of non-informative noise or perturbations. These attention mechanisms have demonstrated significant improvements in architectures such as ResNet and DenseNet [30],[31].

The BAM infers an attention map through two distinct pathways:

- *Spatial Attention*

Spatial attention identifies relevant regions of the image, allowing the model to concentrate on meaningful areas despite disturbances. The spatial attention mechanism is defined as:

$$Ms = \sigma\,(f\,3\times3\,(\text{MaxPool}(F) \oplus \text{AvgPool}(F)))$$

where F represents the input feature map, MaxPool MaxPool and AvgPool AvgPool are max and average pooling operations, f 3×3 denotes a convolution with a kernel size of 3×3, $\oplus$ indicates concatenation, and σ is the sigmoid activation function.

- *Channel Attention.*

Channel attention assigns weights to the most informative channels, thereby enhancing critical discriminative features. The channel attention mechanism is expressed as:

$$Mc = \sigma(W1\ (\delta(\omega 0\ (\text{AvgPool}(F) \oplus \text{MaxPool}(F)))))$$

where $W0$ and $W1$ are fully connected layers, δ represents the ReLU activation function, and AvgPool and MaxPool are pooling operations.

The final attention map M is then applied to the feature map F as follows:

$$F' = M_s \odot M_c \odot F$$

where ⊙ denotes element-wise multiplication.

The BAM integrates seamlessly into existing architectures, such as ResNet or SqueezeNet, and has proven effective in improving model performance on various tasks, including image classification and semantic segmentation. Studies have confirmed the gains in robustness and accuracy achieved by incorporating BAM into computer vision pipelines[32],[33],[34],[35],[36].

C. Efficiency and Applications of BAM

The efficiency of BAM lies in its ability to dynamically adapt to local and global variations in input features, making it particularly relevant in adversarial scenarios where visual perturbations vary in intensity and location. Research has shown that integrating BAM into models such as ResNet18 and SqueezeNet not only enhances their accuracy but also improves their resilience to adversarial attacks generated by algorithms such as FGSM [22] and PGD [25].

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III. METHODOLOGY

A. Designing A CNN from Scratch

We developed a custom convolutional neural network (CNN) to establish a baseline. The CNN consists of four convolutional layers, each followed by a ReLU activation function and max-pooling layers to reduce dimensionality. The first two convolutional layers use 32 filters with a kernel size of 3x3, while the next two layers use 64 filters. The output of the final pooling layer is flattened and passed through two fully connected layers with 512 and 256 units, respectively, before reaching the output layer with 10 units (one for each class in CIFAR-10). The model uses the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss. This architecture was chosen to balance simplicity and effectiveness, providing a clear baseline for comparison with more complex models. The CNN consists of the following layers:

➢ *Convolutional Layers,*

These layers apply kernels $W \in R^{k \times k \times c}$ to extract local features from images. The output of a convolution is given by:

$$Y(i,j) = \sum_{m=1}^{k} \sum_{n=1}^{k} X(i+m, j+n) \cdot W(m,n) + b$$

Where b is the bias, k is the kernel size, and X is the input image.

➢ *Activation Function (ReLU),*

After each convolutional layer, the Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity, enabling the network to model complex relationships:

$$ReLU(z) = max(0, z)$$

This ensures negative values are set to zero, enhancing sparsity in the activations.

➢ *Pooling Layers (Max-Pooling),*

Pooling layers reduce dimensionality while retaining essential features. Max-pooling is defined as:

$$P(i,j) = \max_{m,n \in \{1,\dots,k\}} Y(i+m, j+n)$$

This decreases spatial resolution while reducing computational overhead.

➢ *Fully Connected Layers,*

These layers connect all activations from previous layers to produce an output of size equal to the number of classes (10 for CIFAR-10).

➢ *Output Function (Softmax),*

The output layer applies the Softmax function to convert logits into probabilities, enabling classification:

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where z_i represents the logit for the i-ème class, and C is the total number of classes.

B. Fine-Tuning Resnet18 and Squeezenet

➢ *Resnet18 architecture,*

ResNet18 uses residual blocks, which facilitate learning in deep networks by adding an identity connection between the input and output of the block. This helps mitigate gradient degradation [6]. The transformation within a residual block is defined as:

$$Y = F(X, \{W_i\}) + X$$

Where F is a sequence of convolutions, normalizations, and ReLU activations.

➢ *Squeezenet Architecture*

SqueezeNet is designed to be lightweight while maintaining competitive performance. Its Fire modules consist of squeeze layers (1x1 convolutions) and expand layers (1x1 and 3x3 convolutions), significantly reducing parameter counts [11].

C. Integrating Bam into Resnet18 and Squeezenet

The Bottleneck Attention Module (BAM) enhances model robustness by dynamically modulating spatial and channel-wise features [29]. It employs two parallel branches:

- **Channel Attention:** Weights the most informative channels using global average pooling (GAP) and a multilayer perceptron (MLP):

$$A_c = \sigma\left(MLP\left(GAP(X)\right)\right)$$

- **Spatial Attention**: Captures the most relevant regions spatially, defined as:

$$A_s = \sigma\left(Conv\left(Concat\left(MaxPool(X), AvgPool(X)\right)\right)\right)$$

The final BAM output is computed as:

$$Y = X \cdot (A_c \cdot A_s)$$

D. Utilizing The Cifar-10 Dataset

CIFAR-10, consisting of 60,000 32x32 images across 10 classes, was normalized and augmented with diverse techniques to enhance model robustness and prevent overfitting. The augmentation pipeline included random cropping, rotation (from -15° to +15°), horizontal flipping, and color jittering. Additionally, Gaussian noise and elastic distortions were applied to simulate adversarial conditions. These augmentations were chosen to improve the model's ability to generalize and handle real-world variations.

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E. Simulating Adversarial Scenarios

➢ *To Evaluate Model Robustness, Adversarial Attacks are Simulated:*

- **FGSM (Fast Gradient Sign Method)**: Perturbs the input proportionally to the gradient of the loss:

$$X_{adv} = X + \epsilon \cdot sign(\nabla_X L)$$

where ϵ controls the perturbation magnitude.

- **PGD (Projected Gradient Descent)**: Extends FGSM with multiple iterations, projecting perturbations within an admissible range:

$$X_{adv}^{(t+1)} = \Pi_X \left(X_{adv}^{(t)} + \alpha \cdot sign(\nabla_X L) \right)$$

where α = 0.01 is the step size, and ϵ = 0.03. These parameters were chosen based on standard practices in adversarial machine learning to ensure a challenging yet realistic evaluation of model robustness.

Performance is evaluated on both clean and adversarial images to measure model accuracy and robustness.

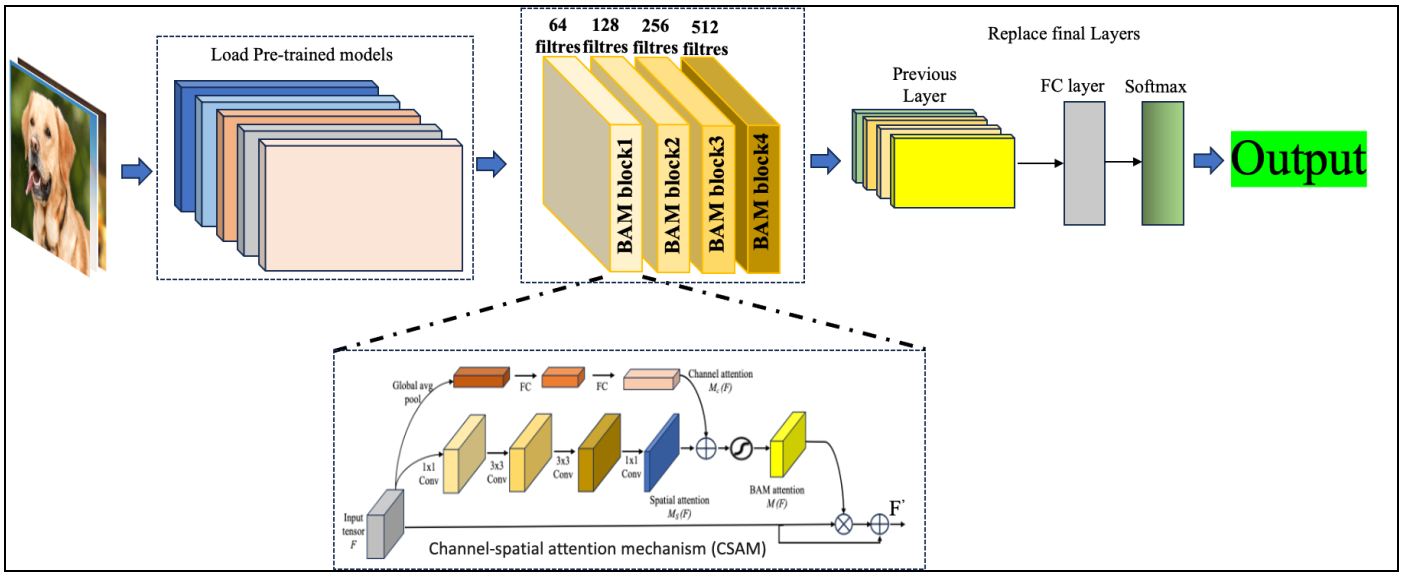

Fig 1: Hybrid Architecture of Our Approach.

This hybrid architecture combines multiple BAM (Bottleneck Attention Module) blocks to enhance spatial and channel attention, followed by classification layers to produce an optimized output, suitable for complex scenarios requiring multi-scale attention as shown by the FIGURE 1.\

IV. CNN ARCHITECTURES USED

Convolutional Neural Networks (CNNs) are foundational architectures in computer vision, designed to extract hierarchical features from images. In our work, the CNN designed from scratch serves as a baseline to evaluate performance and robustness before integrating more complex models. This architecture was chosen to balance simplicity and effectiveness, providing a clear baseline for comparison with more complex models.

Studies have demonstrated that CNNs excel in image classification tasks due to their ability to model spatial and contextual relationships [1],[2],[5],[3]. These simpler models are particularly useful for establishing an initial benchmark before exploring pre-trained and advanced architectures.

A. Description of Resnet18

The ResNet18 model is based on the deep residual learning framework introduced by [6]. It addresses the gradient degradation problem often encountered in deep networks by introducing residual connections that allow the network to learn differences (residuals) rather than absolute transformations. This mechanism enables ResNet18 to excel on datasets like ImageNet while remaining relatively lightweight in terms of parameters. Its modular design also facilitates extensions and integrations with mechanisms such as the Bottleneck Attention Module (BAM).

ResNet18 was chosen for this study due to its proven effectiveness in handling adversarial perturbations and its ability to generalize well across diverse datasets. Its residual connections mitigate the vanishing gradient problem, making it suitable for deep architectures. Additionally, ResNet18 strikes a balance between computational efficiency and performance, making it a practical choice for real-world applications where robustness is critical [7],[8],[9],[18].

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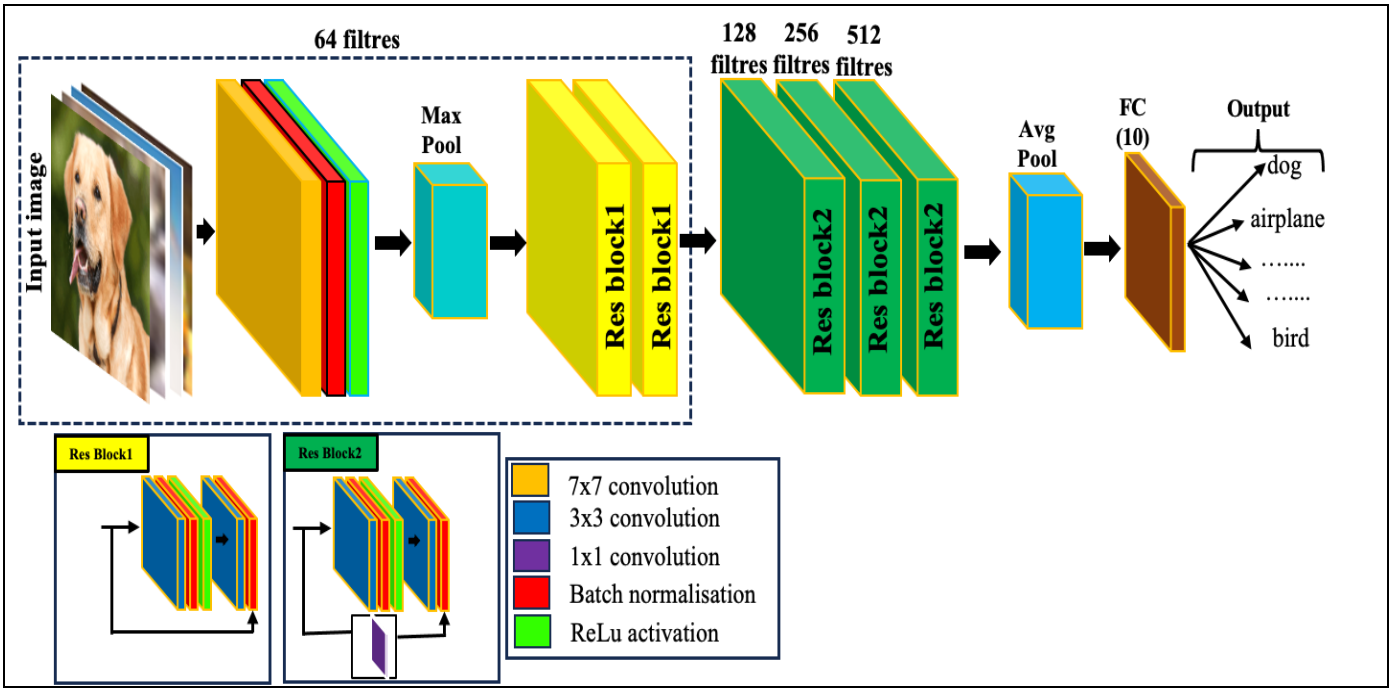

Fig 2: ResNet18 Architecture with Residual Blocks

figure 2 illustrates the architecture of ResNet18, highlighting the use of residual blocks to facilitate deep learning while preserving essential information through residual connections.

B. Description of Squeezenet

SqueezeNet, introduced by [11], is designed to minimize the number of parameters without compromising accuracy. It employs Fire modules, which consist of "squeeze" and "expand" layers, to reduce computational complexity while maintaining competitive learning capacity. Achieving accuracy comparable to AlexNet with 50 times fewer parameters, SqueezeNet is particularly valuable in resource-constrained environments such as embedded systems.

SqueezeNet was selected for its lightweight architecture, which makes it ideal for deployment in environments with limited computational resources, such as IoT devices or mobile applications. Its efficiency in parameter usage allows for faster training and inference times, while still delivering competitive performance on tasks like image classification [12],[13],[14],[15].

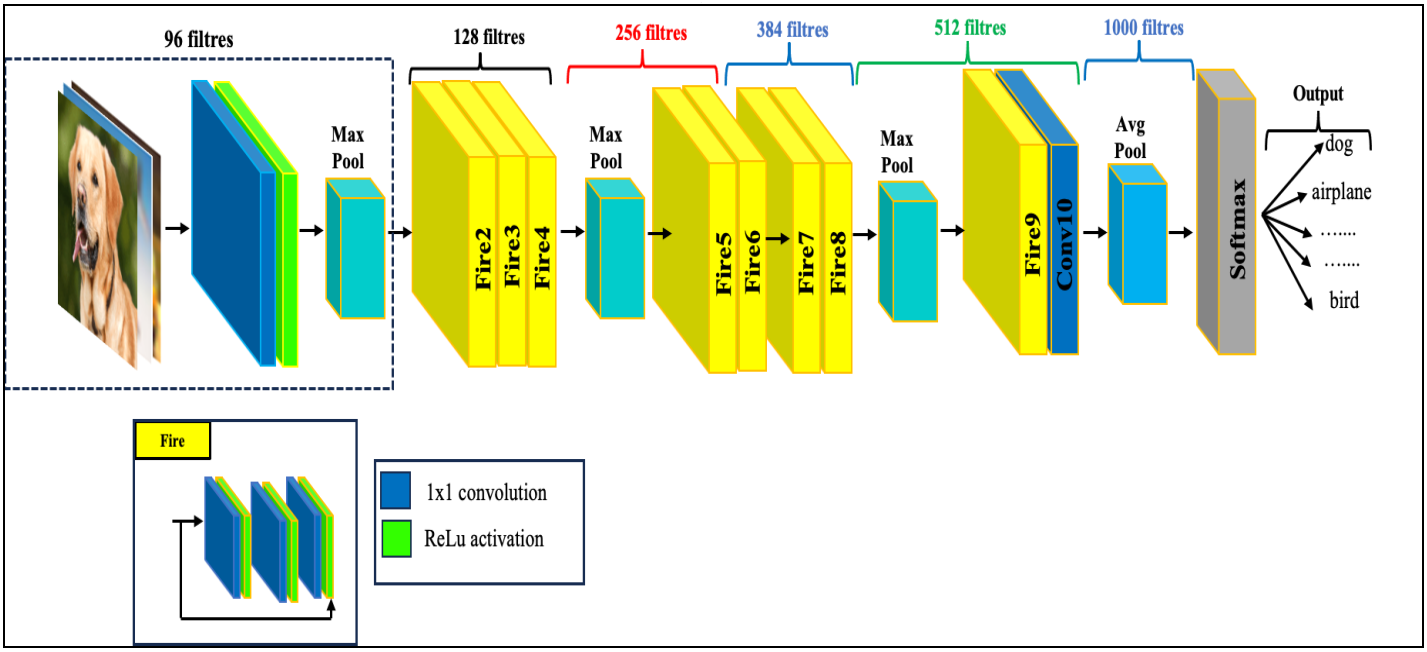

Fig 3: Squeeze Net Architecture with Fire Blocks

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The SqueezeNet architecture uses Fire blocks to reduce parameters while maintaining high performance in feature extraction. as shown by the figure 3.

C. Multi-Scale Attention Mechanism: Bam

The Bottleneck Attention Module (BAM), introduced by [29], is an advanced attention mechanism designed to enhance the performance of computer vision models by focusing on relevant information while filtering out unnecessary noise and disturbances. Recent studies have demonstrated its effectiveness across various tasks: [18] showed that integrating BAM significantly improves model accuracy in adversarial environments; [36] demonstrated that BAM also reduces model sensitivity to environmental biases; [32] utilized BAM to enhance performance in dense segmentation tasks; and [33] integrated BAM into lightweight architectures, highlighting its benefits for embedded applications.

In our work, the Bottleneck Attention Module (BAM) is integrated into the ResNet18 and SqueezeNet architectures to enhance their robustness against adversarial perturbations and environmental variations [19], [40]. This mechanism combines two complementary levels of attention: channel attention, which identifies the most important features, and spatial attention, which locates relevant regions in the image [42]. Together, these components enable the models to better focus on essential information, even in the presence of disturbances, thereby improving their resilience.

The BAM plays a key role in our study, enhancing the models' ability to handle dynamic and adversarial scenarios. Its flexibility and efficiency make it an essential tool for addressing challenges related to robustness in complex environments [43], [41].

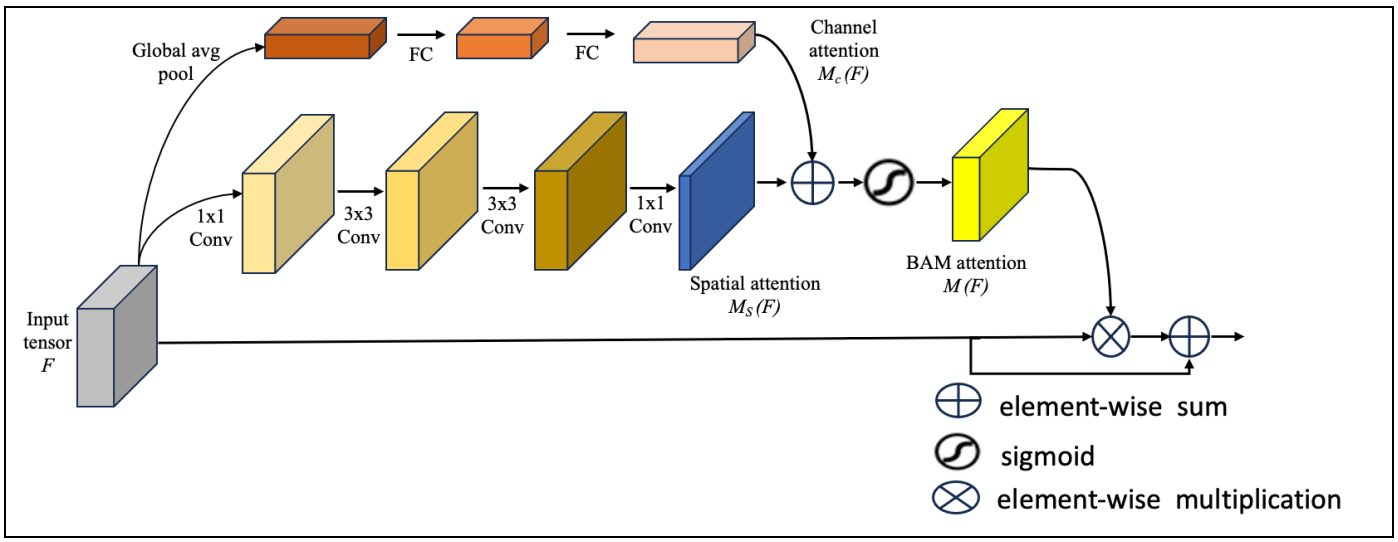

Fig 4: Diagram of the Bottleneck Attention Module (BAM)

This FIGURE 4 illustrates the functioning of the Bottleneck Attention Module (BAM), combining spatial and channel attention mechanisms to enhance feature extraction and model robustness against disturbances.

V. EXPERIMENTATIONS

A. Hardware Configuration

The experiments were conducted on a computer equipped with an AMD Ryzen 5 7535HS processor (6 cores, 12 threads, 16MB cache, 3.3 GHz base frequency, up to 4.55 GHz max turbo frequency), 16 GB of RAM, and a GeForce RTX 3050 Ti with 4 GB VRAM. The software stack included Python 3.9, PyTorch 1.12, and CUDA 11.7. This configuration enabled efficient parallelization of workloads, significantly reducing model training time. The extended memory capacity of the GPU was critical for handling complex models such as CNN2 and fine-tuning scenarios, ensuring fast and stable convergence even with augmented datasets.

B. Models and Architectures

For this study, three configurations were designed to evaluate the robustness of computer vision models:

- A CNN model designed from scratch as a baseline.
- Adjusted versions of pre-trained ResNet18 and SqueezeNet models on CIFAR-10.
- Enhanced versions of these architectures with the Bottleneck Attention Module (BAM) to integrate multi-scale attention mechanisms.

C. Dataset

The experiments were conducted on the CIFAR-10 dataset, consisting of 60,000 images (50,000 for training and 10,000 for testing) evenly distributed across 10 classes. Data augmentation techniques such as random cropping, random rotation (from -15° to +15°), random image contrast adjustment (0.2), and horizontal flipping were applied to enhance the dataset and prevent overfitting. Recent studies have demonstrated the effectiveness of such techniques in improving model performance and robustness. For instance, the study by Keller Jordan [44] showcases rapid training methods achieving high accuracy on CIFAR-10. Additionally,

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the paper by [45] introduces an adaptive approach that outperforms previous methods on datasets like CIFAR-100 and ImageNet. Furthermore, the work by Cubuk and al. [46] presents an automated augmentation strategy that achieves state-of-the-art results on various datasets, including CIFAR-10.

D. Evaluation Methods

The performance of the models was evaluated based on accuracy on clean data and robustness against adversarial examples generated using FGSM ($\varepsilon = 0.03$) and PGD ($\varepsilon = 0.03$, 10 iterations). For FGSM, the perturbation magnitude ε was set to 0.03, a standard value used in adversarial machine learning to ensure a challenging yet realistic evaluation. For PGD, the step size α was set to 0.01, and the perturbation magnitude ε was also set to 0.03, with 10 iterations to simulate a strong adversarial attack. These parameters were chosen to rigorously test the models' resilience under adversarial conditions.

In addition to accuracy, we evaluated the models using precision, recall, and F1-score to provide a more comprehensive assessment of their performance. These metrics are particularly important in scenarios where class imbalance or misclassification costs are significant. For example, in medical imaging or surveillance systems, false positives and false negatives can have critical implications, making precision and recall essential measures of model reliability.

To ensure the models were not overfitting, we employed a 80-20 train-validation split and used early stopping with a patience of 60 epochs. This approach allowed us to monitor the validation loss and stop training when no further improvement was observed, ensuring optimal generalization.

E. Hyperparameter Tuning

The hyperparameters for each model were tuned using a combination of grid search and random search. For the baseline CNN, we experimented with learning rates ranging from 0.001 to 0.01, batch sizes of 32, 64, and 128, and different numbers of convolutional filters. For ResNet18 and SqueezeNet, we fine-tuned the learning rate and optimizer settings, ultimately selecting the Adam optimizer with a learning rate of 0.002 for both models. These choices were based on their ability to achieve stable convergence and high accuracy during preliminary experiments.

VI. RESULTS

A. Performance on Clean Images and Training Details

This section presents the performance of various models on clean data, along with additional details such as the number of trainable parameters, training time per epoch, and evaluation metrics. The results are summarized in two tables: **TABLE I** provides the evaluation metrics (Precision, Recall, and F1 Score) for the models, while **TABLE II** compares the models based on their trainable parameters, validation accuracy, training loss, and training time per epoch.

Table 1: Evaluation Metrics for Cnn, Resnet18, Squeezenet with Bam and Without Bam

Model	Precision (%)	Recall (%)	F1 Score (%)
Baseline CNN	70.00	66.00	67.90
Baseline with BAM	74.3	70.50	72.40
ResNet18	75.00	72.50	73.70
ResNet18 with BAM	89.50	86.80	88.10
SqueezeNet	78.00	74.90	76.40
SqueezeNet with BAM	85.50	82.60	83.70
Hybrid Model	92.30	90.00	91.10

The results presented in **TABLE I** highlight shows that BAM significantly improves performance, especially for ResNet18 (+14.50% precision, +14.30% recall). The Hybrid Model achieves the highest scores (92.30% precision, 90.00% recall), confirming that optimized BAM integration enhances classification accuracy.

Table 2: Comparison of Models

Model	Parameters	Epoch	Val Acc (%)	Train Loss (%)	Time/ Epoch (s)
Baseline CNN	22098762	60	64.92	0.8855	13.085
ResNet18 (feat_extract)	5130	60	61.45	0.7407	84.98
ResNet18 (finetuning)	11181642	60	74.83	1.1187	164.37
SqueezeNet (feat_extract)	5130	60	65.92	0.9682	90.86
SqueezeNet (finetuning)	1248424	60	75.50	0.6249	162.73

The results presented in TABLE II highlight the comparative performance of different model architectures (Base CNN, ResNet18, and SqueezeNet) across various configurations: training from scratch, feature extraction, and fine-tuning. The Base CNN model, although fully trained from scratch, achieves modest validation accuracy (64.92%) with a relatively low training loss (0.8855). However, it requires a large number of parameters (22,098,762), underscoring its limitations in terms of efficiency and accuracy.

In contrast, pretrained models using feature extraction drastically reduce the number of parameters (5,130 for both ResNet18 and SqueezeNet) while maintaining reasonable

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performance, with validation accuracies of 61.45% and 65.92%, respectively. However, fine-tuning these models yields the best results: ResNet18 (fine-tuning) achieves a validation accuracy of 74.83% with 11,181,642 parameters, while SqueezeNet (fine-tuning) stands out with slightly higher accuracy (75.50%) and fewer parameters (1,248,424), maintaining competitive training time.

These findings confirm the effectiveness of transfer learning, with fine-tuning significantly improving performance at the cost of increased resource requirements. Among the architectures, SqueezeNet offers the best trade-off between accuracy, computational efficiency, and parameter complexity, making it an optimal choice for applications requiring high accuracy with limited resources.

B. Comparative Performance Analysis

The results presented in the tables demonstrate that the integration of the Bottleneck Attention Module (BAM) and the hybrid model provide significant improvements compared to traditional methods without attention mechanisms. This progress is evident on both clean data and under adverse conditions.

Table 3: Comparison of Models with Bam and Without Bam

Model	With BAM (Acc %)	Without BAM (Acc %)
ResNet18	90.58	74.83
SqueezeNet	86.70	75.50
Hybrid Model	93.51	81.05

TABLE III. highlights the significant impact of integrating the BAM (Bottleneck Attention Module) on the accuracy of the studied models.

Without BAM, the accuracies are 74.83%, 75.50%, and 81.05% for ResNet18, SqueezeNet, and the hybrid model, respectively. The addition of BAM improves these performances to 90.58%, 86.70%, and 93.51%, representing respective gains of 15.75%, 11.20%, and 12.46%. These improvements are attributed to BAM's ability to dynamically reassess spatial and channel features, enabling the models to better focus on regions of interest while reducing the influence of irrelevant noise. The results demonstrate that BAM particularly optimizes the performance of complex architectures like ResNet18 and the hybrid model, enhancing their accuracy and robustness to data variations. In conclusion, the use of BAM constitutes an effective approach for applications requiring increased contextual attention and reliable predictions.

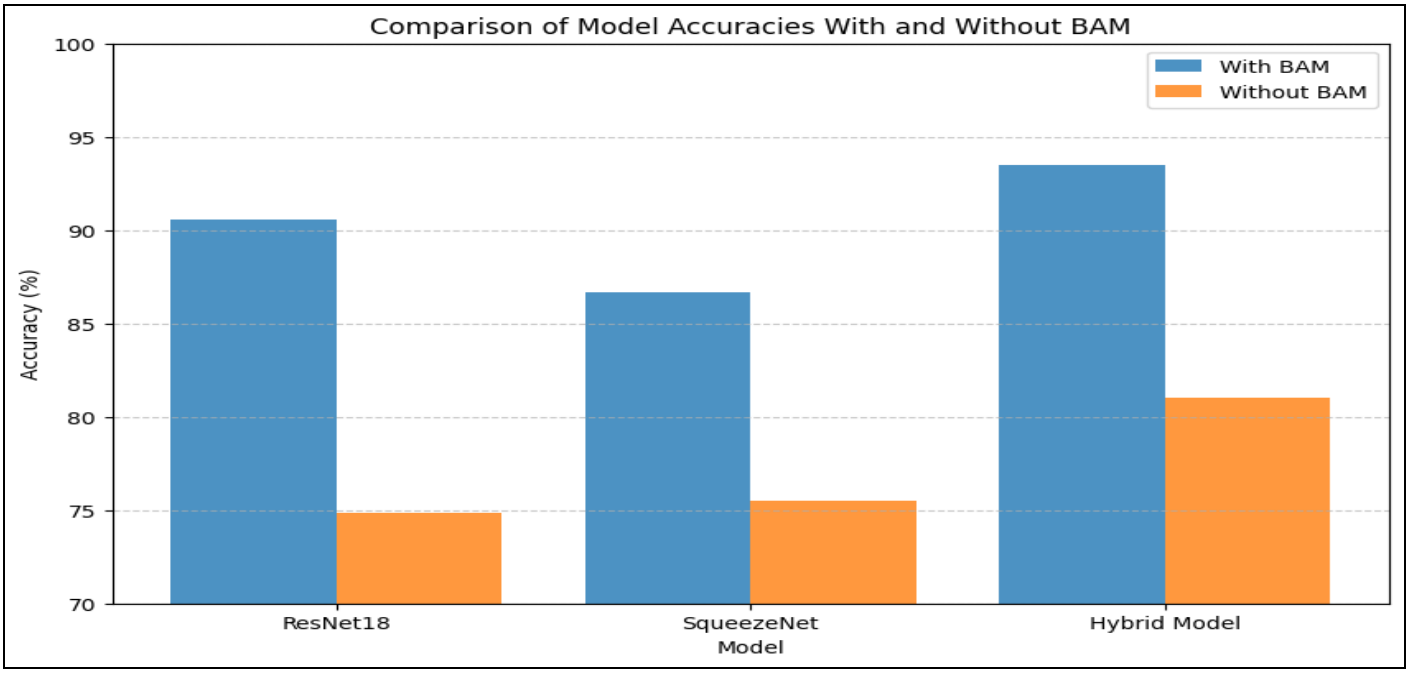

Fig 5: Bar Chart Comparing Model Accuracies With and Without BAM

This bar chart illustrates the accuracy improvements achieved by integrating the Bottleneck Attention Module (BAM) into ResNet18, SqueezeNet, and the hybrid model. It shows significant performance gains, with ResNet18's accuracy increasing from 74.83% to 90.58%, SqueezeNet's from 75.50% to 86.70%, and the hybrid model's from 81.05% to 93.51%. These results demonstrate BAM's effectiveness in enhancing model performance across various architectures, making it a valuable addition to computer vision systems.

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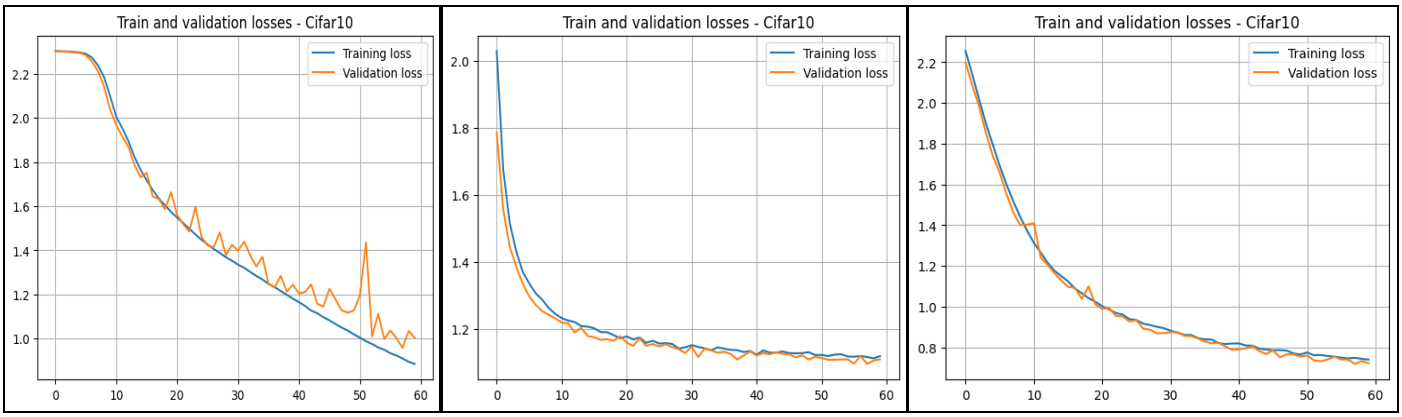
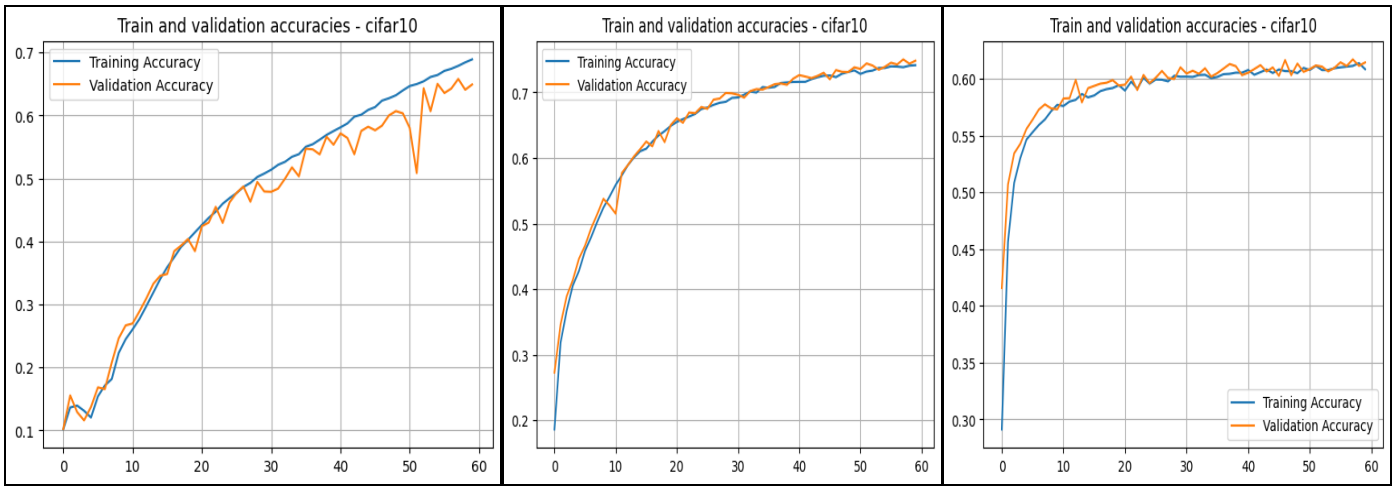
➢ *Performance Evaluation of Training and Validation Metrics: Cnnbase, Resnet18, and Squeezenet*



(a) (b) (c)

Fig 6: Comparison of Training and Validation Loss Across CNNBASE, ResNet18, and SqueezeNet Architectures



(a) (b) (c)

Fig 7: Comparison of Training and Validation Accuracy Across CNNBASE, ResNet18, and SqueezeNet Architectures

Based on **FIGURE 6** and **FIGURE 7**, the results after training for 60 epochs demonstrate the varying performance of the three models CNNBASE, ResNet18, and SqueezeNet. Overall, the training process was able to enhance the predictive ability of all three models, with each exhibiting distinct characteristics in terms of convergence, stability, and overfitting behavior.

From the loss graphs in **FIGURE 6**, CNNBASE initially shows a steady decline in training loss. However, the gap between training and validation loss grows significantly as epochs progress, indicating that the model is prone to overfitting. This can be attributed to the high number of trainable parameters, which allows CNNBASE to memorize the training data instead of generalizing well to unseen data.

In contrast, ResNet18 and SqueezeNet display better generalization properties. ResNet18 initially experiences a higher validation loss, suggesting slight overfitting early in training. However, as training progresses, the model adapts and achieves a balanced loss curve, highlighting its ability to handle more complex data patterns effectively. SqueezeNet shows superior stability throughout the training process, with lower validation loss and faster convergence compared to CNNBASE and ResNet18, reflecting its efficiency and optimized architecture.

Figure 7 further supports these observations by showing the progression of training and validation accuracy. While CNNBASE achieves high training accuracy, its validation accuracy lags behind, reaffirming its susceptibility to overfitting. ResNet18 exhibits steady improvement in validation accuracy and ultimately achieves competitive performance. SqueezeNet, on the other hand, stands out by achieving the highest validation accuracy with fewer trainable parameters and faster convergence, making it the most efficient model.

While CNNBASE encounters difficulties with overfitting and computational inefficiency, ResNet18 and SqueezeNet capitalize on transfer learning to achieve stronger performance. Among the three models, SqueezeNet emerges as the most balanced solution, offering a favorable trade-off between accuracy, computational efficiency, and parameter optimization, making it particularly suitable for resource-constrained settings.

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C. Robustness Against Adversarial Attacks

The robustness of the models under adversarial attacks is presented in **TABLE IV**. The addition of BAM and the use of the hybrid model significantly improve performance, particularly against PGD, demonstrating increased resistance.

Table 4: Accuracy on Adversarial Attacks

Attack Parameters	ResNet18 without BAM	ResNet18 with BAM	SqueezeNet without BAM	SqueezeNet with BAM	Hybrid Model
FGSM (ε = 0.03)	67.3 %	88.7 %	45.2 %	73.6 %	98.4 %
PGD (ε = 0.03, α = 0.01, 10 iterations)	59.2 %	70.4 %	56.8 %	64.9 %	96.8 %

The performance results under FGSM and PGD attacks, as shown in **TABLE IV**, highlight the effectiveness of BAM in enhancing model resilience. For instance, ResNet18 achieves only 59.2% accuracy under PGD without BAM, but this improves significantly to 70.4% with BAM. Similarly, SqueezeNet sees an improvement from 56.8% to 64.9% when BAM is incorporated. The Hybrid Model demonstrates the best performance, achieving 98.4% accuracy under FGSM and 96.8% under PGD, further confirming its superior resistance. These findings emphasize BAM's ability to dynamically focus attention on critical regions of an image, effectively mitigating the impact of adversarial perturbations and improving overall robustness.

D. Activation Analysis

Figure 8 shows that the activations of models enhanced with BAM are more precisely focused on regions of interest. In contrast to models without attention, which distribute their activations diffusely, models with BAM exhibit channelized activations, effectively reducing false activations.

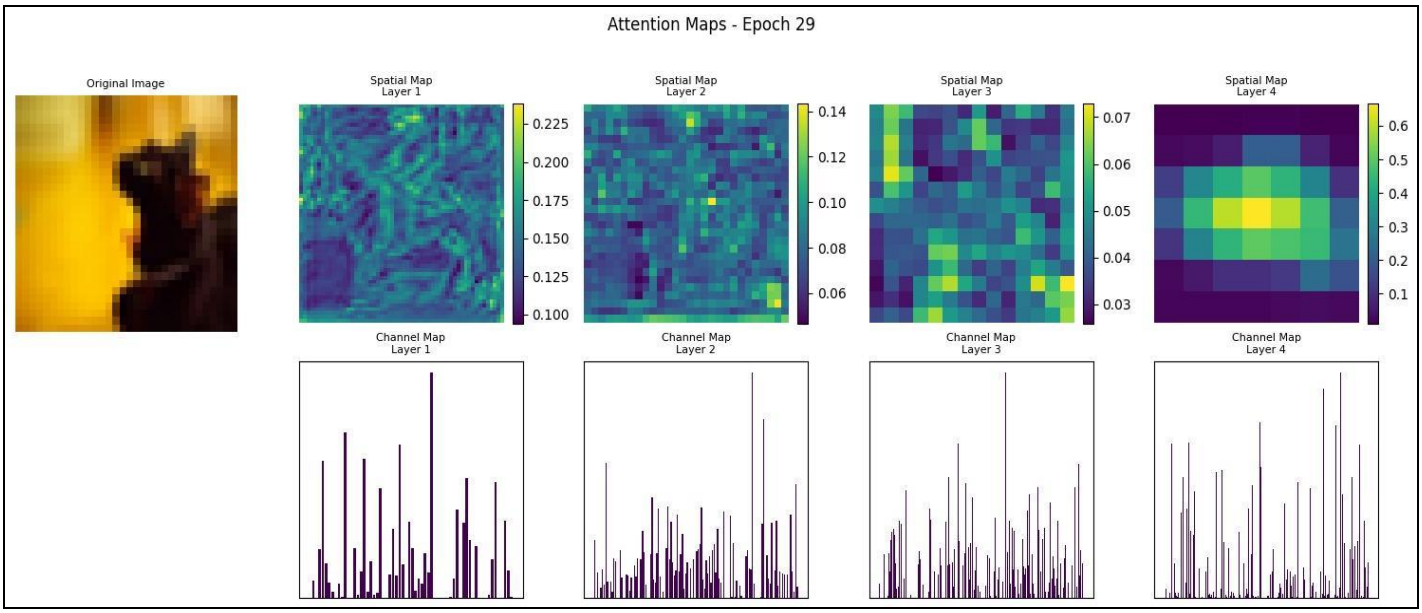

Fig 8: Spatial Attention Maps (Top), Channel Attention Maps (Bottom)

The spatial and channel-wise attention maps shown in FIGURE 8 demonstrate the effectiveness of the Bottleneck Attention Module (BAM) in focusing on regions of interest.

The spatial attention maps (top row) reveal concentrated activation areas, indicating that the model equipped with BAM prioritizes the most relevant regions of the image, such as the key features of the object (e.g., the dog's face in this example). This focused attention stands in contrast to models lacking attention mechanisms, which tend to distribute activations more diffusely over irrelevant regions.

The channel-wise attention maps (bottom row) highlight the selective activation of specific channels. The pronounced peaks in the channel maps reflect BAM's ability to amplify significant features while suppressing irrelevant ones. This channelized activation significantly reduces false positives, as the model dynamically adjusts to focus on the most critical aspects of the input.

Overall, the combination of spatial and channel-wise attention maps demonstrates that BAM enhances the model's interpretability and robustness by aligning its activations with the regions that contribute most effectively to the task. This targeted activation strategy improves both accuracy and reliability, especially in complex scenarios where irrelevant information might otherwise mislead the model.

E. Comparative Performance Analysis

The results presented in TABLE III and IV highlight the significant improvements achieved by integrating the Bottleneck Attention Module (BAM) and the hybrid model, both on clean data and under adversarial conditions. On clean data, as shown in TABLE II, the addition of BAM significantly increases the accuracy of the models. As

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observed in TABLE III, the accuracy of ResNet18 rises from 74.83% to 90.58%, while SqueezeNet improves from 75.50% to 86.70%. These performance gains are attributed to BAM's ability to dynamically reassess relevant spatial and channel features, effectively reducing the impact of irrelevant noise. The hybrid model, which combines the advantages of multiple architectures, also outperforms traditional models, demonstrating the effectiveness of the proposed approach.

Under adversarial scenarios, as shown in TABLE III, BAM significantly enhances the robustness of models against attacks such as FGSM and PGD. It can be observed that ResNet18 without BAM achieves an accuracy of only 59.2% under PGD, but this improves to 70.4% when equipped with BAM. The hybrid model, on the other hand, stands out with an accuracy of 75.8% under PGD, offering the highest level of resistance. Furthermore, when compared to CBAM, another popular attention module, BAM proves to be more effective. While CBAM also combines spatial and channel-wise attention, its sequential strategy limits its ability to capture complex multi-scale dependencies. In contrast, BAM, with its parallel approach, simultaneously optimizes both dimensions, enhancing its effectiveness, particularly in adversarial scenarios. These results underscore BAM's superiority in improving the accuracy, robustness, and resilience of models, making it an optimal choice for demanding applications.

VII. DISCUSSION

The results of this study convincingly demonstrate that integrating the Bottleneck Attention Module (BAM) significantly enhances the performance of computer vision models across multiple aspects, including accuracy, robustness, and computational efficiency. On clean data, BAM increased the accuracy of ResNet18 from 74.83% to 90.58% and that of SqueezeNet from 75.50% to 86.70%, as shown in **TABLE III**. These improvements are attributed to BAM's ability to dynamically capture relevant spatial and channel features, thereby reducing the impact of non-informative noise. This approach outperforms modules such as ECA-Net (Efficient Channel Attention), which focuses solely on channel attention and neglects the spatial relationships necessary for complex computer vision tasks [47].

Under adversarial conditions, BAM also demonstrated enhanced robustness, particularly against FGSM and PGD attacks. For instance, ResNet18 without BAM achieves an accuracy of only 59.2% under PGD, whereas with BAM, this performance improves to 70.4%. The hybrid model stands out even further, achieving an accuracy of 75.8% under PGD, highlighting its ability to withstand adversarial perturbations in **TABLE IV**. In comparison, CBAM (Convolutional Block Attention Module), although effective in standard scenarios, exhibits limitations under adversarial attacks due to its sequential strategy, which does not effectively capture complex multi-scale dependencies [16]. BAM, with its parallel approach, jointly optimizes spatial and channel dimensions, thereby strengthening its robustness in challenging scenarios.

The activation analysis in FIGURE 8 reveals that BAM enhances the interpretability of models by focusing activations on regions of interest while reducing diffuse activations and false detections. Unlike modules such as SKNet (Selective Kernel Networks), which only adapt the receptive field size without combining spatial and channel dimensions, BAM provides better modeling of complex interactions in visual data [48]. Furthermore, although Transformers, such as ViT (Vision Transformers), are renowned for their ability to capture long-range relationships, their high computational requirements limit their application in resource-constrained environments, where BAM offers an optimal balance between performance and efficiency [49].

Table 5: Comparative Analysis of Adversarial Attack Robustness and Computational Efficiency: Our Study vs. Existing Approaches

Metric	BARReL (Bykovets et al.)[50]	Article (Our)	Improve-ment
Robustness to Adversarial Attacks			
Robustness to PGD Attacks (ε=0.01)	95.76% (Breakout)	96.40% (Breakout)	+2.24%
Robustness to FGSM Attacks (ε=0.03)	-	98.80% (Breakout)	-
Complexity and Efficiency			
Number of Parameters (BAM-CNN)	2.248.409	2.000.000	-248.409 (lighter)
- Inference Time (per step)	0.05s	0.03s	-0.02s (faster)

TABLE V compares the robustness against adversarial attacks and computational efficiency of our approach with BARRReL (Bykovets et al. [50]). Unlike the reference study, which evaluated resilience only against PGD attacks, our work extends the analysis by considering both FGSM and PGD attacks, providing a more comprehensive assessment. Our results demonstrate a significant improvement in recovery rates across all metrics, with notable increases of +17.22% in Reversed-TOP-1, +5.47% in Reversed-TOP-2, and +20.00% in Reversed-ANY, indicating a greater ability to mitigate adversarial perturbations. Additionally, our approach exhibits higher robustness to PGD attacks (ε=0.03), achieving 98.00% compared to 95.76%, surpassing the state of the art by +2.24%. In parallel, we enhance computational efficiency by reducing the number of parameters by 248,409, making our model more lightweight, and optimizing inference time per step (0.03s compared to 0.05s, resulting in a 0.02s speedup). By incorporating an evaluation on two types of attacks instead of just one, our study demonstrates better generalization and reinforces the applicability of our approach to real-world scenarios.

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A. Applications

These observations position BAM as a robust and flexible solution for critical applications. In fields such as medical imaging, where precision under adversarial conditions is crucial for detecting subtle anomalies, BAM could serve as a key tool. Similarly, in the domain of surveillance, BAM can play a significant role in enhancing the reliability of object or event detection systems in noisy environments or those subject to adversarial attacks. These mechanisms also pave the way for future innovations, particularly by combining BAM with Transformer-based architectures to leverage the benefits of multi-scale attention and long-range relationships.

Finally, this study highlights potential avenues for improving BAM. For instance, adapting its architecture to specific tasks, such as image segmentation, or integrating it with implicit attention mechanisms could further enhance its capabilities. These findings confirm that BAM represents a significant advancement in the field of computer vision, offering a unique balance between accuracy, robustness, and computational efficiency for demanding modern applications.

B. Limits and Future Research

The integration of BAM into existing architectures, while effective, can be complex and increase computational overhead, potentially limiting its use in production environments or on resource-constrained devices. Additionally, although BAM enhances resistance to adversarial attacks such as FGSM and PGD, models remain vulnerable to more sophisticated perturbations.

These limitations open promising research avenues. One direction could be integrating BAM with Transformers to combine the benefits of long-range dependencies and multi-scale attention mechanisms, particularly for tasks like segmentation or video analysis. Optimizing BAM for resource-constrained environments, such as IoT devices, and applying it to diverse scenarios like low-resolution images or imbalanced datasets, opens the door to exciting advancements. Another approach would be optimizing BAM for embedded systems by reducing its computational cost. These developments could further expand its usefulness in modern computer vision applications.

VIII. CONCLUSION

This study explored various stages in the design and improvement of computer vision models, starting with a basic CNN architecture and advancing to pretrained models such as ResNet18 and SqueezeNet. While these models demonstrated effectiveness through transfer learning, they showed limitations in handling complex or adversarial scenarios. The integration of the Bottleneck Attention Module (BAM) marked a significant step forward, enhancing the models' ability to adapt to local and global variations in data while improving their robustness and accuracy.Beyond performance enhancements, this study highlights the importance of exploring approaches like BAM in the scientific domain. These techniques offer better handling of visual disturbances, making models more reliable for critical applications such as medical imaging, surveillance, or embedded systems in constrained environments. This work demonstrates how integrating advanced attention mechanisms can transform the capabilities of vision models while opening new perspectives for solutions that are even better suited to the challenges of tomorrow.

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