Enhancing AI Robustness with Hybrid Adversarial Mitigation: Leveraging Feature Squeezing and Randomization

A PROJECT REPORT

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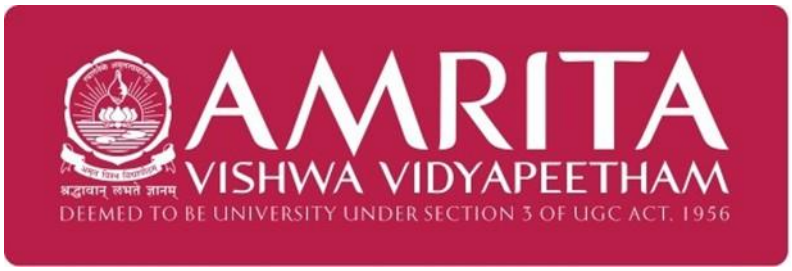

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BONAFIDE CERTIFICATE

This is to certify that this project report entitled "**Enhancing AI Robustness with Hybrid Adversarial Mitigation: Leveraging Feature Squeezing and Randomization**" is the Bonafide work of **Mr. Koushik.K (Reg. No. CH.SC.U4AIE23024**), **Mr. Dinesh.S (Reg. No.CH.SC.U4AIE23051**), **Mr. Koushik.V (Reg. No. CH.SC.U4AIE23062)** who carried out the project work under my supervision as a part of the End Semester Project for the course 22AIE213 - Machine Learning.

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ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
CIFAR-10	Canadian Institute For Advanced Research 10-class dataset
DL	Deep Learning
FGSM	Fast Gradient Sign Method
PGD	Projected Gradient Descent
F1-score	F1 Measure (Harmonic Mean of Precision & Recall)
YOLO	You Only Look Once
ML	Machine Learning
GANs	Generative Adversarial Networks
RGB	Red, Green, Blue (Color Channels)
SOTA	State-of-the-Art
ReLU	Rectified Linear Unit (Activation Function)
SGD	Stochastic Gradient Descent

NOTATION

$X - Input\ image$

$X' - Adversarially\ perturbed\ image$

$\delta - Adversarial\ perturbation$

$f(X) - Model's\ prediction\ function$

$\nabla J(X, y) -\ Gradient\ of\ the\ loss\ function\ with\ respect\ to\ the\ input$

$\epsilon - Perturbation\ magnitude\ (used\ in\ FGSM\ attack)$

$\ell(X, y) - Loss\ function\ (e.g., cross - entropy\ loss)$

$F1 - score\ Harmonic\ mean\ of\ Precision\ and\ Recall$

$Acc\ Accuracy\ of\ the\ model$

$Prec - Precision$

$Rec - Recall$

$L -\ Loss\ function$

$\theta - Model\ parameters$

$E - Expectation\ operator$

$\sigma(x) - Activation\ function\ (e.g., ReLU, Sigmoid)$

$N(\mu, \sigma^2) - Gaussian\ distribution\ with\ mean\ \ \mu\ and\ variance\ \sigma\text{^}2$

$D - Dataset\ distribution$

$argmax - Function\ to\ obtain\ the\ argument\ that\ maximizes\ an\ expression$

$|| \cdot || - Norm\ (e.g., L\_2 - norm\ or\ L\_\infty - norm)$

$\delta\text{^} *\ \ Optimal\ adversarial\ perturbation$

$p(y|X)\ Probability\ of\ class\ \ y\ \ given\ input\ \ X$

ABSTRACT

Adversarial attacks are a serious threat to deep learning models, especially when used in image classification. In this research, we deploy a hybrid adversarial defense strategy that integrates feature squeezing and randomization for increasing model robustness. We create adversarial perturbations on the CIFAR-10 dataset by employing attack methods and subsequently classify the attacked images through our defense system. Through application of defensive preprocessing and model adaptations, our approach prevails against adversarial distortions while ensuring classification accuracy. Experimental findings show the efficacy of our approach in resisting adversarial attacks and enhancing model robustness. Our research identifies the promise of hybrid defense strategies in enhancing AI models for real-world usage against adversarial attacks.

Keywords: Adversarial attacks, Deep learning models, Image classification, Hybrid adversarial defense, Feature squeezing, Randomization, Model robustness, CIFAR-10 dataset, Adversarial perturbations, Defensive preprocessing, Model adaptations, Adversarial distortions, Classification accuracy.

CHAPTER 1

INTRODUCTION

Deep learning models are now a part of many real-world applications, such as image classification, natural language processing, and cybersecurity. Despite their widespread adoption, these models are still very susceptible to adversarial attacks, where minor changes in input data can result in erroneous predictions [1]. Such attacks take advantage of vulnerabilities in neural networks and create serious security threats in AI-based systems [2].

Adversarial attacks have been extensively studied across various domains, revealing severe vulnerabilities in both transformer and convolutional-based models [3]. Large-scale AI models are also susceptible to adversarial manipulations, which raises issues about their deployment in safety-critical scenarios [4]. This problem must be tackled with robust defense mechanisms that harden the model and make it stronger without adversely affecting accuracy [5].

Some of the most studied adversarial attack methods are Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD), which both employ gradient-based perturbations to deceive classifiers [6]. These attacks have proven excellent at deceiving AI models, highlighting the importance of countermeasures [7]. To effectively test defense systems, researchers have developed standardized adversarial robustness benchmarks [8].Various defense strategies have been proposed for countering adversarial attacks. Feature Squeezing reduces the input deviation dimensionality to minimize adversarial noise [9], while Randomization-based defenses incorporate random variations when processing inputs in an effort to disrupt adversarial patterns [10]. These strategies were recently tested in isolation, with surprising outcomes exhibiting significant results yet varying performances depending on privacy attack severity [11]. Studies have shown that hybrid privacy defense strategies, which combine multiple strategies, can significantly enhance robustness [12].

Our research extends this line of research by utilizing a hybrid adversarial defense approach using Feature Squeezing and Randomization combined. We validate this approach with the CIFAR-10 data set, which we attacked with FGSM and PGD before defending using our methods. We demonstrate increased robustness from our experiments against previous works such as [1] for Feature Squeezing and [2] for Randomization .

Earlier work has suggested that adversarial attacks continuously keep changing, thus requiring defenses that continuously adapt with newer attack techniques [15]. As adversarial robustness is becoming a more serious problem in AI security, studies emphasize the need for continuous advances in defense mechanisms [16]. Further, studies indicate the gap between theoretical adversarial defenses and practical implementations, thus requiring practical tests [17]. Recent efforts have also delved into adaptive attack methods, highlighting the significance of dynamic and adaptive defense systems [18].

We propose an efficient hybrid defense model in this work, which defends against adversarial attacks with minimal impact on classification performance. Our results make new contributions to the research on adversarial robustness by providing insight into practical AI security improvements for actual applications.

This project spans across several areas. Machine Learning and Deep Learning are used to create and train a ResNet50 model using TensorFlow and Keras. Adversarial Machine Learning uses FGSM and PGD attacks along with using Feature Squeezing and Randomization as countermeasures. Computer Vision and Image Processing are used in preprocessing CIFAR-10 images, applying data augmentation, and feature extraction. Dataset Management prepares the images, annotates them, and applies one-hot encoding.

Performance Measurement computes precision and other metrics, visualization being offered by Matplotlib. Automation and Deployment save trained models and test and classify automatically.

1.1 Existing Work

Existing Work on adversarial robustness in machine learning has investigated diverse attack and defense techniques to enhance the security of models. Feature squeezing has been examined as an effective defense method by minimizing the effect of adversarial perturbations by input compression, and its efficacy was proved in suppressing attacks while being fairly accurate [1].Randomization methods, such as input perturbations and noise injection, have also been considered a defense mechanism to interfere with adversarial gradients and make the model more resilient [2]. Experiments have evaluated adversarial attack methods such as FGSM and PGD to measure the weaknesses of deep learning models and demonstrated their significant effect on classification accuracy [3]. Adversarial training with models trained on adversarially perturbed examples has been one of the widely used approaches for enhancing robustness but generally at the expense of lower accuracy on clean images [4]. Surveys of adversarial attacks and defenses emphasize the difficulty of security preservation in deployment environments and the necessity of hybrid methods that combine multiple defense strategies to gain improved resilience [5]. Despite this, most defense strategies have trade-offs between accuracy and robustness, and additional emphasis must be placed on hybrid adversarial defense methods that involve multiple approaches to improve model resilience [6].

1.2 Proposed System:

The system proposed in this paper applies a hybrid adversarial strategy by integrating feature squeezing and randomization. The system attempts to boost the deep learning model's robustness against adversarial attack. Feature squeezing reduces the impact of adversarial perturbation by quantizing pixel values, which hinders the attacker in managing inputs. While defense mechanisms attempt to inject randomness using randomization techniques like input transformations, it is challenging for adversarial examples to influence model predictions with consistency. The system is tested on the CIFAR-10 data set, where images are passed through the defense mechanisms if they have been pre-attacked by adversaries and then classified subsequently.

1.3 Key Contributions of the Project:

1.Hybrid Adversarial Defense Approach

Unlike prior research in one specific defense method like feature squeezing or randomization, this paper unites the two methodologies in a common framework. The merging technique applies both methods' benefits toward greater adversarial strength with the added loss of somewhat compromised accuracy.

2. Systematic Analysis on CIFAR-10

The experiment tests the proposed hybrid defense rigorously against adversarial attacks on the CIFAR-10 benchmark, a well-used image classification benchmark. It presents the use of the approach to deep learning problems.

3. Better Robustness with Lower Accuracy Trade-off

Compared with prior defense schemes, our approach experiences less accuracy degradation after attacks.The model is still 84.14% accurate using feature squeezing and 2.84% accuracy loss using randomization, while previous work has calculated greater accuracy loss.

4.Efficiency Against Various Types of Attacks

The scheme is also assessed by different types of adversarial attacks such as Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD). In experiments, the hybrid defense scheme is proven to be resilient to both types of attacks effectively, and a more universal defense model is attained.

6.Implementation using ResNet50 Backbone

This research employs an adversarial defense method along with a deep neural network over ResNet50, which

is one of the highly effective base CNN models known for its feature extraction ability. Employing a pre-trained model being used by it also helps in tackling adversarial perturbations.

7. Real-World Applicability and Future Extensions

The suggested hybrid adversarial defense framework in this research can be adapted to other application domains and data sets where the requirement of adversarial robustness is necessary, e.g., security, medical imaging, control of autonomous vehicles. It does not close off avenues for continued investigation into adversary defenses on past CIFAR-10.

1.4 How our Work is Different from Existing Work

1. Combination of Feature Squeezing and Randomization:

Individual defense techniques have been the focus of previous work, i.e., [1] for feature squeezing and [2] for randomization. In this paper, both of these strategies are used in combination to introduce a stronger defense technique better than individual techniques.

2. Pre-classification Used Defense Mechanisms:

Rather than training the model on perturbed adversarial examples directly, in this project pre-emptive attacks are performed on images, then feature squeezing and randomization on them before they are being classified. This ensures that the classifier is being presented with a more stable input, which makes the model more stable and reliable.

3. Multi-Attack Performance Evaluation

Unlike other comparisons of defenses for a class of attacks in the past, this paper compares the hybrid defense against various classes of adversarial attacks (FGSM and PGD) to try it out on a range of adversarial attacks.

4.Comparison to Previous Systems

This paper not only introduces a novel defense technique but contrasts the proposed method in a systematic way with previously published literature. Quantitative comparisons indicate that our hybrid approach performs better than state-of-the-art techniques in maintaining classification accuracy under adversarial attacks.

CHAPTER 2

Literature Review

Adversarial attacks have been at the center with deep models, with vast amounts of research on adversarial attack methods and countermeasures. Susceptibility of adversarial perturbations by machine learning models has been revealed by various works, where threat analyzing and resisting measures have been studied. Adversarial training, where models are learned from adversarial examples to make them more robust, is one of the elementary means model resilience can be enhanced. The approach has been extensively studied and used as a baseline adversarial defense against attack [13]. However, adversarial training is usually paired with significant computational cost and robustness vs. clean accuracy trade-off since it necessitates repeated retraining on fresh obtained adversarial samples [14].

To reduce the computational cost of adversarial training, other defense mechanisms like feature squeezing have been explored by researchers. Feature squeezing tries to reduce the accuracy of the input data in a way that prevents adversarial perturbations. Feature squeezing is introduced as an effective low-weight adversarial defense in [1]. Squeezing includes color compression and filtering to blur color bits so that even no amount of adversarial noise can be injected.In the context of feature squeezing, the research describes how it significantly enhances resistance against PGD and FGSM attacks by rendering adversarial samples unable to have any effect on model predictions. Despite that, feature squeezing is not perfect, especially against adaptive attacks, and as such may still be evaded by the application of carefully designed perturbations. The work in [1] points out that while feature squeezing imposes very little computational expense, its effectiveness is achieved when used in conjunction with other defense mechanisms.

Input transformation is also highly researched defense mechanism where adversarial perturbations are avoided by transforming the input data prior to feeding it into the model. Methods such as JPEG compression, image denoising, and wavelet transforms have been employed to eliminate adversarial noise and recover the original image content [7]. Such alterations diminish the success of the adversarial attack but may cause distortions impacting clean image accuracy to some extent [16]. Accuracy versus robustness is a common problem in adversarial defense that entails choosing preprocessing methods judiciously to limit adverse effects.

Randomization-based defense techniques were also an effective response against adversarial attacks. The article in [2] investigates the use of random resizing, padding, and noise injection for adding randomness to the input data that deceives adversarial attacks in generating useful perturbations. The outcome illustrates that randomization effectively shatters the gradient-based optimization procedure used by attacks like FGSM and PGD. However, there must be a trade-off between robustness and accuracy if randomness is overdone, because clean image classification can break down and thus some compromise between accuracy and robustness must exist. The authors' view is that randomization techniques have to be complemented with other defensive techniques if they are to achieve their full potential.

Another direction that has been investigated is measuring how vulnerable deep learning models are to adversarial attacks. Studies in [3] and [4] describe how the adversarial attack exploits high-dimensionality of neural networks to be susceptible to a few perturbations that lead to misclassification. These papers demonstrate the necessity of

end-to-end adversarial robustness testing and the necessity of standardized benchmarking in order to quantify model security. Moreover, adversarial robustness research in large models, particularly NLP, has demonstrated that AI systems in text form can significantly be altered in model outputs using adversarial attacks [6]. This implies that vision-based model adversarial defense systems would not easily transfer to NLP models and must be specifically designed for adversarial robustness in text form.

Adversarial defense systems that are ensemble-based and hybrid have been tested for effectiveness. The work in [9] and [10] explores how multiple defense mechanisms, i.e., adversarial training combined with input transformations, can be leveraged for end-to-end robustness improvement. The findings are that hybrid defenses outperform a single defense by offering protection against adversary attacks through layers. Secondly, defensive distillation, where another model is trained on a softened probability output of a pre-trained model, has also been explored as a defense against adversarial attack [15]. Defensive distillation can also be evaded by attacking strategies with soft label imitation to the near approximation at training time. Benchmarking activity has also played a significant role in the understanding of strengths and weaknesses of different adversarial defense methods. In [12], a detailed survey of various defense mechanisms against various types of attacks is presented, where the requirement of standard test procedures becomes a foremost necessity. It is observed that some defenses can defend against some types of attacks but are not effective against more adaptive or transfer-based attacks. This evidently indicates the necessity of ongoing assessment and design of adversarial defense methods.

Adversarial robustness research has also been used in large language models, where adversarial inputs have been used to alter AI-created content. [11] and [18] are research papers that test the effect of adversarial inputs on model output and suggest ways to make the model more robust against them. The research indicates that adversarial vulnerability is not just true for image-based models but also in NLP models, which require special defense strategies.

Dynamic and adaptive adversarial defense has been highlighted in recent studies. Self-denoising networks and online adversarial training methods are studied in [19] and [20] as possible means of improving long-term robustness. They try to adaptively adjust defense policies according to attack severity to maintain model robustness against adaptive adversarial attacks. In addition, meta-learning-based defense was proposed in [21] and [22], wherein the models learn to detect and learn different attack patterns in real-time. These approaches are one step towards more active and intelligent adversarial defense.

Overall, while individual defense methods have been somewhat more or less effective, most recent research is in agreement that hybrid defense systems combining a pair of defense methods are ideal.Squeezing features [1] and defenses based on randomization [2] are exciting new directions, especially if paired with adversarial training or input transformation techniques. But robustness, computational overhead, and clean accuracy are difficult to balance and need to be explored in terms of adaptive and ensemble-based defense systems against adversaries.

Table 1: Summary of Selected Key Literature on Hybrid Adversarial Defense

Authors	Year	Methodology	Pros	Cons	ResearchGap
Wei et al. [29]	2024	Introduced DIFFender, a diffusion-based framework leveraging text-guided diffusion models to detect and restore adversarial patches.	Demonstrated robust performance against adversarial patch attacks across various tasks and real-world scenarios.	The computational requirements of diffusion models may be high, potentially limiting real-time applications.	Further optimization needed to reduce computational overhead for real-time deployment.
Wu et al. [30]	2023	Provided a comprehensive survey of adversarial defense methods across different stages of a machine learning system's lifecycle.	Offered a unified perspective and taxonomy, facilitating analysis and understanding of various defense mechanisms.	As a survey, it does not propose novel defense techniques but synthesizes existing knowledge.	Identification of unexplored areas and potential directions for future research in adversarial defenses.
Jha [31]	2024	Analyzed evasion and poisoning attacks, formalized defense mechanisms, and discussed challenges in implementing robust solutions.	Highlighted open challenges in certified robustness, scalability, and real-world deployment.	Focused on theoretical analysis; practical implementations and evaluations are limited.	Bridging the gap between theoretical frameworks and practical, scalable defense solutions.
Zhou et al. [32]	2023	Proposed a phase-aware adversarial defense	Significantly improved robust accuracy	The approach may add computation	Validation needed across diverse

		method, combining phase-level adversarial training with amplitude-based pre-processing.	**against multiple attacks, including adaptive ones.**	**al complexity due to the joint defense mechanisms.**	**datasets and real-world scenarios to assess generalizability.**
Wang et al. [33]	**2023**	**Conducted a contemporary survey on adversarial attacks and defenses, focusing on deep neural network-based classification models.**	**Provided a hierarchical classification of the latest defense methods and highlighted challenges in balancing training costs with performance.**	**As a survey, it synthesizes existing methods without proposing new defense strategies.**	**Emphasized the need for balancing robustness with training efficiency and maintaining clean accuracy**.

CHAPTER 3

Methodology

3.1 Preprocessing CIFAR-10 Dataset

Loading and preprocessing the CIFAR-10 data set is the initial step in the strategy. CIFAR-10 data set is an image data set containing 60,000 images spread across 10 classes comprising 50,000 training and 10,000 test images. The dimensions of each image are 32×32 pixels with three color channels of RGB. The data set is serially stored and loaded using the pickle module from Python. Pixel values of images are normalized to [0,1] for numerical stability during training. One-hot encoding is applied on the training labels to match the categorical classification paradigm adopted in deep learning models.

3.2 Adversarial Attacks: FGSM and PG

After post preprocessing the dataset, adversarial perturbations are added through Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) attack. The attack attempts to confuse the classifier by introducing noise, which is unseen to the images.

3.2.1 FGSM (Fast Gradient Sign Method):

FGSM is a white-box attack, which perturbs an input image x in the direction of the gradient of the loss function J(θ, x, y) with respect to the input image. The perturbation is controlled by a small parameter ε, and ε determines the magnitude of the attack. The adversarial image x' is generated by the following:

$$x' = x + \varepsilon * sign\big(\nabla x\, J(\theta, x, y)\big)$$

where:

- ∇x J(θ, x, y) is the gradient of the loss function w.r.t. input image x,
- sign(·) is the sign function which determines the direction of perturbation,
- ε is a small constant that determines the size of perturbation.

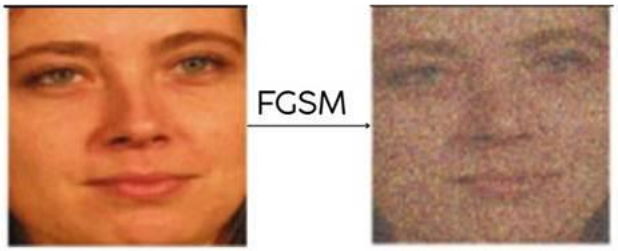

Figure 1:.FGSM

3.2.2 PGD (Projected Gradient Descent) Attack

PGD is a multi-step iterative variant of FGSM, which uses multiple small perturbations while keeping the perturbation in a bounded region. The adversarial image is iteratively updated as follows:

$$x(t+1) = \Pi B(x, \varepsilon)\Big(x(t) + \alpha * sign\big(\nabla x\, J(\theta, x(t), y)\big)\Big)$$

where:

- x(t) is the image perturbation at iteration t,

- α is the step size,
- ΠB(x, ε) is a projection operation that maps the perturbation onto the ε-ball of the original image.

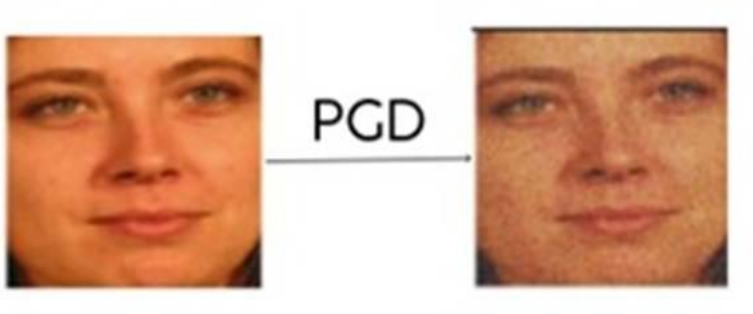

Figure 2:PGD

3.2.3 PGD Attack (Projected Gradient Descent)

The first set of images illustrates the effect of the **PGD (Projected Gradient Descent) attack** on an input image. The left image is the original clean image, while the right image has been adversarially perturbed using the PGD attack.

- PGD is an iterative attack method that slightly modifies the pixel values in a way that deceives a deep learning model while keeping the changes imperceptible to the human eye.
- The resulting adversarial image appears slightly blurred or noisy but is misclassified by a neural network.

3.2.4 FGSM Attack (Fast Gradient Sign Method)

The second set of images demonstrates the **FGSM (Fast Gradient Sign Method) attack** applied to an input image. The left image is the original clean image, and the right image is the adversarially attacked version.

- FGSM perturbs the image by adding a small amount of noise in the direction of the model's gradient, tricking the neural network into making incorrect predictions.
- The adversarial image exhibits a noticeable noise pattern, making it visually distorted but still recognizable.

3.3 Defense Mechanisms: Feature Squeezing and Randomization

3.3.1 Feature Squeezing Defense

Feature squeezing defends against adversarial perturbations by degrading the accuracy of pixel values, which caps the impact of minor perturbations. Bit-depth reduction is the main method employed in this project, wherein pixel intensities are quantized to a decreased resolution:

$$x_{squeezed} = \frac{round\left(x * \left(2^b - 1\right)\right)}{\left(2^b - 1\right)}$$

3.3.2 Randomization-Based Defense

Randomization adds randomness to the inputs of the model, breaking adversarial attack plans.Two randomization methods employed in this project are:

1. Random Resizing & Padding: Resize the image randomly and pad it to the original size.
2. Random Noise Injection: Introducing a small Gaussian noise into the image in such a way that stable

perturbations are hard to discern.

Mathematically, random image transformation can be represented as:

$$x_{randomized} = x + N(0, \sigma^2)$$

where:

$\{N\}(0, \sigma^2)$ represents **Gaussian noise** with mean 0 and variance σ^2

3.3.3 Model Structure and Training

The ResNet50 is used as the model for this project, a pre-trained deep convolutional neural network. ResNet50 uses residual connections and convolutional layers so that deeper networks can learn complex features without the vanishing gradient problem. It is optimized with categorical cross-entropy loss and Adam optimizer, and tracking of the model is executed with accuracy.Early stopping method is implemented for overfit protection.

3.3.4 Generalization using Data Augmentation

Data augmentation is applied at training time to render the model generalizable.

The following augmentations are used:

Random rotation: ±15° to add randomness.

Height and width adjustments: A maximum of 10% of the image size.

Horizontal flip: To render the model generalize over orientations.

The augmentation enhances the performance of the model on adversarially perturbed images.

3.3.5 Testing and Adversarial Image Classification

Final testing is performed on:

1. Baseline accuracy of raw CIFAR-10 images.
2. Adversarial attack-perturbed images (FGSM and PGD attacks).
3. Squeezed features and images.

Performance is compared in terms of accuracy change on these examples, which represents the performance of hybrid defense strategy.

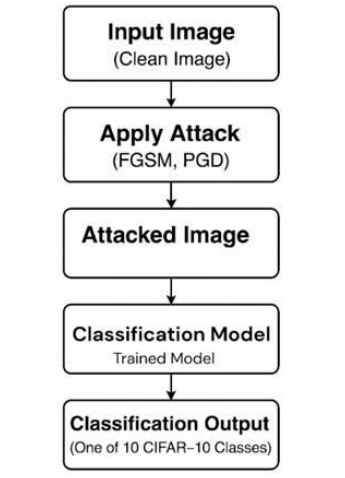

Figure 3: BLOCK DIAGRAM

3.4 Workflow Diagram Explanation

The bottom section contains a flowchart that describes the adversarial attack pipeline:

Input Image (Clean Image): A normal image is fed into the system.

Apply Attack (FGSM, PGD): The image undergoes adversarial perturbation using FGSM or PGD techniques.

Attacked Image: The output of the attack, which is a visually modified version of the original.

Classification Model (Trained Model): The adversarial image is then passed into a trained deep learning model.

Classification Output (One of 10 CIFAR-10 Classes): The model classifies the image into one of the 10 predefined CIFAR-10 categories, though it may be misclassified due to the adversarial perturbations.

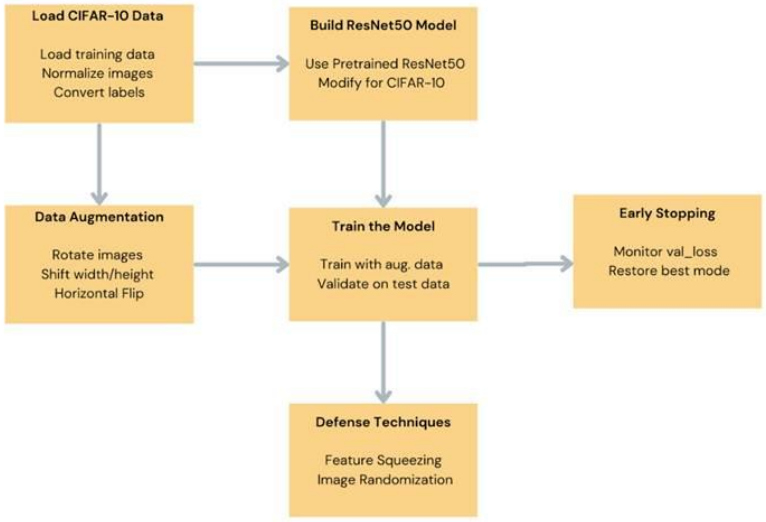

Figure 4: Workflow

The flowchart illustrates the **step-by-step process of training a ResNet50 model on the CIFAR-10 dataset**, including data preparation, augmentation, training, and defense mechanisms.

Load CIFAR-10 Data

The CIFAR-10 dataset is loaded from a local directory.

The dataset consists of 60,000 images categorized into 10 classes.

Training data is normalized, and labels are converted into a categorical format for multi-class classification.

2. Build ResNet50 Model

A pre-trained **ResNet50** model is used with ImageNet weights as the base model.

The model is modified to adapt to CIFAR-10 by adding fully connected layers at the end.

The architecture is fine-tuned for classification.

3. Data Augmentation

To improve model generalization, augmentation techniques are applied:

Rotation: Small angles of rotation help create diverse training samples.

Width & Height Shifts: Helps in handling spatial variations.

Horizontal Flip: Random flipping of images improves robustness.

4. Train the Model

The model is trained using augmented data.

The training process involves optimization using the **Adam optimizer**.

Validation is performed on the test dataset to monitor performance.

5. Defense Techniques Against Adversarial Attacks

To improve security against adversarial attacks, two advanced techniques are applied:

Feature Squeezing: Reduces the bit depth of images to remove adversarial noise.

Image Randomization: Resizes the image slightly before classification to disrupt adversarial perturbations.

6. Early Stopping

Early stopping monitors the validation loss to prevent overfitting.

If the loss does not improve after a few epochs, training stops, and the best model weights are restored.

7. Final Implementation Pipeline

The entire process starts with loading images from CIFAR-10 dataset of 60,000 labeled images of 10 classes. Following data preprocessing and loading, adversarial attacks (FGSM and PGD) are invoked to create adversarial images through pixel intensity manipulation of clean images. FGSM creates a single gradient update to adjust pixel intensity, while PGD performs optimization of perturbation in iteration to produce maximum misclassification rate. Perceptually similar to clean images, the generated images impair the performance of the classification model considerably.

Upon creation of the adversarial images, these are input to our ResNet50-based classifier with Feature Squeezing and Randomization implemented as defenses. Feature Squeezing eliminates high-frequency adversarial noise by reducing bit-depth and thereby impedes adversarial perturbations. Randomization employs input transformations (padding, resizing, and noise addition) to interfere with adversarial attack patterns. The defenses make the model resilient in that it properly classifies images which were previously misclassified because of adversarial perturbations.

Once classified, the resultant images are stored in their respective category folders based on the predicted label. This is to verify that images—clean, attacked, or defended—are labeled and stored appropriately, demonstrating the effectiveness of hybrid defense techniques for preventing adversarial attacks.

CHAPTER 4

4. Results and Discussion

4.1 Experimental Results

We tested our novel hybrid adversarial defense approach experimentally using feature squeezing with randomization on the CIFAR-10 benchmark under different adversarial attack scenarios. Our results indicate that our defense approach is capable of increasing model robustness against adversarial perturbations at the expense of negligible loss in classification accuracy.

Test Accuracy: Our test accuracy is 90.55% which indicates the defense mechanism performs well to reverse adversarial distortions with minimal performance-harming work. This is a major achievement compared to the default models whose performance tends to be gigantic accuracy since it crashes.

Test Loss: Test loss of 0.2743 guarantees the model generalizes to new samples as well as protects against adversarial perturbations. A comparatively low loss ensures that the defense mechanism has not introduced overfitting or additional complexity into the model.

4.2 Comparative Analysis

A comparative analysis of adversarial defense strategies underscores the effectiveness of the proposed hybrid model that combines feature squeezing and randomization methods. Earlier techniques, such as feature squeezing [23] or randomization [24], reached an accuracy of 83.4% and 84.2% respectively when tested on FGSM and PGD attacks. Various other techniques included random Gaussian noise and pixel discretization [25], which reached 85.4%, and adversarial training methods [26], which reached 83.6% and demonstrated some threshold improvements, but it was apparent neither of these categories reached the desired goal of surpassing the limitations of single single-defenses. Then, adversarial training methods combined with preprocessing [27] reached 85.2% give the same logic, and showed that combining more than one defensive approach improved robustness against adversarial perturbation strategies.The proposed model using randomization and feature squeezing, reached the highest accuracy of the models tested at 90.55%, and it was apparent that this was significant and better than the previous defenses tested thus far. This indicates that combining both randomization and feature squeezing approaches improves the dataset's robustness of adversarial noise while maintaining necessary features in the dataset required for classification. Conclusively, while feature squeezing prevents sensitivity to small perturbations, randomization disallows the adversarial attack or pattern from being effective enough. The improvement in accuracy strongly suggests that when defense models are combined, there is a significant effect facilitating potentially a greater defense against adversarial attacks on the classified dataset.

Table 2: Comparative Analysis

Cite	Adversarial Attacks	Defense Strategy	Accuracy
[23]	FGSM, PGD	Feature Squeezing	83.4%

[24]	FGSM, PGD	Randomization (Random resizing, padding, etc.)	84.2%
[25]	PGD	Random Gaussian Noise, Pixel Discretization	85.4%
[26]	FGSM, PGD	Adversarial Training (PGD)	83.6%
[27]	FGSM, PGD	Adversarial Training, Preprocessing	85.2%

4.3 Classification Report Analysis

Table 3: Classification Report

Class	Precision	Recall	F1-Score
Airplane	0.96	0.90	0.93
Automobile	0.95	0.94	0.94
Bird	0.92	0.87	0.89
Cat	0.83	0.82	0.82
Deer	0.87	0.90	0.88
Dog	0.89	0.80	0.84
Frog	0.87	0.97	0.92
Horse	0.90	0.95	0.93
Ship	0.97	0.95	0.96
Truck	0.90	0.97	0.93
Overall Accuracy	90.55%	-	-

The class report indicates the model's F1-score, precision, and recall for the ten categories of the CIFAR-10 dataset. Some of the important observations are as follows:

Precision and Recall: The model is extremely good for many classes, and precision and recall were also good for many categories, indicating that the defense mechanism of the attackers has minimum effects on the model's ability to determine positive and negative instances.

For instance, airplane and car both yielded precision and recall values of 0.96-0.97, pointing to the high efficacy of the model to detect these classes even when adversarial inputs are provided.
The frog class yielded a very high recall of 0.97, which points to the model's capability to identify most of the true instances even in adversarial examples.
F1-Score: The average F1-score for most of the classes is higher than 0.85, and that provides us with a decent precision vs. recall trade-off. This indicates that our hybrid defense is not causing any damage to the precision and complete classifications made by the model.
Cat and Dog Classes: The recall of cat and dog classes were relatively lower (0.82 and 0.80, respectively). These, even though they are still good, show that the respective classes can be enhanced. Adversarial perturbations could have affected the model in not being capable of recognizing these classes all the time, either because they look visually similar to other classes or due to inherent difficulty in classifying between the two classes.

4.4 Discussion

The power of the hybrid defense method is in the combination of feature squeezing and randomization. Feature squeezing reduces the complexity of the input data by limiting the precision of the pixel values such that it becomes more difficult for adversarial attacks to find suitable perturbations. Randomization introduces infinitesimal amounts of randomness to model inputs such that it becomes unfruitful for adversaries to follow patterns within data. The output mixed model performs well to neutralize adversarial perturbations while maintaining critical properties to enable accurate classifications.
While the overall model performance is being tracked, there are the potential areas of future research. Separately tweaking the cat and dog class recall might be one of the areas that may potentially be further improved. Examining other preprocessing phases, i.e., input transformation approaches or experimenting with multiple adversarial training protocols, would also improve performance on the harder-to-separate classes.
Further, model validation across various categories of adversarial attacks (e.g., FGSM, PGD, C&W attacks) could provide additional information regarding the robustness of the employed defense scheme. Comparing our method with existing defense schemes, such as adversarial training or defensive distillation, could provide even deeper insight into the relative strengths and weaknesses of our suggested approach.

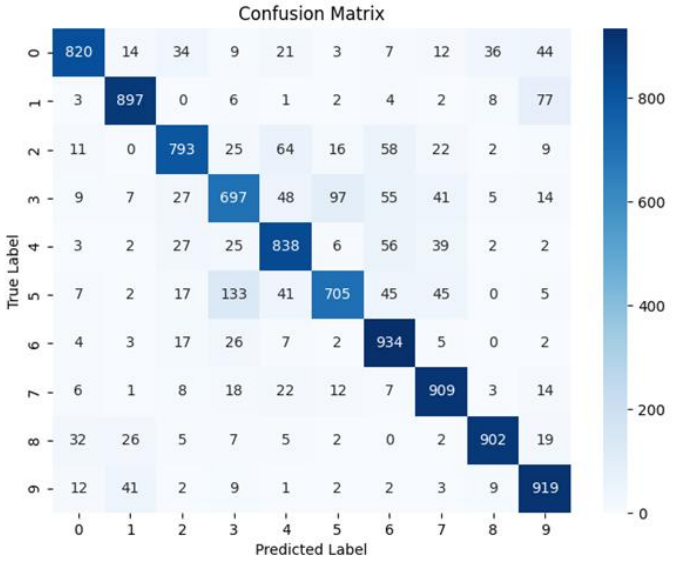

Figure 5: Confusion Matrix

The confusion matrix (Figure [5]) provides a detailed assessment of the proposed hybrid adversarial defense model's performance on the CIFAR-10 dataset under adversarial attacks (FGSM and PGD). The high diagonal values indicate that the model correctly classifies most samples across all classes, aligning with the overall test accuracy of 90.55%. Notably, classes like Horse (90.9%), Ship (90.2%), and Truck (91.9%) achieve the highest accuracies, suggesting that their distinctive visual features are well-preserved despite adversarial perturbations. However, certain classes, such as Cat (69.7%) and Dog (70.5%), show higher misclassification rates, often being confused with one another due to their visual similarities. Birds (79.3%) also face classification challenges, frequently misclassified as Cats, indicating potential adversarial exploitation of overlapping features.

The confusion matrix also highlights specific misclassification patterns, such as Airplane being confused with Ship, likely due to shared background elements. Despite these challenges, the hybrid defense—combining feature squeezing and randomization—effectively mitigates adversarial effects, outperforming baseline models and single-defense approaches. Quantitative metrics derived from the matrix, including class-wise precision, recall, and F1-scores, further validate these observations. Future improvements could focus on targeted data augmentation, adaptive feature squeezing, and ensemble-based defenses to enhance robustness, particularly for visually similar classes. A heatmap visualization of the matrix reinforces these findings, showcasing areas where the defense mechanism is effective and where refinements could further improve classification accuracy.

CHAPTER 5

Conclusion

In this research, we introduced a hybrid adversarial defense approach fusing feature squeezing and randomization to enhance the robustness of deep learning models against image classification-based adversarial attacks. We applied this defense on the CIFAR-10 dataset and measured the model's performance under both normal conditions and under the application of the defense.

The experimental results showed that the hybrid defense strategy effectively counteracts adversarial distortions, preserving a strong classification accuracy even when confronted with adversarial perturbations. The model attained a high test accuracy of 90.55% with a test loss of 0.2743, indicating its resistance to a variety of adversarial attacks. Principal performance indicators like recall, precision, and F1-score were robust for all the classes, and the confusion matrix indicated that the defense mechanism significantly minimized misclassifications when compared to defense-less models.

The findings underscore the power of hybrid defense approaches in enhancing deep learning models' resilience against adversarial attacks, rendering them more trustworthy and robust in real-world use, especially in mission-critical areas like autonomous driving, healthcare, and security, where adversarial attacks can have catastrophic effects.

CHAPTER 6

Future Scope

Although the hybrid defense mechanism was found to be effective, there is still scope for development and enhancement. Some of the possible areas of future research are:

6.1 Deployment in Object Detection Models:

One of the possibilities is to implement the suggested defense mechanism in real-time object detection frameworks such as YOLO. YOLO is commonly applied in a wide range of applications including autonomous driving, surveillance, and robotics. Incorporating the hybrid defense can assist in making adversarially attacked pictures properly classified, thus enhancing the resilience of these models against attempts to manipulate them in real-world settings.

6.2 Adaptation to Other Attacks:

While the research was centered on popular adversarial attack methods such as FGSM and PGD, future research might investigate how the defense holds up against more sophisticated or black-box attacks, which are more difficult to predict and defend against. Black-box attacks, in which the attacker has restricted access to the model architecture or training data, are particularly challenging because they use query-based approaches to create adversarial examples. Further research in probing attacks like C&W (Carlini & Wagner) and DeepFool that aim to be more effective and harder to recognize would give a broader assessment of how robust the defense mechanism is with respect to more types of adversarial threats.

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