Taipei, Taiwan

8-12 December 2025

Hybrid-FGPG: A Novel Fusion of Gradient and Geometric Transformations for Adversarial Vulnerability Evaluation

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This work has received funding from the European Union's Horizon Europe research innovation action programme under grant agreement No. 101135423 – ENACT and the the National Recovery and Resilience Plan 'Greece 2.0' under the European Union's NextGenerationEU framework AMYNA-TN - Grant Agreement no. ΥΠ3ΤΑ-0560908.

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Presentation Structure

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- Q/A

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Introduction, Relevant Work & Contributions

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Introduction

Artificial intelligence models are widely deployed across critical domains such as autonomous driving, traffic systems, and satellite monitoring.

Adversarial examples are small, intentionally crafted perturbations that deceive AI models into producing incorrect predictions. These attacks can remain visually imperceptible while causing serious misclassifications.

In safety-critical domains, even a single misclassification can lead to severe consequences—misinterpreting a stop sign, overlooking a wildfire, or mislabeling satellite imagery.

Traditional gradient-based methods like FGSM and PGD explore limited perturbation directions and rarely account for natural variations such as small rotations or geometric distortions.This gap motivates the development of more realistic and effective adversarial attacks.

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Related Work

2023

Yu et al.

This study Introduces weight-space adversarial attacks that perturb model parameters rather than inputs, showing that tiny weight changes can trigger high-confidence misclassifications in DNNs.

2023

Merzouk et al.

Their study highlights that sequential, policy-driven models are particularly fragile in low-signal scenarios. These insights extend our focus from classification-based pipelines to temporal detection systems, where our Hybrid-FGPG could be adapted to disrupt multi-step decision processes with geometry-aware perturbations.

Gao et al.

Semantic-Preserving Adversarial Attacks combine GAN-driven semantic manipulation with adversarial optimization, producing realistic yet deceptive samples. This approach maintains visual meaning while degrading classifier performance, demonstrating the importance of realistic and structure-aware adversarial perturbations.

2023

Asimopoulos et al.

The Adversarial Attack Generator (AAG) provides a unified toolkit for evaluating models against FGSM, PGD, JSMA, CW, and ZOO attacks. This study standardizes robustness testing across datasets, enabling consistent benchmarking, visualization, and comparative adversarial analysis.

2024

Problem Statement & Research Gap

Problem Statement

- Existing adversarial attacks rely primarily on **gradient direction**, limiting exploration of alternative perturbation paths.
- They fail to capture **natural variations** such as rotations, viewpoint changes, or sensor distortions.
- Generated perturbations often reduce accuracy, yet remain **unnatural, easily detectable**, or inconsistent with real-world conditions.

Research Gap

- No existing approach effectively explores multiple perturbation subspaces beyond simple gradient ascent.
- Lack of methods combining gradient information with geometric transformations to enhance adversarial strength.
- Need for attacks that achieve high misclassification while staying visually subtle, realistic, and difficult to detect.

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Contributions

Hybrid-FGPG: A Novel Gradient + Geometric Adversarial Attack

- We propose Hybrid-FGPG, a new adversarial attack that fuses gradient-based perturbations with pixel-level geometric rotation, enabling exploration of side-directions in the loss landscape..

Modular Adversarial Evaluation Framework

- We design a modular, extensible evaluation pipeline supporting FGSM, PGD, and Hybrid attacks across CIFAR-10, GTSRB, and EuroSAT datasets.
- Cross domain Experimental Validation

Hybrid attacks vs Popular adversarial attacks

- We compare our proposed adversarial attack with traditional adversarial attacks such as FGSM and PGD

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Adversarial Attack Generator Architectural Design

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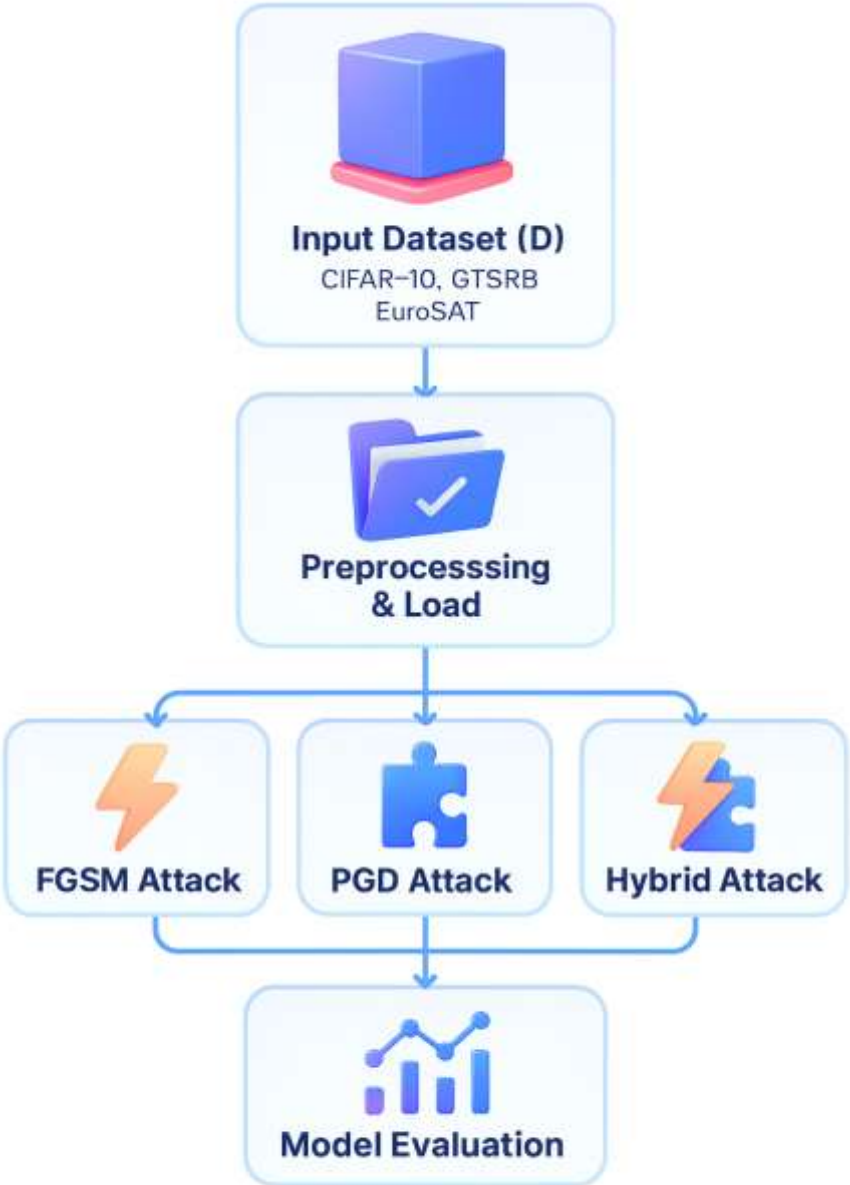
Architecture

- **Modular, extensible, and reproducible design.**
- **Supports multiple datasets (CIFAR-10, GTSRB, EuroSAT).**
- **Enables streamlined experimentation across various attacks.**
- **Three core stages:**
  a) Model Initialization
  b) Attack Execution
  c) Metrics Evaluation & Visualization



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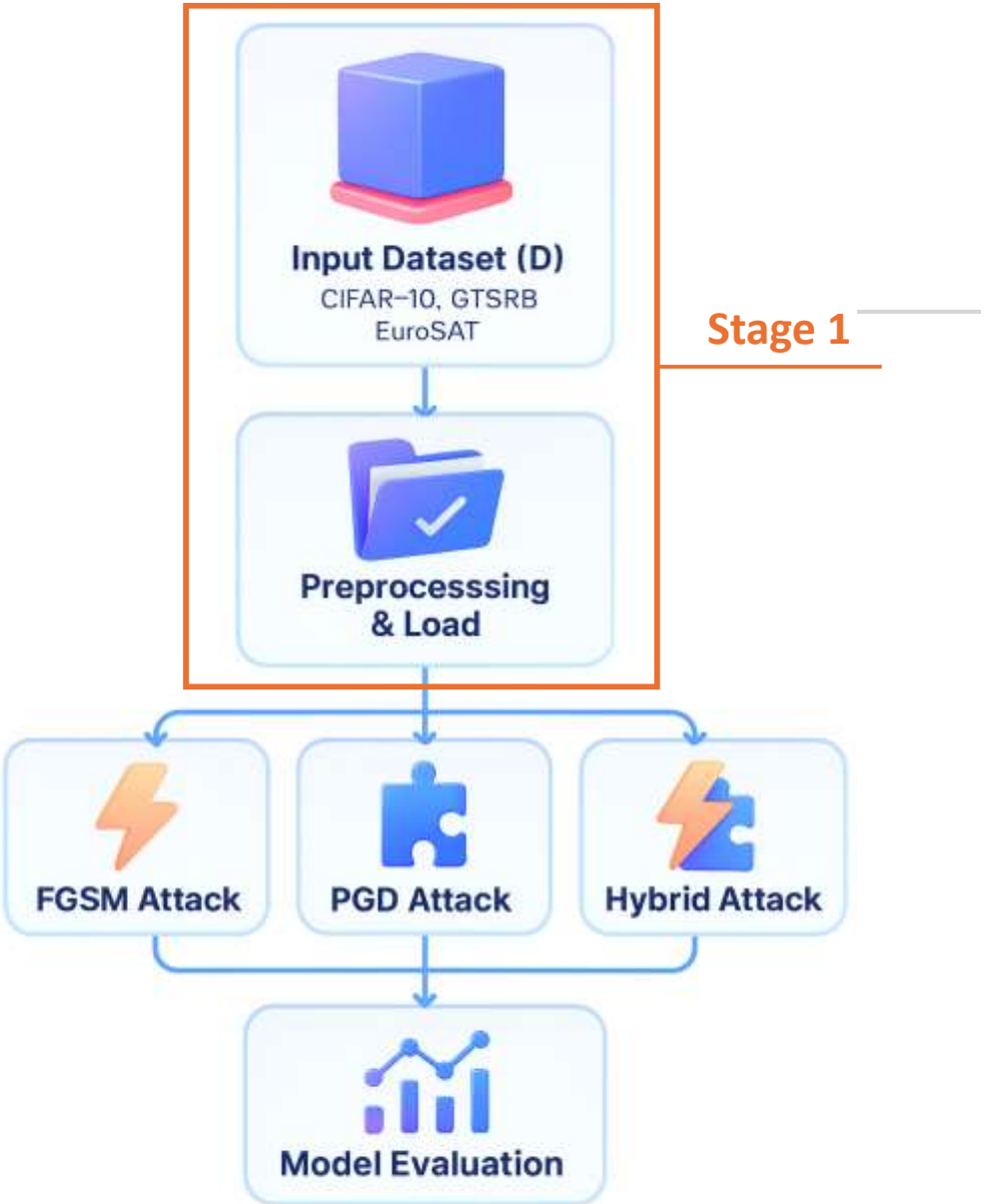
Model Initialization

Model Initialization Phase (Stage 1)

- Loads **ResNet-18** (pretrained or trained from scratch).
- Configured for cross-dataset image classification.
- Optimized for clean inference before attacks are applied.
- Ensures consistent baseline performance across experiments.



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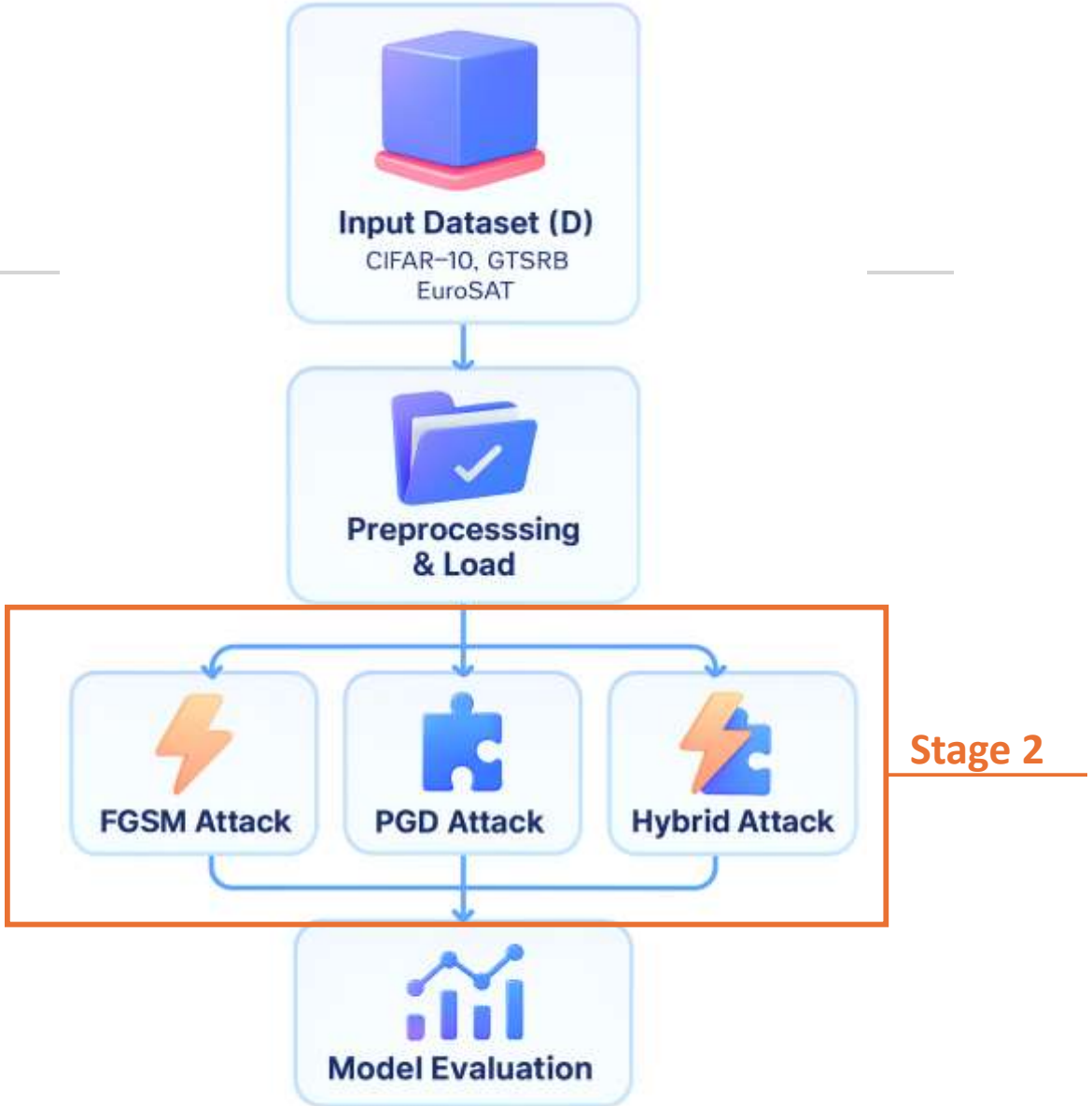
Attack Execution

Attack Execution Phase (stage 2)

- Applies adversarial methods to clean image batches.
- Supported attacks:
  - **FGSM** (single-step gradient)
  - **PGD** (iterative gradient ascent)
  - **Hybrid-FGPG** (gradient + rotational perturbation)
- Each attack perturbs input within controlled constraints.
- Produces adversarial examples for evaluation.



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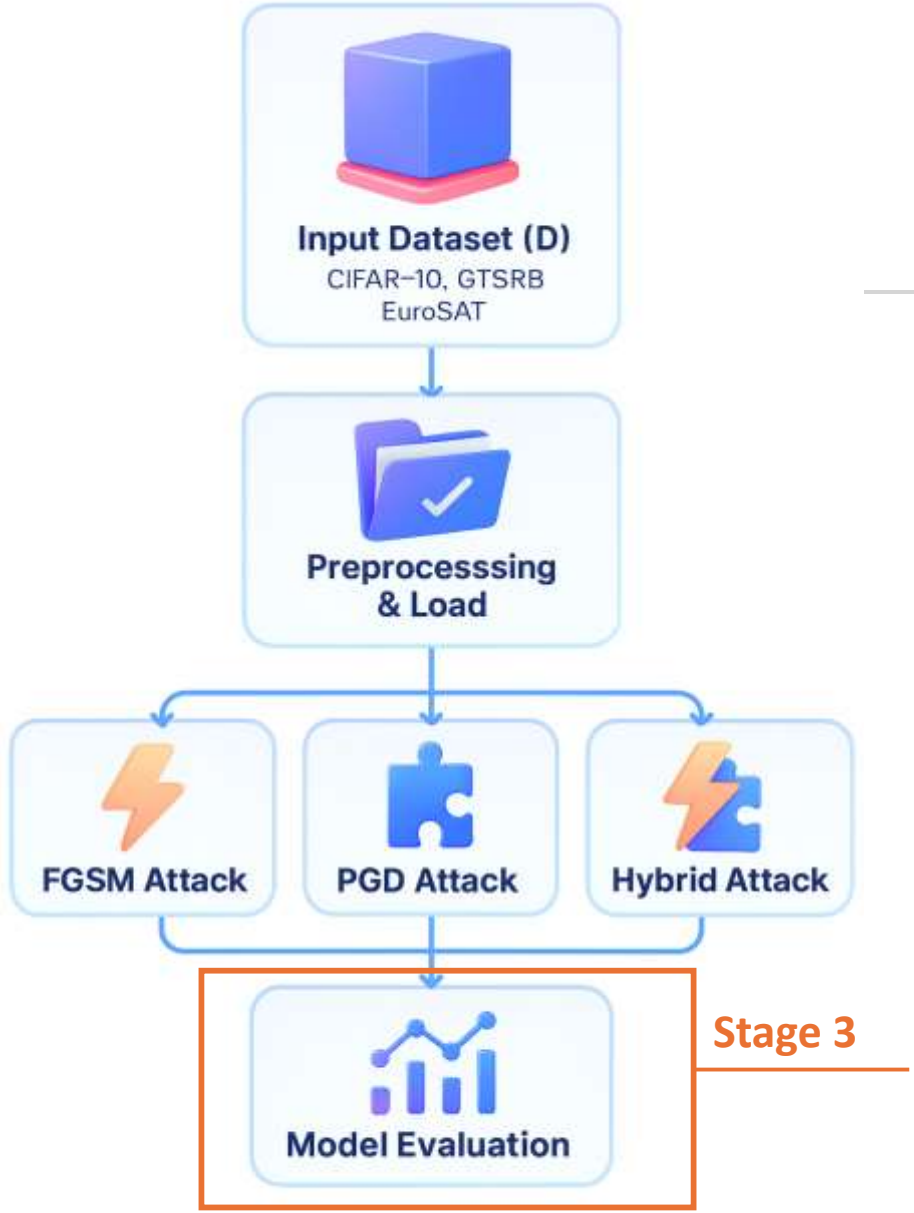
Model Evaluation

Model Evaluation Phase (stage 3)

- Compares predictions on clean vs adversarial images.
- Computes standard metrics:
  Accuracy, Precision, Recall, F1-Score
- Quantifies the effect of each attack on model robustness.
- Provides qualitative insight into each attack's behavior.
- Saves representative examples per dataset and attack type.
- Displays: Clean image, Perturbed image, Predicted labels (clean vs adversarial), Heatmaps



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Adversarial Attacks

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Fast Gradient Sign Method (FGSM)

Overview

FGSM is a fundamental adversarial attack technique that exploits vulnerabilities in machine learning models by adding targeted noise to input data.

- FGSM generates adversarial examples by adding a small, crafted perturbation to the input.
- Perturbation is calculated by taking a step in the direction of the gradient sign of the loss function, maximizing prediction error.
- Efficient and widely used for evaluating the robustness of machine learning models.

Characteristics

- Fast and computationally inexpensive.
- Highly effective for small ε.
- Limited exploration of perturbation space (singe direction).

FGSM Process

1. Input Data (e.g., Image)
2. Loss Function & Gradient Calculation
3. Sign of Gradient (Direction)
4. Adversarial Example (Original + ε·sign(∇J))

$$x_{adv} = x + \varepsilon \cdot \text{sign}(\nabla_x J(\theta, x, y))$$

- adv_x → Adversarial data
- x → Original data
- y → Original input label
- ϵ → Multiplier to ensure the perturbations are small
- θ → Model parameters
- J → Loss function. In our case, the CrossEntropy function

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Project Gradient Descent (PGD)

Overview

PGD is an iterative, white-box attack methods that apply controlled, small perturbations to input data, aiming to mislead deep learning models into misclassification.

- Iteratively applies perturbations in the gradient direction to maximize the model's prediction error.
- PGD executes FGSM in small steps, repeatedly projecting perturbations to keep them undetectable.

Characteristics

- Stronger than FGSM
- Iterative, multi-step refinement
- Considered a "universal first-order adversary"
- Still restricted to gradient direction only

PGD Formula

FGSM

$$x_{t+1} = \Pi_\epsilon(x_t + \alpha \cdot \text{sign}(\nabla_x L(f(x_t), y)))$$

x_{t+1} → Updated adversarial example at iteration $t + 1$

x_t → Current adversarial example at iteration t

y → True class label of the input

α → Step size for each PGD update (small gradient step)

ϵ → Maximum allowed perturbation (radius of the ε-ball)

$\Pi_\epsilon(\cdot)$ → Projection operator that keeps the perturbation within the ε-ball

$\nabla_x L(f(x_t), y)$ → Gradient of loss w.r.t. the input

$f(\cdot)$ → Target neural network model

L → Loss function (CrossEntropy in our case)

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Hybrid Adversarial Attack

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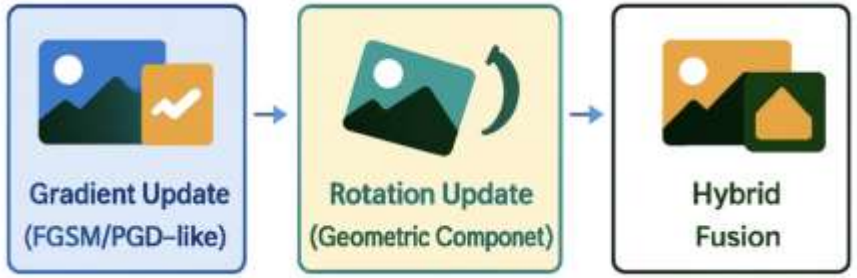
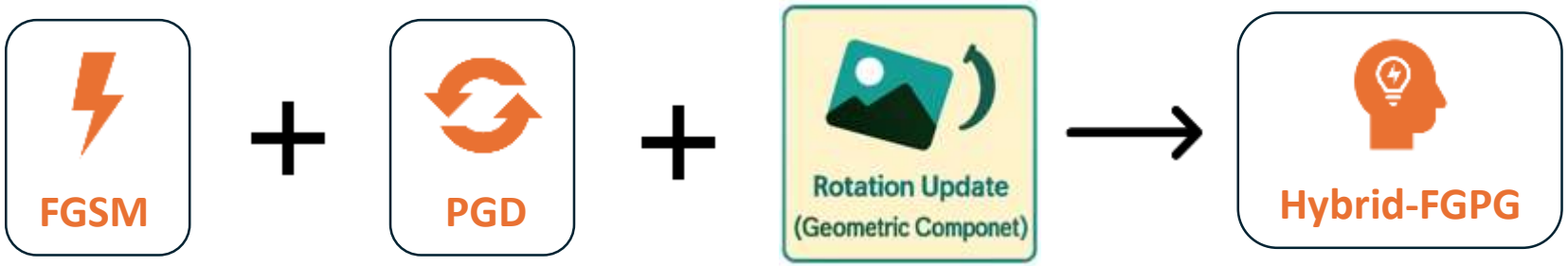
Hybrid Attack



A Novel Adversarial Attack Method

Combining Fast Gradient Sign Method and Projected Gradient Descent with perturbation guidance and rotation



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Hybrid-FGPG: Architecture and Update Rule

Architecture Overview

- **Fast Gradient Initialization:** Begins with FGSM-style perturbation to rapidly push input towards high-loss region
- **Iterative Updates:** Performs a small number of updates similar to PGD (typically 5-10 steps)
- **Perturbation Rotation:** At each step, rotates perturbation direction by angle θ using deterministic/stochastic strategy
- **Angular Diversity:** Explores "side directions" in loss landscape, avoiding overfitting to sharp local minima

Key Advantages

- Lightweight compared to standard PGD
- Less predictable perturbations
- Better transferability

Update Rule

$$\delta_{t+1} = \text{Proj}_{\epsilon}[\delta_t + \alpha \cdot \text{sign}(\nabla_x L(f(x + \delta_t), y))] + R_\theta(\delta_t)$$

δt: Accumulated perturbation at iteration

α: Step size

Projϵ: Projects perturbation within $\ell\infty$ ball

Rθ: Rotation function perturbing by angle θ

Rotation Mechanism

Perturbation rotation introduces diversity by rotating signed gradient in a fixed 2D subspace

Uses low-dimensional projections to escape local maxima

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Evaluation & Results

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Experimental Setup

System Configuration

Implementation: PyTorch framework for all experiments

Hardware: NVIDIA 4060 GPU for computation

Evaluation Protocol: Standard dataset partitions used

Testing: Evaluation performed exclusively on test sets

Evaluation Focus

Attack effectiveness across varied domains

Performance comparison with baseline attacks

Robustness against different model architectures

Computational efficiency assessment

Datasets

CIFAR-10

Classes: 10 object categories
Format: RGB images
Resolution: 32×32 pixels
Domain: Natural images

GTSRB

Classes: 43 traffic signs
Format: RGB images
Resolution: Resized to 32×32 pixels
Domain: Traffic recognition

EuroSAT

Classes: 10 land use types
Format: RGB images
Resolution: 64×64 pixels
Domain: Satellite imagery

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Evaluation Metrics

Accuracy

$$\frac{1}{N}\sum_{j=1}^{N}\mathbb{1}(y_j = \hat{y}_j)$$

Precision

$$\frac{1}{C}\sum_{i=1}^{C}\frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FP}_i + \epsilon}$$

Recall

$$\frac{1}{C}\sum_{i=1}^{C}\frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FN}_i + \epsilon}$$

F1 Score

$$\frac{1}{C}\sum_{i=1}^{C}\frac{2 \cdot \mathrm{Precision}_i \cdot \mathrm{Recall}_i}{\mathrm{Precision}_i + \mathrm{Recall}_i + \epsilon}$$

N: Total number of test samples

y_j: ground truth label

$\hat{y}_j$: predicted label

ϵ: small constant to prevent division by zero

$TP \rightarrow$ True Positives

$TN \rightarrow$ True Negatives

$FP \rightarrow$ False Positives

$FN \rightarrow$ False Negatives

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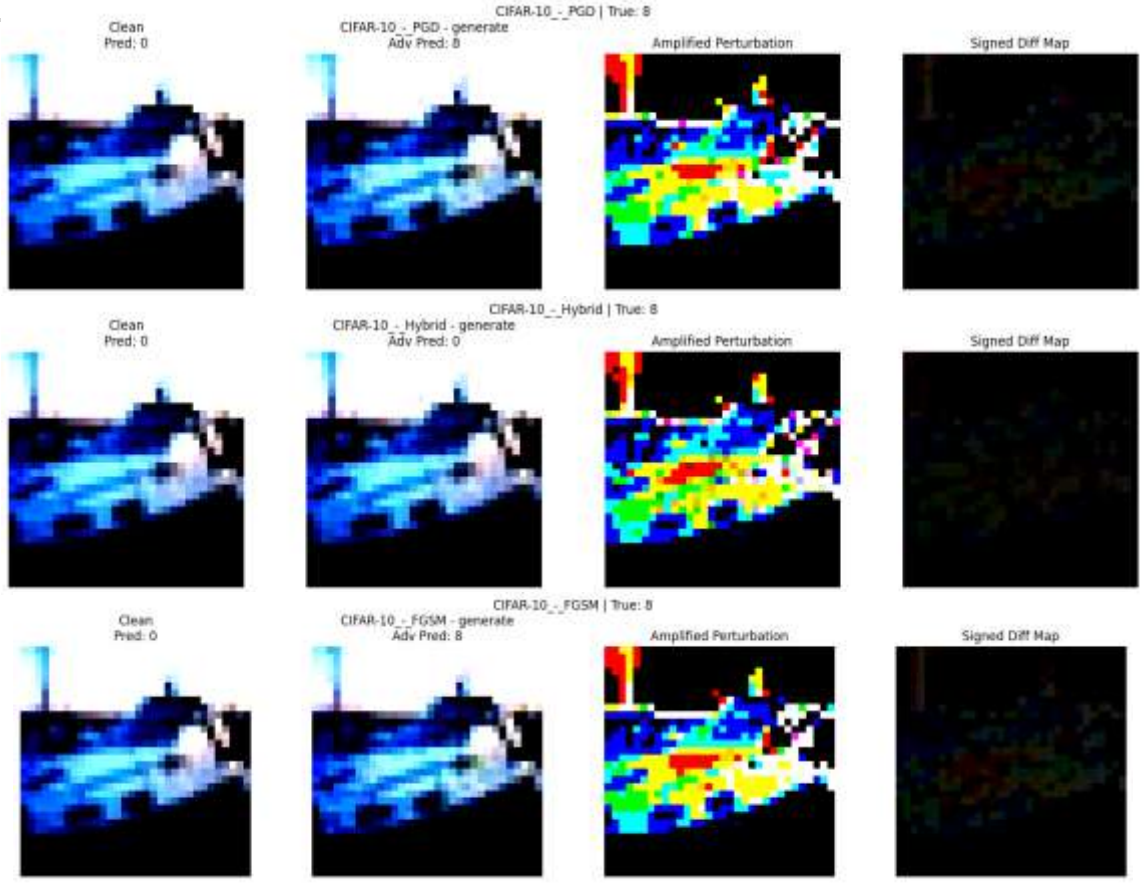
Experimental Results

CIFAR-10 Classification Performance

Scenario	Accuracy	Precision	Recall	F1-score
Clean	0.81	0.82	0.81	0.81
Adv – Hybrid	**0.12**	**0.18**	**0.13**	**0.11**
Adv- FGSM	0.62	0.63	0.61	0.61
Adv - PGD	0.58	0.59	0.57	0.57

The CIFAR-10 results show a dramatic performance drop under the Hybrid attack, with accuracy falling from 0.81 to 0.12, compared to 0.62 under FGSM. This highlights the Hybrid method's stronger attack potential on natural image datasets.



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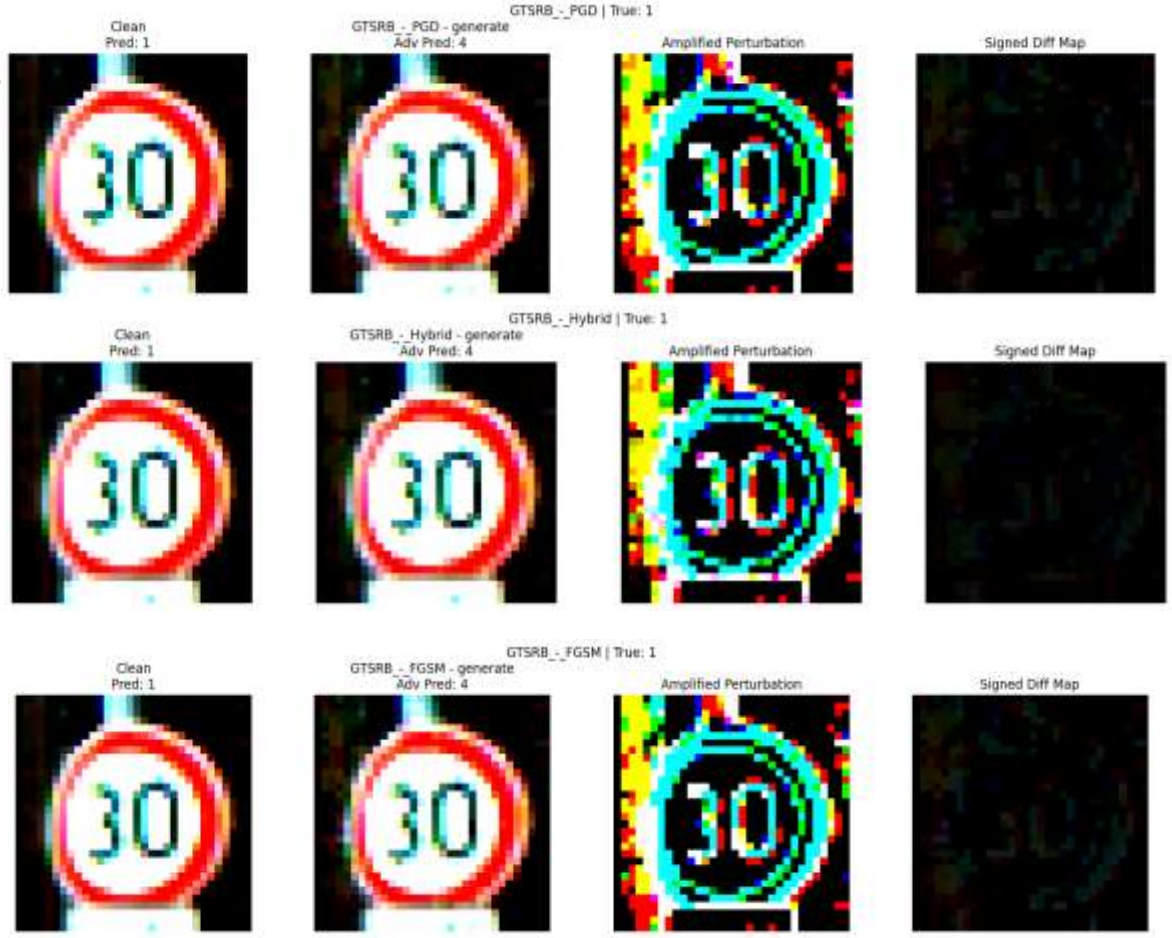
Evaluation results

GTSRB Classification Performance

Scenario	Accuracy	Precision	Recall	F1-score
Clean	0.92	0.89	0.88	0.86
Adv – Hybrid	**0.25**	**0.28**	**0.22**	**0.21**
Adv- FGSM	0.79	0.76	0.73	0.71
Adv - PGD	0.75	0.71	0.69	0.67

For GTSRB, which contains 43 traffic sign classes, the Hybrid attack once again proves more effective, dropping accuracy to 0.25. FGSM, while impactful, allows the model to retain 0.79 accuracy, showing that Hybrid uncovers deeper vulnerabilities in fine-grained classification settings.



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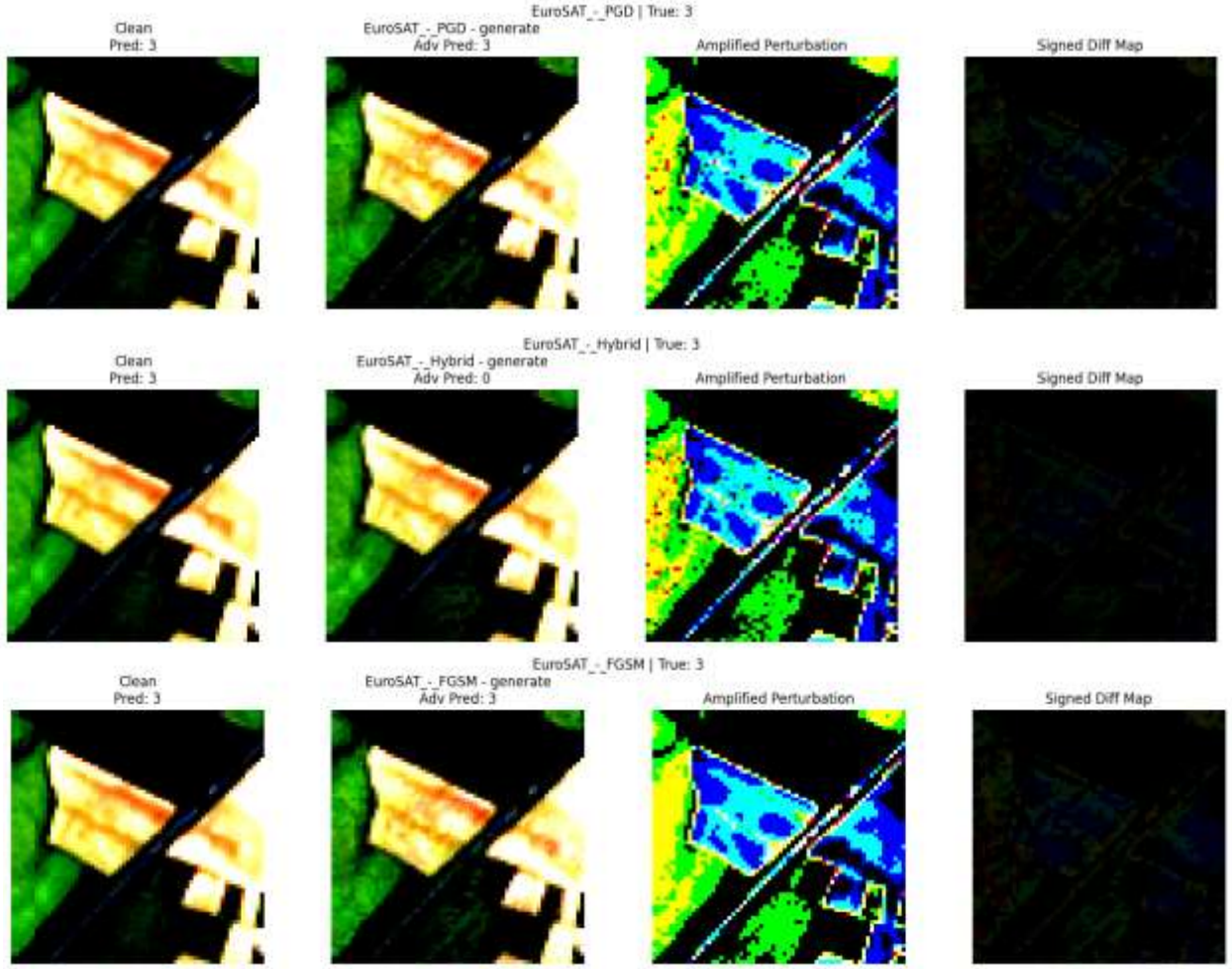
Evaluation results

EuroSAT Classification Performance

Scenario	Accuracy	Precision	Recall	F1-score
Clean	0.95	0.95	0.94	0.94
Adv – Hybrid	**0.08**	**0.07**	**0.10**	**0.05**
Adv- FGSM	0.70	0.75	0.68	0.68
Adv - PGD	0.71	0.74	0.70	0.70

In the case of EuroSAT, a dataset composed of remote sensing images, the Hybrid attack is especially effective, reducing accuracy to only 8%, a stark contrast to the 70% accuracy preserved under FGSM. This implies that Hybrid attacks are not only powerful but also adaptable to more structured visual domains.



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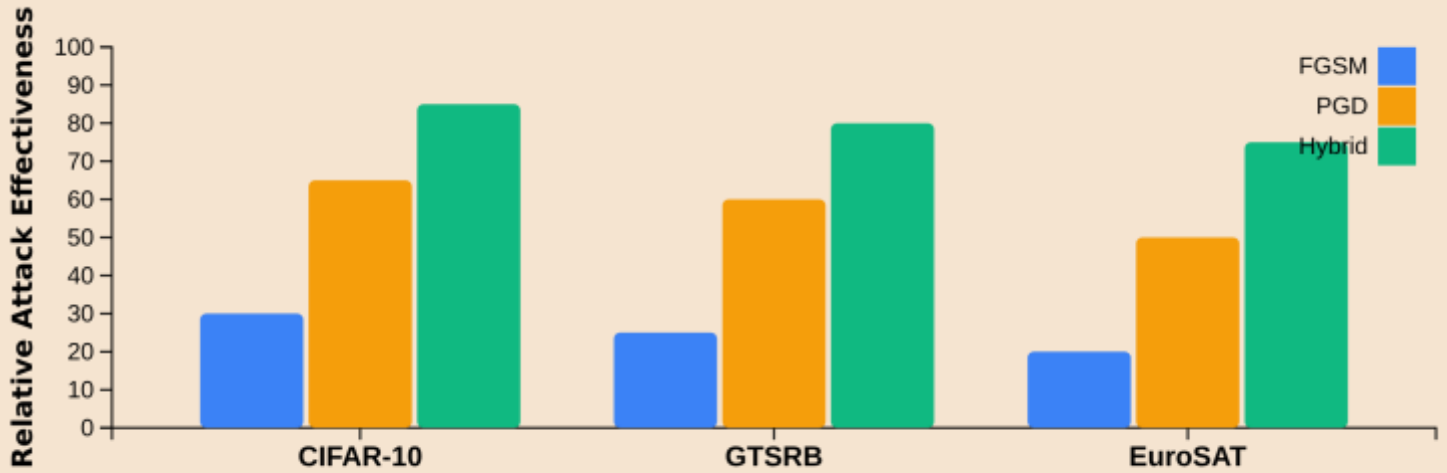
Hybrid Attack Performance Analysis

Key Findings

- Hybrid attack consistently causes more severe classification performance degradation than FGSM across all datasets
- Combination of gradient-aligned and spatially-transformed perturbations makes Hybrid highly effective at evading standard convolutional models
- Models trained on natural images (CIFAR10) show different robustness patterns compared to those trained on satellite (EuroSAT) or traffic sign (GTSRB) imagery

Comparative Attack Performance



Note: Conceptual representation of relative attack effectiveness

CIFAR-10

Natural images show distinct robustness patterns

GTSRB

Traffic sign imagery has different vulnerability profiles

EuroSAT

Satellite imagery shows marked differences in resilience

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Visual Comparison and Qualitative Results

CIFAR-10

FGSM Perturbation: Coarse noise patterns

PGD Perturbation: Strong but detectable

Hybrid Perturbation: Targeted, minimal deviation

GTSRB

FGSM Perturbation: Coarse noise patterns

PGD Perturbation: Strong but detectable

Hybrid Perturbation: Targeted, minimal deviation

EuroSAT

FGSM Perturbation: Coarse noise patterns

PGD Perturbation: Strong but detectable

Hybrid Perturbation: Targeted, minimal deviation

Key Insights

- Hybrid attack achieves successful misclassification with minimal perceptual deviation
- Perturbation heatmaps confirm Hybrid focuses on semantically critical regions
- Hybrid consistently reduces adversarial accuracy more than FGSM
- Hybrid attack bypasses both perceptual and statistical defenses

Perturbation Heatmap Focus Areas

- Textures
- Corners
- Edges

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Conclusions and Future Work

Key Achievements

- Novel Hybrid adversarial attack development
- Superior performance against FGSM and PGD
- Effective across CIFAR-10, GTSRB, and EuroSAT datasets
- Targeted semantic region exploitation

Research Implications

This work introduced a **novel Hybrid adversarial attack** and **evaluated its effectiveness** against standard white-box attacks such as FGSM and PGD on CIFAR-10, GTSRB, and EuroSAT datasets. The proposed Hybrid method strategically **combines gradient-based perturbations with structured transformations,** achieving significantly **lower adversarial accuracy** while preserving visual similarity.

Quantitative results showed that the **Hybrid attack consistently outperformed** other methods in degrading model performance, while **qualitative visualizations highlighted the subtle yet impactful nature of its perturbations.** Heatmap analyses revealed that the **Hybrid attack targets semantically meaningful regions,** emphasizing its potential to exploit deep model vulnerabilities more effectively.

Future Work

Black-box Extensions
Extend framework to black-box attack scenarios

Ensemble Transferability
Evaluate transferability across model ensembles

Robust Detection
Develop detection mechanisms for hybrid attacks

Adversarial Training
Integrate mitigation techniques into training pipelines

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