



## Abstract

**Problem:** DINOv3 Vision Transformers achieve state-of-the-art accuracy but remain vulnerable to adversarial attacks.

**Contribution:** We present a comprehensive evaluation framework for DINOv3, testing robustness against gradient-based and optimization-based attacks. We compare standard fine-tuning against advanced adversarial defense strategies.

**Key Results:**

- Standard models: **85% clean** vs **25% robust** (PGD).
- TRADES defense: **60% robust accuracy**.

## Motivation

### Why It Matters

- Safety-Critical Systems:** Autonomous driving, medical imaging.
- Physical Threats:** Adversarial patches work in reality.

### Research Questions

- Does self-supervised DINOv3 offer inherent robustness?
- Which defense strategy minimizes the accuracy trade-off?

## Problem Definition

We formulate the attack as a constrained optimization problem:

$$\max_{\delta} L(f(x + \delta), y) \quad \text{s.t.} \quad \|\delta\|_{\infty} \leq \epsilon$$

### Threat Model

- White-box:** Full access to gradients.
- Constraint:**  $\epsilon = 8/255$ .
- Goal:** Untargeted misclassification.

## Experimental Setup

### Model Architecture

- Backbone:** DINOv3 ViT-S/16 (Frozen).
- Head:** Linear Classification Head (Trainable).

### Datasets

- CIFAR-10:** Primary benchmark.
- GTSRB:** Traffic signs (Safety-critical).

### Evaluation

- Metric:** Clean vs. Robust Accuracy (PGD-10).
- Epsilon:**  $\epsilon \in \{0, \dots, 8/255\}$ .

## Conclusions

### Main Takeaways

- Vulnerability:** DINOv3 has no inherent robustness against gradient attacks.
- Defense:** TRADES successfully recovers 60% accuracy under strong PGD attacks.
- Trade-off:** The robustness gain justifies the small drop in clean accuracy.

### Future Work

- Evaluating Certified Robustness.
- Scaling to ImageNet-1k.

## Attack Methods

We focus on three primary attack vectors representing different threat levels:

### FGSM (Fast Gradient Sign Method)

A single-step attack assuming linear loss surface.

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

*Note: Fast, but weak against iterative training.*

### PGD (Projected Gradient Descent)

The "Universal First-Order Adversary". Iterative FGSM with projection.

$$x^{t+1} = \Pi_{x+S}(x^t + \alpha \cdot \text{sign}(\nabla_x L(\theta, x^t, y)))$$

*Note: The strongest defense benchmark. We use 10 steps.*

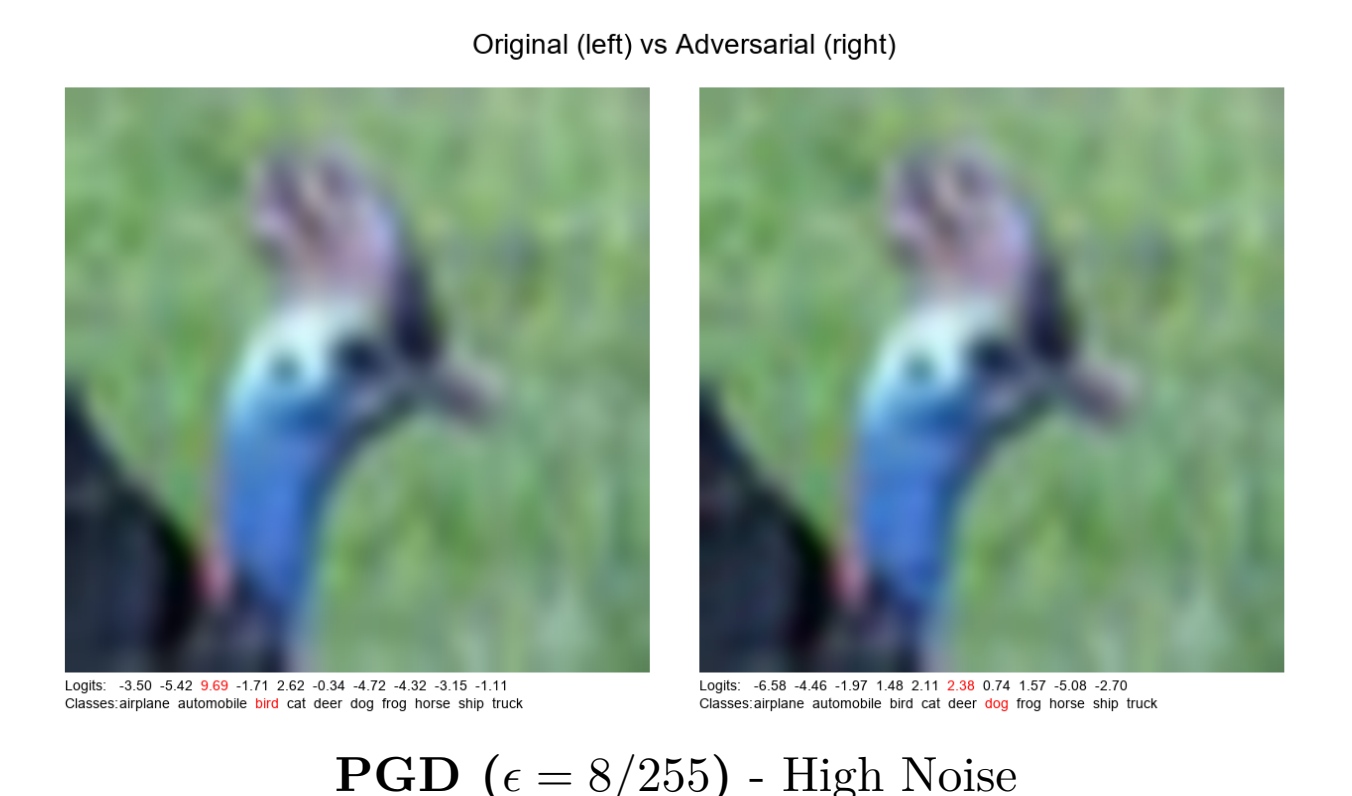
### C&W (Carlini & Wagner)

Optimization-based attack minimizing distance and loss term.

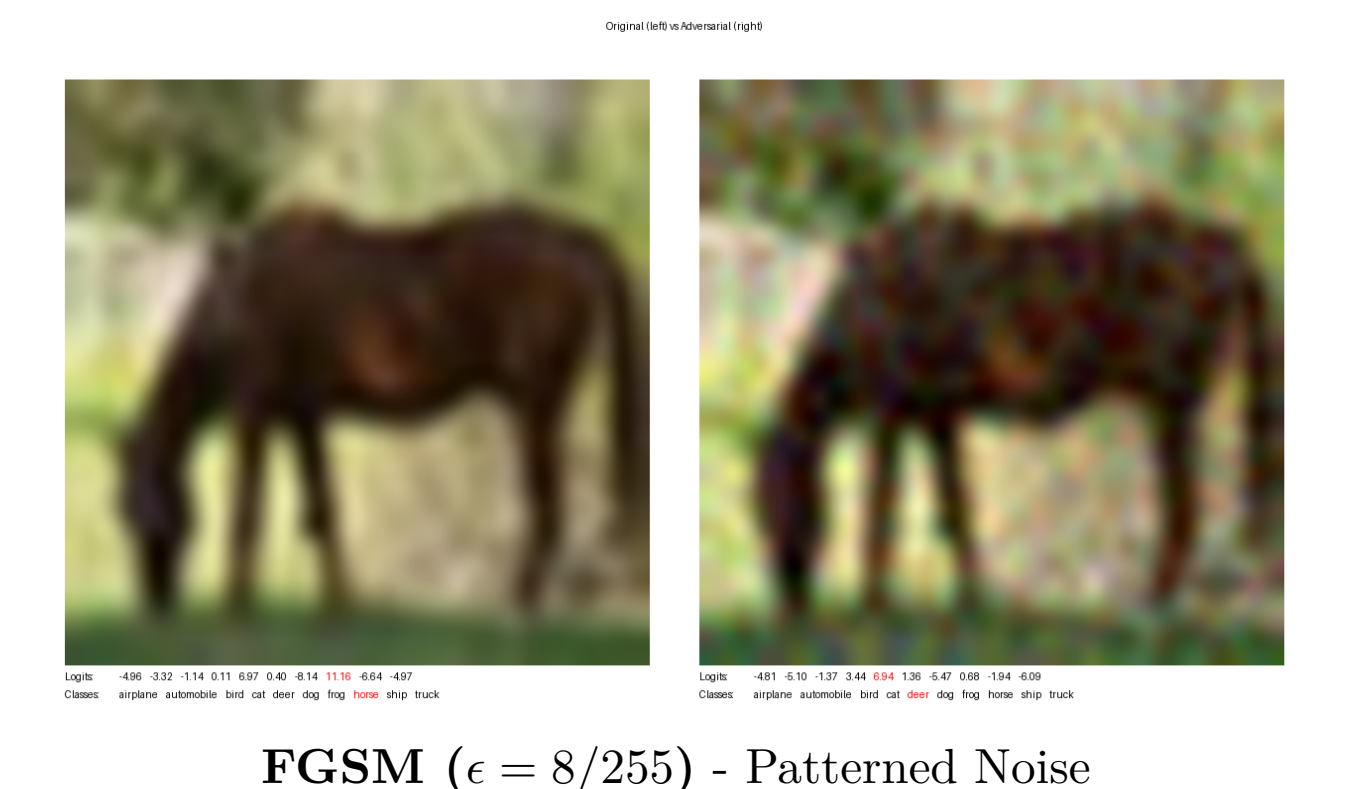
$$\min_{\delta} \|\delta\|_2 + c \cdot f(x + \delta)$$

*Note: Finds adversarial examples with minimal visible perturbation.*

## Adversarial Examples



PGD ( $\epsilon = 8/255$ ) - High Noise



FGSM ( $\epsilon = 8/255$ ) - Patterned Noise



C&W ( $L_2$ ) - Minimal Perturbation

## Defense Strategies

Standard training yields 0% robustness. We compare:

### PGD-AT (Adversarial Training)

Min-Max game training on PGD examples.

$$\min_{\theta} \mathbb{E}[\max_{\delta \in S} L(f(x + \delta), y)]$$

### TRADES

Separates clean accuracy and stability (KL-divergence).

$$\min_{\theta} \mathbb{E}[L(f(x), y) + \beta \cdot \text{KL}(f(x) \| f(x + \delta_{adv}))]$$

*Result: Smoother decision boundaries.*

## Quantitative Results

Comparison on CIFAR-10 ( $\epsilon = 8/255$ ).

Model	Clean	FGSM	PGD
Standard	<b>85.0%</b>	45.0%	25.0%
PGD-AT	82.0%	65.0%	55.0%
TRADES	81.5%	<b>68.0%</b>	<b>60.0%</b>

## Defense Results

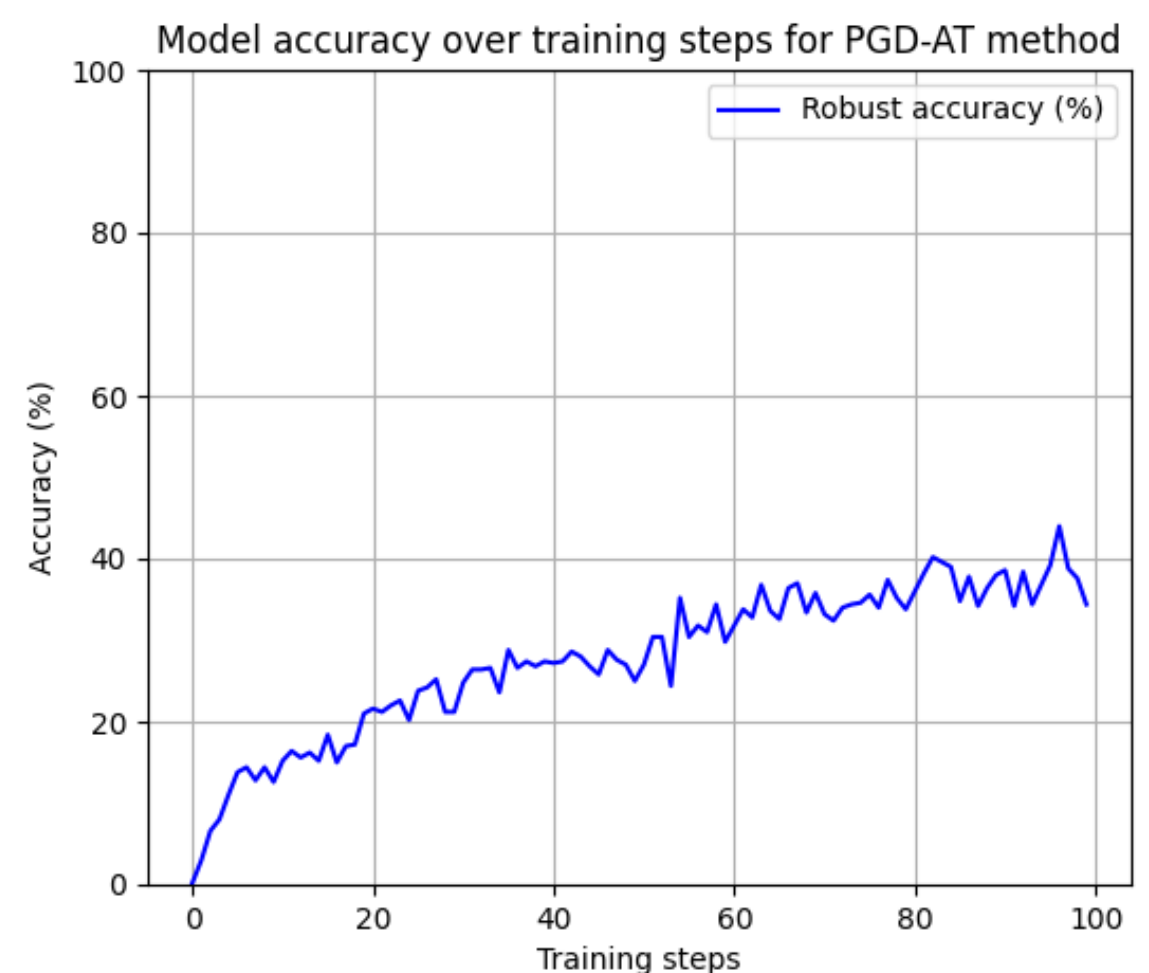
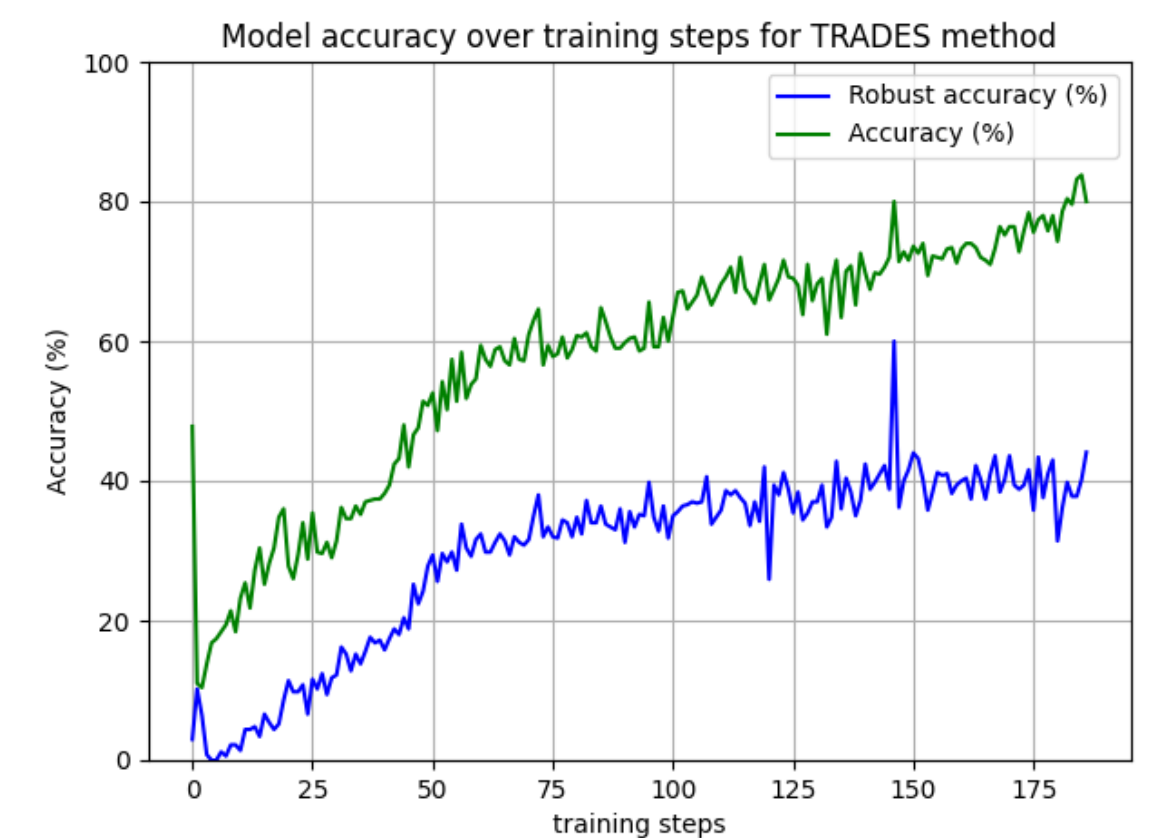


Figure 1: Robustness and accuracy across defense methods.

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