DINOmite: Adversarial Robustness of DINOv3 Vision Transformers

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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.

Motivation

Why It Matters

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

Research Questions

1. Does self-supervised DINOv3 offer inherent robustness?
2. 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.

Evaluation

- **Metric:** Clean vs. Robust Accuracy (PGD-10).
- **Epsilon:** $\epsilon \in \{0, \ldots, 8/255\}$.
- **Attacks:** FGSM, PGD, C&W.
- **Defenses:** PGD-AT, TRADES.

Conclusions

Main Takeaways

- **Adversarial Training Effectiveness:** DINO-pretrained ViTs are vulnerable to attacks like PGD. However, defenses like PGD-AT or TRADES significantly enhance robustness, mirroring Madry et al.'s findings for CNNs.
- **Trade-offs:** Increased robustness introduces a performance penalty on clean data, causing a noticeable drop in standard accuracy.
- **Visual Differences:** C&W attacks generate perturbations that are less perceptible to the human eye than those produced by PGD and FGSM.

Future Work

- Evaluating Certified Robustness.
- Scaling to ImageNet-1k and GTSRB.
- Testing diverse attack methods (e.g., AutoAttack).
- Exploring advanced defenses (e.g., MART).

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.

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

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

C&W (L_2) - Minimal Perturbation

Original (left) vs Adversarial (right)

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

Original (left) vs Adversarial (right)

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

Original (left) vs Adversarial PGD (right)

Defense Strategies

Standard training yields 0% robustness. We evaluate two state-of-the-art defenses:

PGD-AT (Adversarial Training)

A min-max game formulation (Madry et al.). The inner loop generates strong adversarial examples, while the outer loop updates the model to resist them.

$$\min_{\theta} \mathbb{E}_{(x,y)\sim D}[\max_{\|\delta\|_\infty \leq \epsilon} L(f_\theta(x+\delta), y)]$$

Key Idea: Train directly on the worst-case examples.

TRADES

Separates loss into natural accuracy and robustness regularization (Zhang et al.). It minimizes KL-divergence between predictions on clean and adversarial inputs.

$$\min_{\theta} \mathbb{E}[\underbrace{L(f(x), y)}_{\text{Natural}} + \beta \cdot \underbrace{\text{KL}(f(x) \| f(x+\delta))}_{\text{Robustness}}]$$

Key Idea: Enforce smoothness of the decision boundary.

Defense Results

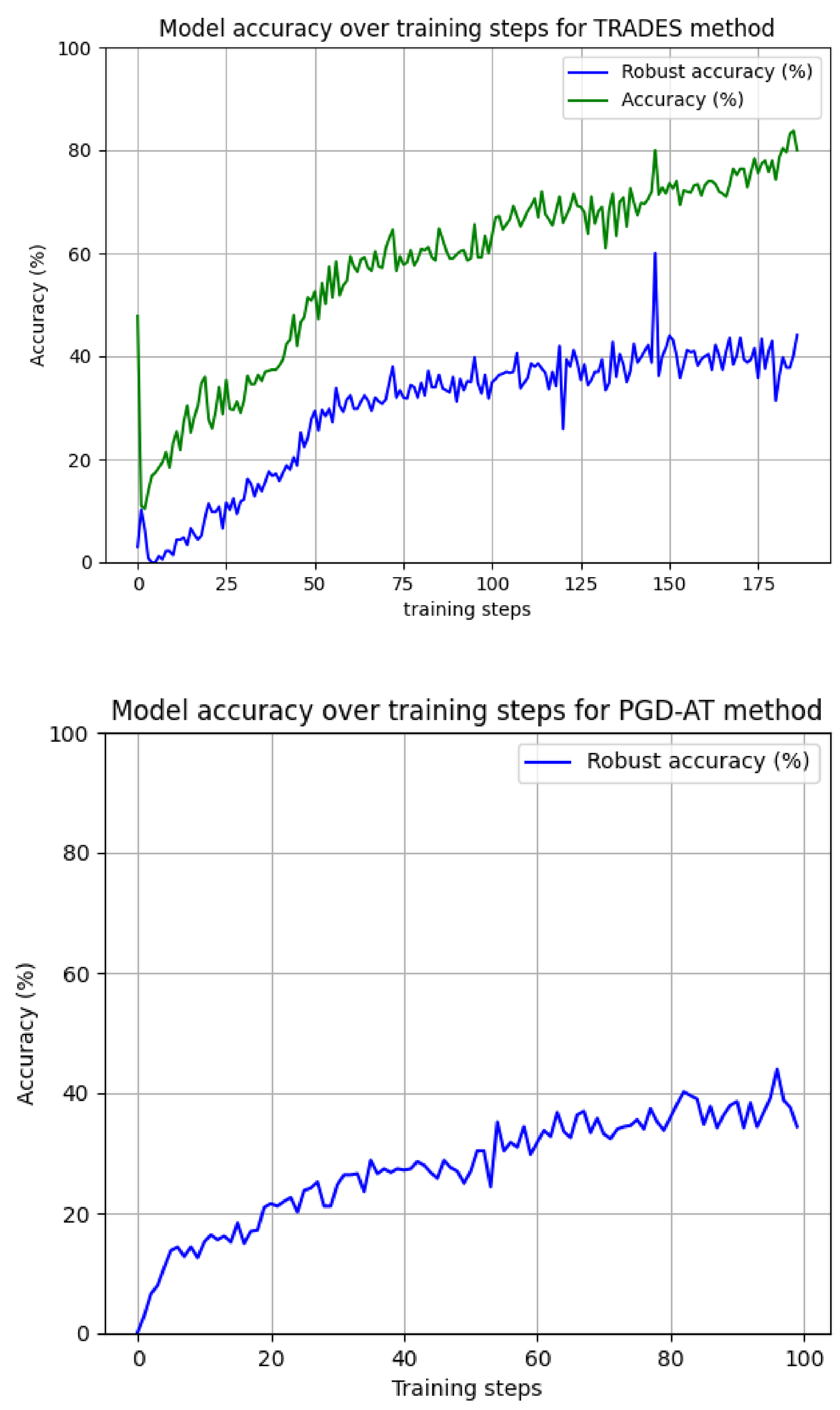

Figure 1: Robustness and accuracy across defense methods.

Quantitative Results

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

Model	Clean	PGD
Standard	**96.56%**	0.00%
PGD-AT	77.19%	**40.62%**
TRADES	81.25%	35.94%

References

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