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.
- **GTSRB:** Traffic signs (Safety-critical).

Evaluation

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

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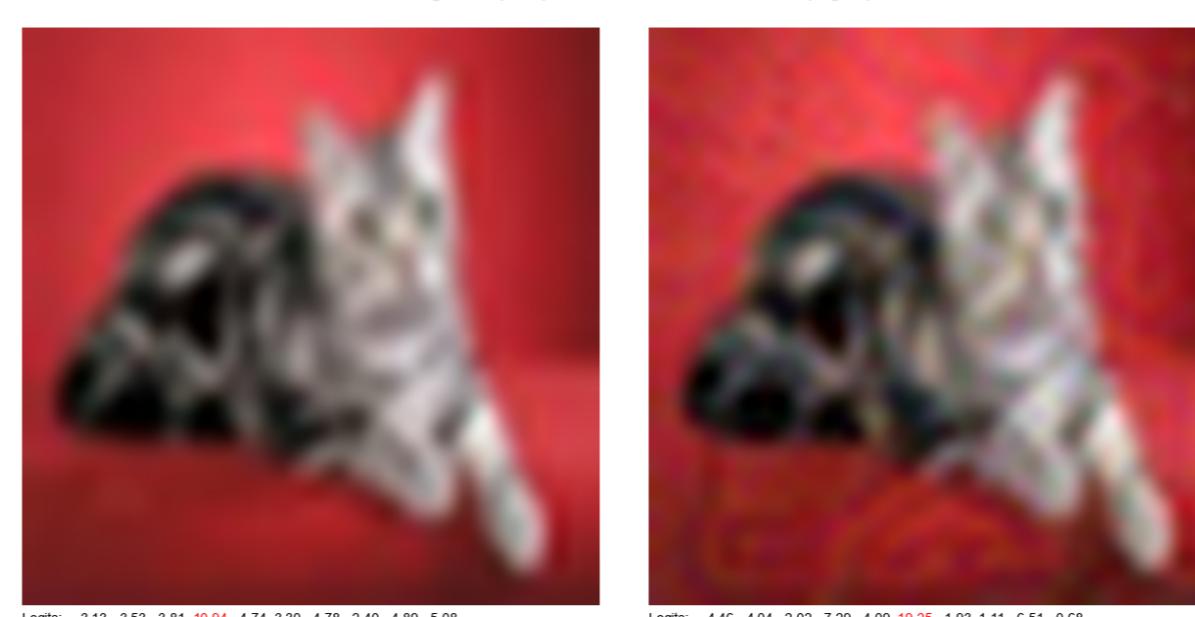
FGSM ($\epsilon = 8/255$) - Patterned Noise

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

Defense Strategies

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

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.

Defense Results
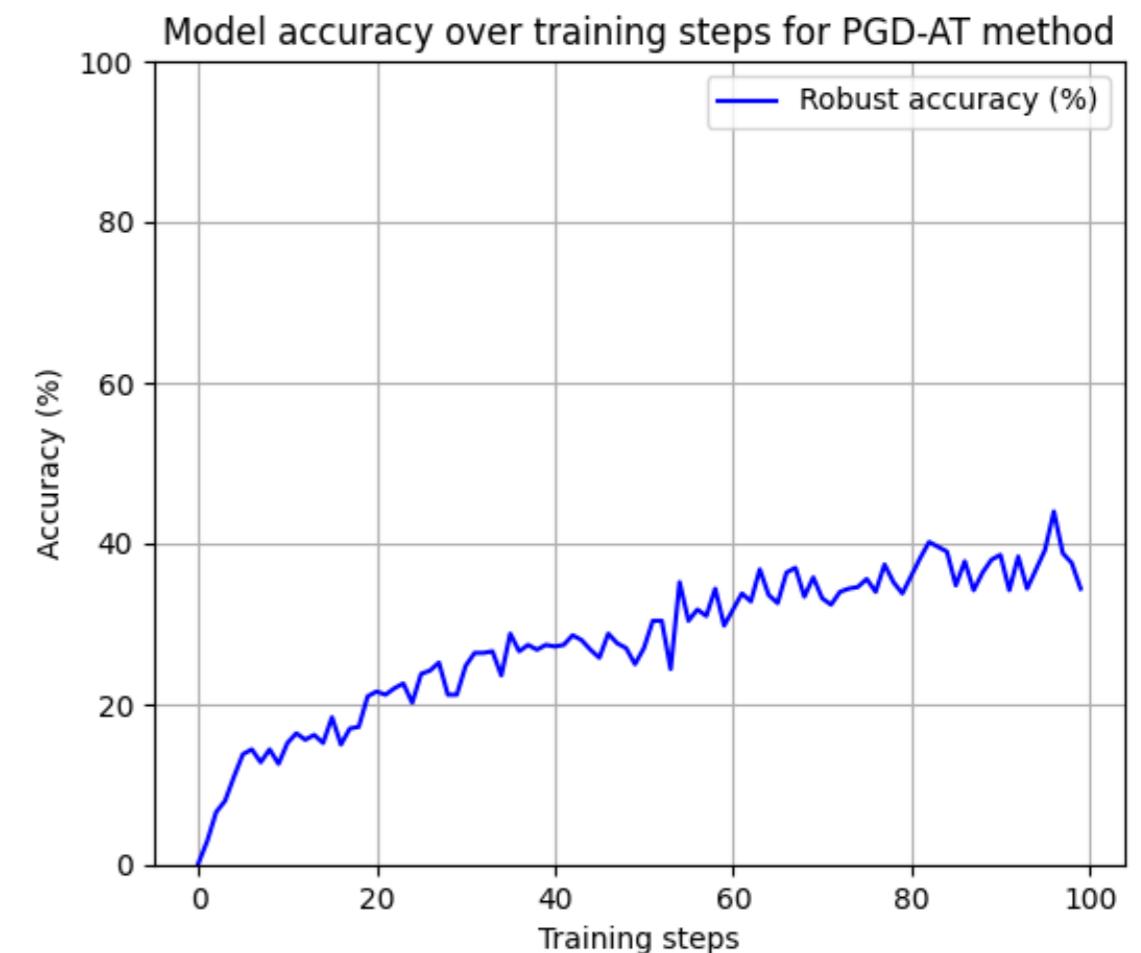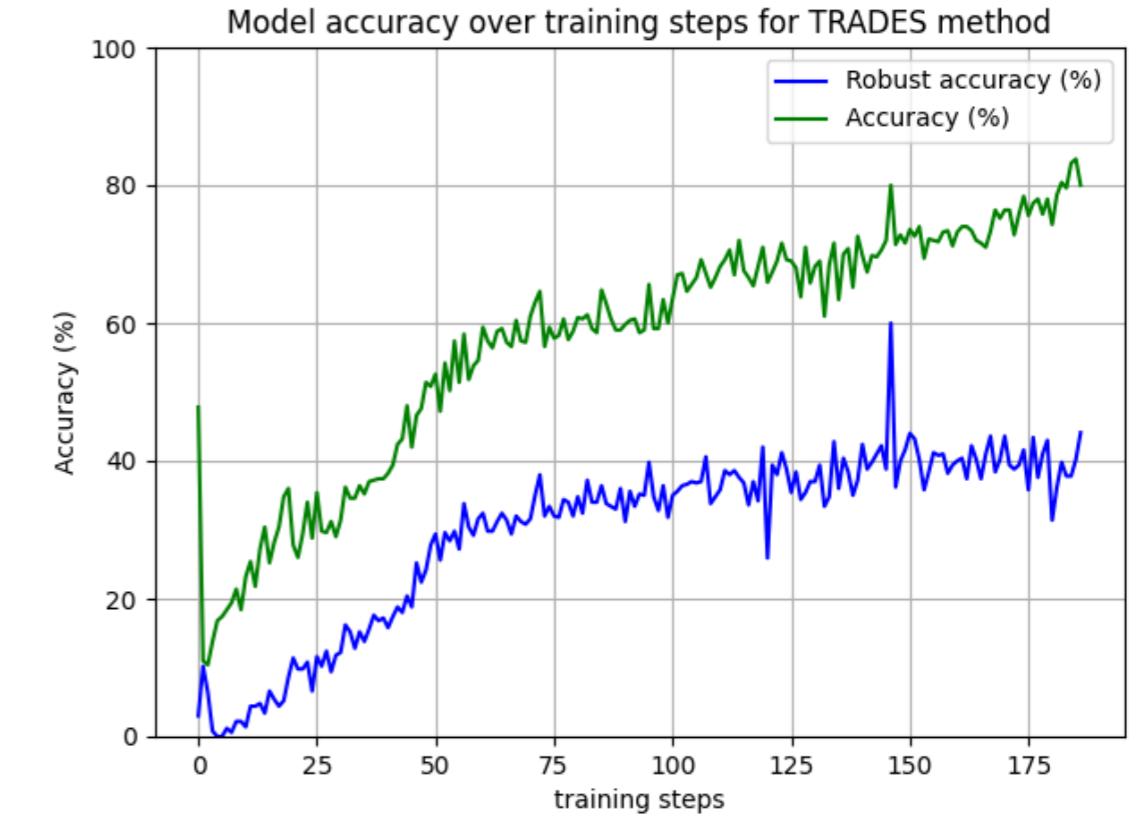
Figure 1: Robustness and accuracy across defense methods.

Quantitative Results

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

Model	Clean	FGSM	PGD
Standard	**85.0%**	45.0%	25.0%
PGD-AT	82.0%	65.0%	55.0%
TRADES	81.5%	**68.0%**	**60.0%**

References

1. Goodfellow et al. (2015). *Explaining and Harnessing Adversarial Examples.* arXiv:1412.6572
2. Moosavi-Dezfooli et al. (2016). *DeepFool: A Simple and Accurate Method to Fool Deep Neural Networks.* arXiv:1511.04599
3. Madry et al. (2018). *Towards Deep Learning Models Resistant to Adversarial Attacks.* arXiv:1706.06083
4. Carlini & Wagner (2017). *Towards Evaluating the Robustness of Neural Networks.* arXiv:1608.04644
5. Zhang et al. (2019). *Theoretically Principled Trade-off between Robustness and Accuracy.* arXiv:1901.08573
6. Kurakin et al. (2017). *Adversarial Examples in the Physical World.* arXiv:1607.02533
7. Wang et al. (2020). *Improving Adversarial Robustness Requires Revisiting Data Augmentation and Training.* OpenReview: rklOg6EFwS