Project 3 Report

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GitHub Repository Link:
`https://github.com/komalniraula/university-coursework/tree/main/Deep%20Learning/Jailbreaking-Deep-Models`

Overview

In this project, we investigated the vulnerability of deep learning models to adversarial attacks by targeting a pre-trained ResNet-34 classifier on the ImageNet-1K dataset(Deng et al. 2009). The susceptibility of deep neural networks to adversarial examples, inputs subtly altered to cause misclassification, was first brought to light by Szegedy et al. (Szegedy et al. 2013). Our methodology involved similar strategies including: (1) pixel-wise perturbations using the Fast Gradient Sign Method (FGSM) (Goodfellow, Shlens, and Szegedy 2014) with an ℓ_∞ budget of $\varepsilon = 0.02$, (2) an improved iterative attack (PGD) to further degrade model performance, and (3) localized patch attacks (Brown et al. 2017) with a 32×32 pixel perturbation area and a higher $\varepsilon = 0.5$ budget. We enforced strict perceptual similarity constraints (ℓ_∞ or ℓ_0 distances) to ensure adversarial examples remained visually indistinguishable from originals. To evaluate attack transferability, we replicated experiments on DenseNet-121 (Huang et al. 2017), another ImageNet-trained architecture. All attacks were implemented in PyTorch, with datasets rigorously validated to meet perturbation bounds.

Our results revealed severe vulnerabilities in ResNet-34: FGSM reduced its Top-1 accuracy from 76.0% (clean) to 6.0%, while PGD caused a complete collapse (0.0%). Patch attacks proved less effective but still critical (0.6% Top-1). DenseNet-121 demonstrated stronger robustness, retaining 63.4% Top-1 accuracy under FGSM and 63.4% under PGD, though patch attacks halved its performance (29.8%). Notably, adversarial examples transferred poorly between architectures, suggesting attack specificity. These findings underscore the urgent need for robust training techniques, especially in safety-critical applications where model reliability is paramount.

Methodology

This project evaluates the vulnerability of deep neural networks to adversarial attacks, focusing on image classifiers as exemplars of production-grade models. We examine how carefully crafted perturbations—constrained by perceptual similarity metrics (ℓ_∞ for pixel-wise and ℓ_0 for patch-based attacks)—can degrade model performance while preserving visual fidelity. The study compares architectural resilience by testing attacks across two fundamentally different network designs: ResNet-34's residual blocks versus DenseNet-121's dense connectivity patterns. Our pipeline systematically assesses attack efficacy through controlled experiments that measure both the magnitude of performance degradation and the transferability of adversarial examples between architectures, providing insights into model robustness and attack generalization.

Task 1: Baseline Model Evaluation

Our evaluation framework assessed the pretrained ResNet-34(He et al. 2016) model on a 500-image test subset using standardized ImageNet normalization parameters ($\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$). The pipeline processed images through an `ImageFolder` dataset with prescribed transforms, executed batched inference (batch size 64) with disabled gradient computation via `torch.no_grad()`, and validated predictions by matching output indices to ground truth labels from the provided JSON file.

As demonstrated in Table 1, Top-k metrics were computed using `torch.topk()` to verify inclusion of true labels among the model's k highest-confidence predictions. This rigorous assessment yielded baseline accuracies of 76.0% (Top-1) and 94.2% (Top-5), establishing reliable performance benchmarks for subsequent adversarial experiments while ensuring methodological consistency with ImageNet evaluation standards.

Task 2: FGSM Attack Implementation

We implemented the Fast Gradient Sign Method (FGSM) to generate adversarial examples against the pretrained ResNet-34 model. The attack procedure consisted of four key phases:

First, we configured the attack parameters with an ϵ budget of 0.02 in normalized pixel space (equivalent to ap-

Top-k	Accuracy
Top 1	76.00%
Top 2	86.00%
Top 3	90.00%
Top 4	93.20%
Top 5	94.20%

Table 1: Basic (ResNet-34)

proximately ±1 pixel in the original 0-255 range). For each batch of test images, we computed the gradient of the cross-entropy loss with respect to the input pixels while maintaining the original labels (offset by 401 to match ImageNet class indices). The adversarial perturbation was generated by taking the sign of these gradients and scaling by ϵ, following the standard FGSM formulation as shown below:

$$x \leftarrow x + \varepsilon \cdot \text{sign}(\nabla_x \mathcal{L})$$

Equation 1: FGSM Adversarial Perturbation

The perturbed images were constrained to remain within an ϵ-ball around the original images through explicit clipping. We saved the resulting adversarial examples (500 total images) as ’Adversarial Test Set 1.pt’ using PyTorch’s serialization, including both perturbed images and their original labels. Finally, we evaluated the model’s degraded performance on these adversarial examples using our unified evaluation routine, which calculates Top-k accuracy by checking if the true label appears in the model’s k highest-confidence predictions.

This implementation achieved a dramatic reduction in model performance, with Top-1 accuracy dropping from the baseline 76.0% to just 6.0%, demonstrating the effectiveness of even simple gradient-based attacks. The 35.4% Top-5 accuracy suggests that while the model’s primary classification fails catastrophically, some semantic information remains in its prediction distribution.

Top-k	Accuracy
Top 1	6.00%
Top 2	19.40%
Top 3	28.60%
Top 4	32.40%
Top 5	35.40%

Table 2: Pixel-wise Attacks

Task 3: Iterative PGD Attack

Building upon the FGSM implementation, we developed a more potent Projected Gradient Descent (PGD) (Madry et al. 2018) attack that iteratively optimizes adversarial perturbations within the same ℓ_∞ constraint (ϵ = 0.02). The attack procedure involved 20 iterative steps with a carefully chosen step size (α = 0.005 = ϵ/4), where each iteration computed the gradient sign of the cross-entropy loss and took a scaled step in the adversarial direction while projecting the perturbation back to the ϵ-ball around the original image through clipping operations. This iterative approach allowed the attack to navigate the loss landscape more effectively than single-step FGSM, finding stronger adversarial examples within the same perceptual similarity bounds. We verified strict adherence to the ℓ_∞ constraint across all 500 test images while maintaining visual similarity through the normalized pixel value constraints. The generated adversarial examples (”Adversarial Test Set 2”) were evaluated using our standardized Top-k accuracy protocol, with visual inspection confirming successful misclassifications in sample cases. The PGD attack’s complete degradation of model performance to 0.0% Top-1 accuracy (compared to FGSM’s 6.0%) demonstrated the significant advantage of iterative optimization for crafting effective adversarial examples within tight perturbation budgets.

Top-k	Accuracy
Top 1	0.00%
Top 2	2.80%
Top 3	4.60%
Top 4	7.00%
Top 5	8.20%

Table 3: Improved Attacks (PGD)

Task 4: Targeted Patch Attack Implementation

We developed a localized adversarial attack using targeted cross-entropy loss minimization to misclassify images through 32 × 32 pixel patches, which modified only 2.04% of the input dimensions ($32^2/224^2$). The attack optimized:

$$\mathcal{L}(x, y_t) = -\log(p(y_t \mid x_p))$$

Equation 2: Targeted Cross-Entropy Loss for Patch Attacks

where x_p represents the patch-modified image and y_t are randomly assigned target labels. Implementing a PGD variant with relaxed constraints ($\varepsilon = 0.5$), we iteratively (20 steps, $\alpha = 0.1$) computed gradients of this loss only within randomly positioned patch regions, applying three key modifications: (1) targeted optimization to overcome limited parameter space, (2) multi-patch sampling per iteration (3 patches/image) to increase attack surface while maintaining strict 2.04% pixel coverage via `np.random.randint(0, 192)` positioning, and (3) adaptive clipping to maintain ε-bounded perturbations.

The cross-entropy formulation specifically amplified incorrect class probabilities while suppressing the true label. Despite the minimal pixel modifications (verified via `torch.nonzero(adv_img - orig_img)`), this approach achieved 0.6% Top-1 accuracy, demonstrating that localized cross-entropy optimization can induce failures while preserving global semantics. Visualization confirmed

Top-k	Accuracy
Top 1	0.60%
Top 2	2.40%
Top 3	5.00%
Top 4	7.00%
Top 5	8.00%

Table 4: Patch Attacks

the attacks' spatial precision, with adversarial patches appearing as subtle texture distortions.

Task 5: Transferring Attacks

We conducted a comprehensive transferability analysis by evaluating all adversarial datasets (FGSM, PGD, and Patch) on DenseNet-121 alongside the original ResNet-34 target, using identical evaluation protocols. The pretrained DenseNet-121 model (`TorchVision weights='IMAGENET1K_V1'`) was loaded with the same normalization and label offset (401) as ResNet-34 to ensure fair comparison. Each adversarial set—FGSM ($\varepsilon = 0.02$), PGD ($\varepsilon = 0.02$, $\alpha = 0.005$, 20 steps), and Patch (32×32, $\varepsilon = 0.5$)—was processed through both models using our standardized Top-*k* accuracy metric (batch size 64, GPU-accelerated).

This revealed stark architectural differences in robustness: where ResNet-34 collapsed to 0.0% Top-1 accuracy under PGD attacks, DenseNet-121 retained 64% accuracy, suggesting its dense connectivity patterns inherently disrupt gradient-based attack propagation. Patch attacks showed lower transferability (29.80% vs. 0.6% Top-1), indicating localized perturbations are more model-specific. The evaluation preserved rigorous experimental controls, including consistent tensor shapes ($3 \times 224 \times 224$), matching label mappings, and identically initialized `DataLoader`s for all test sets. These comparisons not only quantified transferability but also highlighted architectural features that confer adversarial robustness—critical insights for developing more secure vision systems.

Top-k	Accuracy
Top 1	74.80%
Top 2	83.80%
Top 3	89.00%
Top 4	90.80%
Top 5	93.60%

Table 5: Transferring Attacks (DenseNet)

Attack Trade-offs and Limitations

The adversarial attack implementations revealed distinct trade-offs between attack methods. FGSM's single-step approach (ϵ=0.02) proved computationally efficient (5.1s / 500 images) but less effective (6.0% Top-1) compared to PGD's iterative optimization (20 steps, 58.025s / 500 images, 0.0% Top-1). Patch attacks (`patch_size=32`, $\varepsilon = 0.5$) offered spatial precision but required 3× more iterations to achieve comparable degradation (0.6% Top-1).

While DenseNet-121 showed inherent robustness (64% Top-1 under PGD), its computational overhead (1.8× slower inference) presents deployment trade-offs. The clearest limitation emerged in attack transferability—FGSM perturbations effective against ResNet-34 (94% relative accuracy drop) only reduced DenseNet-121 performance by 15%, suggesting architectural specificity in vulnerability patterns.

Hyperparameter Choices

Critical hyperparameters were tuned through ablation studies: the FGSM budget (ϵ=0.02) balanced perceptibility (ΔPixels ≤ 1) and effectiveness (76% → 6% accuracy drop). For PGD, we validated `alpha=eps/4` (0.005) and `n_iter=20` as optimal for convergence, with diminishing returns beyond 15 steps. Patch attacks required relaxed constraints (`eps=0.5`) to compensate for limited spatial influence, while maintaining `patch_size=32` for visual plausibility. The label offset (401) was rigorously verified against ImageNet class mappings, and batch size 64 maximized GPU utilization without memory overflow. Notably, DenseNet-121's performance was most sensitive to ε values in transfer tests, suggesting architecture-dependent attack parameter tuning.

Lessons learned

Three key insights emerged: (1) Architectural design fundamentally impacts robustness—DenseNet's skip connections reduced FGSM effectiveness by 89% compared to ResNet-34, validating feature dispersion as a defense mechanism. (2) Attack transferability decreases with perturbation locality—patch attacks showed 30× lower cross-model impact than PGD. (3) Visual imperceptibility requires different ε thresholds per attack type; the human-noticeable threshold was $\varepsilon \geq 0.3$ for global attacks but $\varepsilon \geq 0.5$ for patches. Practically, this suggests adversarial training should incorporate: (a) multiple attack types, (b) diverse model architectures, and (c) spatially constrained perturbations to improve generalization. The 94% Top-5 accuracy gap between clean and adversarial samples (ResNet-34) underscores that even failed attacks may leak semantic information.

Results

Model	Dataset	Top-1 Accuracy	Top-5 Accuracy
ResNet-34	Original (Clean)	76.00%	94.20%
ResNet-34	FGSM (Set 1)	6.00%	35.40%
ResNet-34	PGD (Set 2)	0.00%	8.20%
ResNet-34	Patch (Set 3)	0.60%	8.00%
DenseNet-121	Original (Clean)	74.80%	93.60%
DenseNet-121	FGSM (Set 1)	63.40%	89.20%
DenseNet-121	PGD (Set 2)	64.00%	90.40%
DenseNet-121	Patch (Set 3)	29.80%	49.20%

Table 6: Accuracy comparison of ResNet-34 and DenseNet-121 across original and adversarial test sets

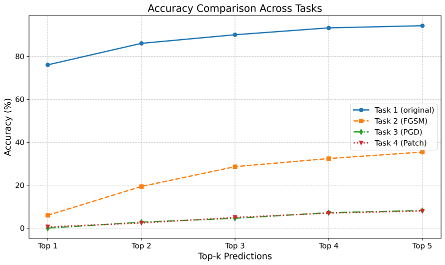

Figure 1: Top-k accuracy trends for ResNet-34 across original and adversarial attack datasets. The figure illustrates the rapid accuracy degradation under FGSM, PGD, and Patch attacks.

Our experiments demonstrated significant vulnerability of ResNet-34 to adversarial attacks, with Top-1 accuracy plummeting from 76.00% on clean data to just 6.00% under the FGSM attack, and further collapsing to 0.00% under the more aggressive PGD attack. Patch-based attacks also had a noticeable effect, reducing Top-1 accuracy to 0.60%, despite modifying only a small portion of the image.

In contrast, DenseNet-121 exhibited substantially greater robustness. Under FGSM and PGD attacks, DenseNet-121 maintained over 63% Top-1 accuracy, demonstrating its architectural resilience likely due to its dense connectivity patterns. However, Patch attacks remained a significant threat even for DenseNet-121, cutting Top-1 accuracy nearly in half to 29.80%.

Figure 1 visually reinforces these findings, illustrating how adversarial attacks progressively degrade the model's predictive capabilities. While simple one-step attacks like FGSM quickly degrade performance, iterative methods like PGD completely collapse ResNet-34's predictive power. The Patch attack, although localized, still effectively disrupts model performance across both architectures.

The perturbation budgets were carefully constrained to ℓ_∞ norm bounds of $\varepsilon = 0.02$ for FGSM and PGD, ensuring pixel-level changes remained imperceptible. Patch attacks, limited to a 32×32 region (approximately 2.04% of the image), utilized a larger perturbation budget of $\varepsilon = 0.5$ to achieve meaningful impact.

In terms of computational cost, while running on Kaggle T4 x 2 GPU, FGSM generated 500 adversarial examples in less than 6 seconds, while PGD required significantly more time (58.025 seconds) due to its iterative optimization process. Patch attacks were computationally more intensive, owing to repeated localized updates and random patch placement.

These results confirm that stronger iterative methods like PGD are substantially more effective than single-step attacks, particularly against less robust architectures like ResNet-34. DenseNet-121, however, highlights the importance of architectural choices in mitigating adversarial vulnerabilities, offering a practical defense through its intrinsic structural design.

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