Adversarial Robustness of Traffic Sign Recognition:

Evaluating FGSM Attack on Models





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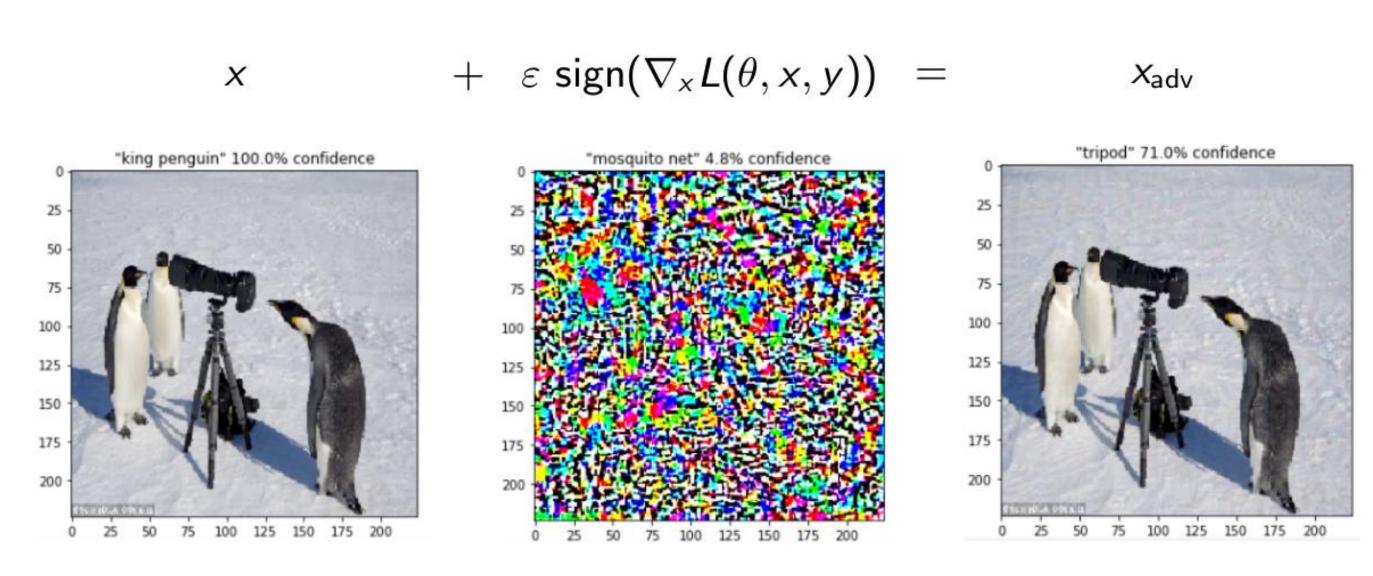
Introduction

- Traffic sign recognition is critical for autonomous driving and public road safety.
- Machine learning (ML) models, while accurate, are vulnerable to adversarial attacks like Fast Gradient Sign Method(FGSM).
- Core question: Are modern ML models more robust against FGSM attacks without explicit defenses compared to older architectures?

FGSM Attack

(Fast Gradient Sign Method)

Perturbs input images to trick models ε values used: 0.001, 0.005, 0.01, 0.02, 0.03, 0.05, 0.1



AlexNet (Old)

Optimizer: SGD | Epochs: 50

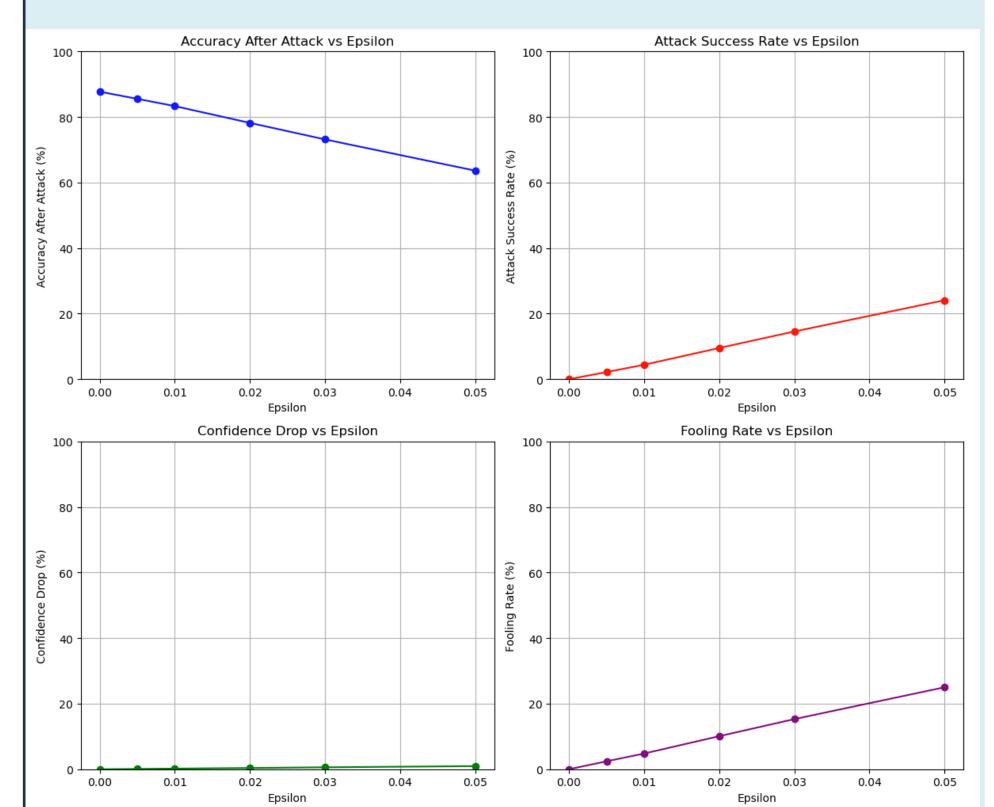
CNN-VGG based (Mid)

Optimizer: Adam | Epochs: 50

EfficientNet B0(Modern)

Optimizer: Adam | Pretrained B0 | Epochs: 10

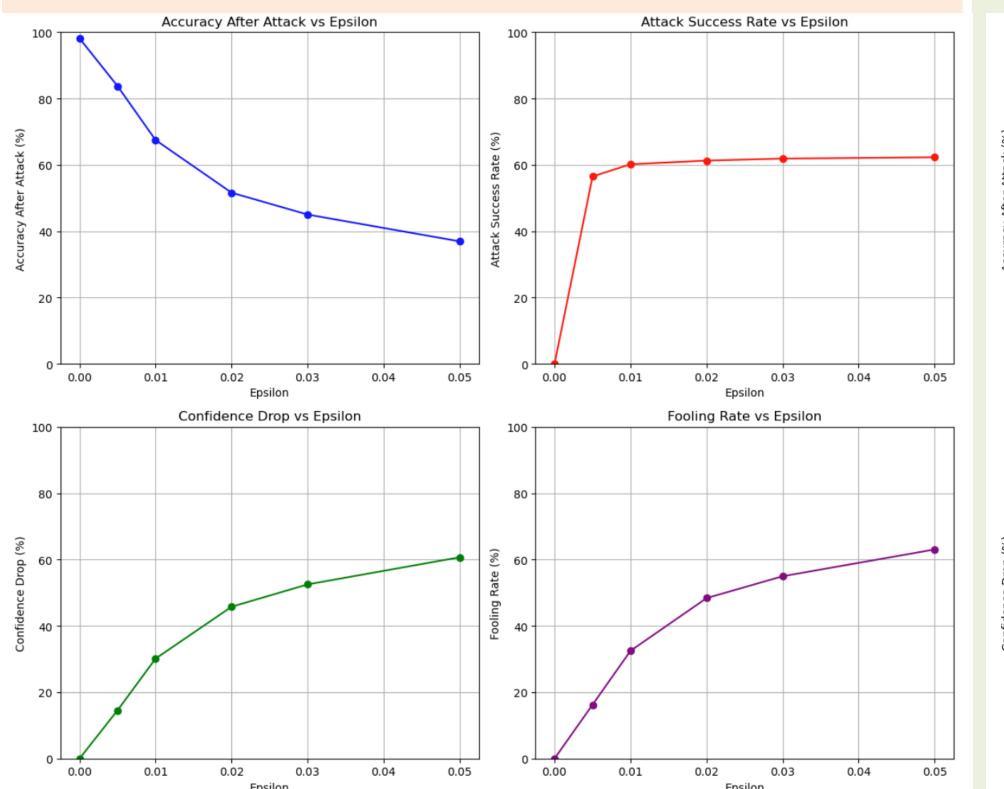
FGSM attack result



- Worst Accuracy on Clean Data
 - Accuracy: 87.72%
- **Best Robustness to FGSM**
- At ε = 0.05 Accuracy drops to 63.63%

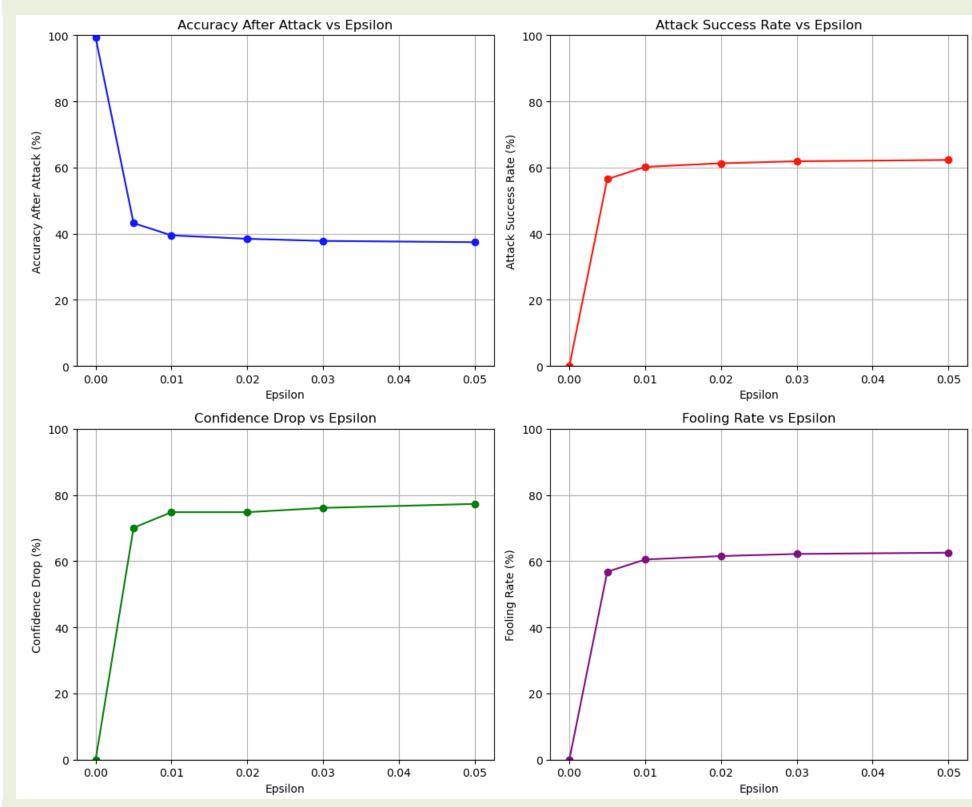
• At **ε** = 0.01 Accuracy drops to 83.32%

FGSM attack result



- Good Accuracy on Clean Data
 - Accuracy: 98.15%
- Bad Robustness to FGSM
 - At ε = 0.01 Accuracy drops to 67.50% • At ε = 0.05 Accuracy drops to 36.95%

FGSM attack result



- Best Accuracy on Clean Data
 - Accuracy: 99.30%
- Bad Robustness to FGSM
 - At ε = 0.01 Accuracy drops to 43.20%
 - At **ε** = 0.05 Accuracy drops to 37.44%
 - But low drop rate after

Data

- Dataset: German Traffic Sign Recognition Benchmark (GTSRB)
 - 43 traffic sign classes
 - High-quality labeled images
- Preprocessing:
 - Greyscale conversion
 - Data normalization
 - Split: 80% training / 20% testing
- GTSRB is widely used in both classification and adversarial robustness research.

Why?

- Deep-architecture model
- Outdated design
- Quite heavy
 - Take long to train,
 - High memory usage
 - Slow inference

Why?

- Shallow-architecture Model
- Compact design

Lightweight 💢

- Less time to train,
- Low memory usage
- Fast inference

Why?

- Very Deep architecture model
- Modern design
- Heavy
 - Moderate training time
 - High memory usage
 - Slowest inference
- Transfer learning -> Sensitive to FGSM
- Accuray 88% after Adversarial Training



- I. J. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and harnessing adversarial examples," in International Conference on Learning Representations (ICLR), 2015.
- H. Singh, "Acc 97.4% sign classification (alexnet/vggnet/cnn)." https://www.kaggle.com/ code/harbhajansingh21/acc-97-4-sign-classification-alexnet-vggnet-cnn/, 2022. Accessed: 2025-05-14.