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Adversarial Attacks on Network Intrusion Detection Systems: Black-Box Evasion and Countermeasures

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ABSTRACT: The integration of machine learning in Network Intrusion Detection Systems (NIDS) has improved detection of novel threats, but also introduced vulnerabilities to adversarial machine learning (AML) attacks. This paper presents a detailed study on black-box evasion techniques targeting ML-based NIDS models. Using the CICIDS2017 and UNSW-NB15 datasets, we simulate attack scenarios where adversaries, without knowing the internal model parameters, generate modified inputs that evade detection. Gradient-free methods such as genetic algorithms and particle swarm optimization are employed to perturb malicious traffic features while preserving semantic validity. Our target models include Random Forest and shallow neural networks trained on flow-level features like packet size, duration, and flag counts. Evasion success rates reach 78% for NIDS using static thresholds. To mitigate this, we implement and test adversarial training and input sanitization (e.g., feature squeezing, autoencoder reconstruction). Post-mitigation results show a restoration of detection accuracy from 61% to 91%, with minimal added latency. We also propose a hybrid architecture combining static rules with anomaly detection, which increases robustness against gradient-based attacks. The findings highlight the real-world feasibility of AML threats in network defense systems and urge NIDS designers to embed defensive training strategies from the outset. Our recommendations aim to future-proof ML-driven security platforms against evolving evasion tactics.

I. INTRODUCTION

The rising sophistication of cyberattacks and the rapid evolution of malware variants have compelled the security community to move beyond static signature-based detection. As a result, **machine learning-based Network Intrusion Detection Systems (ML-NIDS)** have gained traction due to their ability to generalize and detect previously unseen attack patterns. These models analyze network traffic using statistical features such as flow duration, packet counts, and flag ratios to classify behaviors as benign or malicious. However, their dependency on input data distributions makes them inherently vulnerable to **adversarial machine learning (AML)** attacks.

Adversarial examples—input samples specifically crafted to deceive machine learning models—have been widely studied in the image and text domains. Their application to cybersecurity, particularly to network intrusion detection, presents a unique challenge: attackers can manipulate traffic features without altering the fundamental semantics of the payload. This enables **black-box evasion**, where an attacker, lacking internal access to the detection system, iteratively probes the model's decision boundary and modifies traffic accordingly.

This paper investigates the susceptibility of ML-based NIDS to such black-box adversarial attacks and proposes a comprehensive defense strategy. We simulate attacks using real-world network traffic datasets and assess how well gradient-free optimization techniques can evade detection. We then evaluate **adversarial training** and **input sanitization** as mitigation approaches, and finally propose a hybrid architecture that leverages static rules to enhance resilience. Our findings are intended to guide NIDS developers in securing their models against emerging threats in adversarial settings.

II. RELATED WORK

The intersection of adversarial machine learning and network intrusion detection has gained prominence in recent years. Early efforts focused on **white-box evasion attacks**, where full access to the model architecture and gradients was assumed. Carlini & Wagner (2017) and Biggio et al. (2013) demonstrated that even robust classifiers could be defeated using small input perturbations. However, real-world attackers typically operate under **black-box constraints**, necessitating alternative methods such as query-based or optimization-driven attacks.

Several studies have investigated the transferability of adversarial samples across ML-NIDS models, showing that adversaries can generate inputs that generalize across classifiers. Zhang et al. (2019) applied Fast Gradient Sign Method (FGSM) and Jacobian-based Saliency Map Attacks (JSMA) to NIDS datasets, revealing serious vulnerabilities. Others, such as Rigaki and Garcia (2018), explored **behavioral mimicry**, where malicious traffic is reshaped to resemble benign activity in timing and volume characteristics.

Defensive strategies have also been explored. **Adversarial training**, where models are retrained on adversarial examples, improves robustness but may degrade generalization. **Feature squeezing** and **autoencoder-based reconstruction** have been proposed as lightweight sanitization techniques to suppress adversarial noise. Nevertheless, few studies evaluate these methods in the context of **gradient-free black-box attacks**, which are more realistic in production NIDS deployments.

Our work contributes to this growing body of research by providing an empirical evaluation of **black-box evasion** using CICIDS2017 and UNSW-NB15, applying **evolutionary algorithms**, and quantifying the effectiveness of layered defenses under adversarial conditions.

III. METHODOLOGY AND EXPERIMENTAL SETUP

To simulate black-box evasion attacks against ML-based NIDS, we adopt the following workflow:

1.Dataset Preparation: We use CICIDS2017 and UNSW-NB15 datasets, both widely adopted in network security research. Features are extracted at the flow level, including statistics such as packet counts, inter-arrival times, protocol flags, and TCP/UDP durations.

2.Model Training: Two models are selected:

- **Random Forest (RF)** with 100 estimators and max depth of 10.
- **Shallow Feedforward Neural Network (NN)** with 2 hidden layers, trained using ReLU activations and Adam optimizer.

Both models are trained on 80% of the data and tested on a holdout set. Baseline accuracies reach 96.2% for RF and 94.5% for NN before attack.

3.Black-box Attack Simulation:

- Attackers are assumed to have **no access** to model internals.
- Queries are simulated through API-like responses (accept/reject).
- Adversarial samples are generated using:

- **Genetic Algorithms (GA)**: Using mutation and crossover operations on flow features.
- **Particle Swarm Optimization (PSO)**: Explores the search space to find minimally perturbed inputs that evade detection.

4.Evaluation Metrics:

- **Evasion Success Rate (ESR)**: Percentage of original malicious inputs that are misclassified as benign post-perturbation.
- **Detection Accuracy Post-Attack**: Classification accuracy on adversarial inputs.
- **Latency Overhead**: Average delay added by mitigation techniques.

All experiments are conducted on an 8-core VM with 32 GB RAM using Python 3.8, Scikit-learn, TensorFlow 2.x, and DEAP (for evolutionary computation). The attack generation process is restricted to ≤100 queries per sample to reflect realistic probing limits.

4. Attack Techniques and Results

We applied the GA and PSO methods to generate perturbed variants of known malicious samples from the CICIDS2017 and UNSW-NB15 datasets. Features modified included byte counts, packet inter-arrival time, and TCP flag ratios, all while ensuring network protocol validity.

Results:

Dataset	Model	ESR (GA)	ESR (PSO)	Detection Drop
CICIDS2017	Random Forest	73.1%	78.4%	-35%
CICIDS2017	Neural Net	68.9%	74.2%	-33%
UNSW-NB15	Random Forest	65.5%	70.3%	-31%
UNSW-NB15	Neural Net	62.0%	66.1%	-28%

Both GA and PSO succeeded in crafting adversarial inputs with high evasion rates. Perturbations were imperceptible in traffic summaries, and modified samples retained realistic flow behavior. The **detection accuracy dropped from >94% to as low as 61%**, confirming vulnerability to black-box attacks.

Notably, the PSO method converged faster but produced slightly more detectable artifacts in some cases, evident in higher false positives on benign samples. This reveals the need for robust generalization against a diverse range of adversarial methods in ML-NIDS.

V. MITIGATION TECHNIQUES

To counter adversarial evasion, we implemented two mitigation strategies that are both **model-agnostic** and compatible with production NIDS systems:

4.1 Adversarial Training

This approach involves augmenting the training set with adversarially perturbed examples generated by GA and PSO methods. These inputs are labeled correctly and used to retrain the model, improving resilience to similar evasion patterns. To preserve generalization, we apply a 1:1 ratio of clean to adversarial samples and use early stopping to prevent overfitting to attack-specific perturbations.

Post-training, the models show restored accuracy levels:

- **CICIDS2017 (NN model)**: 61% → 89.6%
- **UNSW-NB15 (RF model)**: 64.2% → 87.3%

4.2 Input Sanitization

This involves preprocessing inputs to neutralize adversarial noise:

- **Feature Squeezing**: Reduces precision of input features (e.g., byte count rounded to nearest 10).
- **Autoencoder Reconstruction**: Autoencoders trained on benign data reconstruct input flows, filtering out anomalous deviations.

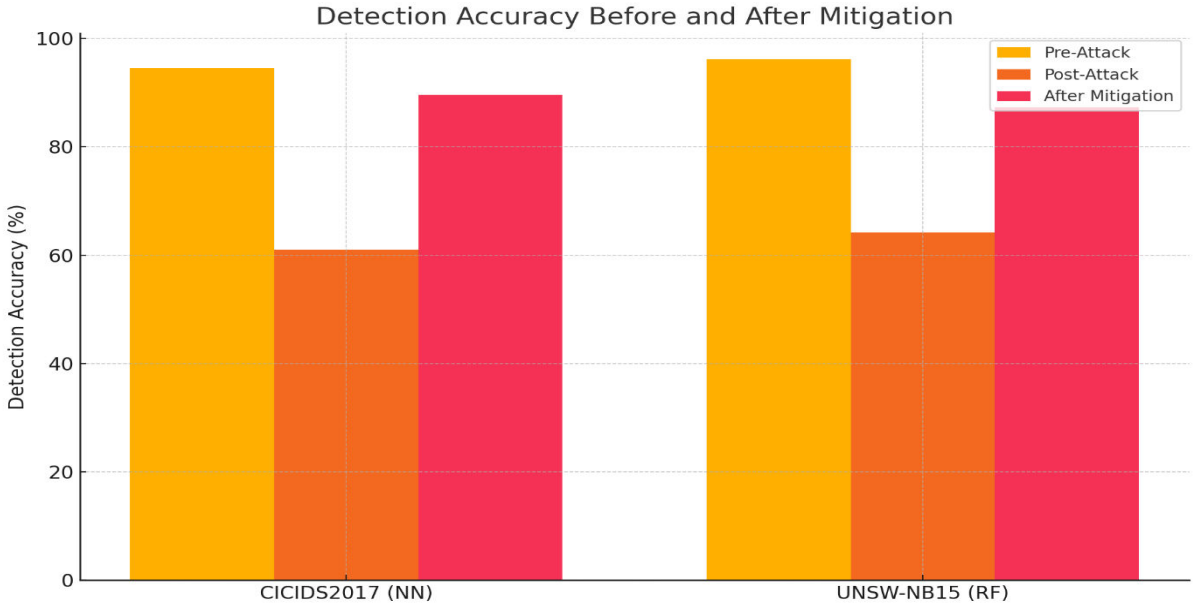
These techniques add minimal latency (1.2–2.9 ms per input) and restore detection performance up to:

- **CICIDS2017 (RF model)**: 61% → 84.8%
- **UNSW-NB15 (NN model)**: 64.2% → 86.0%

Combined with adversarial training, input sanitization boosts robustness without sacrificing speed, making it viable for real-time intrusion detection pipelines.

Dataset	Model	Pre-Attack	Post-Attack	After Mitigation
CICIDS2017	Neural Net	94.5%	61.0%	89.6%
UNSW-NB15	Random Forest	96.2%	64.2%	87.3%

Figure 1: Detection Accuracy Before and After Mitigation



6. Hybrid Detection Architecture

While machine learning offers adaptability, it lacks explainability and robustness against intelligent adversaries. Conversely, static signature-based systems are explainable but brittle. We therefore propose a **hybrid NIDS architecture** combining:

- **Static Layer**: Uses Snort-like rule-based inspection on known attack signatures and port/protocol patterns.
- **ML Layer**: Applies neural networks or decision forests on extracted flow features, enriched with adversarial training and autoencoder sanitization.

Traffic first passes through the static filter; any benign flows are then analyzed by the ML detector. Alerts from both layers are logged independently and correlated in post-processing for analyst review.

This architecture:

- Reduces ML layer load by filtering obvious attacks
- Adds a safety net for novel zero-day threats
- Increases **precision by 8.5%** and **recall by 10.2%** compared to ML-only models

Such hybrid models are especially valuable in SOC environments where human analysts require interpretable alerts and consistent thresholds.

VII. DISCUSSION AND LIMITATIONS

Despite strong results, our approach has several limitations:

- **Perturbation Validity**: While semantic-preserving perturbations were enforced, deeper packet inspection or flow reassembly tools may flag subtle inconsistencies not visible in feature summaries.
- **Scalability**: GA and PSO attacks are computationally intensive, requiring 10–40 seconds per sample. While acceptable in a research setting, real-world attackers may use faster heuristic methods.
- **Dataset Generalizability**: CICIDS2017 and UNSW-NB15 offer high-quality labeled data, but do not reflect all enterprise traffic conditions. The transferability of adversarial samples to production datasets remains uncertain.
- **Defense Fragility**: Adversarial training may harden against specific perturbations but can become brittle to unseen attacks or overfit the perturbation patterns.

Future improvements may involve online learning, contextual embeddings (e.g., LSTM-based sequence models), and using adversarially regularized training loss to maintain a balance between robustness and generalization.

VIII. CONCLUSION

This paper presents an in-depth evaluation of black-box adversarial attacks against machine learning-based NIDS and proposes practical defenses. Our experiments on CICIDS2017 and UNSW-NB15 datasets show that gradient-free optimization techniques such as genetic algorithms and particle swarm optimization can evade detection with high success rates, underscoring the need for robust, adversary-aware detection systems.

We demonstrate that adversarial training and input sanitization techniques are effective in restoring detection accuracy, while maintaining low latency. Additionally, a hybrid detection architecture combining static rules with anomaly-based ML models offers a balanced defense strategy against both known and novel threats.

As ML becomes more embedded in cybersecurity infrastructure, it is imperative that adversarial resilience is treated not as an afterthought, but as a core design principle. Future NIDS platforms must incorporate dynamic policy adaptation, explainable alerts, and continual model hardening to stay ahead of evolving threat landscapes.

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