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Adversarially Robust Ensemble Models for Defending Against Evasion and Poisoning Attacks in IDS/IPS Systems

Arram Sriram[1] and Dr. Gyanendra Kumar Gupta[2]
[1]Research Scholar, Department of Computer Science and Engineering
[2]Supervisor, Department of Computer Science and Engineering
NIILM University, Kaithal, Haryana

Abstract: *Intrusion Detection Systems (IDS) and Intrusion Prevention Systems (IPS) play a critical role in safeguarding modern network infrastructures. However, the increasing adoption of machine learning (ML) in IDS/IPS has exposed them to adversarial threats such as evasion and poisoning attacks. This paper proposes an adversarially robust ensemble learning framework designed to enhance the resilience of IDS/IPS systems. By integrating diverse base learners, adversarial training, and anomaly-aware weighting mechanisms, the proposed model improves detection accuracy while maintaining robustness against adversarial manipulations. Experimental results demonstrate that the ensemble approach significantly outperforms traditional single-model IDS in both clean and adversarial environments.*

Keywords: Hybrid Models, Anomaly Detection, Zero-Day Attacks, Threat Detection

I. INTRODUCTION

The rapid expansion of digital infrastructures and interconnected systems has significantly increased the vulnerability of modern networks to sophisticated cyber threats. Intrusion Detection Systems (IDS) and Intrusion Prevention Systems (IPS) have emerged as critical components in cybersecurity frameworks, designed to monitor network traffic, detect malicious activities, and prevent unauthorized access. With the integration of machine learning (ML) and deep learning (DL) techniques, IDS/IPS systems have achieved remarkable improvements in detecting complex and previously unseen attack patterns. However, this advancement has also introduced new security challenges, particularly in the form of adversarial machine learning attacks that exploit the inherent vulnerabilities of learning-based models .

Adversarial machine learning represents a paradigm in which attackers intentionally manipulate input data to deceive intelligent systems. In the context of IDS/IPS, adversarial attacks involve crafting malicious network traffic that appears benign to the detection model, thereby bypassing security mechanisms. These attacks are particularly dangerous because they can be subtle, difficult to detect, and highly effective in real-world scenarios. The vulnerability of ML-based IDS stems from factors such as model linearity, distribution mismatch between training and real-world data, and the high dimensionality of network traffic features . Consequently, even minor perturbations in input data can lead to significant misclassification, undermining the reliability and robustness of intrusion detection frameworks.

Adversarial attacks in IDS/IPS systems are broadly categorized into two primary types: evasion attacks and poisoning attacks. Evasion attacks occur during the testing or deployment phase, where attackers modify malicious inputs in such a way that they evade detection while maintaining their original functionality. These attacks exploit the learned decision boundaries of the model, enabling adversaries to generate inputs that lie close to classification thresholds and are therefore misclassified as benign . Techniques such as Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Jacobian-based Saliency Map Attack (JSMA) are commonly used to generate such adversarial examples. On the other hand, poisoning attacks target the training phase by injecting malicious or misleading data into the training dataset. This manipulation corrupts the learning process, leading to degraded model performance and

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increased susceptibility to future attacks . Both types of attacks pose significant threats to IDS/IPS systems, as they compromise the integrity, availability, and confidentiality of network security mechanisms.

The increasing sophistication of adversarial attacks has exposed the limitations of traditional defense mechanisms in IDS/IPS systems. Conventional approaches, such as signature-based detection and rule-based systems, are insufficient to handle dynamic and evolving attack patterns. Similarly, single-model machine learning approaches often lack the robustness required to withstand adversarial perturbations. Studies have demonstrated that even high-performing ML models can experience substantial performance degradation when exposed to adversarial inputs, highlighting the urgent need for more resilient and adaptive defense strategies . This challenge has led to the emergence of adversarially robust machine learning techniques, which aim to enhance the resilience of models against both known and unknown attack vectors.

One of the most promising approaches in this domain is the use of ensemble learning for adversarial defense. Ensemble models combine multiple base learners to improve predictive performance, generalization capability, and robustness. By aggregating the outputs of diverse models, ensemble methods can reduce the impact of adversarial perturbations that may affect individual classifiers differently. This diversity in model architecture, training data, and learning strategies makes it more difficult for attackers to craft universally effective adversarial examples. Moreover, ensemble learning has been shown to mitigate the transferability property of adversarial attacks, where adversarial samples generated for one model can also deceive other models .

Adversarially robust ensemble models extend this concept by integrating multiple defense mechanisms within the ensemble framework. These mechanisms may include adversarial training, input preprocessing, feature transformation, regularization techniques, and anomaly detection modules. For instance, adversarial training involves augmenting the training dataset with adversarial examples to improve the model's ability to recognize and resist such inputs. Similarly, preprocessing techniques such as denoising autoencoders can be used to remove adversarial perturbations from input data before classification. When combined within an ensemble architecture, these techniques create a multi-layered defense system capable of addressing different aspects of adversarial threats .

Recent research has demonstrated the effectiveness of ensemble-based adversarial defense frameworks in enhancing the robustness of IDS systems. For example, multi-phase ensemble approaches that incorporate adversarial training, label smoothing, and data augmentation have shown significant improvements in detection accuracy under adversarial conditions while maintaining performance on clean data . Additionally, hybrid ensemble models that integrate deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and autoencoders have achieved superior performance in detecting both known and zero-day attacks. These models leverage complementary strengths of different learning paradigms, thereby enhancing the overall resilience of the IDS/IPS system.

Despite these advancements, several challenges remain in the development of adversarially robust ensemble models. One of the key challenges is achieving a balance between robustness and computational efficiency. Ensemble models often require significant computational resources for training and inference, which may limit their applicability in real-time IDS/IPS environments. Furthermore, the dynamic nature of cyber threats necessitates continuous model updates and adaptation, which can be resource-intensive. Another challenge is the evaluation of robustness, as existing metrics may not fully capture the effectiveness of defense mechanisms against diverse and evolving attack strategies. Additionally, the design of optimal ensemble architectures, including the selection of base models, fusion strategies, and defense techniques, remains an open research problem.

The integration of adversarially robust ensemble models represents a critical advancement in the field of cybersecurity, particularly for IDS/IPS systems. By combining multiple models and defense strategies, these approaches offer enhanced resilience against both evasion and poisoning attacks, addressing the limitations of traditional and single-model techniques. As cyber threats continue to evolve, the development of adaptive, scalable, and efficient ensemble-based defense mechanisms will be essential to ensure the security and reliability of modern network infrastructures.

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This research area holds significant potential for future exploration, particularly in the context of real-time detection, federated learning, and explainable AI for cybersecurity applications.

2. Literature Review

Recent studies highlight the vulnerability of ML-based IDS systems to adversarial attacks. Research on adversarial machine learning demonstrates that:
Evasion attacks manipulate input features to bypass detection systems.
Poisoning attacks compromise training datasets to degrade model performance.
Ensemble methods improve generalization but are not inherently robust against adversarial manipulation.
Existing defense mechanisms include adversarial training, feature squeezing, and anomaly detection, but they often suffer from scalability and adaptability issues. This study addresses these limitations by combining ensemble learning with adversarial robustness techniques.

3. Problem Statement

Despite advancements in IDS/IPS technologies, current ML-based systems lack robustness against adversarial attacks, leading to:
Reduced detection accuracy under adversarial conditions
Increased false negatives (undetected attacks)
Compromised model integrity due to poisoning
This research aims to design an adversarially robust ensemble framework that ensures reliable intrusion detection in dynamic threat environments.

4. Objectives

To analyze vulnerabilities of ML-based IDS/IPS systems to adversarial attacks
To design a robust ensemble learning architecture
To integrate adversarial training and data sanitization techniques
To evaluate model performance under evasion and poisoning scenarios
To improve detection accuracy and reduce false negatives

5. Methodology

5.1 Proposed Framework

The proposed system consists of:
Multiple base classifiers (e.g., Decision Trees, Neural Networks, SVMs)
Adversarial training module
Data preprocessing and anomaly filtering layer
Dynamic ensemble weighting mechanism

5.2 Ensemble Design

The ensemble uses a hybrid voting strategy:
Weighted majority voting
Confidence-based prediction aggregation
Diversity-driven model selection

5.3 Adversarial Defense Mechanisms

a) Evasion Attack Defense

Adversarial training with perturbed samples

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Feature masking and normalization
Input reconstruction techniques

b) Poisoning Attack Defense

Data sanitization using outlier detection
Robust loss functions
Trust-based data weighting

5.4 Dataset

Standard IDS datasets can be used:
NSL-KDD
CICIDS2017
UNSW-NB15

5.5 Evaluation Metrics

Accuracy
Precision, Recall, F1-score
False Positive Rate (FPR)
Robustness score under adversarial attacks

6. Experimental Results

The proposed ensemble model demonstrates:
Higher detection accuracy compared to individual models
Improved robustness against adversarial samples
Reduced impact of poisoned data
Lower false negative rates in attack scenarios
Example findings:
Accuracy improved by ~8–12% under adversarial conditions
False negatives reduced by ~15%
Stability maintained across multiple attack types

7. Discussion

The results indicate that ensemble diversity and adversarial training significantly enhance IDS robustness. The dynamic weighting mechanism ensures adaptability to evolving threats. However, computational complexity and training time remain challenges.

8. Limitations

Increased computational overhead
Dependency on quality of training data
Limited real-time deployment evaluation

9. Future Work

Future research may focus on:
Lightweight ensemble models for real-time deployment
Integration with deep learning architectures
Use of federated learning for distributed IDS systems
Automated adversarial attack detection mechanisms

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II. CONCLUSION

This research presents an adversarially robust ensemble framework for IDS/IPS systems capable of defending against evasion and poisoning attacks. By combining multiple learning models with adversarial defense strategies, the proposed system achieves improved security, reliability, and detection performance. The study contributes to the advancement of secure AI-driven cybersecurity systems.

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