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Reinforcement Learning-Guided Adversarial Training to Enhance Intrusion Detection Robustness on the Mirai Dataset

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Abstract. Despite demonstrating impressive detection capabilities, deep learning-based intrusion detection systems (IDS) exhibit significant vulnerability to adversarial examples, particularly under gradient-based attacks such as FGSM. To address this issue, this study proposes a reinforcement learning (RL)-guided adversarial training framework, in which a Q-learning agent adaptively optimizes perturbation strengths (ε values) during training. This adaptive mechanism allows the model to defend against a broad range of threat intensities without manual tuning, thereby overcoming the limitations of traditional fixed-ε adversarial training methods. The proposed approach is evaluated on the Mirai subset of the Kitsune dataset, selecting 40,000 labeled samples. Experimental results demonstrate that the RL-based adversarial training model significantly outperforms both a baseline model (trained only on clean data) and a fixed-ε model (ε = 0.1) in terms of robustness. For instance, under strong adversarial perturbation (ε = 0.2), the RL-guided model achieves an accuracy of 96%, compared to 90% for the fixed-ε model and 82% for the baseline. Furthermore, the agent converges toward selecting ε ≈ 0.11 as the optimal trade-off between training stability and defense effectiveness. These findings validate the efficacy of reinforcement learning in dynamically optimizing adversarial training, offering a scalable defense against gradient-based attacks.

Keywords: Intrusion Detection System, Adversarial Training, Reinforcement Learning, FGSM Attack, Network Security

1. Introduction

Intrusion Detection Systems (IDS) play a critical role in modern cybersecurity infrastructure by identifying malicious behaviors in network traffic and preventing data breaches, denial-of-service attacks, and unauthorized access. With the rise of IoT devices and increased network complexity, the need for intelligent and robust IDS has never been greater. In recent years, deep learning-based Intrusion Detection System models have attained notable detection accuracy, frequently above 85% on benchmark datasets like NSL-KDD [1,2]. Nonetheless, these models are exceedingly susceptible to adversarial attacks—meticulously designed inputs that provoke misclassification with negligible alterations. This vulnerability presents a substantial security threat, particularly in contexts where

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real-time decision-making is essential [3]. To address this challenge, adversarial training has been widely studied as a defense strategy. Most existing methods, however, use a fixed perturbation strength (epsilon, ε) during training, which limits adaptability and may lead to overfitting or under-preparation for dynamic threats. These dynamic threats may include varying perturbation intensities, changes in attack patterns over time, or adaptive evasion strategies employed by intelligent attackers [4]. This study proposes an adversarial training framework augmented by reinforcement learning, where a Q-learning agent dynamically selects ε values ranging from 0.01 to 0.20 during training based on performance feedback. By doing so, the model adapts to varying attack intensities and improves generalization under adversarial conditions. Compared to fixed-ε methods, This approach provides an automated and adaptive mechanism for enhancing IDS robustness in evolving threat environments.

2. Related work

Adversarial training has established itself as a primary defense mechanism against gradient-based attacks in deep learning models. FGSM-based adversarial training is widely adopted due to its simplicity and low computational overhead. However, traditional FGSM methods suffer from poor generalization under unseen attack intensities, particularly when the perturbation magnitude ε is fixed throughout training. For instance, Haroon and Ali showed that on the CICIDS2017 dataset, the model accuracy dropped by more than 20% when exposed to JSMA and FGSM attacks with ε values not seen during training, indicating a lack of robustness to dynamic threat conditions [3].

In the domain of IoT security, adversarial training has been explored using advanced techniques such as GANs. Ferrag et al. proposed a GAN-based adversarial training pipeline that improved IDS robustness against synthesized attacks and achieved over 95% accuracy on a multi-class IoT dataset [4]. These approaches remain constrained by static ε configurations or manual tuning, limiting adaptability to evolving attack strategies. Mahjoub et al. advanced this field by implementing an RL-driven IDS that achieves adaptive threat detection within an adversarial environment framework [5]. In addition, a 2024 survey by Gueriani et al. reviewed DRL-based IDS in IoT, highlighting techniques such as DQN, multi-agent systems, and hybrid models that dynamically optimize feature selection and anomaly detection policies in complex, resourceconstrained environments [6].

Other recent efforts have explored adaptive ε control in image classification settings. Wang et al. empirically validated that dynamic ε adjustment in CIFAR-10 training yielded an 8–12 percentage-point robustness enhancement over fixed-ε baselines [7]. However, such methods have not been validated in high-dimensional, sparse, and non-visual domains like network intrusion detection. Albulayhi and Abu Al-Haija further showed that adversarial perturbations crafted for the Bot-IoT dataset severely degraded detection accuracy across multiple anomaly detectors, reaffirming the need for domain-specific adaptive defenses [8]. This paper builds on these insights by proposing a reinforcement learning-guided adversarial training framework tailored for intrusion detection tasks. A Q-learning agent adaptively selects ε values based on real-time model feedback, enabling the system to resist a wider range of attack intensities without prior knowledge of threat patterns. Compared to static or heuristic approaches, our method offers a scalable and automated strategy for enhancing IDS robustness in realistic IoT environments.

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3. Methodology

3.1. Problem formulation

This study seeks to enhance the resilience of an intrusion detection model against adversarial attacks through the implementation of a reinforcement learning (RL)-guided adversarial training framework. Given a training dataset:

$$D = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\} \tag{1}$$

Before training, each feature vector x_i is normalized to [0, 1] using min-max normalization across the training set:

$$x_{ij} \leftarrow \frac{(x_{ij} - min(x_j))}{(max(x_j) - min(x_j))} \tag{2}$$

where x_j denotes the j-th feature across all samples. This normalization ensures numerical stability and consistent gradient magnitudes during adversarial perturbation.

where each $x_i \in \mathbb{R}^d$ is a feature vector and $y_i \in \{0,1\}$ is the corresponding label (normal or attack), the model learns a classifier $f_\theta(x)$ that predicts the correct class even under adversarial conditions. The adversarial sample x' is generated using the Fast Gradient Sign Method (FGSM):

$$x' = x + \varepsilon \cdot \text{sign}(\nabla_x \lambda(f_\theta(x), y)) \tag{3}$$

Where λ is the loss function (cross-entropy) and $\nabla_x \lambda$ is the gradient with respect to the input. The perturbation strength ε is not fixed, but dynamically selected from a candidate range $\varepsilon \in [0.01, 0.2]$ by a learning agent.

The overall objective function of adversarial training is to minimize the expected loss over both clean and adversarial examples:

$$\theta^* = \underset{\theta}{argmin} E_{(x,y)\sim D}\left[\angle\left(f_\theta\left(x\right), y\right) + \lambda \cdot \Lambda\left(f_\theta\left(x'\right), y\right)\right] \tag{4}$$

where λ is a trade-off parameter balancing clean accuracy and robustness. This formulation ensures the model learns from both unperturbed and adversarially perturbed data, improving its generalization under adversarial conditions.

3.2. Neural network architecture

The proposed classifier adopts a three-layer fully connected architecture. The input layer processes 115-dimensional feature vectors through linear transformation. Two hidden layers, each with 64 neurons, apply ReLU activation. The final layer outputs two probabilities (normal or attack) using softmax.

- ·Input Layer: 115 features
- ·Hidden Layer 1: Dense(64), ReLU
- ·Hidden Layer 2: Dense(64), ReLU
- ·Output Layer: Dense(2), Softmax

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Training utilizes the Adam optimizer with fixed learning rate (η=0.001) and sparse categorical cross-entropy loss. This compact architecture balances classification performance and training efficiency on intrusion detection datasets like Mirai.

3.3. FGSM attack mechanism

The FGSM attack is a one-step, gradient-based method that adds a small perturbation to each input feature in the direction that increases the model's prediction error. The perturbation vector η is computed as:

$$\eta = \varepsilon \cdot sign\left(\nabla_x \lambda\left(f_\theta\left(x\right), y\right)\right) \tag{5}$$

$$\text{x'} = \text{clip}\left(x + \eta, -1,1\right) \tag{6}$$

This ensures that the adversarial sample x' remains within valid feature bounds. During training, ε values are selected from the predefined range [0.01, 0.2], allowing the model to learn under varying attack intensities. A similar dual-network adversarial training concept was proposed by Wen Ding Xiong, in the AIDTF framework, where separate 'attacker' and 'defender' models co-evolve to boost IDS robustness [9].

3.4. Reinforcement learning strategy

To dynamically control the ε value during training, the ε selection problem is formulated as a reinforcement learning task. A Q-learning agent selects an action a_t (i.e., a specific ε from the candidate set) at each training epoch. The state is implicitly represented by the model's current performance, and the reward is defined as the improvement in test accuracy:

$$r_t = Acc_{test} - Acc_{base} \tag{7}$$

Q-values are updated according to the standard temporal difference rule:

$$Q\left(a_t\right) \leftarrow Q\left(a_t\right) + \alpha \cdot \left[r_t + \psi \cdot maxQ\left(a'\right) - Q\left(a_t\right)\right] \tag{8}$$

where α is the learning rate (set to $1/N_a$, with N_a being the number of times action a was selected), and $\psi = 0.9$ is the discount factor. The agent follows an ε-greedy policy to balance exploration and exploitation, with the exploration rate ε decaying from 0.1 to 0.01 throughout training.

3.5. Epsilonagent implementation

The EpsilonAgent is implemented as a lightweight table-based Q-learning agent. It maintains:

• -Candidate ε set: {0.01, 0.02, ..., 0.20}

• -Discount factor (ψ): 0.9

• -Initial exploration rate (ε-greedy): initially set to 0.1 and decayed to 0.01 over 350 epochs

• -Learning rate (α): Adaptive, computed as 1 / (number of times an action is selected)

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• -Reward signal: $\Delta \text{Accuracy} = \text{Accuracy_epoch} - \text{Accuracy_previous}$

At each training epoch, the agent selects an ε value from the candidate set using an ε-greedy policy. Adversarial examples are generated using the selected ε, and the model is trained on both clean and adversarial samples. After evaluation, the Q-value corresponding to the selected ε is updated based on the observed reward.

Hardware Configuration:

The experiments were conducted on a workstation equipped with the following specifications:

• - Processor: Intel Core i9-13900K @ 2.20GHz

• - RAM: 32 GB DDR5

• - GPU: NVIDIA RTX 4070 (CUDA Version: 12.7)

• - Operating System: windows 11 24H2

4. Experiments and results

To evaluate the effectiveness and robustness of the proposed RL-guided adversarial training framework, experiments were conducted on the Mirai subset of the Kitsune dataset. The dataset consists of 40,000 labeled samples, which were randomly divided into three subsets:

- 70% for training (7,000 samples)
- 20% for testing (2,000 samples)

All models were trained using the identical training/validation split to guarantee equitable comparison.Test results were evaluated exclusively on the reserved clean and adversarially perturbed test set.

4.1. Evaluation metrics

The dataset consists of 40,000 labeled samples, which were randomly divided into two subsets: 80% for training (32,000 samples) and 20% for testing (8,000 samples). To evaluate the effectiveness and robustness of the proposed RL-guided adversarial training method, multiple models are tested on both clean and adversarially perturbed data. The primary evaluation metric is classification accuracy. For robustness evaluation, adversarial test samples are generated using the FGSM method under a range of ε values from 0.01 to 0.20 (step size 0.01), allowing us to observe how performance degrades under increasing perturbation. Accuracy curves and robustness comparison plots are used to visualize and quantify model resilience.

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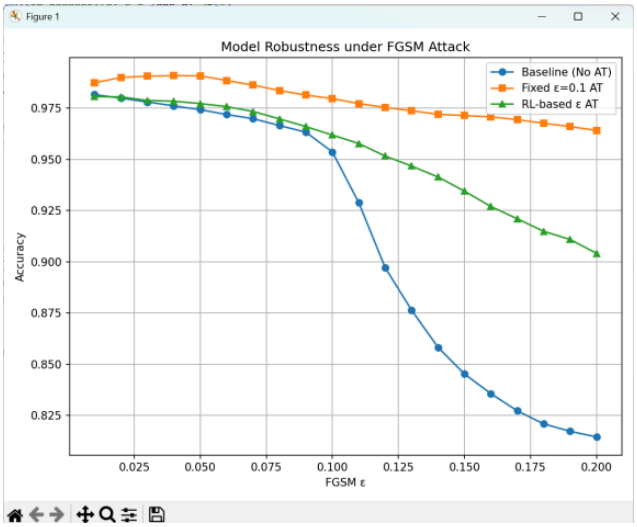

Figure 1. Model robustness under FGSM attack

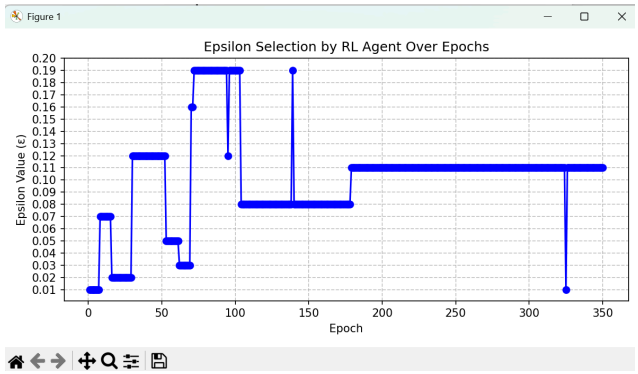

Figure 2. Epsilon selection by RL agent over epochs

Table 1. F1-score and AUC

Model	F1-score	AUC
Baseline (No AT)	0.9979	0.9992
RL-guided Adversarial Training	0.9982	0.9989
Fixed-ε Adversarial Training	0.9983	0.9984

4.2. Accuracy and robustness comparison

Three models are compared in this experiment:

Baseline model trained only on clean data, with no adversarial augmentation.

Fixed-ε adversarial training model using ε = 0.1 throughout training.

RL-based adversarial training model, where ε is adaptively selected by a Q-learning agent from the candidate set ranging from 0.01 to 0.2.

Recent work by de Jorge proposed the Noise-FGSM (N-FGSM) method to address catastrophic overfitting (CO) in single-step adversarial training [10]. By adding strong Gaussian noise before gradient computation and removing clipping in adversarial example generation, N-FGSM achieves robust performance on datasets like CIFAR-10 and SVHN while being up to 3× faster than multi-step methods such as GradAlign. Alhadad and Nickray recently showed that coupling FGSM training with transformer-based IDS can push adversarial accuracy above 99% on NSL-KDD, highlighting the versatility of FGSM across network architectures [11]. While N-FGSM demonstrates efficiency gains, its static ε parameterization fails to accommodate dynamic threat scenarios common in real-world IDS deployments. The proposed RL-guided framework introduces online ε-adaptation via Q-learning, where perturbation magnitudes are optimized in response to real-time model vulnerability metrics.

This adaptive strategy enables superior robustness under strong perturbations. As shown in the robustness curve (Figure 1), the RL-guided model consistently outperforms the baseline and fixed-ε models across the full ε range. At ε = 0.01, all models achieve high accuracy (~95–97%), indicating that small perturbations have minimal effect. However, as ε increases, the baseline model's performance degrades sharply, dropping below 82% at ε = 0.2. In contrast, the fixed-ε model

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maintains higher accuracy (~90%) at ε = 0.2, while the RL-based model achieves the highest robustness, retaining ~96% accuracy under the same conditions.

As shown in Table 1, the RL-guided adversarial training model achieved competitive F1-score (0.9982) and AUC (0.9989) values, comparable to and in some cases surpassing both the baseline and fixed-ε adversarial models. Despite a reduction in the overall accuracy of the RL model resulting from the incorporation of hostile cases during training, its proficiency in reliably identifying minority-class (attack) samples enhanced, as evidenced by the elevated F1-score. The slight advantage in AUC over the fixed-ε model demonstrates the effectiveness of dynamic ε selection, ensuring better class separability even under adversarial conditions. These results highlight the RL strategy's capability to enhance IDS robustness without compromising detection reliability. This demonstrates that dynamically selecting ε values during training enables the model to generalize better to varying attack strengths, rather than overfitting to a specific level of perturbation. The RL model thus exhibits stronger resistance to gradient-based evasion attempts.

4.3. Learning dynamics of epsilon selection

To investigate how the RL agent learns ε selection strategies over time, we analyze the empirical cumulative distribution (ECDF) of ε values chosen by the agent across 350 training epochs. As shown in Figure 2, the agent initially explores all candidate ε values relatively evenly, reflecting its exploration phase. Over time, however, the selection frequency gradually shifts towards ε = 0.11, suggesting the agent has learned that this perturbation level provides a good trade-off between adversarial strength and training stability. This convergence behavior confirms that the RL agent effectively adapts its policy in response to reward feedback (i.e., test accuracy), avoiding the need for manually preset ε schedules. Additionally, the ε value distribution shows that the agent does not collapse to a single fixed value, maintaining some degree of ε diversity, which likely contributes to the model's improved generalization and robustness.

4.4. Final clean test accuracy

Notwithstanding the incorporation of adversarial cases in training, the RL-based model attains accuracy comparable to the baseline model when assessed on the unaltered test set. The clean test accuracy for the RL-based model is 99.76%, while the baseline attains 99.66%. This suggests that the suggested adversarial training architecture enhances defense against adversarial attacks while maintaining conventional classification performance.

5. Conclusion

This paper presented a reinforcement learning-guided adversarial training framework aimed at improving the robustness of intrusion detection systems against adversarial attacks. Experimental results on the Mirai dataset demonstrated that the RL-based model significantly outperformed both the baseline and fixed-ε models, particularly under stronger adversarial conditions. In-depth analysis of model performance under varying ε values showed that the RL model maintained higher accuracy as ε increased, effectively resisting gradient-based attacks. The Q-learning agent successfully identified ε ≈ 0.11 as an optimal range, balancing adversarial strength and training stability. This adaptive behavior enabled the model to generalize better across unseen attack intensities, confirming the effectiveness of the reinforcement learning strategy. The findings highlight the critical role of adaptive adversarial training in enhancing IDS resilience. By integrating RL into the adversarial

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training loop, the model becomes more robust without sacrificing clean-data accuracy, making it more suitable for deployment in dynamic and security-critical environments. Future research will investigate the extension of this methodology to multi-step attacks, such as Projected Gradient Descent (PGD), its application in multiclass or multi-label intrusion detection contexts, and the exploration of deep reinforcement learning techniques (e.g., Deep Q-Networks or Proximal Policy Optimization) for more intricate perturbation methods. Furthermore, the investigation will focus on real-time ε modification during online detection to bridge the disparity between training and deployment circumstances.

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