World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

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Reinforcement learning-based phishing detection model

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World Journal of Advanced Research and Reviews, 2025, 25(01), 2291-2295

Publication history: Received on 15 December 2024; revised on 24 January 2025; accepted on 27 January 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.25.1.0256

Abstract

Phishing attacks are a persistent cybersecurity threat, exploiting human vulnerabilities via deceptive emails and malicious URLs. This project introduces a novel Reinforcement Learning (RL)-based system to automate phishing detection and response. By employing advanced RL algorithms, such as Deep Q-Learning and Policy Gradient methods, the system dynamically learns to identify phishing indicators within email content and URLs through Natural Language Processing (NLP) and feature extraction techniques. The RL agent continuously adapts its detection strategies based on evolving threats and user feedback, aiming to minimize false positives while accurately identifying malicious activities. Upon detecting potential threats, the system initiates automated responses, including alert notifications, URL blocking, and user warnings, thereby enhancing security measures. Implementing this RL-based solution within Security Operations Centers (SOCs) or email security platforms offers a scalable, real-time defense against phishing attacks. This approach effectively safeguards sensitive information and strengthens organizational resilience against cyber threats.

Keywords: Reinforcement Learning; Phishing Detection; Automated Response; Deep Q-Learning; Policy Gradient; URL Analysis; Threat Mitigation

1. Introduction

Phishing is a cybercrime technique where attackers impersonate legitimate entities to steal sensitive information, such as credentials or financial details. It has evolved from simple email scams to highly sophisticated attacks targeting businesses and individuals. The global impact of phishing includes financial losses, identity theft, and data breaches, making it a pressing concern in cybersecurity. Phishing attacks have evolved into a major cybersecurity concern, exploiting vulnerabilities in human behavior and traditional systems. These attacks deceive users into revealing sensitive information, such as credentials or financial data, by masquerading as legitimate entities. Existing detection methods, including email filters and URL blacklists, are static and unable to adapt to the evolving nature of phishing techniques.

To address these limitations, this study explores Reinforcement Learning (RL) as an adaptable and dynamic approach to phishing detection. Unlike static models, RL enables the system to learn from interaction and feedback in dynamic environments, providing a robust mechanism for detecting zero-day attacks. To counteract the threats posed by phishing attacks, this project introduces a Reinforcement Learning-Based Phishing Detection Model, leveraging Deep Q-Learning and Policy Gradient methods to dynamically identify and mitigate phishing attempts. By analyzing email content and URLs through Natural Language Processing (NLP), the system adapts to emerging attack patterns, ensuring a robust and effective defense mechanism.

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The limitations of existing phishing detection models necessitate a more adaptive approach. Current systems, such as rule-based models, rely on static rules and heuristics, rendering them ineffective against sophisticated or zero-day phishing attacks. Similarly, traditional machine learning models lack the ability to dynamically adapt to evolving phishing patterns, resulting in a high rate of false positives. These systems often struggle with imbalanced datasets, where the focus on the majority class (legitimate URLs) biases the detection process and reduces sensitivity to phishing URLs. Additionally, delayed response times due to reliance on manual reporting further hinder the effectiveness of these models.

The proposed system addresses these shortcomings through innovative techniques. It employs Double Deep Q-Learning Networks (DDQN), utilizing a dual-network mechanism to enhance decision-making by separating quick, reactive decisions from stable, long-term pattern validation. To tackle the issue of imbalanced datasets, the system incorporates the ICMDP framework, which focuses on identifying phishing URLs without introducing bias toward legitimate ones. Moreover, the model facilitates automated and real-time responses, dynamically flagging, blocking, and mitigating phishing threats to ensure swift and effective countermeasures.

A two-step verification mechanism integrates an "online network" for immediate pattern recognition and a "target network" for validating suspicious URLs against a historical database. This dual-network system significantly improves accuracy, reduces false positives, and enhances adaptability to real-world challenges such as imbalanced datasets and evolving phishing tactics. Together, these innovations create a dynamic and robust phishing detection model capable of addressing modern cybersecurity threats effectively.

2. Literature Review

Phishing is a prevalent cyberattack technique where attackers impersonate legitimate entities to deceive individuals into revealing sensitive information such as login credentials, banking details, or personal identification. Over the years, phishing tactics have evolved significantly, making them harder to detect using traditional methods. Detection systems are critical for safeguarding sensitive information and minimizing the damage caused by these attacks. Despite conventional methods such as email filtering and URL blacklists, these systems often fail to detect sophisticated phishing attacks, especially those exploiting real-time vulnerabilities. The growing volume of cyberattacks necessitates advanced techniques capable of dynamically adapting to new phishing strategies. Reinforcement learning (RL), a machine learning paradigm known for its adaptability, offers a promising solution to the limitations of static detection systems by introducing mechanisms that learn from interaction and feedback in dynamic environments.

Maci et al. (2023) [1] emphasize that the limitation of these early systems was their inability to evolve with the increasing complexity of phishing schemes, making them less effective over time. This paved the way for the integration of more advanced techniques to address these shortcomings.

Smadi et al. (2017) [2] elaborate on the persistent challenges faced by traditional phishing detection methods. They specifically point out how static rule-based systems were unable to effectively counter the evolving nature of phishing attacks. As cybercriminals continually refined their techniques, they found ways to bypass these simplistic models, thus leading to a higher number of undetected phishing attempts and missed threats. The failure of these systems to adapt to emerging threats highlighted the need for more flexible, adaptive solutions, which would later be provided by machine learning and, ultimately, reinforcement learning techniques.

2.1. Integration of Machine Learning Models in Phishing Detection

The shift from static rule-based systems to machine learning (ML) techniques marked a significant improvement in phishing detection. Kumar et al. (2024) [3] explore the incorporation of machine learning algorithms such as logistic regression and decision trees into phishing detection systems. These models leveraged a variety of features, including lexical (text-based), host-based (website attributes), and content-based (email or webpage content) characteristics to make more accurate classifications. By training these models on labeled data, they were able to improve detection rates compared to traditional rule-based systems. However, these machine learning models, while an improvement, still had significant limitations. As they were based on static data and relied on predefined training sets, they could not adapt quickly to new or unknown phishing attempts. Their inability to continuously update and learn from real-time data remained a key challenge, especially in the face of rapidly evolving phishing techniques.

2.2. Deep Learning for Phishing Detection

With the increasing complexity of phishing attacks, deeper and more complex models began to be employed. Chatterjee et al. (2019) [4] discuss the use of deep learning techniques such as Convolutional Neural Networks (CNNs) and

Recurrent Neural Networks (RNNs) in phishing detection systems. These models are particularly effective at identifying complex patterns in both textual content and URLs, which are often critical for detecting phishing attempts. CNNs are adept at extracting spatial features, making them suitable for analyzing webpage structures, while RNNs excel at processing sequential data, which is useful for analyzing email content or web traffic over time.

However, despite the improved performance of deep learning models, Chatterjee et al. (2019) [4] point out that these approaches come with their own set of challenges. Deep learning models are computationally intensive, requiring significant resources for both training and real-time deployment. Additionally, they are susceptible to adversarial attacks—strategies designed to deceive the model into making incorrect predictions by subtly manipulating input data. These vulnerabilities made deep learning-based phishing detection systems impractical for resource-constrained environments or for applications that require real-time, low-latency detection.

2.3. Reinforcement Learning-Based Phishing Detection Systems

The introduction of reinforcement learning (RL) marked a paradigm shift in phishing detection by allowing systems to dynamically learn and adapt to new data over time. As Maci et al. (2023) [1] explain, RL models, such as Double Deep Q-Networks (DDQN) and Imbalanced Classification with Markov Decision Processes (ICMDP), offer a significant advancement in phishing detection by enabling real-time learning and decision-making. Unlike traditional machine learning models, RL systems are capable of continuously learning from interactions with the environment, allowing them to adjust their strategies based on new data and evolving threats.

One key feature of RL is the concept of exploration and exploitation, which allows these systems to experiment with different actions (exploration) and focus on the most successful ones (exploitation). In the context of phishing detection, this means that RL models can adapt their detection strategies over time, improving their accuracy in identifying phishing attempts while minimizing false positives. Smadi et al. (2017) [2] further elaborate on the role of DDQN in RL-based phishing detection, where two neural networks are used: an online network for making quick decisions and a target network for providing stable evaluations. This dual-network setup helps mitigate the problem of instability and improves the overall reliability of the system.

2.4. Key Components of RL-Based Phishing Detection

Alsharnouby et al. (2015) [6] emphasize the importance of the ICMDP framework in addressing the challenge of imbalanced datasets. Phishing detection systems often deal with a disproportionate number of benign cases compared to phishing cases, leading to an imbalance that can skew the performance of the system. The ICMDP framework, by incorporating rewards for correct classifications and penalties for errors, helps strike a balance between sensitivity and precision, which is essential for effective phishing detection.

Furthermore, RL-based systems enable real-time detection and mitigation of phishing attempts. Elluri et al. (2023) [8] describe how these systems not only identify phishing URLs but also actively block them, alert users in real-time, and continuously update their detection policies based on new information. The ability to rapidly adapt and respond to emerging phishing tactics is a key advantage of RL, making these systems particularly suitable for integration with platforms such as Security Operations Centers (SOCs), where scalability and the need for constant updates are crucial.

Mittal et al. (2023) [5] discuss the role of automated response mechanisms in RL-based phishing detection systems. By automating actions such as blocking phishing URLs, alerting users, and triggering other defense mechanisms, these systems reduce the need for manual intervention and minimize the impact of phishing attacks. Automated responses not only enhance the efficiency of phishing detection but also improve the speed at which threats are neutralized, preventing potential damage to users and organizations.

3. Results

This section presents the evaluation of the proposed RL-based phishing detection and response system and discusses its outcomes in detail. The analysis includes the methodology's performance metrics, comparative advantages over traditional systems, and the significance of results.

3.1. RL-Based Detection Framework

The proposed framework employs a systematic approach to detect phishing URLs effectively. The initial step involves extracting key features, such as URL length, subdomain count, and the presence of special characters. These features

are critical for distinguishing phishing URLs from legitimate ones and serve as the foundation for further analysis and model training.

The next stage focuses on training the reinforcement learning model. A reward mechanism is implemented to encourage correct classifications and penalize incorrect ones. This adaptive learning process enables the model to improve its accuracy over time, making it capable of handling diverse phishing patterns with enhanced precision. The training ensures that the system remains robust against new and evolving phishing tactics.

In the final stage, the system operates in real-time to classify incoming URLs dynamically. Leveraging the insights gained during training, the framework adapts its strategies to address a wide range of phishing scenarios. This dynamic and responsive approach ensures the system's effectiveness in identifying and mitigating phishing attempts, providing a reliable solution for enhanced cybersecurity.

3.2. Dataset Preparation

A synthetic dataset comprising 2,000 URLs (balanced between phishing and legitimate URLs) was generated using the URL Dataset Generator. The dataset featured diverse characteristics, ensuring robust model training and testing. Preprocessing steps included normalization to enhance data quality and compatibility with the RL model.

3.3. Performance Evaluation

The system's effectiveness was assessed using key performance metrics:

- **Accuracy**: Achieved 96%, indicating reliable overall performance.
- **Precision**: Measured at 94%, signifying a high proportion of correctly identified phishing URLs.
- **Recall**: Recorded at 95%, highlighting the system's ability to detect phishing URLs without missing significant cases.
- **F1-Score**: Calculated at 94.5%, showcasing balanced performance across precision and recall.

The RL-based system outperformed traditional and machine learning-based models in detecting phishing URLs, while maintaining a low false positive rate.

4. Discussion

The proposed methodology demonstrates significant advancements over traditional phishing detection techniques by leveraging reinforcement learning. Unlike static models, this system adapts to new phishing tactics, improving its effectiveness over time. The integration of natural language processing (NLP) for content analysis further enhances the system's capabilities, ensuring precise and context-aware phishing detection.

The low false positive rate minimizes unnecessary disruptions, while the high F1-score reflects a balanced and effective detection strategy. These findings underscore the potential of RL-based approaches for adaptive, real-time cybersecurity solutions.

4.1. Future Scope

The future of the RL-based phishing detection system includes enhancing its adaptability to advanced phishing techniques, supporting multiple languages, and integrating with broader cybersecurity platforms. Expanding to other areas of cybersecurity, leveraging real-time threat intelligence, and exploring alternative RL algorithms will improve efficiency. Incorporating user behavior analysis, a human-in-the-loop mechanism, and testing with real-world datasets can further enhance accuracy and scalability. Additionally, multi-modal data integration will strengthen detection capabilities, contributing to the development of advanced self-learning systems for tackling evolving cyber threats.

5. Conclusion

This project presents a novel RL-based phishing detection and response system to address the limitations of traditional detection methods. By employing Deep Q-Learning and Policy Gradient techniques, the system demonstrates dynamic, adaptive learning capabilities to efficiently identify phishing attempts in email content and URLs. The integration of NLP for content analysis and automated response mechanisms ensures reduced response times and mitigates the risks posed by phishing attacks.

The system's continuous adaptation through reinforcement learning enables it to handle new and sophisticated phishing tactics, which are often missed by conventional models. By minimizing false positives and delivering real-time automated responses, the system enhances organizational and individual cybersecurity measures.

The proposed solution is scalable, adaptive, and effective in combating phishing threats, making it a valuable tool for safeguarding sensitive information. This study contributes to advancing cybersecurity frameworks and sets the foundation for self-learning security systems essential for addressing the increasing sophistication of cyber threats.

Compliance with ethical standards

Acknowledgments

We extend our sincere gratitude to our guide, Mr. C. V. Ajay Kumar, Assistant Professor, Department of CSE (Artificial Intelligence & Machine Learning), ACE Engineering College, for his guidance and support throughout this project. We also express our profound thanks to Dr. Soppari Kavitha, Professor and Head of the Department of CSE (AI & ML), ACE Engineering College, for her invaluable support, encouragement, and time.

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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