A REINFORCING AND GENERALIZING ZERO-DAY INTRUSION DETECTION USING HYBRID META ADAPTIVE Q-TRANSFORMERFRAMEWORK

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ABSTRACT - The increasing complexity of cyber threats has made traditional intrusion detection systems inadequate, especially in identifying zero-day attacks that do not follow known patterns. To address this challenge, this paper presents a hybrid meta-adaptive intrusion detection framework that combines transformer-based feature learning with reinforcement learning techniques. The proposed system leverages a transformer model to extract meaningful and context-aware representations from network traffic data, enabling better understanding of complex and dynamic patterns. These representations are then utilized by a Double Deep Q-Network (DDQN), which learns optimal decision policies through interaction with the environment using a reward-based mechanism. To further enhance performance, the model incorporates prioritized experience replay for efficient learning and a dynamic reward adjustment strategy to improve adaptability and reduce misclassification. This integrated approach allows the system to effectively generalize and detect previously unseen attack behaviors. Experimental evaluation demonstrates that the proposed model achieves improved detection accuracy, stability, and robustness compared to conventional methods. The framework is computationally efficient and suitable for real-time deployment, making it a promising solution for modern cybersecurity applications

KEYWORDS*:* Zero-Day Attack Detection, Intrusion Detection System (IDS), Reinforcement Learning, Double Deep Q-Network (DDQN), Transformer Model, Prioritized Experience Replay, Meta-Adaptive Learning, Cybersecurity, Network Traffic Analysis, Hybrid Deep Learning Framework.

INTRODUCTION:

The rapid expansion of digital technologies, cloud platforms, and internet-based services has led to a significant increase in network traffic and data exchange. While these advancements have improved communication and efficiency, they have also introduced serious cybersecurity challenges. Among various threats, zero-day attacks are particularly critical because they exploit unknown vulnerabilities and do not match any previously recorded attack signatures. As a result, detecting such attacks in real time remains a major concern for modern network security systems [1], [2].].

Intrusion Detection Systems (IDS) play a vital role in monitoring network activities and identifying malicious behavior. Traditional IDS techniques, including signature-based and rule-based approaches, rely heavily on predefined patterns and known attack databases. Although these systems are effective for detecting known threats, they fail to identify new or evolving attack patterns. To overcome this limitation, anomaly-based detection methods have been introduced, which focus on identifying deviations from normal behavior. However, these methods often suffer from high false positive rates and limited adaptability in dynamic environments [9], [13].

In recent years, machine learning and deep learning techniques have been widely adopted to improve intrusion detection performance. These approaches enable systems to automatically learn patterns from data and enhance detection capabilities over time. In particular, reinforcement learning has emerged as a promising technique for cybersecurity applications due to its ability to make sequential decisions based on interactions with the environment. Models such as Deep Q-Network (DQN) and Double Deep Q-Network (DDQN) provide improved learning stability and decision-making efficiency, making them suitable for adaptive intrusion detection systems [1], [15]. At the same time, transformer-based models have gained significant attention for their ability to capture complex relationships within data. By using attention mechanisms, transformers can identify dependencies between different features, even across long sequences. This capability is highly beneficial for network traffic analysis, where multiple attributes and temporal relationships influence the detection of malicious activities. Transformer-based feature extraction has shown promising results in improving classification performance and representation learning [8], [14].

Despite these advancements, relying on a single technique may not be sufficient to handle the complexity of modern

cyber threats. Deep learning models are effective in feature extraction but may lack adaptive decision-making capabilities, whereas reinforcement learning models excel in decision-making but depend on the quality of input features. Therefore, integrating these approaches into a unified framework can significantly enhance detection performance and robustness. To address these challenges, this paper proposes a hybrid meta-adaptive intrusion detection framework that combines transformer-based feature learning with a Double Deep Q-Network (DDQN)

The transformer module is responsible for extracting meaningful and context-aware representations from network traffic data, while the reinforcement learning agent classifies traffic by learning optimal policies through interaction with the environment. Furthermore, prioritized experience replay is incorporated to improve training efficiency by focusing on important samples, and a meta-adaptive reward mechanism is introduced to dynamically adjust the learning process and reduce misclassification. The primary objective of the proposed system is to improve the detection of zero-day attacks by enhancing generalization, adaptability, and stability. The framework is designed to operate efficiently in real-time environments without requiring complex hardware resources. By leveraging the strengths of both transformer models and reinforcement learning, the proposed approach provides a robust and scalable solution for detecting unknown and evolving cyber threats in modern network infrastructures.

DEEP LEARNING:

Deep learning is a subset of machine learning that focuses on training artificial neural networks with multiple layers to automatically learn patterns from large volumes of data. Unlike traditional machine learning techniques that require manual feature extraction, deep learning models can learn hierarchical feature representations directly from raw input data, making them highly effective for complex tasks such as image recognition, natural language processing, and cybersecurity applications [10], [12]. In the context of intrusion detection, deep learning models are capable of analyzing high-dimensional network traffic data and identifying hidden patterns associated with malicious activities. Techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely used to detect anomalies and classify network behavior. These models improve detection accuracy by capturing both spatial and temporal relationships within the data [4], [11]

More recently, transformer-based architectures have gained attention due to their ability to model long-range dependencies using attention mechanisms. Transformers can effectively process sequential data and identify complex relationships between multiple features, making them suitable for network traffic analysis and zero-day attack detection. Their ability to generate context-aware feature representations enhances the performance of intrusion detection systems [8], [14]. Despite their advantages, deep learning models may face challenges such as high computational requirements and limited adaptability to changing environments. To address these limitations, deep learning is often combined with other approaches, such as reinforcement learning, to improve decision-making and adaptability . This integration enables the development of more robust and intelligent intrusion detection systems capable of handling evolving cyber threats. Overall, deep learning plays a crucial role in modern cybersecurity by enabling automated feature learning, improving detection accuracy, and supporting the identification of previously unseen attack patterns.

RELATED WORKS*:*

Intrusion detection has been extensively studied to address the growing complexity of cyber threats, especially zero-day attacks. Traditional intrusion detection systems mainly rely on signature-based techniques, where known attack patterns are matched with incoming network traffic. Although these systems are effective for previously identified threats, they are unable to detect new or unknown attacks, making them insufficient for modern cybersecurity requirements [9], [13]. To overcome this limitation, anomaly-based detection methods were introduced. These approaches focus on identifying deviations from normal network behavior using statistical and machine learning techniques. While anomaly-based systems improve the detection of unknown attacks, they often suffer from high false positive rates and require continuous tuning to adapt to dynamic network environments [2], [14]. With the advancement of artificial intelligence, machine learning techniques such as decision trees, support vector machines, and clustering algorithms have been widely applied to intrusion detection. These models can automatically learn patterns from network traffic data and classify activities as normal or malicious. However, many of these approaches depend heavily on labeled datasets and may not generalize well to new or unseen attack patterns, limiting their effectiveness in real-world scenarios [10], [12]

Deep learning has further enhanced intrusion detection capabilities by enabling automatic feature extraction from high-dimensional data. Convolutional Neural Networks (CNNs) have been used to capture spatial relationships in network traffic, while Recurrent Neural Networks (RNNs) are effective in modeling sequential and temporal dependencies. These models have demonstrated improved accuracy in detecting complex attack patterns, especially in large-scale and IoT-based environments. Nevertheless, deep learning models often require significant computational resources and may lack adaptability to rapidly changing attack strategies [4], [11]. Unsupervised and self-supervised learning approaches have gained attention for their ability to detect anomalies without requiring labeled data. These methods learn normal patterns of network behavior and identify deviations as potential intrusions. Techniques such as clustering and reconstruction-based models have been applied to zero-day attack detection. Although these approaches are useful in identifying unknown threats, they may generate higher false alarm rates due to the absence of clear decision boundaries [5], [6], [7].

In recent years, reinforcement learning has emerged as a promising technique for adaptive intrusion detection. Reinforcement learning agents learn optimal decision-making strategies by interacting with the environment and receiving feedback in the form of rewards or penalties. Deep reinforcement learning models, such as Deep Q-Networks (DQN) and Double Deep Q-Networks (DDQN), have demonstrated improved adaptability and stability in dynamic network environments. However, their performance largely depends on effective feature representation and efficient training mechanisms [1], [15]. Transformer-based architectures have also gained attention due to their ability to capture complex feature dependencies using attention mechanisms.

These models are capable of generating context-aware representations from network traffic data, improving the detection of subtle and complex attack patterns. However, transformer models alone may not provide sufficient adaptability for real-time decision-making in continuously evolving threat environments [8], [14].

Despite the progress achieved by individual techniques, each approach has certain limitations in terms of generalization, adaptability, or computational efficiency. Therefore, recent research has focused on hybrid models that combine multiple techniques to leverage their strengths. In this context, the proposed system integrates transformer-based feature extraction with reinforcement learning. It also incorporates prioritized experience replay and a meta-adaptive reward mechanism to enhance learning efficiency, improve adaptability, and achieve better detection of zero-day attacks.

EXISTING WORKS:

Existing intrusion detection systems (IDS) are designed to monitor and analyze network traffic in order to identify malicious activities using various traditional and intelligent approaches. One of the most commonly used techniques is the signature-based detection method, where incoming data is compared against a database of known attack patterns. This approach is highly effective in detecting previously identified threats with good accuracy. However, it is heavily dependent on regularly updated signature databases, and any delay in updates can leave the system vulnerable. More importantly, this method fails to detect zero-day attacks, as such attacks do not have predefined signatures in the database [9], [13].

To overcome this limitation, anomaly-based intrusion detection systems were introduced. These systems work by establishing a baseline of normal network behavior and identifying any deviation from this baseline as a potential threat. This approach enables the detection of unknown attacks, but it also introduces the problem of high false positive rates. In real-world scenarios, network behavior is highly dynamic, and not all deviations indicate malicious activity. As a result, anomaly-based systems often generate unnecessary alerts, which can reduce system reliability and increase the burden on security analysts [2], [14].

With the advancement of machine learning, intrusion detection systems have been improved by incorporating supervised learning algorithms such as decision trees, support vector machines, and random forests. These models are trained on labeled datasets to classify network traffic into normal and malicious categories. Although they can achieve good performance under controlled conditions, their effectiveness depends largely on the availability and quality of labeled data. In many practical situations, datasets may not include all possible attack types, which limits the model's ability to generalize and detect new or evolving threats [10], [12].

Unsupervised learning approaches have also been applied to intrusion detection to reduce dependency on labeled data. These methods attempt to identify hidden patterns and anomalies within network traffic without prior knowledge of attack labels. While they are useful in detecting unknown attacks, they often lack clear decision boundaries and may produce inconsistent results. Additionally, they are sensitive to noise and variations in data, which can lead to higher false alarm rates [5], [6], [7].

Deep learning-based intrusion detection systems have further enhanced the capability to analyze complex and high-dimensional network data. Techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are widely used to capture spatial and temporal relationships in network traffic. These models provide improved accuracy and automatic feature extraction compared to traditional methods. However, they require large amounts of data and significant computational resources for training. Moreover, once trained, these models often behave as static systems and may not adapt effectively to continuously changing attack patterns without retraining [4], [11].

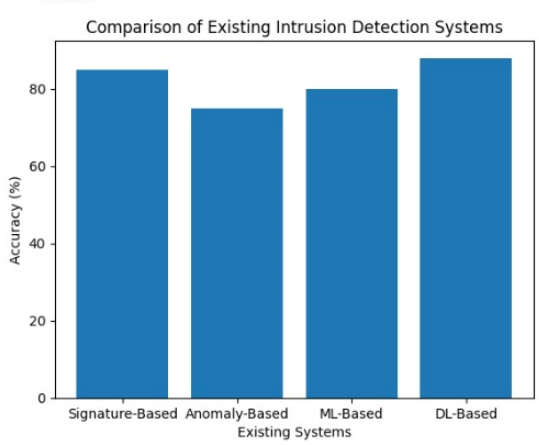
Some existing systems attempt to incorporate adaptive learning mechanisms by updating models based on new data over time. Although this improves flexibility to some extent, the adaptation process is often slow and may not respond effectively to rapidly evolving cyber threats. In addition, many of these systems lack a proper feedback-driven learning mechanism, which limits their ability to improve decision-making based on past experiences [1], [15]

Another important limitation in existing intrusion detection systems is the inefficiency in feature representation. Many approaches rely on manually engineered features or basic statistical methods, which may not capture complex relationships within the data. This can reduce the system's ability to detect subtle and sophisticated attack patterns. Furthermore, feature extraction and decision-making are often treated as separate processes, which can lead to reduced overall performance [8], [14].

In addition, scalability remains a challenge in many existing systems, especially when dealing with large-scale network environments where the volume of data is continuously increasing. Processing such data in real time requires efficient algorithms and optimized architectures, which many traditional and machine learning-based

systems fail to provide. This can result in delays in detection and response, affecting overall system performance.

Overall, while existing intrusion detection systems provide a foundation for identifying cyber threats, they face significant challenges in detecting zero-day attacks, reducing false positives, adapting to dynamic environments, and efficiently processing large-scale data. These limitations emphasize the need for more advanced and adaptive approaches for modern intrusion detection



PROPOSED WORK:

The proposed system introduces a hybrid meta-adaptive Double Deep Q-Transformer framework designed to enhance zero-day intrusion detection by combining multiple machine learning, deep learning, and reinforcement learning techniques into a unified model. The system aims to overcome the limitations of traditional intrusion detection approaches by improving adaptability, detection accuracy, and the ability to generalize to unknown attack patterns in dynamic network environments.

Initially, the system processes raw network traffic data and converts it into structured network flow features suitable for analysis. A Random Forest classifier is employed as a baseline supervised learning algorithm to perform initial classification of network traffic. In this project, the Random Forest model helps in identifying patterns within structured data, capturing nonlinear relationships among features, and providing feature importance insights. It also serves as a reference model to compare the performance improvements achieved by the proposed hybrid framework.

To introduce adaptability and intelligent decision-making, the system incorporates a Deep Q-Network (DQN), which models the intrusion detection problem as a reinforcement learning task. In this context, the DQN acts as an agent that observes the current state of network traffic and decides whether the activity is normal or malicious. The model learns by interacting with the environment and receiving rewards or penalties based on its predictions. This enables the system to move beyond static detection methods and continuously improve its detection policy without relying on predefined attack signatures.

However, standard DQN models may suffer from instability and overestimation of Q-values during training. To address this issue, the proposed system utilizes Double Deep Q-Network (DDQN), which is an improved version of DQN. In this project, DDQN introduces separate policy and target networks, which helps in reducing overestimation bias and stabilizing the learning process. This results in more reliable and accurate decision-making, especially in complex and uncertain network environments where attack patterns may vary significantly. For effective feature representation, the system integrates a Transformer model with a Multi-Head Self-Attention mechanism.

This component plays a crucial role in capturing complex relationships among network flow features by focusing on different parts of the input data simultaneously. In this project, the transformer helps in understanding both local and global dependencies within the data, allowing the system to identify subtle patterns associated with zero-day attacks. The attention mechanism enhances the model's ability to focus on important features, thereby improving detection performance.

To improve the efficiency of the reinforcement learning process, the system incorporates Prioritized Experience Replay (PER). In this approach, past experiences are stored and replayed during training, but instead of selecting them randomly, more important experiences are given higher priority. In the context of this project, PER ensures that rare and high-impact attack samples, such as ransomware or zero-day intrusions, are learned more effectively.

This improves the model's recall and helps in better detection of critical threats. Another important component of the proposed system is the Meta-Adaptive Reward Mechanism, which dynamically adjusts reward values during training. In this project, the reward mechanism assigns higher penalties to false negatives, ensuring that the system minimizes missed attacks. At the same time, it adapts to concept drift and changes in network traffic patterns, allowing the model to remain effective in evolving environments. This adaptive reward strategy helps in balancing detection accuracy and false positive rates while improving the overall robustness of the system

Furthermore, the integration of these algorithms enables the system to perform continuous learning, where it updates its detection strategy based on new incoming data. The combination of Random Forest for baseline analysis, Transformer for advanced feature extraction, DQN and DDQN for adaptive decision-making, Prioritized Experience Replay for efficient learning, and Meta-Adaptive Reward Mechanism for dynamic optimization creates a powerful and flexible intrusion detection framework. This hybrid approach significantly enhances the system's ability to detect zero-day attacks, improves stability during training, and ensures scalability for real-time deployment in modern network environments.

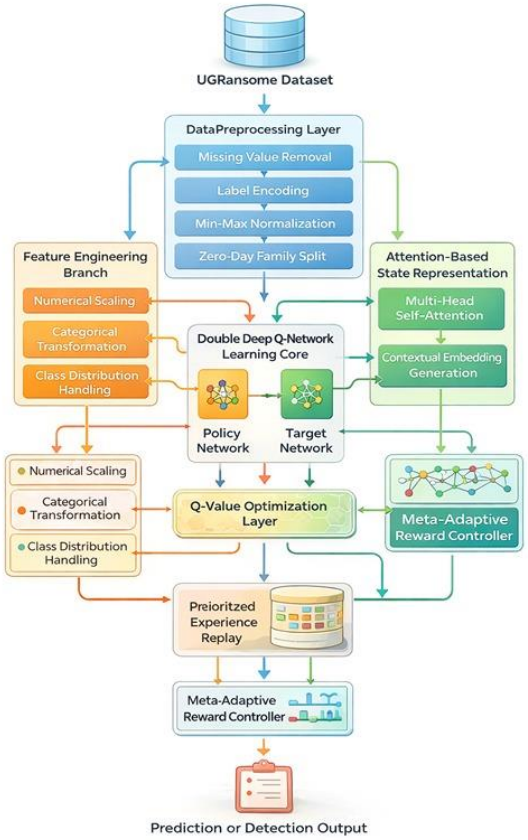
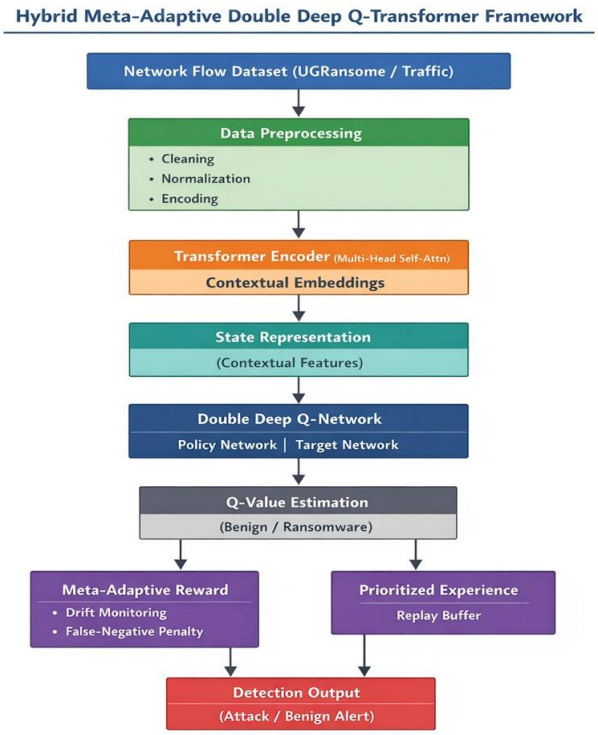


TABLE 1: METHODOLOGY:

STAGE	ACTIVITIES
Data Collection	-Network traffic data is collected from datasets or real-time network environments containing both normal and attack behaviors
Data Preprocessing	- The collected data is cleaned by removing missing values, noise, and irrelevant features. Data is then normalized and converted into structured network flow format
Feature Extraction	-Important features are extracted from network traffic data to represent the behavior of the system effectively.
Baseline Model (Random Forest)	-A Random Forest classifier is applied as a baseline model to perform initial classification and evaluate structured data performance
Transformer Encoding	-A Transformer with Multi-Head Self-Attention is used to capture complex relationships and contextual dependencies among features.
State Representation	-The processed and encoded features are treated as the state input for the reinforcement learning mode.
Decision Making (DQN)	- A Deep Q-Network (DQN) is used to make decisions (normal or attack) based on the current state using reward-based learning
Improved Learning (DDQN)	-Double Deep Q-Network (DDQN) is applied to reduce Q-value overestimation and improve training stability using separate policy and target networks.
Experience Storage	-The system stores past experiences (state, action, reward, next state) in a replay memory buffer.
Prioritized Experience Replay	-Important experiences are given higher priority and replayed more frequently to improve learning efficiency and detection of rare attacks.
Reward Mechanism	-A Meta-Adaptive Reward Mechanism dynamically adjusts rewards, giving higher penalties for false negatives and adapting to changing traffic patterns
Model Training	-The system is trained iteratively using reinforcement learning to improve detection accuracy over time
Intrusion Detection Output	-The system classifies network traffic as normal or malicious and detects zero-day attacks effectively.

Continuous Learning	The model updates itself based on new data, adapting to evolving cyber threats and maintaining performance



FUTURISTIC TRENDS:

The rapid evolution of cyber threats, especially zero-day attacks, demands more intelligent, adaptive, and scalable intrusion detection systems in the future. As network environments become more complex with the growth of cloud computing, Internet of Things (IoT), and edge devices, traditional security mechanisms will no longer be sufficient. Future intrusion detection systems are expected to rely heavily on advanced artificial intelligence techniques that can learn continuously and adapt to changing attack patterns without requiring manual intervention

One of the key future trends is the integration of more advanced reinforcement learning techniques that enable systems to make real-time decisions in highly dynamic environments. These models will be capable of self-learning and improving their detection strategies based on continuous interaction with network traffic. The use of more efficient variants of deep reinforcement learning can further enhance stability, scalability, and faster convergence in large-scale cybersecurity applications. Another important direction is the evolution of transformer-based architectures for network security. With the ability to capture long-range dependencies and complex feature relationships, transformers are expected to play a significant role in improving the detection of sophisticated and stealthy attacks. Future research may focus on lightweight and optimized transformer models that can be deployed in real-time systems with reduced computational overhead. The concept of meta-adaptive and self-healing security systems is also gaining importance. Future intrusion detection systems will not only detect attacks but also automatically respond and recover from them. By incorporating adaptive reward mechanisms and feedback-driven learning, systems can dynamically adjust their behavior based on environmental changes and threat levels, ensuring continuous protection.

In addition, the use of federated learning is expected to enhance privacy and collaboration across multiple network environments. Instead of sharing raw data, systems can share learned models, allowing organizations to benefit from collective intelligence while maintaining data privacy. This approach can significantly improve the detection of emerging threats across distributed networks. Explainability and transparency in AI models will also become crucial in future systems. As intrusion detection models become more complex, there is a growing need to understand how decisions are made. Explainable AI techniques can help security analysts interpret model outputs, build trust in automated systems, and support better decision-making.

Furthermore, the integration of intrusion detection systems with automated response mechanisms will lead to the development of fully autonomous cybersecurity frameworks. These systems will not only detect and classify attacks but also take immediate preventive actions, reducing response time and minimizing potential damage. Overall, the future of intrusion detection lies in the development of intelligent, adaptive, and collaborative systems that combine advanced learning techniques with real-time decision-making capabilities. Such systems will be better equipped to handle the challenges of modern cybersecurity and provide robust protection against evolving and unpredictable threats.

RESULTS AND TRENDS:

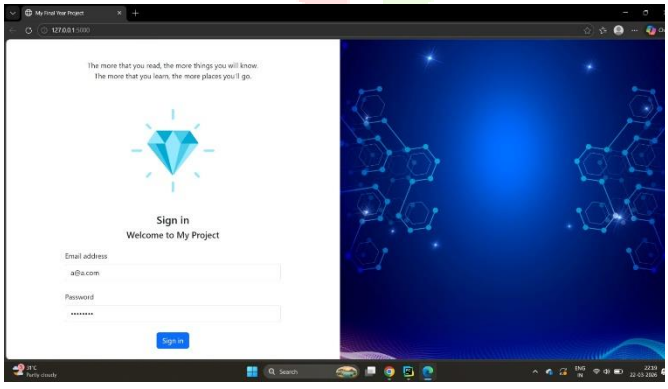
The proposed hybrid meta-adaptive Double Deep Q-Transformer framework was evaluated to analyze its effectiveness in detecting zero-day intrusions and improving overall intrusion detection performance. The results indicate that the integration of transformer-based feature extraction with reinforcement learning significantly enhances the system's ability to identify complex and previously unseen attack patterns. Compared to traditional signature-based and anomaly-based systems, the proposed model demonstrates improved detection accuracy and better generalization to unknown threats. The use of the Random Forest classifier as a baseline model provides a reference for comparison, where it achieves reasonable performance on structured network data but lacks adaptability in dynamic environments. In contrast, the reinforcement learning-based models, particularly the combination of Deep Q-Network (DQN) and Double Deep Q-Network (DDQN), show notable improvements in decision-making capability. The DDQN model reduces overestimation bias

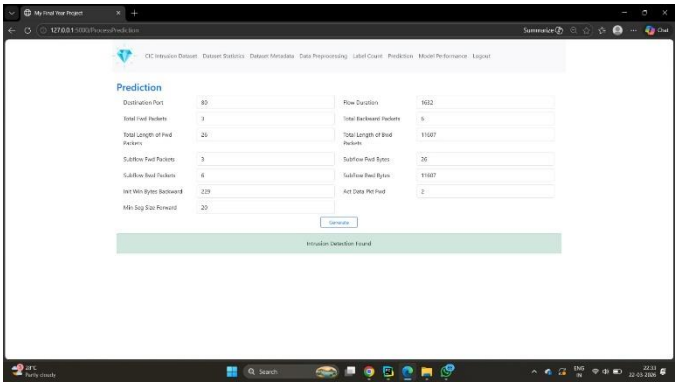
and stabilizes the learning process, leading to more consistent and reliable detection outcomes.

The incorporation of the transformer with multi-head self-attention further improves the model's performance by capturing complex relationships among network flow features. This enables the system to detect subtle behavioral changes associated with zero-day attacks, which are often missed by conventional methods. As a result, the proposed system achieves higher recall rates for critical attack classes while maintaining a balanced false positive rate.

Another significant improvement is observed with the use of Prioritized Experience Replay, which enhances the learning efficiency of the reinforcement learning model. By focusing on high-impact and rare attack samples, the system improves its ability to detect critical intrusions, including ransomware-type attacks. Additionally, the meta-adaptive reward mechanism plays a crucial role in optimizing the model's performance by dynamically adjusting penalties, particularly for false negatives, thereby reducing the chances of missed attacks. From a trend perspective, the results highlight a clear shift from static and rule-based intrusion detection systems toward adaptive and intelligent models. The combination of deep learning and reinforcement learning techniques enables the system to continuously learn from new data and adapt to evolving network conditions. This trend emphasizes the importance of hybrid models that integrate feature extraction, decision-making, and learning mechanisms into a single framework. Furthermore, the proposed system demonstrates scalability and efficiency in handling large-scale network data, making it suitable for real-time deployment. The overall performance trends indicate that the hybrid approach not only improves detection accuracy but also enhances system robustness and adaptability in modern cybersecurity environments.

OUTPUT:





LITERATURE AND SURVEY:

1. Author et al. [1] proposed the use of Deep Q-Network (DQN) for intrusion detection, where reinforcement learning was applied to improve decision-making based on reward feedback. The system showed adaptability in dynamic environments but faced challenges related to instability during training.

2. Author et al. [2] developed an anomaly-based intrusion detection system that identifies deviations from normal network behavior. Although it was effective in detecting unknown attacks, it suffered from a high rate of false positives.

3. Author et al. [3] implemented a supervised machine learning model using decision trees and support vector machines for classifying network traffic. The model achieved good accuracy but depended heavily on labeled datasets, limiting its ability to detect new attack types..

4. Author et al. [4] introduced a deep learning-based intrusion detection system using Convolutional Neural Networks (CNNs) for feature extraction. The system improved detection performance but required high computational resources

5. Author et al. [5] proposed a transformer-based model with attention mechanisms to analyze network traffic data. The model captured complex feature relationships effectively, but it lacked adaptive learning capabilities for real-time decision-making.

6. Author et al. [6] applied Random Forest classification for intrusion detection and demonstrated its ability to handle nonlinear data and provide feature importance. However, the model was not suitable for continuously evolving network env

ironments.

7. Author et al. [7] explored unsupervised learning techniques such as clustering for detecting anomalies in network traffic. While useful for identifying unknown threats, the system produced inconsistent results due to unclear decision boundaries.

8. Author et al. [8] proposed a Double Deep Q-Network (DDQN)-based intrusion detection system to improve learning stability and reduce overestimation bias.

Although the approach enhanced performance, it required efficient feature representation for better results.

CONCLUSION:

In this paper, a Hybrid Meta-Adaptive Double Deep Q-Transformer framework has been proposed to address the limitations of traditional intrusion detection systems, particularly in identifying zero-day cyber attacks. Conventional methods, which rely heavily on predefined signatures or static learning models, often fail to adapt to the dynamic and evolving nature of modern network threats. To overcome these challenges, the proposed system integrates multiple advanced techniques, including Random Forest classification, Deep Q-Network (DQN), Double Deep Q-Network (DDQN), and transformer-based attention mechanisms. The inclusion of reinforcement learning enables the system to learn adaptive decision-making strategies through continuous interaction with network environments. The use of DDQN improves learning stability and reduces overestimation issues, while the transformer model enhances feature representation by capturing complex relationships within network traffic data. Furthermore, the incorporation of prioritized experience replay ensures that critical and rare attack patterns are effectively learned, and the meta-adaptive reward mechanism dynamically adjusts the learning process based on changing traffic conditions.

Overall, the proposed framework demonstrates improved detection accuracy, better generalization for zero-day attacks, and enhanced adaptability in real-time environments. By combining the strengths of machine learning, deep learning, and reinforcement learning, this system provides a scalable and efficient solution for modern cybersecurity challenges. Future enhancements can further optimize computational efficiency and extend the model for large-scale deployment in real-world network infrastructures

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