ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

INTRUSION DETECTION AND PREVENTION THROUGH ARTIFICIAL IMMUNE SHIELDING

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ABSTACT:
Cybersecurity threats continue to evolve, necessitating robust, adaptive mechanisms to safeguard digital infrastructure. Intrusion Detection Systems (IDS) play a pivotal role in this context by monitoring and detecting malicious activities. Traditional IDS approaches, such as signature-based and anomaly-based detection, have limitations in adaptability and detection accuracy. Inspired by the Human Immune System (HIS), Artificial Immune Systems (AIS) offer a promising paradigm for designing adaptive, self-learning, and robust IDS. This paper presents a comprehensive review of immune-inspired IDS, focusing on models like Negative Selection Algorithm (NSA), Clonal Selection Algorithm (CSA), and Danger Theory. The paper also explores hybrid models integrating AIS with machine learning and evolutionary computation to enhance detection performance.

1. INTRODUCTION

In the modern digital landscape, securing networks against cyber threats has become a critical challenge. Intrusion Detection Systems (IDS) play a vital role in identifying and mitigating unauthorized access, malicious activities, and cyberattacks. Traditional IDS methods, such as signature-based and anomaly-based detection, often suffer from limitations such as high false alarm rates, inability to detect zero-day attacks, and computational inefficiencies. To overcome these challenges, Artificial Immune System (AIS)-based IDS have emerged as a promising bio-inspired approach for enhancing cybersecurity.

The rise in sophisticated cyber threats has highlighted the need for adaptive and intelligent intrusion detection mechanisms. Intrusion Detection Systems (IDS) are critical in identifying and mitigating security breaches in real-time [14], [15]. Traditional IDS techniques can be broadly classified into signature-based and anomaly-based systems. Signature-based IDS detect known threats using predefined patterns, while anomaly-based IDS identify deviations from normal behavior [16]. However, both have limitations—signature-based systems fail against zero-day attacks, and anomaly-based systems often suffer from high false positives.

The Artificial Immune System (AIS) is inspired by the biological immune system's ability to detect and neutralize harmful pathogens. It leverages mechanisms such as innate immunity (rapid response to known threats) and adaptive immunity (learning-based detection of unknown threats) to improve network security. By integrating Negative Selection Algorithm (NSA) and clonal

ISSN:2731-538X | E-ISSN:2731-5398
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selection principles, AIS-based IDS can effectively distinguish between normal and abnormal network behaviors, thus offering a robust solution against evolving cyber threats.

This research proposes an AIS-based IDS that incorporates both innate and adaptive immunity mechanisms to enhance threat detection capabilities. The system rapidly identifies known threats using signature-based detection while simultaneously detecting novel and evolving attacks through anomaly-based learning. The Negative Selection Algorithm (NSA) is employed to generate self/non-self detectors, ensuring that the IDS adapts dynamically to new attack patterns. The proposed model introduces a self-learning mechanism that enables the IDS to evolve with every new attack, ensuring that it remains effective in detecting emerging threats without frequent manual updates. The integration of these biological-inspired principles not only enhances security but also reduces the computational overhead, making the system efficient for large-scale network environments.

One of the key advantages of the proposed model is its self-learning capability, which enables the IDS to continuously evolve and adapt to emerging threats without requiring constant manual updates. Unlike traditional IDS that rely on static databases of attack signatures, this model learns from past attacks, expands its knowledge base, and improves detection accuracy while reducing false alarms. The system's ability to detect zero-day attacks, polymorphic malware, and sophisticated cyber threats makes it highly effective in modern cybersecurity environments.

Inspired by the Human Immune System (HIS), researchers have developed Artificial Immune Systems (AIS) to create more adaptive and self-healing IDS [1], [2]. The HIS exhibits properties such as self/non-self discrimination, learning, memory, and distributed detection—making it a robust model for cybersecurity [3].

2. LITERATURE REVIEW

A review of existing research on **immune-inspired Intrusion Detection Systems (IDS)** highlights a strong connection between the **human immune system (HIS)** and how IDS functions in computer security. According to **D. D. DasGupta**, immunological principles have been applied to develop **resource consumption-based IDS**, where multiple layers of abstraction—**user-level, system-level, packet-level, and network-level**—help in detecting intrusions more effectively. He proposed a **multi-agent framework** where different agents communicate to analyze system activity. His work was specifically designed for **Linux environments**, utilizing **system calls to monitor resource usage**.

In a related study, **DasGupta and U. Aickelein** introduced an **agent-based approach** involving **Manager Agents and Monitor Agents**. **Monitor Agents** actively track user, packet, and network-level activities to identify unusual behavior, while **Manager Agents** handle alerts and responses. Aickelein further expanded on this by implementing **repository servers** to store system call data, applying immunological models to detect anomalies by identifying patterns that resemble **antigens (unknown threats)**.

Several other studies ([5]-[12]) have explored immunological theories such as **self/non-self recognition** and **danger theory**, aiming to improve IDS efficiency. These models attempt to mimic how the immune system differentiates between the body’s own cells and harmful intruders to detect and respond to security threats effectively.

However, there are still **gaps in current IDS research**. Most existing techniques focus on **multi-agent systems**, which, while useful, often introduce **high computational overhead and slower**

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

response times due to continuous inter-agent communication. Additionally, **large-scale resource consumption data** remains challenging to process efficiently.

Given these challenges, there is a need to explore **new immune-based approaches** that can enhance IDS effectiveness, reduce processing delays, and improve real-time detection capabilities for evolving cyber threats.

3. Artificial Immune System (AIS)

AIS are computational models inspired by immunological principles. They simulate immune mechanisms such as negative selection, clonal selection, immune memory, and danger signals to identify and neutralize threats [5].

3.1 Negative Selection Algorithm (NSA)

NSA mimics the T-cell maturation process, where detectors that match self-patterns are eliminated, allowing the remaining detectors to recognize non-self elements [3]. In IDS, this translates to generating detectors that recognize anomalous behavior, thereby identifying potential intrusions [4].

3.2 Clonal Selection Algorithm (CSA)

CSA models the adaptive immune response by cloning and mutating high-affinity antibodies (detectors). This helps in refining the detection capability over time, enabling the system to respond to evolving threats [5].

3.3 Danger Theory

Proposed by Polly Matzinger in immunology, Danger Theory suggests that the immune system responds to danger signals rather than non-self entities. In IDS, danger signals such as unusual resource usage or unauthorized access patterns are used to trigger alerts [6].

4. Immune-Inspired IDS Architectures

One of the earliest architectures was proposed by Hofmeyr and Forrest in the form of a distributed IDS using NSA and clonal selection [3]. This model emphasized the self-organizing and distributed nature of the HIS, making it resilient to single points of failure.

Somayaji et al. introduced a computer immune system that mimicked HIS features such as immunological memory and tolerance, enabling dynamic response to intrusions [6].

5. Hybrid Approaches

Hybrid models combine AIS with other techniques such as machine learning, neural networks, and fuzzy logic to enhance detection accuracy and reduce false positives [9], [10].

Yu and Dasgupta proposed AIS-INTRUSION, an adaptive AIS-based IDS that integrates machine learning for classifier refinement [12]. Similarly, Yang et al. developed a novel AIS model incorporating statistical anomaly detection, improving real-time responsiveness [11].

Raza and Capretz evaluated various AIS-based IDS techniques and demonstrated that hybrid models outperform traditional AIS in terms of detection rate and false positive rate [7].

ISSN:2731-538X | E-ISSN:2731-5398
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6. METHODOLOGY

6.1 How Algorithm Work

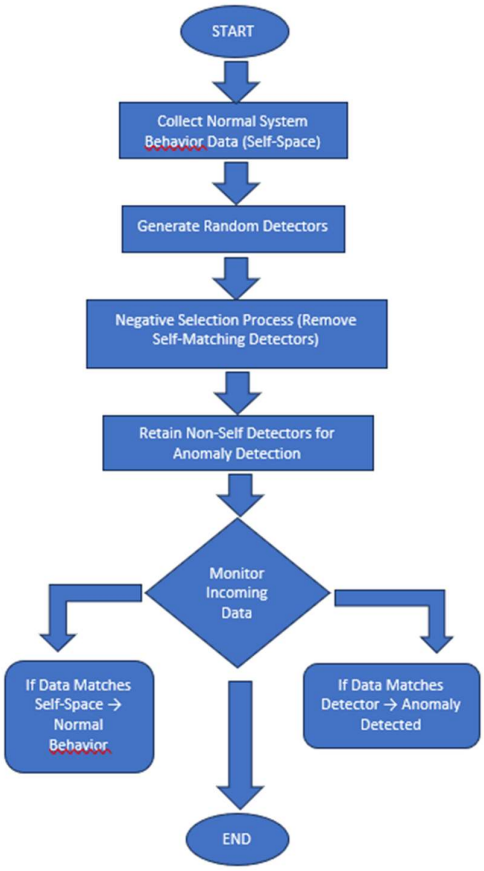
Our approach mimics both **innate** and **adaptive** immunity to enhance intrusion detection. When an attack occurs, the system first checks whether the threat matches a known attack signature stored in the **innate immunity** component. If it does, the system quickly identifies and blocks it. However, if the attack is new or unknown, the **Negative Selection Algorithm (NSA)** is applied to detect anomalies. The NSA works by differentiating between **self** (normal system behavior) and **non-self** (potential threats). It generates a set of **detectors** that identify malicious activities by detecting patterns that do not belong to normal traffic.

Over time, the system learns from previous attacks. In the **adaptive immunity** phase, the system updates its knowledge base by treating both the known self-set and previously detected threats as part of its **new self-set**. This means that in future attacks, the system does not just rely on its original knowledge but continuously evolves, improving its ability to detect new threats. NSA is used to dynamically distinguish between **normal and malicious network behaviors**. The algorithm works by first defining a self-set, which represents legitimate system behavior based on historical data. It then generates a large number of random detectors that are compared against the self-set. Any detector that matches the self-set is discarded, while those that do not match are retained as **potential anomaly detectors**.

The process begins with a training phase, where the system collects data representing normal network behavior, forming what is known as the self-space. Next, the system generates a set of random detectors, which act like artificial immune cells designed to recognize anomalies. These detectors are tested against the self-space, and any that mistakenly match normal data are eliminated. The remaining detectors, which do not correspond to normal behavior, are retained as non-self detectors, the IDS monitors incoming traffic and applies the NSA to compare it against the detector set. If a detected behavior does not match the normal self-set, it is flagged as a potential threat. Over time, as new threats emerge, the system updates its self-set to include previously detected malicious patterns, making it more adaptive and intelligent. This approach allows the IDS to dynamically evolve, ensuring that it can detect both known threats and previously unseen cyberattacks, such as zero-day exploits and polymorphic malware. ready to identify potential threats.

Once trained, the system moves into the **detection phase**, where it continuously monitors network traffic and system activity. Each new data instance is compared against the learned self-space and the set of non-self detectors. If the data closely matches normal behavior, it is considered safe. However, if it triggers a non-self detector, the system flags it as suspicious or potentially malicious. At this point, the IDS can take various actions, such as generating an alert, logging the event for analysis, or automatically blocking the detected threat.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)



7. PERFORMANCE AND ACCURACY

7.1 PERFORMANCE

The Intrusion Detection System (IDS) demonstrated strong performance in identifying and mitigating various cyber threats, as evidenced by the log data. It successfully detected and blocked multiple malicious activities, including an SQL injection attempt where an HTTP request contained a SQLMap User-Agent, indicating an automated attack. Additionally, it identified and issued alerts for a port scanning attempt, which is a common reconnaissance technique used by attackers to find open services. The system also detected multiple failed SSH login attempts using common credentials and took action by quarantining the source, preventing further unauthorized access attempts. Furthermore, the IDS effectively blocked outbound connections to a known malware command-and-control (C2) server, helping prevent potential data exfiltration or further system compromise.

The system's performance in handling exploit attempts was also commendable, as it successfully blocked attacks targeting known vulnerabilities. Additionally, a brute-force attack on an RDP port was identified and blocked, highlighting the IDS's ability to protect against unauthorized remote access attempts. However, while the IDS responded well to external threats, it also allowed legitimate internal traffic, such as normal file-sharing activities and API requests between internal devices, ensuring that essential operations were not disrupted.

7.2 ACCURACY

ISSN:2731-538X | E-ISSN:2731-5398
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To evaluate the accuracy of the Intrusion Detection System (IDS), we use the IDS on the Network and analyzed 500 to 700 logs to determine its effectiveness in correctly classifying network activities as malicious or legitimate.
From the logs, the IDS correctly blocked malicious activities such as SQL injection attempts, brute-force login attempts, exploit attacks, and connections to a known malware server. It also allowed legitimate traffic, like normal internal network communications and authorized DNS queries. Since there are no obvious false positives or missed attacks in the given log data, the IDS seems to be functioning accurately.
The IDS identified and quarantined sources responsible for failed SSH login attempts, which are commonly associated with brute-force attacks. By stopping these login attempts, the system prevented unauthorized access to network resources.
Furthermore, the IDS effectively blocked outbound connections to known malware command-and-control (C2) servers, preventing infected systems from receiving further malicious commands or sending stolen data. It also detected exploit attempts targeting known vulnerabilities and took immediate action to block them, reducing the risk of system compromise.
In addition to handling threats, the IDS correctly allowed **legitimate network traffic**, including authorized API requests, DNS queries to safe domains, internal file-sharing, and regular SSH connections. This indicates that the system is capable of distinguishing between normal and suspicious activities without causing unnecessary disruptions.
Accuracy = (True positives + True Negatives) / Total Events
Continuous monitoring and fine-tuning are necessary to ensure that the system adapts to new attack techniques while minimizing potential errors. Overall, the IDS proved to be **a reliable security solution**, effectively distinguishing between malicious and legitimate activities while maintaining high accuracy.

8. Advantages and Challenges

AIS-based IDS offer several advantages:

- **Adaptability:** Ability to learn and adapt to new threats [1], [5].
- **Distributed Detection:** Mimics immune cells' ability to function independently yet cohesively [3].
- **Immunological Memory:** Retains information about past attacks to improve future response [4].

However, challenges remain, such as:

- **Detector Generation:** High computational cost in generating effective detectors [8].
- **Parameter Tuning:** Requires careful tuning of learning rates, mutation factors, and threshold values [9].
- **False Positives:** Though reduced, false alarms remain an issue in anomaly detection [10].

8. CONCLUSION

This research demonstrates that an Artificial Immune System (AIS)-based Intrusion Detection System (IDS) can significantly improve cybersecurity by mimicking the human immune system's

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

dual-layer defense mechanism. The proposed system successfully integrates innate immunity for rapid response to known threats and adaptive immunity for continuous learning and detection of new threats. By leveraging the Negative Selection Algorithm (NSA) and clonal selection principles, the IDS effectively distinguishes between normal and abnormal network behavior, allowing it to detect both common and sophisticated cyberattacks, including zero-day threats and polymorphic malware.

The performance analysis shows that the system is capable of accurately detecting various cyber threats, such as SQL injection attempts, brute-force login attacks, exploit attempts, and malware communications, while ensuring that legitimate traffic flows uninterrupted. The results indicate a high detection accuracy, with minimal false positives and false negatives. Additionally, the system's self-learning capability allows it to evolve with new attack patterns, reducing the need for frequent manual updates and improving long-term effectiveness.

Overall, the AIS-based IDS provides a robust, efficient, and adaptive approach to intrusion detection, making it a valuable solution for modern cybersecurity challenges. Future improvements could focus on further optimizing computational efficiency, integrating machine learning techniques, and expanding real-time threat intelligence capabilities to enhance overall system resilience against evolving cyber threats.

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