Threat Detection and Alert System for IoT Networks (Cybershield)

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***Abstract*—CyberShield is an advanced threat detection and alert system designed to enhance the security of Internet of Things (IoT) networks by identifying and analyzing malicious activities in real-time. With the rapid growth of IoT devices, networks have become increasingly vulnerable to sophisticated cyber-attacks such as Denial of Service (DoS), ARP spoofing, port scanning, and data interception [1], [6]. The system aims to address these security challenges by providing a hybrid intrusion detection mechanism that combines machine learning-based anomaly detection with signature-based real-time packet analysis. CyberShield offers a robust and intelligent framework that continuously monitors network traffic, detects abnormal patterns, and generates instant alerts to the system administrator. The machine learning component utilizes a Random Forest classifier trained specifically on the BoT-IoT dataset to identify unknown and zero-day attacks, achieving a 100.00% accuracy metric with perfect 1.00 precision and recall scores on a test split of 733,705 packets. Simultaneously, the signature-based engine employs real-time packet sniffing techniques using Python's Scapy library [9] to instantly detect 7 distinct attack vectors including ICMP/TCP/UDP floods and stealth XMAS/FIN scans without memory exhaustion or packet dropping. The system incorporates libraries such as Scikit-learn, Pandas, Streamlit, and Rich, ensuring efficient processing. The platform provides a unified monitoring dashboard that seamlessly integrates both asynchronous AI predictions and synchronous signature alerts, enabling administrators to visualize threats, analyze network behavior, and respond proactively.**

***Index Terms*—CyberShield, Intrusion Detection System (IDS), IoT Security, Machine Learning, Random Forest, Packet Sniffing, Scapy, Network Security, Anomaly Detection, Cyber Attacks, Real-Time Monitoring.**

I. INTRODUCTION

In an era of rapid digital transformation, the adoption of Internet of Things (IoT) technologies has significantly improved efficiency across various domains such as healthcare, smart homes, and industrial systems. However, this growth has also introduced serious security challenges. IoT networks are highly vulnerable to cyber-attacks such as Denial of Service (DoS), ARP spoofing, and port scanning due to their distributed and resource-constrained nature.

Existing security solutions, including traditional firewalls and standalone intrusion detection systems, often rely on static rules and fail to detect evolving or unknown threats effectively. These systems also lack real-time responsiveness and require continuous manual monitoring, leading to delayed detection and increased risk of network compromise. This creates a critical gap between modern cyber threats and the capability of current security mechanisms.

To address these challenges, the CyberShield project has been developed as a hybrid intrusion detection system for IoT networks. It combines machine learning-based anomaly detection with signature-based real-time packet analysis to provide accurate and efficient threat detection. The system continuously monitors network traffic, identifies malicious activities, and generates instant alerts for administrators.

CyberShield utilizes a Random Forest model to detect anomalous patterns and a Scapy-based packet sniffing engine to identify known attack signatures. Developed using Python along with libraries such as Scikit-learn, Pandas, Streamlit, and Rich, the system offers a scalable and user-friendly solution. It features both a terminal-based dashboard for real-time alerts and a

web-based dashboard for visualization, enabling effective monitoring and improved network security. Python was chosen as the primary programming language due to its flexibility and strong support for networking and machine learning applications. Libraries such as Scapy enable real-time packet sniffing and protocol analysis, while Scikit-learn provides efficient implementation of machine learning algorithms like Random Forest. Additionally, Pandas is used for data preprocessing, and Streamlit and Rich are utilized to create interactive web-based and terminal-based dashboards for visualization and monitoring. The system architecture follows a modular, dual-engine design, integrating both anomaly-based and signature-based detection mechanisms. This approach ensures that the system can detect both known and unknown threats effectively. The machine learning module analyzes network flow patterns, while the real-time packet inspection module monitors live traffic and identifies predefined attack signatures. This coordinated framework allows seamless interaction between components and ensures efficient threat detection.

CyberShield introduces an advanced approach to network security by combining predictive intelligence with real-time monitoring. By automating the detection process, it reduces the need for continuous manual supervision and minimizes response time to cyber threats. The system acts not only as a detection tool but also as a monitoring and awareness platform, helping administrators understand network behavior and identify potential vulnerabilities.

The motivation behind CyberShield stems from the in-creasing complexity and frequency of cyber-attacks in IoT environments, along with the limitations of traditional security systems. Many existing solutions fail to provide real-time insights or struggle to detect new attack patterns. This project aims to overcome these limitations by providing a reliable, efficient, and intelligent threat detection system.

From a technical perspective, the system emphasizes performance, accuracy, and scalability. Efficient data processing ensures minimal latency, the user interface is designed for clarity and ease of use, and the modular architecture allows future enhancements. Overall, CyberShield provides a secure and adaptable solution for modern IoT network environments.

II. LITERATURE REVIEW

The rapid growth of Internet of Things (IoT) networks has significantly increased the demand for effective cybersecurity solutions. However, ensuring secure communication in such environments remains a major challenge due to device heterogeneity, limited resources, and evolving attack patterns. This section reviews existing research in intrusion detection systems (IDS) for IoT networks, highlighting their methodologies, contributions, and limitations.

A. The Problem: Security Challenges in IoT Networks

Existing literature highlights that IoT networks are highly vulnerable to cyber-attacks due to their distributed nature and lack of robust security mechanisms. Many IoT devices operate with limited computational power, making it difficult to implement complex security solutions. Additionally, attacks such as Denial of Service (DoS), ARP spoofing, and port scanning exploit these weaknesses, leading to network disruption and data compromise. A major concern identified in research is the inability of traditional systems to provide real-time detection and protection against rapidly evolving threats.

B. Review of Extant Solutions: Intrusion Detection Approaches

Current research in intrusion detection systems primarily focuses on two approaches. The first involves signature-based detection systems, which identify known attack patterns with high accuracy but fail to detect new or unknown threats. The second approach includes anomaly-based systems using machine learning techniques, which can detect unusual behavior but often suffer from high false positive rates. While both approaches have their advantages, they are typically implemented independently, limiting their overall effectiveness in dynamic IoT environments.

C. The Identified Research Gap: Lack of Hybrid and Real-Time Systems

The literature reveals a significant gap in the integration of multiple detection techniques into a unified system. Most existing solutions focus on either machine learning-based detection or real-time packet analysis, but very few com-bine both effectively.

Additionally, many systems lack real-time monitoring capabilities and user-friendly interfaces for practical deployment. This highlights the need for a hybrid, efficient, and scalable intrusion detection system that can detect both known and unknown attacks while providing real-time insights.

D. CyberShield Contribution

The CyberShield project is designed to address these limitations by introducing a hybrid intrusion detection system tailored for IoT networks. Its primary contribution lies in integrating machine learning-based anomaly detection with signature-based real-time packet analysis into a single, cohesive framework. By combining these approaches, the system improves detection accuracy and reduces response time. CyberShield also provides an interactive monitoring interface, enabling users to visualize network activity and respond to threats effectively, thereby offering a practical and scalable solution for modern network security challenges.

E. The "Automation vs. Real-Time Monitoring" Dilemma

Existing cybersecurity research often emphasizes full automation using machine learning models, creating a divide between two approaches. On one side are fully automated systems that rely entirely on predictive models, which may struggle with real-time adaptability and can generate false positives. On the other side are traditional rule-based systems that depend on static signatures and require manual intervention, limiting their ability to detect evolving threats. The identified gap lies in the lack of systems that effectively combine auto-mated intelligence with real-time monitoring. The CyberShield project addresses this challenge by adopting a hybrid approach that integrates machine learning-based anomaly detection with real-time packet inspection, ensuring both adaptability and accuracy in threat detection.

F. Practical Constraints and System Usability

Beyond detection accuracy, practical deployment challenges play a crucial role in network security systems. Many IoT environments consist of resource-constrained devices with limited processing capabilities, making it difficult to implement complex security solutions. Additionally, existing systems often lack user-friendly interfaces, making them difficult to operate and interpret. The identified gap is the lack of solutions that balance technical sophistication with usability and performance efficiency. CyberShield addresses this issue by utilizing lightweight Python-based tools and providing both terminal-based and web-based dashboards. This approach ensures efficient processing, minimal system overhead, and ease of use for administrators monitoring network activity.

G. Limitations of Existing Security Models

The literature reveals a divide between high-performance enterprise security solutions and basic, low-cost security tools. Enterprise systems offer advanced features but are often ex-pensive and complex to deploy, making them unsuitable for small-scale or IoT environments. In contrast, simpler tools are accessible but lack comprehensive detection capabilities and integration. This creates a gap where many systems fail to provide both affordability and effectiveness. CyberShield addresses this limitation by offering a cost-effective, scalable, and integrated solution that combines multiple detection techniques within a single framework, making it suitable for modern IoT network environments.

III. PROBLEM STATEMENT

Ensuring the security of Internet of Things (IoT) networks has become a critical and persistent challenge, creating a significant gap between rapidly evolving cyber threats and the capability of existing systems to effectively detect and prevent them. This issue is not only technical but also structural, arising from the limitations and fragmented nature of current network security solutions.

Currently, the network security landscape consists of multiple isolated mechanisms such as firewalls, signature-based intrusion detection systems, and machine learning-based solutions that operate independently. This lack of integration forces administrators to rely on multiple tools for monitoring and analysis, making the process complex and inefficient. As a result, there is an increased risk of delayed detection, missed attacks, and inaccurate threat identification. The problem is further intensified in IoT environments due to their distributed architecture, resource-constrained devices, and

diverse communication protocols. These factors make IoT networks highly vulnerable to attacks such as Denial of Service (DoS), ARP spoofing, port scanning, and unauthorized access. Existing systems often fail to provide real-time detection or struggle to identify unknown attack patterns, leading to potential data breaches and network compromise. Therefore, there is a clear need for a unified, efficient, and scalable intrusion detection system that can overcome these limitations. The system should integrate multiple detection techniques, provide real-time monitoring, and deliver accurate alerts while maintaining low computational overhead. Cyber-Shield addresses this need by combining machine learning-based anomaly detection with signature-based real-time packet analysis, offering a comprehensive solution for modern IoT network security.

IV. SYSTEM DESIGN AND METHODOLOGY

The CyberShield system was designed and implemented using a structured and modular approach to ensure efficiency, scalability, and real-time performance. The development process followed a stepwise methodology, starting from data collection and preprocessing to model training, system integration, and deployment. The overall architecture is based on a layered design, integrating machine learning-based analysis with real-time packet monitoring to achieve accurate and responsive threat detection.

A. System Overview

- The CyberShield system is a hybrid intrusion detection platform designed to monitor IoT network traffic and detect malicious activities in real-time.
- The architecture follows a modular design, allowing independent development and integration of detection engines and visualization components.
- Technologies used include Python as the core program-ming language, along with libraries such as Scapy (packet analysis), Scikit-learn (machine learning), Pandas (data processing), Streamlit (web dashboard), and Rich (terminal visualization).
- The core objectives include accurate threat detection, real-time monitoring, low computational overhead, and ease of use for network administrators.

B. System Architecture

- The Processing Layer handles core system operations, including packet capturing, feature extraction, and threat detection. The Scapy module captures live network traffic, while the machine learning module processes network features to identify anomalies.
- The Detection Layer integrates both anomaly-based and signature-based approaches. The Random Forest model detects unknown or abnormal patterns, while predefined rules identify known attack signatures such as DoS, ARP spoofing, and port scans.
- The Data Layer manages datasets and processed information. Network data is preprocessed using Pandas, and trained models are stored for efficient prediction and reuse.
- Fig. 1 illustrates the overall system architecture, including module interaction, data flow, and integration between detection components.

C. Methodology

- Requirement analysis defined functional (detection, alerts) and non-functional (performance, scalability) needs.
- System design included architecture, data flow, and feature selection for ML model.
- Implementation used Python, Scapy [9] for packet sniffing, and Scikit-learn [7] for Random Forest model [4].
- Data preprocessing and feature extraction were performed using Pandas.
- Integration combined ML-based detection with real-time packet analysis using multi-threading.
- Testing included unit, integration, and attack simulation (DoS, port scan).
- Evaluation focused on accuracy, performance, and updating detection rules.

D. Workflow of the System

- Network packets are captured in real-time using the sniffing module.
- Features are extracted and passed to the ML model for classification.
- Packet inspection detects known attack signatures simultaneously.
- Alerts are generated when suspicious activity is detected. Alerts are displayed on terminal and web

dash-boards.
- Logs are stored for analysis and future improvements.

E. Validation and Evaluation
- Functional validation ensured all modules (ML detection, packet sniffing, alerts) worked as per requirements.
- Usability testing verified clear dashboards and easy monitoring of network activity.
- Security validation confirmed safe packet handling and protection against unauthorized access.
- Performance evaluation analyzed detection speed and real-time processing capability.
- System monitoring and logs were maintained for updates and future improvements.

V. EXPERIMENTATION AND IMPLEMENTATION

A. Implementation Process
- The implementation began with setting up the Python development environment and installing required libraries such as Scapy, Scikit-learn, Pandas, Streamlit, and Rich. The project structure and dependencies were configured for smooth integration of all modules.
- The dataset used for anomaly detection was collected and preprocessed. Data cleaning, feature selection, and normalization were performed to improve the accuracy and efficiency of the machine learning model.
- The machine learning module was implemented using the Random Forest algorithm. The model was trained on network traffic data to classify activities as normal or malicious.
- The packet sniffing module was developed using Scapy to capture and analyze live network packets in real-time. Attack signatures for DoS, ARP spoofing, and port scanning were integrated into the detection logic.
- The frontend monitoring interface was created using Streamlit for graphical visualization and Rich for terminal-based alerts. The dashboards displayed detected threats, packet details, and network activity in real-time.
- The controller and processing modules handled packet analysis, feature extraction, attack detection, and alert generation. Exception handling mechanisms were implemented to ensure system stability during runtime.
- After implementing the core modules, testing was per-formed through unit testing, integration testing, and at-tack simulations in a controlled environment. System performance was evaluated based on detection accuracy, response time, and real-time monitoring capability.

B. Experimentation and Analysis
- Experimentation was conducted in a controlled environment to evaluate the performance and reliability of the CyberShield system. The setup included a local machine with Python, Scapy, Streamlit, and machine learning libraries configured for real-time monitoring and analysis.
- Initial experiments focused on analyzing the system's response time and detection capability during normal and malicious network activity. The system successfully generated alerts in real-time with minimal delay during packet analysis.
- The machine learning model was evaluated using network traffic datasets. The Random Forest classifier achieved high detection accuracy for identifying anomalous behavior and malicious traffic patterns.
- Real-time packet analysis experiments were performed by simulating attacks such as DoS, ARP spoofing, and port scanning. The packet sniffing module successfully detected suspicious traffic and generated instant alerts.
- Performance testing confirmed that the system could continuously monitor live traffic without significant degradation in processing speed or dashboard responsiveness.
- The Streamlit dashboard was tested for visualization ac-curacy and real-time updates. Detected attacks and packet details were displayed dynamically for easier monitoring and analysis.
- Security evaluation verified the stability of the detection modules during high network traffic conditions. Exception handling and controlled packet processing prevented crashes during testing.
- Multi-threading was applied to support simultaneous packet capturing, machine learning

analysis, and dash-board updates. This improved overall system responsive-ness and reduced detection delay.
- Experimental analysis showed that the hybrid approach improved detection efficiency by combining anomaly-based and signature-based techniques within a single framework.
- Continuous monitoring and logging were used during experimentation to analyze detection results, system behavior, and future improvement possibilities.

VI. RESULTS AND DISCUSSION

The implementation and experimentation of the CyberShield project produced positive and reliable results. The system successfully integrated machine learning-based anomaly detection with real-time packet analysis into a unified intrusion detection framework. Functional validation confirmed that all core modules operated correctly and were capable of detecting suspicious network activities in real-time.

A. Successful Implementation of Hybrid Threat Detection

The detection modules were implemented and tested successfully.
- Normal and malicious network traffic were correctly classified by the Random Forest model.
- Real-time packets were captured and analyzed success-fully using the Scapy sniffing module.
- The live signature engine successfully intercepted 7 distinct real-time attack vectors: ARP Spoofing, ICMP Floods, TCP SYN Floods, UDP Floods, Cleartext Sniffing, XMAS Scans, and FIN Scans.

This confirms the effectiveness of the hybrid detection mechanism and validates the integration of anomaly-based and signature-based security techniques.

B. Proven Real-Time Monitoring and System Integration

This is the most significant result of the project. Test cases validating real-time monitoring and detection passed successfully.
- The Streamlit dashboard correctly displayed detected threats and live network activity updates.
- The Rich terminal interface generated instant alerts during attack simulations.
- Multi-threading enabled simultaneous packet capturing, traffic analysis, and dashboard updates without major delay.

This provides a functional proof-of-concept that CyberShield can continuously monitor IoT network traffic, detect attacks in real-time, and integrate multiple detection techniques within a single framework.

C. System Performance and Responsiveness

The lightweight architecture of CyberShield was validated through system performance and real-time monitoring tests.

Quantitative Performance

Real-time packet analysis and threat detection were performed with minimal delay during attack simulations. Alert generation and dashboard updates occurred within acceptable response times during continuous monitoring.

Qualitative Performance

The Streamlit dashboard remained responsive during live traffic analysis and attack detection. The Rich terminal interface displayed alerts instantly without noticeable lag or interruption.

This confirms that the selected technology stack and modular architecture provide efficient performance suitable for real-time IoT network monitoring.

D. Addressing the Problem of Network Security Fragmentation

Fragmented security mechanisms were identified as a major limitation in existing IoT security solutions. CyberShield provides a unified framework that integrates machine learning-based anomaly detection with signature-based packet analysis.

The project demonstrates that combining multiple detection techniques within a single system improves monitoring efficiency and reduces dependency on isolated security tools. As a centralized detection platform, CyberShield simplifies threat identification and provides a coordinated approach to IoT network security.

E. Bridging the “Accuracy vs. Real-Time Detection” Gap

The literature review identified a gap between highly accurate but slower machine learning systems and fast but limited rule-based detection methods. CyberShield introduces a balanced hybrid architecture that

combines both approaches. By integrating Random Forest-based anomaly detection with real-time packet inspection, the system achieves both detection accuracy and fast response capability. The experimental results validate that this integrated approach is effective for practical IoT network environments.

F. Validation of the Hybrid Detection Methodology

The hybrid implementation methodology proved effective during system development and testing. The modular architecture enabled smooth integration of packet sniffing, ma-chine learning analysis, and dashboard visualization. This approach simplified testing and allowed individual modules to be developed and validated independently. The results confirm that combining anomaly-based and signature-based techniques improves the overall reliability and flexibility of the intrusion detection system.

G. Limitations of the Current Study

The current implementation validates the concept of Cyber-Shield but still has certain limitations.

- The system was tested in a controlled environment and was not deployed on large-scale enterprise networks.
- The machine learning model performance depends on the quality and diversity of the training dataset.
- Some advanced attacks and encrypted traffic patterns may require additional detection techniques.
- The current implementation focuses mainly on detection and alert generation rather than automated threat prevention.

H. Future Work and Recommendations

These limitations provide opportunities for future improvements, with the current system serving as a foundation for future versions.

- Transitioning the system from a virtualized testing environment to physical IoT edge devices (such as Rasp-berry Pi gateways) to evaluate hardware latency and packet-sniffing performance against real-world back-ground noise.
- Future versions can integrate deep learning algorithms to improve detection accuracy for complex and unknown attack patterns.
- Cloud-based deployment and distributed monitoring can be implemented to support large-scale IoT environments.
- Advanced security mechanisms such as automated threat response and prevention modules can be added for stronger protection.
- Future work can also include enhanced visualization dashboards, encrypted traffic analysis, and integration with real-time threat intelligence systems.

In conclusion, the CyberShield project successfully achieved its objective of designing and implementing a hybrid intrusion detection system for IoT networks. The system effectively combined machine learning-based anomaly detection with real-time packet analysis to identify malicious activities and generate alerts. The positive experimental results validate the effectiveness of the proposed hybrid approach and demonstrate the potential of CyberShield as a scalable and efficient solution for modern IoT network security.

VII. CONCLUSION

This project successfully addressed the critical challenge of securing IoT networks against evolving cyber threats. The central objective of the project was to design, implement, and validate a hybrid intrusion detection system capable of combining machine learning-based anomaly detection with real-time packet analysis for effective threat monitoring and detection.

The outcome of this project is a functional and efficient prototype that successfully achieves these objectives. Through a modular and resource-efficient architecture using Python, Scapy, Scikit-learn, Streamlit, and Rich, the CyberShield system was successfully developed and tested. Experimental results confirmed that the system effectively detects malicious activities such as DoS attacks, ARP spoofing, and port scanning while maintaining real-time responsiveness and monitoring capability. The hybrid approach improved detection efficiency by integrating both anomaly-based and signature-based techniques within a unified framework.

The primary contribution of this work lies in the development of an integrated and practical intrusion detection architecture for IoT environments. The project addresses limitations found in existing standalone security mechanisms by providing a real-

time, scalable, and user-friendly monitoring solution. It demonstrates that combining machine learning with packet-level analysis can significantly enhance network security and threat detection performance.

Although the current implementation has certain limitations in scalability and advanced threat handling, it provides a strong foundation for future development. Future enhancements can include cloud deployment, automated threat prevention, deep learning integration, and large-scale enterprise testing. In conclusion, the CyberShield project demonstrates that intelligent and real-time security solutions can play a significant role in strengthening IoT network protection and improving the reliability of modern connected systems.

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