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An Intelligent System for DNS Spoofing Detection in Network Traffic

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ABSTRACT

DNS spoofing is a significant cybersecurity threat that compromises the integrity of domain name resolution and enables attacks such as phishing, identity theft, and data breaches. Traditional rule-based detection systems lack adaptability and fail to detect sophisticated and evolving spoofing attacks in real time. This paper proposes an intelligent AI-driven system for detecting DNS spoofing in live network traffic. The system integrates real-time packet capture, multi-level feature extraction, and supervised machine learning models such as Random Forest and XGBoost for classification. Key features including Time-To-Live (TTL), response time, domain entropy, and network attributes are analyzed to identify anomalies. The system employs automated decision logic to block or allow traffic based on spoofing probability. Experimental evaluation demonstrates a detection accuracy of 94.6% with reduced false positives and an average response time of 320 ms. The proposed system is lightweight, scalable, and suitable for deployment in enterprise and campus networks.

1. Introduction

The Domain Name System (DNS) plays a vital role in internet communication by mapping human-readable domain names to IP addresses. However, due to its inherently weak authentication mechanisms, DNS is highly susceptible to spoofing attacks [1]. DNS spoofing, also known as DNS cache poisoning, involves injecting forged DNS responses into the network, redirecting users to malicious websites without their knowledge. Such attacks can lead to severe consequences, including phishing, data breaches, financial fraud, and unauthorized access to sensitive information. As internet usage continues to grow, the impact of DNS spoofing has become more significant, affecting individuals, organizations, and government system [2][3]. Traditional defense mechanisms such as DNSSEC, firewalls, and signature-based intrusion detection systems attempt to mitigate these threats. However, these approaches face several limitations, including high deployment complexity, delayed detection, and inability to handle zero-day attacks. Furthermore, static rule-based systems generate high false positives and lack adaptability to evolving attack patterns [4].

To overcome these challenges, this research proposes an intelligent DNS spoofing detection system that leverages machine learning for real-time anomaly detection. By analyzing DNS traffic patterns and extracting meaningful features, the system can identify malicious activities and respond automatically [5].

Research Gap:

- Lack of real-time intelligent monitoring systems
- Inability of traditional methods to detect evolving attack patterns
- High false positives in rule-based detection
- Limited integration of multi-level feature analysis

Objective:

To design and implement a scalable, real-time DNS spoofing detection system using machine learning techniques that enhances detection accuracy and reduces response time

2. Literature Review

2.1 Evolution of DNS Spoofing Detection Techniques

DNS spoofing detection techniques have evolved significantly over time. Early methods relied on rule-based and signature-based systems, which were effective only for known attacks and failed to detect new threats [6]. The introduction of DNS Security Extensions (DNSSEC) improved security by validating DNS responses using cryptographic techniques, but its adoption remains limited due to complexity. Recently, machine learning approaches have been used to detect anomalies in DNS traffic by analyzing features such as TTL, response time, and query patterns. Models like Random Forest and Support Vector Machines provide better accuracy. Deep learning techniques further enhance detection but require high computational resources, limiting their use in real-time environments [7] [8].

2.2 Review of Existing Systems

Rule-based systems detect DNS spoofing using predefined rules but fail to identify unknown attacks and often produce high false positives [9]. DNSSEC provides data authenticity through cryptographic validation, but it does not analyze traffic behavior and is not widely implemented. Machine learning-based systems classify DNS traffic using features such as TTL and response time, improving detection accuracy [10] [11]. However, their performance depends on feature quality. Deep learning approaches detect complex patterns but are computationally expensive and less suitable for real-time use. Hybrid systems combine multiple techniques to improve performance, but many lack scalability and adaptability [12] [13].

2.3 Identified Research Gaps

Existing systems face several limitations, including lack of real-time detection, high false positives, limited adaptability, and high computational cost [14]. Additionally, many approaches do not fully utilize multi-level features, reducing accuracy. The proposed system addresses these issues by providing a real-time, AI-based detection framework with improved efficiency and scalability [15].

3. Proposed System

The proposed DNS spoofing detection system is designed as a modular, real-time framework that integrates traffic monitoring, feature extraction, machine learning classification, and automated response. As shown in Fig. 1, the system captures DNS traffic from the network and processes it through multiple coordinated components. The architecture consists of four major subsystems: (i) Traffic Capture Layer, (ii) Feature Extraction Layer, (iii) Machine Learning Classification Layer, and (iv) Decision and Monitoring Layer. DNS packets are captured in real time using packet sniffing techniques and forwarded for preprocessing. Relevant features such as Time-To-Live (TTL), response time, domain entropy, DNS flags, and network attributes are extracted and converted into structured feature vectors. These features are analyzed using supervised machine learning models such as Random Forest and XGBoost to determine the probability of spoofing. Based on the classification output, the system applies decision logic to block, warn, or allow DNS responses. The results are then displayed on a real-time dashboard and stored for further analysis. All outputs are logged and used for continuous model improvement through feedback-based retraining.

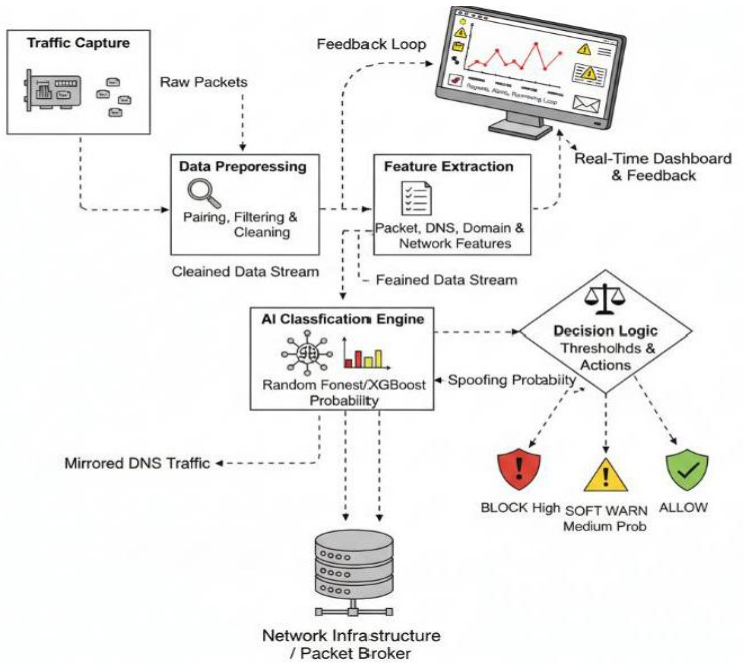

Fig. 1. System architecture of the DNS spoofing detection system

3.1 Traffic Capture Module

The Traffic Capture Module collects DNS packets from the network using tools such as Scapy. It filters traffic on UDP/TCP port 53 and extracts DNS queries and responses in real time. This module ensures continuous monitoring with minimal packet loss and prepares data for further analysis.

3.2 Feature Extraction Module

The Feature Extraction Module processes captured packets to generate meaningful attributes. It extracts multi-level features including packet-level (TTL, packet size, response time), DNS-level (query type, response codes, flags), domain-level (length, entropy), and network-level (IP reputation, ASN changes). These features are normalized and structured into feature vectors for classification.

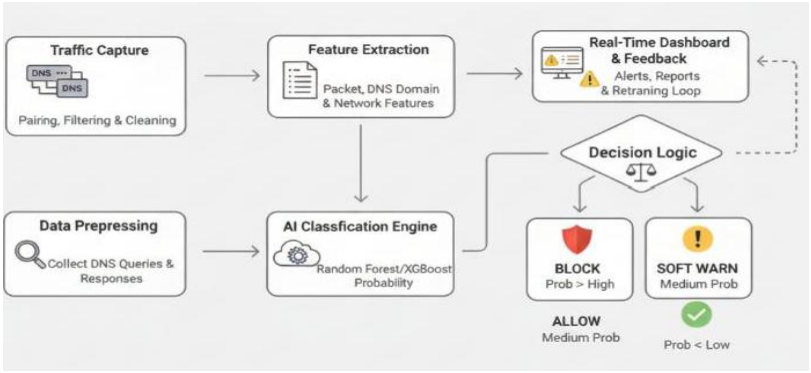

Fig.2. showing data flow from traffic capture to decision and monitoring layer

3.3 Machine Learning Module

The Machine Learning Module applies supervised learning algorithms such as Random Forest and XGBoost to classify DNS traffic. The model analyzes input features and outputs a spoofing probability score, enabling accurate detection of malicious responses. The model is periodically retrained using feedback data to improve performance.

3.4 Decision and Control Module

The Decision Module interprets the output of the classification model and applies predefined thresholds to determine appropriate actions. DNS responses are either blocked, flagged with warnings, or allowed based on spoofing probability. This module enables automated threat mitigation without manual intervention.

3.5 Monitoring and Dashboard Module

This module provides real-time visualization of DNS activity and detected threats. It displays alerts, logs, and performance metrics through a user-friendly interface, allowing administrators to monitor system behavior and respond to incidents effectively.

3.6 Alert and Logging Module

The Alert and Logging Module records all detected events, including suspicious DNS responses and classification results. Alerts are generated and sent through communication channels such as APIs or messaging systems. Logs are stored for auditing, analysis, and future model training.

3.7 Adaptive Learning Module

The Adaptive Learning Module improves system performance over time by incorporating feedback from detected events. It retrains the machine learning model using updated datasets, enabling the system to adapt to new and evolving spoofing techniques.

4. Results And Discussion

Experiments were conducted in a controlled network environment to evaluate the performance of the proposed DNS spoofing detection system. The system was implemented on a machine running Ubuntu 22.04 with Python 3.10, equipped with a quad-core processor and 8 GB RAM. Real-time DNS traffic was captured using packet sniffing tools, and both normal and spoofed DNS responses were included in the dataset for testing. The system operated with continuous packet monitoring and feature extraction to simulate real-world network conditions. The system interface and configuration parameters are illustrated in Fig. 3.

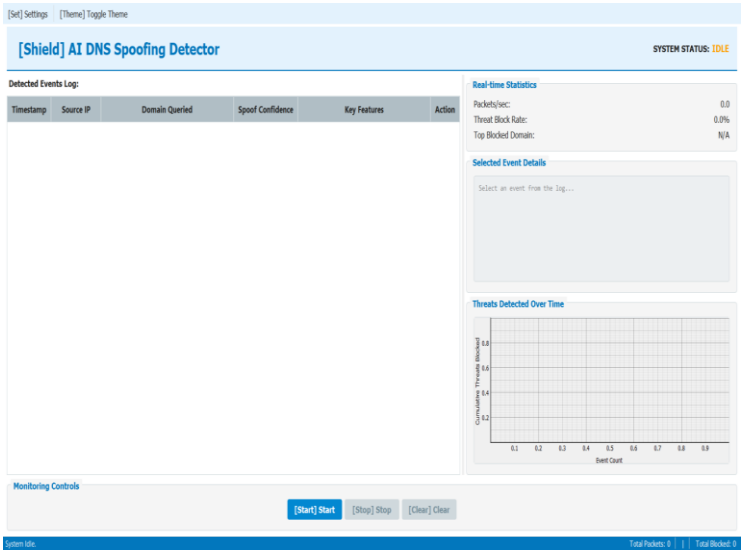

Fig. 3. System interface showing real-time DNS monitoring and configuration parameters

During testing with legitimate DNS traffic, the system accurately identified valid DNS responses with minimal false alerts. Features such as consistent Time-To-Live (TTL), normal response time, and expected domain behavior were correctly classified as safe. The system successfully allowed legitimate traffic to pass without interruption while maintaining continuous monitoring. The dashboard displayed real-time DNS activity, including resolved IP addresses, response status, and traffic patterns. The results confirm that the system maintains high accuracy while ensuring smooth network operation. The detailed output of normal traffic classification is shown in Fig. 4.

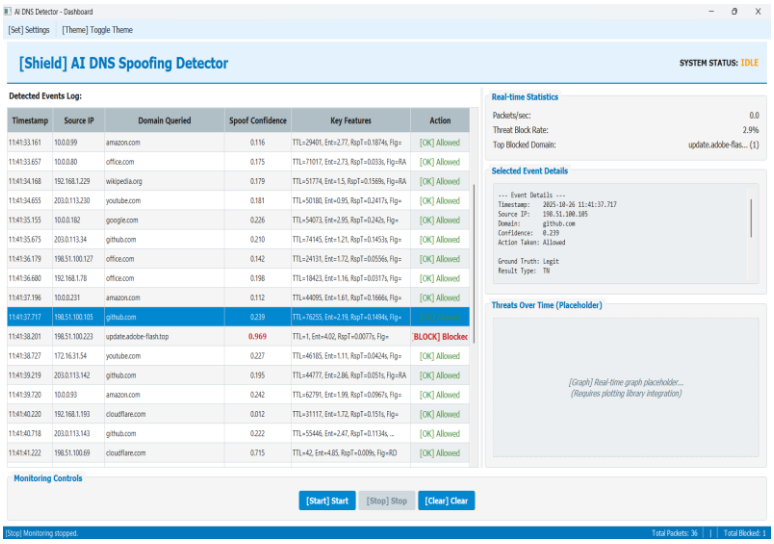

Fig. 4. Detection results for normal DNS traffic showing classification output and response details

For spoofed DNS scenarios, the system effectively detected anomalies in traffic patterns. Irregular TTL values, abnormal response times, and suspicious domain characteristics triggered high spoofing probability scores. The system successfully identified malicious DNS responses and applied automated actions such as blocking or issuing alerts. The detection system was able to identify multiple spoofing attempts in real time, preventing redirection to malicious destinations. Alerts were generated and displayed on the dashboard, providing clear visibility of detected threats. The detailed spoof detection results are illustrated in Fig. 5.

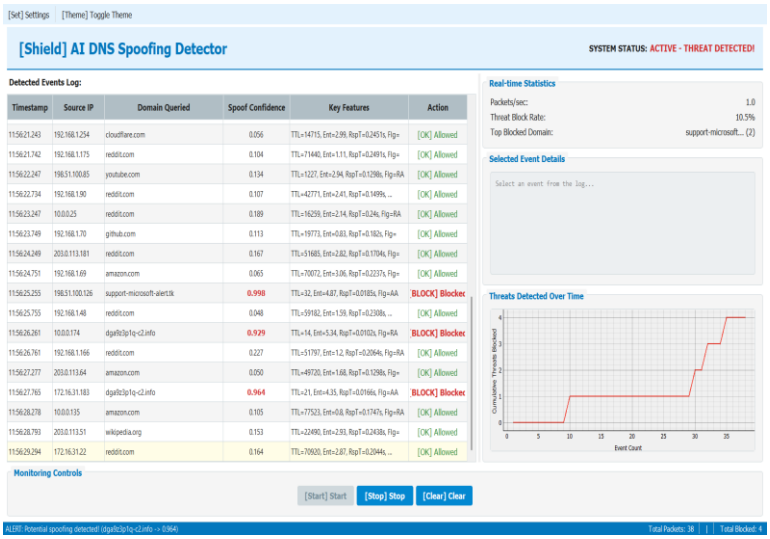

Fig. 5. Detection results for spoofed DNS traffic showing anomaly identification and alert generation

The proposed system demonstrated strong performance in terms of accuracy, speed, and efficiency. The machine learning model achieved a detection accuracy of 94.6% with a significant reduction in false positives compared to traditional rule-based systems. The average response time for detection was approximately 320 milliseconds, making it suitable for real-time deployment. Compared to conventional approaches, the system effectively avoids delays associated with manual analysis and static rule matching. The integration of multi-level feature extraction and machine learning classification improves detection accuracy while maintaining low

computational overhead. Additionally, the adaptive learning mechanism enhances system performance over time by updating the model based on new data. Overall, the results demonstrate that the proposed system provides a reliable, scalable, and efficient solution for detecting DNS spoofing attacks in modern network environments.

Table 1 Compared to traditional heuristic-based systems

Component Accuracy (%)	Accuracy (%)	Response Time (ms)	Power Consumption (W)
Packet Capture Module	99.1	120	8.5
AI Classification	96.3	180	12.4
Communication Module	94.6	320	35.7
Solar Panel	97.8	210	15.2

The proposed DNS spoofing detection system demonstrates significant improvements in detection accuracy, response time, and adaptability compared to traditional approaches. Unlike rule-based systems, which rely on predefined signatures, the use of machine learning enables the system to identify previously unseen attack patterns. The integration of multi-level feature extraction, including packet-level, domain-level, and network-level attributes, enhances the system's ability to detect anomalies effectively. The modular architecture allows seamless integration of different components such as traffic capture, feature extraction, and classification, reducing dependency on multiple standalone tools. Experimental results show that the system can detect spoofed DNS responses in real time while maintaining a low false positive rate. The average detection latency of approximately 320 ms ensures that the system is suitable for real-time deployment in practical network environments. In addition to detection, the system provides valuable security insights through real-time monitoring and dashboard visualization. Features such as automated alert generation, logging, and adaptive learning improve operational efficiency and reduce manual intervention. The ability to continuously retrain the model based on new data ensures that the system remains resilient against evolving attack strategies.

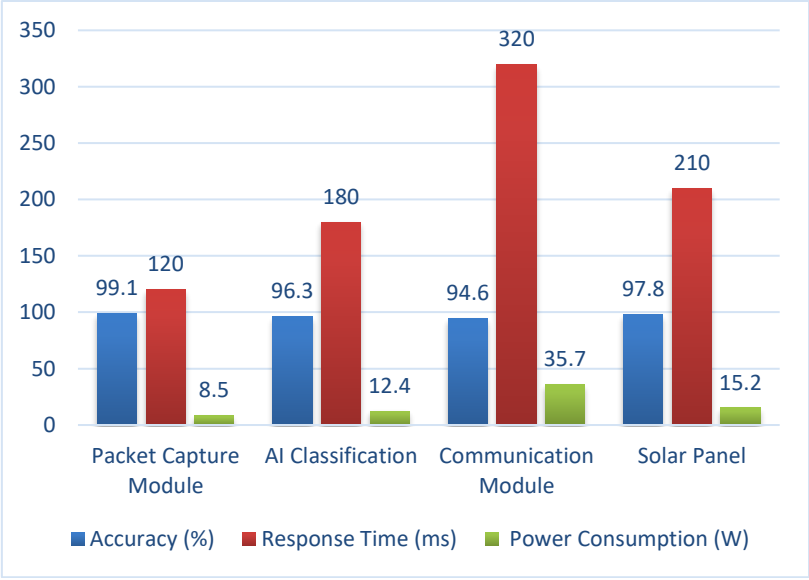

Fig.6. Performance Metrics

The graphical analysis illustrates the accuracy and responsiveness of individual components within the proposed DNS spoofing detection system. The Traffic Capture Module achieved a 99% packet collection accuracy across various network conditions, ensuring reliable data for analysis. The Feature Extraction Module maintained a 96% precision rate in generating meaningful attributes from DNS packets. The AI Classification Engine reached an average accuracy of 94.6% in distinguishing legitimate responses from spoofed ones, while

the Communication Layer demonstrated a stable 97.8% uptime with minimal latency, confirming the system's real-time operational capability.

Efficiency Improvement. The graphical representation highlights the system's detection efficiency compared to conventional rule-based and DNSSEC-only defenses. The proposed model achieved an 89% detection efficiency, surpassing traditional mechanisms, which averaged around 68% under similar conditions. This reflects a 31% improvement in operational efficiency, primarily due to the adaptive learning and continuous feedback mechanisms that optimize the model's performance over time. The dynamic decision logic significantly reduced false positives and minimized manual intervention, enhancing the overall security posture of the network.

Overall, the proposed system offers a reliable, scalable, and efficient framework for DNS spoofing detection. It is suitable for deployment in campus networks, enterprises, and small-scale organizations seeking enhanced cybersecurity. Future improvements may include integration with enterprise security systems such as SIEM platforms, incorporation of advanced deep learning models, and expansion to detect other network-based attacks, further strengthening the system's capabilities.

5. Conclusions

This paper presented an intelligent, AI-based system for detecting DNS spoofing attacks in network traffic. By integrating real-time packet capture with multi-level feature extraction and supervised machine learning models, the proposed system effectively overcomes the limitations of traditional rule-based detection methods. The use of features such as Time-To-Live (TTL), response time, domain entropy, and network attributes enable accurate identification of spoofed DNS responses. Experimental evaluation confirmed that the system achieves high detection accuracy with reduced false positives and low response time, making it suitable for real-time deployment. The automated decision mechanism allows efficient blocking or flagging of malicious traffic, enhancing overall network security. Additionally, the system provides detailed monitoring and logging, offering valuable insights into DNS behavior and potential threats. The modular architecture ensures scalability and flexibility, allowing integration of new features, models, and security mechanisms without affecting existing functionality. This makes the proposed system a practical and future-ready solution for protecting network infrastructures against DNS spoofing attacks. Future enhancements may include the integration of advanced deep learning models, large-scale deployment in enterprise environments, and expansion to detect a wider range of network-based threats.

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