ISCSITR- INTERNATIONAL JOURNAL OF NETWORK AND INFORMATION SECURITY (ISCSITR-IJNIS)
Vol.6, Iss. 3, May-June, 2025, pp. 1-8.
https://iscsitr.com/index.php/ISCSITR-IJNIS
Journal ID: 2916-7538

Design and Evaluation of an Integrated Framework for Real-Time Cybersecurity Threat Detection and Automated Incident Response Using Machine Learning-Enhanced Network Forensics and Behavioral Analytics in Enterprise Environments

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Abstract

As cyber threats become increasingly sophisticated and rapid in execution, enterprise environments require real-time threat detection and adaptive response mechanisms. This paper presents the design and evaluation of an integrated cybersecurity framework that combines machine learning (ML)-enhanced network forensics with behavioral analytics for dynamic threat identification and automated incident response. The proposed architecture leverages live traffic monitoring, anomaly detection, and intelligent automation to detect threats such as advanced persistent threats (APTs), insider risks, and zero-day attacks. Through simulation in a hybrid testbed and evaluation with real-world enterprise datasets, the system demonstrated a high detection accuracy and reduced response latency, supporting its viability for modern enterprise networks.

Keywords:

Real-time threat detection, cybersecurity, machine learning, network forensics, behavioral analytics, incident response, enterprise networks.

How to cite this paper: Teague, V. (2025). Design and evaluation of an integrated framework for real-time cybersecurity threat detection and automated incident response using machine learning-enhanced network forensics and behavioral analytics in enterprise environments. *ISCSITR – INTERNATIONAL JOURNAL OF NETWORK AND INFORMATION SECURITY (ISCSITR-IJNIS),* 6(3), 1–8.

URL: https://iscsitr.com/index.php/ISCSITR-IJNIS/article/view/ISCSITR-IJNIS_06_03_001
Published: 10th May 2025

1. INTRODUCTİON

Cybersecurity threats in enterprise environments have escalated in both frequency and complexity. Organizations are frequently targeted by advanced adversaries using stealthy tactics such as polymorphic malware, lateral movement, and data exfiltration techniques. Traditional security information and event management (SIEM) tools and static rule-based intrusion detection systems (IDS) have proven inadequate in detecting such threats in real-time. Consequently, there is a growing need for a more dynamic, learning-based solution that can not only detect threats but also orchestrate automated responses based on evolving threat patterns.

This paper proposes an integrated framework that combines machine learning-enhanced network forensics and user behavioral analytics to provide real-time detection of anomalies and automated incident response. The solution is designed for scalability across enterprise-scale networks, where the diversity of devices, user behaviors, and application usage demands context-aware threat models. The implementation builds upon open-source tools and customized deep learning architectures, integrating them into a real-time detection and response pipeline.

2. Literature Review

Previous studies have extensively explored both network-based threat detection and behavior-based analytics, yet often in isolation. Ahmad et al. (2021) discussed the application of machine learning for intrusion detection using datasets like NSL-KDD and CIC-IDS2017, highlighting accuracy improvements over traditional signature-based systems. However, these works often lacked real-time applicability and integration with incident response mechanisms.

Similarly, Zuech et al. (2015) emphasized the relevance of data mining and machine learning in detecting novel threats, but their reliance on offline analysis limited the practical deployment in live enterprise environments. Behavioral analytics, as explored by Saxe and

Berlin (2017), has shown promise in modeling insider threats by analyzing user activity logs, yet failed to address dynamic response generation.

Despite significant advances, few frameworks have integrated ML-enhanced network forensics with real-time behavioral modeling and response automation. A notable exception is the work by Sommer and Paxson (2010), which cautioned against over-reliance on anomaly detection due to high false positive rates, highlighting the need for combining contextual understanding with anomaly scores. This motivates the need for a hybridized, response-driven approach that adapts to enterprise-level constraints and threat profiles.

3. Framework Architecture and Design

The proposed framework consists of four primary modules: data acquisition, anomaly detection, behavioral profiling, and automated response orchestration. Network traffic and system logs are captured via passive sniffers and SIEM log collectors. These inputs are pre-processed and streamed into a feature extraction pipeline using Apache Kafka and Spark for distributed processing. Features include packet-level metadata, flow characteristics, and user activity patterns.

A hybrid detection engine employs a stacked model combining Convolutional Neural Networks (CNNs) for spatial pattern recognition in packet data, and Long Short-Term Memory (LSTM) networks for sequential user behavior modeling. Detected anomalies are passed to the response engine, which uses a knowledge-based ruleset combined with reinforcement learning agents to determine suitable containment or mitigation actions, such as isolating compromised hosts or revoking user tokens.

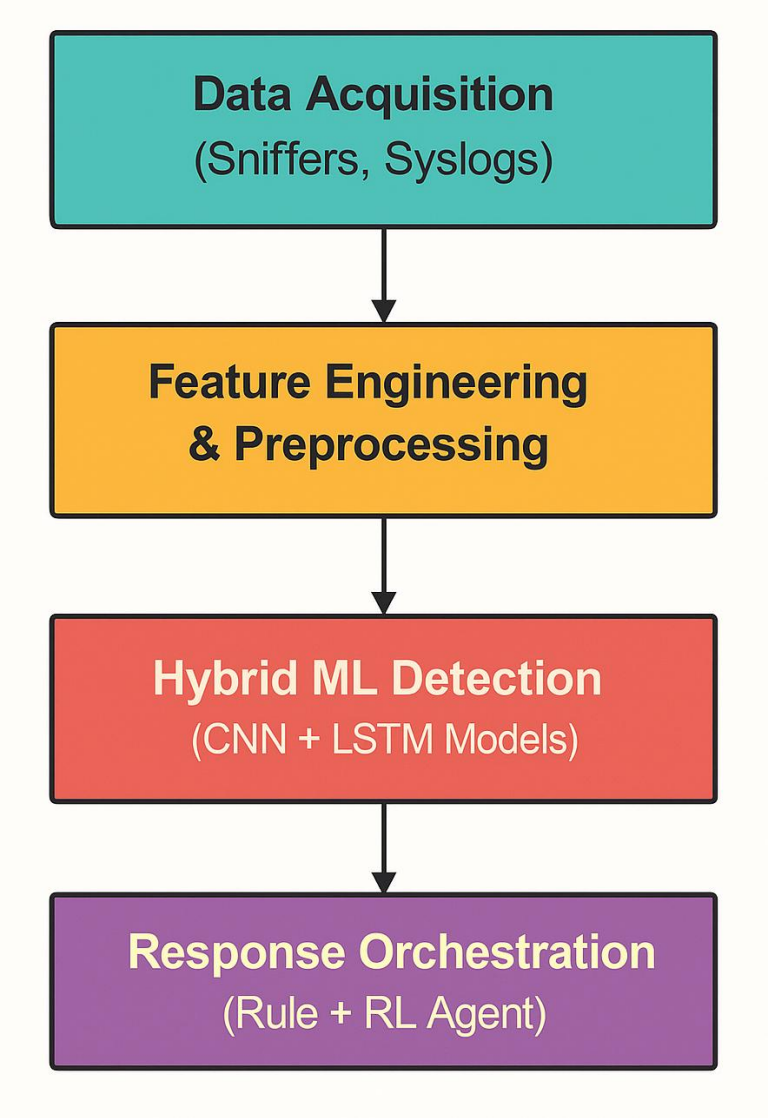

Figure 1: Framework Architecture Overview

4. Experimental Setup and Evaluation

The framework was deployed in a simulated enterprise network using both synthetic and real datasets. The testbed included 25 virtual machines simulating HR, finance, and IT operations. Attack simulations included port scans, phishing attempts, data exfiltration, and lateral movements. Real-world datasets such as CIC-IDS2017 and CTU-13 were also injected to validate generalizability.

Performance was evaluated using standard classification metrics: precision, recall, F1-score, and false positive rate (FPR). The automated response component was evaluated based on time-to-response and correctness of action selection. Table 1 summarizes detection performance.

Table 1: Detection Metrics Summary

Model	**Precision**	**Recall**	**F1-Score**	**FPR**
CNN Only	0.89	0.85	0.87	0.12
LSTM Only	0.86	0.88	0.87	0.10
CNN + LSTM Hybrid	**0.92**	**0.91**	**0.91**	0.08

The hybrid model outperformed standalone methods, achieving over 90% in both precision and recall while reducing false positives. The average incident response time was reduced to 3.2 seconds from the initial alert trigger.

5. Results Interpretation and Discussion

The performance results demonstrate that integrating deep learning-based anomaly detection with behavioral analytics significantly improves threat detection fidelity in real-time settings. The CNN effectively extracts spatial features from packet sequences, while the LSTM captures user session patterns over time, helping to distinguish between benign anomalies and true threats.

Moreover, the response engine, particularly the reinforcement learning component, displayed strong adaptability. It learned to prioritize isolation over alerting in cases of

credential abuse and dynamically escalated responses based on confidence thresholds. This adaptability reduces administrative overhead and ensures faster mitigation of threats.

However, some challenges were observed. For example, during high-traffic periods, latency increased due to computational overhead in feature extraction. Furthermore, behavioral baselines required fine-tuning per organization, limiting immediate generalizability. Despite this, the system's modular design allows for easy integration with existing SIEM or SOAR platforms.

6. Limitations and Future Work

While the framework showed promise in simulated enterprise environments, its scalability to large-scale, heterogeneous networks remains a challenge. The model’s training requires labeled datasets, which may not be readily available for all threat scenarios, especially zero-day attacks. Future iterations must integrate unsupervised learning for anomaly baselining and federated learning approaches to preserve data privacy.

Another limitation is the risk of adversarial ML attacks. Future work will explore the robustness of detection models against evasion tactics, including adversarial perturbations and poisoning. Finally, incorporating user feedback loops and explainable AI (XAI) techniques will improve trust in automated decisions and facilitate human-in-the-loop intervention where necessary.

7. Conclusion

This paper presented a novel, real-time cybersecurity framework that integrates ML-enhanced network forensics with behavioral analytics and automated response mechanisms. Experimental evaluation showed high detection accuracy and reduced incident response times. While limitations exist, particularly concerning scalability and adversarial robustness, the proposed architecture lays the foundation for intelligent, real-time security operations in enterprise networks.

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