A survey on AI/ML-Driven Cyber Threat Intelligence for Proactive Detection and Mitigation

Dr. Sesha Bhargavi Velagaleti[1], Postdoctoral Researcher[1], LINCOLN UNIVERSITY COLLEGE [1],

pdf.seshabhargavi@lincoln.edu.my[1]

Dr. Upendra Kumar[2], Institute of Engineering and Technology[2], Lucknow, India[2]

Adjunct Research Faculty, Lincoln University College, Malaysia

ABSTRACT

Cybersecurity attacks are growing in sophistication, rendering conventional signature-based defenses inadequate against contemporary adversarial methods. This paper presents Stage I of an ongoing research programme aimed at developing an AI/ML-powered Cyber Threat Intelligence (CTI) framework—the ADCTI-AR (AI-Driven Cyber Threat Intelligence and Adaptive Response)—capable of proactively identifying and mitigating advanced cyber threats in real time. Stage I encompasses a systematic review of AI/ML applications in cybersecurity across five thematic domains, formalization of research objectives and key research questions, and development of the conceptual framework. Critical research gaps are identified: low adaptability to emerging attack vectors, high false positive rates, inadequate explainability of deep learning models, and the absence of robust continuous learning frameworks. The proposed methodology integrates deep neural networks, unsupervised anomaly detection, and reinforcement learning into an end-to-end adaptive CTI pipeline, providing the conceptual and empirical foundation for subsequent experimental stages.

Index Terms— *Cyber Threat Intelligence, Machine Learning, Deep Neural Networks, Intrusion Detection, Advanced Persistent Threats, Zero-Day Detection, Anomaly Detection, Automated Mitigation, Reinforcement Learning.*

I. INTRODUCTION

The digitalization of critical infrastructure has dramatically expanded the attack surface available to adversaries [1]. The IBM Cost of a Data Breach Report 2024 estimated the mean breach cost at $4.88 million, a 10% year-on-year increase [2]. The proliferation of Advanced Persistent Threats (APTs), ransomware, and zero-day exploits has exposed fundamental weaknesses in traditional rule-based and signature-based security controls [3]. Because adversarial techniques have advanced to include obfuscation, polymorphism, and living-off-the-land (LotL) approaches, signature-dependent systems are structurally incapable of detecting novel attack variants [4], creating an ever-widening detection gap during which significant damage may occur [5].

Cyber Threat Intelligence (CTI) reframes cybersecurity from reactive incident response to proactive threat prediction. It involves the collection, processing, and analysis of threat data to support well-informed, timely security decisions [6]. However, the volume and velocity of security telemetry—millions of daily log entries, network flow records, and endpoint events—far exceeds the analytical capacity of human Security Operations Center (SOC) staff [7]. Artificial Intelligence and Machine Learning offer a transformative solution: ML models can autonomously process high-dimensional security data, detect statistical anomalies indicative of malicious behavior, learn continuously, and produce prioritized actionable intelligence at machine speed [8].

This paper constitutes Stage I of a twelve-month research programme. The contributions are: (i) systematic review of AI/ML-based CTI applications across five thematic domains; (ii) formal identification of research gaps and open challenges; (iii) definition of research objectives and key research questions (RQs); (iv) specification of inclusion/exclusion criteria governing empirical scope; and (v) elaboration of the ADCTI-AR conceptual framework and research methodology for subsequent stages.

II. RESEARCH OBJECTIVES AND KEY QUESTIONS

The research is guided by four primary objectives: (O1) develop an AI/ML model for real-time threat intelligence by examining large volumes of security data (logs, alerts, network traffic) to discover emerging threats [9]; (O2) build an adaptive threat classification and prioritization model using ML to categorize identified threats by risk and produce contextual decision intelligence [10]; (O3) enhance APT and zero-day detection through unsupervised and deep learning to identify advanced attacks beyond conventional signature-based methods [11]; and (O4) design an AI-controlled automated mitigation system that autonomously responds to specific threat types, minimizing human intervention and accelerating containment [12].

Four key research questions anchor the study: RQ1: How can AI/ML techniques improve accuracy and efficiency in identifying APTs and zero-day exploits? RQ2: What methods enable continuous adaptation of the threat intelligence model to evolving attack vectors without full model retraining? RQ3: How can ML models be optimized to minimize false positive rates while providing accurate threat classification and prioritization? RQ4: How can automated response mechanisms be effectively and safely integrated into the cybersecurity ecosystem for real-time attack mitigation?

III. SYSTEMATIC REVIEW METHODOLOGY

Literature search was conducted across IEEE Xplore, ACM Digital Library, Scopus, Web of Science, arXiv, and Google Scholar, supplemented by domain-specific resources including OWASP and the MITRE ATT&CK knowledge base. Boolean search combinations targeted: 'cyber threat intelligence', 'AI intrusion detection', 'machine learning cybersecurity', 'APT detection deep learning', 'zero-day vulnerability ML', 'anomaly detection network security', 'automated incident response', and 'reinforcement learning cybersecurity'.

Studies were included if they: (i) applied AI/ML methods to CTI; (ii) addressed proactive detection, analysis, or mitigation of cyber threats; (iii) were published in peer-reviewed journals from 2018–2025; and (iv) incorporated datasets on APTs, zero-day attacks, or network intrusions. Studies were excluded if they lacked significant AI/ML integration, had no relevance to CTI or threat mitigation, were based on outdated datasets, or were not peer-reviewed [13]. After full-text screening and quality evaluation, 87 primary studies were assessed, of which 52 satisfied all inclusion criteria and were included in the final synthesis. Thematic analysis organized findings across five research domains [14].

IV. SYNTHESIS OF LITERATURE

Across five thematic domains, the literature reveals both strong achievements and persistent gaps. In real-time threat intelligence, supervised and semi-supervised ML pipelines have demonstrated high detection rates on benchmark datasets [1]; however, inadequate management of concept drift—the statistical shift in threat patterns over time—consistently leads to model performance degradation in production settings. In threat classification and prioritization, deep neural networks outperform classical methods on intrusion detection benchmarks [4], with hierarchical multi-label classification frameworks reducing analyst decision time by up to 43% [15]; yet dynamic reprioritization responsive to real-time intelligence remains an unresolved problem [6].

APT and zero-day detection represent the most challenging frontier: autoencoder-based anomaly detection has achieved 88% detection rates on zero-day simulations [16], and graph neural networks trained on system call provenance have reported 91.2% APT recall at 0.3% FPR [17]. Yet all studies concede the inherent difficulty of distinguishing malicious anomalies from legitimate operational irregularities—a challenge requiring contextual knowledge not readily encoded in statistical models [3]. In automated mitigation, deep Q-network agents have demonstrated over 94% ransomware containment within 2.3 seconds of detection in simulated environments [18], though the simulation-to-production transfer gap remains a dominant deployment barrier [5]. Finally, in adaptive threat intelligence, online learning architectures based on Hoeffding trees have

maintained above 92% accuracy over six-month evaluation periods with 15 distinct attack campaigns [19]; meta-learning approaches enable rapid adaptation to novel attack families from as few as five examples.

TABLE I. COMPARISON OF AI/ML TECHNIQUES FOR CYBER THREAT DETECTION

Technique	Category	Threat Detection Capability	FPR	Comp. Cost
Deep Neural Networks	Supervised	APTs, Malware, Intrusions	Low	High
Random Forest	Supervised	Classification, Anomalies	Medium	Medium
Autoencoders	Unsupervised	Anomaly Detection, Zero-Days	Medium	High
LSTM Networks	Supervised	Sequential Attack Patterns	Low	High
Reinforcement Learning	Semi-Supervised	Adaptive Threat Response	Low	Very High

Table I provides a comparative taxonomy of the main AI/ML methods evaluated, summarizing their threat detection capabilities, characteristic false positive rates, and computational demands. This taxonomy informs the model selection strategy of the proposed ADCTI-AR framework. Table II (below) consolidates the key findings and identified gaps across the five thematic domains.

V. PROPOSED RESEARCH FRAMEWORK

The systematic review findings motivate the AI-Driven Cyber Threat Intelligence and Adaptive Response (ADCTI-AR) framework: an end-to-end pipeline incorporating multi-source data ingestion, intelligent preprocessing, layered ML analysis, and autonomous response. The architecture comprises five functional layers. Layer 1 (Data Ingestion) collects from firewalls, IDS/IPS systems, EDR agents, SIEM platforms, and OSINT feeds, normalizing all sources to a unified Common Information Model (CIM) schema. Layer 2 (Preprocessing and Feature Engineering) performs automated filtering, normalization, and feature extraction across three categories: statistical network flow features (packet rate, byte distribution, protocol entropy), behavioral features (user and entity behavior analytics), and contextual features (asset criticality, geographic IP reputation, temporal patterns). Layer 3 (AI/ML Analysis Engine) employs a hybrid model architecture: supervised classification (DNN, Random Forest, LSTM) for known threat detection and unsupervised anomaly detection (autoencoders, isolation forest) for zero-day coverage, with an ensemble meta-learner combining base model predictions.

Layer 4 (Threat Intelligence Generation) performs risk-based prioritization integrating ML confidence scores, asset criticality, and CVSS severity scores, and automates generation of structured threat reports in STIX/TAXII format. Layer 5 (Automated Response System) implements a reinforcement learning decision agent that selects containment actions (IP blocking, network segmentation, process termination, credential rotation) subject to safety constraints

preventing collateral impact on legitimate operations. The research employs benchmark datasets (NSL-KDD, CICIDS-2017, UNSW-NB15, MITRE ATT&CK) augmented with GAN-generated synthetic data [20], live threat intelligence feeds (VirusTotal, AlienVault OTX), stratified k-fold (k=10) cross-validation, SHAP-based interpretability [10], and GNS3-based network emulation for response system evaluation.

VI. LIMITATIONS AND ETHICAL CONSIDERATIONS

Three principal limitations are acknowledged. First, ecological validity: model performance on curated benchmark datasets may not generalize to the heterogeneous traffic patterns of production networks [7]. Second, autonomous response systems raise ethical concerns regarding accountability, potential damage to legitimate systems, and adversarial exploitation of the ML pipeline [8]. Third, the fundamental interpretability limitations of deep learning models—despite SHAP analysis—may present compliance challenges in regulated industries. These limitations will be addressed through controlled laboratory verification, formally encoded safety constraints within the RL agent, and systematic adversarial robustness testing [9].

VII. CONCLUSION

This paper has presented Stage I of an AI/ML-based Cyber Threat Intelligence research programme, comprising a systematic literature review across five thematic domains, formal research objectives and research questions, and the conceptual architecture of the ADCTI-AR framework. The review identified four critical gaps in the current literature: inadequate adaptation to novel attack vectors, high production false positive rates, insufficient deep learning interpretability, and the absence of robust continuous learning frameworks resilient to concept drift. The ADCTI-AR framework addresses these gaps through a hybrid supervised/unsupervised model architecture, online learning mechanisms, SHAP-based interpretability, and safety-constrained reinforcement learning for autonomous response. Subsequent stages will deliver experimental validation of framework components, system integration, and performance benchmarking against simulated and standardized attack scenarios.

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