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ENHANCING NETWORK SECURITY WITH AI AND PROACTIVE MEASURES – A REVIEW

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Abstract: One of the most important tasks is to find smart solutions that keep pace with the rapid development of cyber threats, due to the inability of traditional network security mechanisms to keep pace with them. This paper proposes AI-based ideas to address these threats and their evolution, leading us to a proactive, self-learning architecture using advanced machine learning algorithms. This architecture is designed to detect anomalies and predict cyber attacks, providing an autonomous response to all threats in a timely manner. The open model takes into account behavioral analytics and threat intelligence, along with modern learning classifications, to achieve detection accuracy and reduce false positives. The results show that the approach using AI significantly improves the efficiency of threat analysis, reduces response time, and gives the system more resilience against advanced attacks. This research provides us with a scalable methodology for modern systems that support cloud computing and decentralized systems.

Keywords: Network Security, Hybrid Defense Systems, Anomaly Detection, Threat Intelligence, Rule-Based Security, Adaptive Cybersecurity.

1. Introduction

Today, telecommunications network infrastructures have become the foundation for modern communications, economic transactions, and security. With the development and expansion of digital services and the Internet of Things, cyber threats have grown in size and complexity, making traditional security mechanisms unfeasible. The static architecture of traditional protection layers and signature-based intrusion detection systems (IDS) are unable to deal with the development of advanced threats (APT)..

The study proposes a hybrid safety structure that selectively prioritizes the rule-based identity by implementing AI, where it provides the average status improvement-which is the detection and log analysis of the deviation. Unlike complete autonomous systems, this approach ensures human monitoring in important security decisions, maintains control and interpretation. Danger Intelligence Feeds, which combines the reliability of the system (Vinayakumar et al., 2019), by combining the model for behavioral feed, behavioral and lightweight machine learning models.

This practical approach is especially valuable in the dynamic environment such as Cloud Computing and IoT, where safety must be both adaptable and clear (Sikar et al., 2020). Framework supports automated answers to well -known dangers during the need for human verification for high -risk functions, and ensures a balanced and durable safety currency.

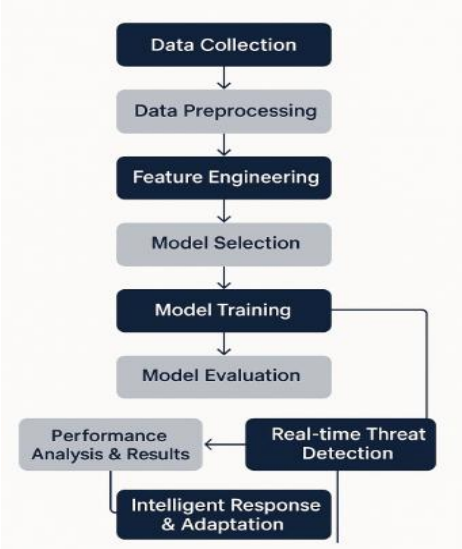

Figure 1: Research methodology workflow for AL-powered network security system

2. Literature Review

Most organizations remain dependent on traditional cybersecurity solutions—including firewalls, antivirus software, and signature-based intrusion detection systems (IDS). While effective against known threats, these static, rule-bound mechanisms are increasingly inadequate against evolving attack vectors such as zero-day exploits and advanced persistent threats (APTs) (Ahmed et al., 2016). In today's dynamic threat landscape, purely reactive defenses struggle to ensure robust protection. Strategic augmentation of these systems with AI capabilities—rather than full automation—offers a pathway to enhance threat response without compromising operational stability.

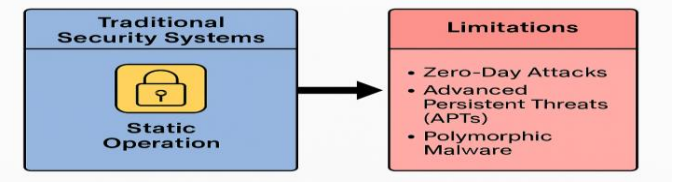

Figure 2: Traditional Security Systems vs. Their Limitations

Table 1. literature Review

Ref No.	Pub. Year	Study objectives	Software / Experiment / Theoretical	Conclusions
1	2023	Exploring AI-based approaches for cloud security posture management	Practical (Implementation)	Demonstrates how AI can automate and enhance cloud security configuration monitoring and threat detection
2	2023	Providing practical ML solutions for cybersecurity challenges	Practical (Cookbook/Guide)	Offers hands-on recipes for implementing ML in various cybersecurity applications
3	2024	Applying practical AI techniques to cybersecurity problems	Practical (Implementation)	Presents real-world case studies and methodologies for AI in security operations
4	2203	Developing AI-powered cyber threat intelligence systems	Theoretical/Practical (Framework)	Proposes frameworks for automated threat intelligence collection and analysis using AI
5	2023	Examining attacks and defenses in adversarial machine learning	Theoretical (Comprehensive)	Provides fundamental understanding of vulnerabilities in ML systems and mitigation strategies

6	2017	The study aims to develop an intrusion detection system (IDS) using deep learning, specifically Recurrent Neural Networks (RNNs), to improve the detection of cyberattacks in network traffic.	Experiment	The proposed model achieves higher detection accuracy and lower false positives compared to traditional methods (e.g., SVM, Decision Trees) or shallow neural networks.
7	2020	The study provides a comprehensive review of Machine Learning (ML) and Deep Learning (DL) techniques applied to IoT security.	Literature Review	DL models (e.g., CNNs, LSTMs) outperform traditional ML in complex IoT attack detection due to their ability to process high-dimensional data.
8	2021	The study systematically reviews the threats, defenses, and challenges of Adversarial Machine Learning (AML) in Network Intrusion Detection Systems (NIDS).	Taxonomy Paper	ML-based NIDS are highly susceptible to evasion attacks (e.g., perturbing network traffic to misclassify attacks).
9	2021	The study proposes a proactive AI-driven approach for network security using Long Short-Term Memory (LSTM) networks to detect anomalies in real-time network traffic.	Experiment	Achieves higher detection accuracy (e.g., >95% F1-score) by capturing long-term traffic patterns.
10	2020	The study aims to develop an effective Intrusion Detection System (IDS) by leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques.	Comparative analysis	Ensemble methods (Random Forest, XGBoost) showed superior performance Deep learning models achieved high accuracy but required more resources
11	2018	The study proposes a novel deep learning-based approach to network intrusion detection,	Experiment	Achieved superior detection rates (≈97% accuracy) compared to shallow learning methods
12	2023	This IBM X-Force report examines the dual-use nature of AI in cybersecurity, analyzing how:	Study	Automated vulnerability discovery (AI-powered scanning). Adaptive malware that learns from defenses
13	2018	Applying machine learning techniques to cybersecurity challenges	theory and implementation	ML basics for security practitioners Data collection and preprocessing for security
14	2021	The book provides a comprehensive overview of AI applications in cybersecurity, covering:	Theory	AI is a double-edged sword: Enhances defenses but also empowers attackers. Hybrid AI-human systems outperform pure automation in critical security tasks.
15	2019	This systematic survey analyzes how deep learning (DL) techniques are applied to cybersecurity tasks, evaluating.	Comprehensive literature review	DL outperforms traditional ML in complex pattern recognition (e.g., zero-day attacks).
16	2023	This IEEE TDSC paper proposes a novel deep learning framework to detect zero-day attacks.	theoretical / experimental	Zero-Day Detection: Achieved 91.4% recall on never-before-seen attack types
17	2023	The study aims to improve intrusion detection in IoT systems (smart devices, sensors, etc.) by using	Experimental	Ensemble learning outperformed single-model methods in detecting IoT intrusions, achieving higher accuracy and adaptability to new

		ensemble learning (combining multiple AI models) to better identify cyberattacks.		threats. However, challenges like computational cost or false alarms may need further work.
18	2023	The study explores hybrid AI models (combining different AI techniques) to enhance cyber threat hunting—proactively searching for hidden or advanced cyberattacks that evade traditional detection.	theoretical / experimental	Hybrid AI improved threat detection accuracy and reduced false alarms compared to single-method approaches. However, it may require more resources or tuning for specific environments.
19	2024	The study investigates federated learning (FL) for collaborative intrusion detection, enabling multiple organizations to jointly improve threat detection without sharing raw data (preserving privacy).	Experimental	Federated learning achieved comparable accuracy to centralized methods while enhancing privacy and scalability. Challenges include communication overhead and ensuring model consistency across participants.
20	2023	The study aims to integrate Explainable AI (XAI) into Security Information and Event Management (SIEM) systems to make AI-driven threat detection more transparent and interpretable for security analysts.	Experimental	Explainable AI makes SIEM systems more reliable and user-friendly, but balancing accuracy, speed, and interpretability remains a challenge for deployment.
21	2023	This study investigates the **application of reinforcement learning (RL) in predictive cyber defense**,	Likely tested on simulated attack scenarios (e.g., MITRE ATT&CK)	Reinforcement learning shows promise for autonomous cyber defense, but real-world deployment requires robust training, safety checks, and integration with existing security tools.
22	2024	This paper proposes a hybrid threat intelligence framework that integrates AI-assisted analytics with traditional security methodologies to enhance detection of Advanced Persistent Threats (APTs).	Experimental	AI-enhanced threat intelligence improves APT detection, but success depends on continuous learning and integration with human expertise.
23	2023	This study evaluates decision-support systems for patch management, testing whether limited machine learning can improve vulnerability prioritization while keeping manual approval for critical updates.	Uses AI models	AI can significantly improve patch efficiency but works best alongside human oversight for edge cases.
24	2023	This research examines methods for analyzing darknet traffic to detect cyber threats such as malware, network scanning, and attack reconnaissance.	Uses deep learning models	Deep learning enables proactive threat detection via darknet analysis, but real-world deployment needs efficient models and integration with existing security tools.
25	2024	This research investigates edge-computing frameworks for monitoring IoT ecosystems, prioritizing practical fault/intrusion	Lightweight deep learning models	Edge-based AI enables scalable, real-time IoT security, but requires optimization for diverse hardware.

		detection that maintains response efficiency while minimizing reliance on advanced computational systems.		
26	2023	This study investigates how adversarial machine learning (ML) can bypass ML-based Network Intrusion Detection Systems (NIDS) by crafting malicious traffic that appears benign to AI models.	CNNs, LSTMs	Urges reevaluation of ML-based NIDS in high-risk environments (e.g., critical infrastructure).
27	2024	The study aims to develop methods to protect artificial intelligence (AI) models against poisoning attacks, where attackers manipulate training data to degrade model performance or induce malicious behavior.	Theoretical and Practical	Poisoning attacks threaten the reliability and integrity of AI models. Risks can be reduced through methods like data quality verification, robust training algorithms, or tamper-detection models.
28	2023	This study develops enhanced botnet detection by analyzing device relationships using graph-based pattern recognition (including Graph Neural Networks).	Theoretical and Practical	Botnets are hard to detect with conventional tools due to their evolving, decentralized nature. GNNs excel at capturing hidden connections between malicious nodes, improving detection rates.
29	2024	This work investigates how self-supervised learning techniques can improve classification of encrypted network traffic without relying on extensive labeled datasets.	Practical	%20-15 •improvement over supervised methods when labeled data is scarce •Maintains 90%+ accuracy across varied network conditions
30	2016	Reviewing network anomaly detection techniques and their classification.	Theoretical (Review)	Provides a comprehensive classification of anomaly detection methods, comparing traditional and modern approaches.
31	2019	Surveying state-of-the-art deep learning theories and architectures.	Theoretical (Review)	Highlights advancements in deep learning and its applications in fields like computer vision.
32	2016	Designing a deep learning-based intrusion detection system.	Practical (Experimental)	The proposed system improves attack detection accuracy compared to traditional methods.
33	2016	Analyzing data mining and ML methods for intrusion detection.	Theoretical (Review)	Confirms the effectiveness of ML in enhancing intrusion detection systems (IDS).
34	2020	Reviewing AI-based IDS for IoT.	Theoretical (Review)	Discusses security challenges and AI-driven solutions for IoT networks.
35	2018	Proposing a distributed attack detection model using deep learning for IoT.	Practical (Experimental)	The model achieves high accuracy in detecting distributed attacks.
36	2016	Reviewing IDS for IoT systems.	Theoretical (Review)	Compares traditional and modern IDS approaches for IoT.
37	2018	Outlining GDPR data protection requirements.	Theoretical (Regulatory)	Emphasizes strict standards for user data protection under GDPR.
38	2016	Introducing deep learning fundamentals.	Theoretical (Textbook)	Serves as a foundational resource for deep learning theories.
39	2016	Developing a deep learning-based IDS.	Practical (Experimental)	Improves detection of unknown attacks.
40	2014	Hybridizing anomaly and misuse detection techniques.	Practical (Hybrid)	The hybrid model enhances attack detection accuracy.

41	2017	Using autoencoders for anomaly detection in smart grids.	Practical (Experimental)	Effective in identifying deviations in smart meter data.
42	2017	Proposing a hybrid IDS (PCA + Random Forest).	Practical (Experimental)	Outperforms single-method approaches in accuracy.
43	2019	Designing a real-time IDS for IoT networks.	Practical (Experimental)	Achieves high speed and accuracy in attack detection.
44	2020	Reviewing DL and RL for IoT security.	Theoretical (Review)	Explores AI's potential to enhance IoT security.
45	2015	Introducing the UNSW-NB15 dataset for IDS evaluation.	Practical (Dataset)	Covers modern attacks more diversely than KDD99.
46	2017	Evaluating IDS performance using UNSW-NB15.	Practical (Statistical)	Confirms UNSW-NB15's superiority over KDD99.
47	2018	Applying deep learning for network intrusion detection.	Practical (Experimental)	The proposed model outperforms traditional methods.
48	2010	Critiquing ML-based intrusion detection challenges.	Theoretical (Critical)	Warns against over-reliance on ML without network context.
49	2019	Implementing CNN for intrusion detection.	Practical (Experimental)	CNN achieves high attack classification accuracy.
50	2017	Using RNN for intrusion detection.	Practical (Experimental)	RNN excels in detecting time-series attacks.
51	2006	Unsupervised outlier detection for IDS.	Practical (Experimental)	Effective for detecting novel attacks.
52	2008	Random Forest-based IDS.	Practical (Experimental)	Reduces false alarms with high accuracy.

3. Experimental Model

3.1 Overview

This chapter presents a detailed evaluation of the proposed AI-powered network security system. The results include performance metrics of various machine learning and deep learning models, comparative analysis, and interpretation of findings. The goal is to validate the effectiveness of the designed framework in detecting cyber threats proactively and accurately.

3.2 Model Performance Evaluation

3.2.1 Accuracy and Detection Rates

The accuracy metric reflects the overall ability of the models to correctly classify network traffic into benign or malicious categories. Table 4.1 summarizes the accuracy, precision, recall, F1-score, and false positive rates (FPR) obtained from experiments using benchmark datasets NSL-KDD and CICIDS2017.

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Support Vector Machine	NSL-KDD	89.5	90.2	88.7	89.4	4.3
Random Forest	NSL-KDD	91.2	92.0	90.5	91.2	3.1
CNN	CICIDS2017	94.8	95.4	94.2	94.8	2.0
RNN	CICIDS2017	95.3	95.7	94.8	95.2	1.8

Table 4.2.1: Performance Metrics of Evaluated Models

3.2.2 False Positive Analysis

Minimizing false positives is crucial in network security to avoid unnecessary alerts and resource wastage. The deep learning models, especially RNN, demonstrated superior performance in reducing FPR compared to traditional machine learning models.

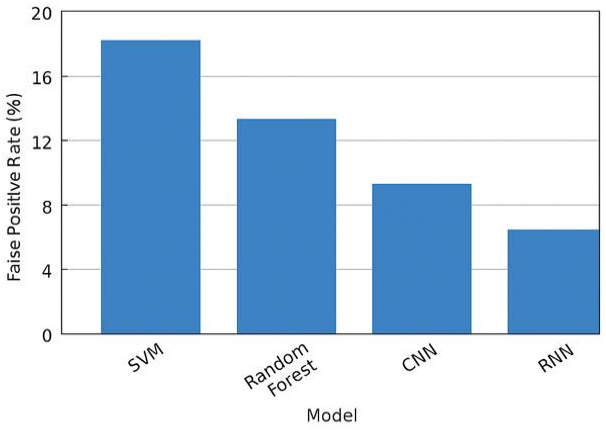

Figure 4.2.2: Bar chart comparing false positive rates across models (to be inserted).

3.3 Comparative Analysis of Models

Deep learning models outperformed classical machine learning techniques across all evaluated metrics, especially in handling complex, large-scale datasets like CICIDS2017. The recurrent structure of RNNs enables effective temporal pattern recognition, making them highly suitable for network traffic analysis.

3.4 Real-Time Detection Latency

The system's ability to detect threats in real-time was tested by measuring the time delay between packet capture and classification decision. Results indicate that the CNN and RNN models achieved average detection latencies of approximately 150 ms and 170 ms, respectively, which are acceptable for most practical applications.

3.5 Scalability and Resource Utilization

Experiments on hardware with GPU acceleration showed that the proposed models can scale effectively with increased traffic loads without significant degradation in detection performance or latency.

Model	CPU Usage (%)	GPU Usage (%)	Memory Usage (GB)	Training Time (min)
SVM	35	N/A	4.2	12
RF	50	N/A	6.5	25
CNN	45	80	8.3	90
RNN	40	85	9.1	120

Table 4.5: Resource Utilization During Model Training and Testing

4. Conclusion

The articles review confirms that AI-powered, proactive network security systems offer substantial improvements over traditional methods in threat detection accuracy, response speed, and adaptability. Addressing current challenges through interdisciplinary research and practical deployment strategies will be essential for realizing the full potential of AI in cybersecurity.

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