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Real-Time Anomaly Detection in Network Traffic Using Hybrid AI Models

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Abstract

The increasing complexity of modern network environments has led to a significant rise in cyber threats, making effective network security a critical requirement. Traditional intrusion detection systems often struggle to identify unknown attacks and generate high false positive rates. Real-time anomaly detection has emerged as an essential approach for identifying suspicious activities and preventing security breaches before they cause significant damage.

This study proposes a hybrid Artificial Intelligence (AI) framework for real-time anomaly detection in network traffic. The proposed model combines Machine Learning and Deep Learning techniques to improve detection accuracy and adaptability. Random Forest is used for feature selection and classification, while Long Short-Term Memory (LSTM) networks capture temporal patterns and behavioral characteristics within network traffic data. The integration of these models enables efficient identification of both known and previously unseen cyber threats.

The methodology involves data collection, preprocessing, feature extraction, model training, and performance evaluation using standard cybersecurity datasets. Experimental results demonstrate that the hybrid AI model achieves higher accuracy, improved detection rates, and lower false positive rates compared to conventional approaches. The framework effectively detects various network attacks while maintaining real-time operational performance.

The findings indicate that hybrid AI models provide a scalable and intelligent solution for modern cybersecurity systems, enhancing network monitoring capabilities and supporting proactive threat detection in dynamic network environments.

Keywords *: Network Security, Anomaly Detection, Artificial Intelligence, Machine Learning, Deep Learning, Cybersecurity, Intrusion Detection.*

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1. INTRODUCTION

The rapid growth of digital technologies, cloud computing, Internet of Things (IoT) devices, and high-speed communication networks has transformed the way organizations manage and exchange information. While these advancements have improved connectivity and operational efficiency, they have also increased the vulnerability of network infrastructures to cyberattacks. Modern networks generate massive volumes of traffic data every second, making it increasingly difficult for security administrators to monitor and identify malicious activities manually. Cyber threats such as Distributed Denial-of-Service (DDoS) attacks, malware infections, phishing campaigns, botnet activities, and unauthorized access attempts continue to evolve in sophistication, posing significant risks to businesses, governments, and individuals.

Traditional network security solutions primarily rely on signature-based intrusion detection systems (IDS), which identify threats by comparing network activities against predefined attack signatures.

Although these methods are effective in detecting known attacks, they often fail to recognize new and previously unseen threats, commonly referred to as zero-day attacks. Furthermore, signature-based systems require continuous updates and may generate a high number of false positives and false negatives, reducing their effectiveness in dynamic network environments. As cybercriminals develop increasingly complex attack strategies, there is a growing demand for intelligent and adaptive security mechanisms capable of detecting anomalies in real time.

Anomaly detection has emerged as a promising approach for identifying suspicious network behavior by analyzing deviations from normal traffic patterns. Unlike traditional methods, anomaly-based detection systems can recognize unknown attacks by learning the characteristics of legitimate network activities and identifying unusual behavior. Recent advances in Artificial Intelligence (AI) have significantly enhanced the capabilities of anomaly detection systems. Machine Learning (ML) algorithms can process large volumes of data, identify meaningful features, and classify network events with improved accuracy. Similarly, Deep Learning (DL) models are capable of learning complex and temporal patterns from network traffic, enabling the detection of sophisticated cyber threats that may not be captured by conventional techniques.

Hybrid AI models, which combine the strengths of Machine Learning and Deep Learning approaches, have gained considerable attention in cybersecurity research. Machine learning techniques such as Random Forest can effectively select relevant features and perform efficient classification, while deep learning architectures such as Long Short-Term Memory (LSTM) networks can analyze sequential and time-dependent traffic patterns. By integrating these complementary capabilities, hybrid AI models can achieve higher detection accuracy, better generalization, and reduced false alarm rates compared to standalone approaches.

This study proposes a real-time anomaly detection framework based on hybrid AI models for network traffic analysis. The framework integrates Random Forest and LSTM techniques to improve the detection of malicious activities in network environments. The primary objectives of the research are to enhance detection accuracy, reduce false positive rates, and provide timely identification of cyber threats. The proposed system is evaluated using benchmark cybersecurity datasets and standard performance metrics, including accuracy, precision, recall, and F1-score. The findings of this research are expected to contribute to the development of intelligent and scalable intrusion detection systems capable of addressing emerging cybersecurity challenges in modern network infrastructures.

2. LITERATURE REVIEW

Network traffic anomaly detection has become a significant area of research in cybersecurity due to the increasing complexity and frequency of cyberattacks. Traditional security mechanisms, such as firewalls and signature-based intrusion detection systems, have been widely used to protect network infrastructures. However, these approaches are often limited in their ability to detect previously unseen attacks and advanced persistent threats. As a result, researchers have increasingly focused on anomaly-based detection techniques that identify abnormal behavior by analyzing deviations from normal network traffic patterns.

Early studies on network anomaly detection primarily employed statistical and rule-based methods. These approaches monitored traffic characteristics such as packet rates, bandwidth usage, and connection patterns to identify suspicious activities. While statistical methods provided a foundation for anomaly detection, they often struggled with large-scale network environments and generated high false positive rates. Consequently, machine learning techniques emerged as a more effective solution for analyzing complex network data and identifying cyber threats.

Machine learning algorithms have demonstrated significant potential in intrusion detection systems. Supervised learning techniques such as Decision Trees, Support Vector Machines (SVM), Naïve Bayes, and Random Forest have been widely applied to classify network traffic into normal and malicious categories. Among these methods, Random Forest has gained popularity due to its high accuracy,

robustness, and ability to handle large datasets with multiple features. Several studies have reported that Random Forest outperforms traditional classification algorithms in detecting various types of cyberattacks, including denial-of-service, probing, and brute-force attacks.

With the advancement of artificial intelligence, deep learning techniques have become increasingly important in cybersecurity applications. Deep learning models can automatically learn complex patterns and feature representations from raw network traffic data without extensive manual feature engineering. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have been successfully utilized for anomaly detection. In particular, Long Short-Term Memory (LSTM) networks have shown excellent performance in analyzing sequential and time-series network data. Since network traffic often exhibits temporal dependencies, LSTM models can effectively capture behavioral patterns and detect anomalies that may be overlooked by traditional machine learning methods.

Recent research has explored hybrid AI models that combine machine learning and deep learning techniques to enhance detection performance. Hybrid approaches leverage the strengths of multiple algorithms, enabling more accurate and reliable anomaly detection. For example, Random Forest can be used for feature selection and dimensionality reduction, while LSTM networks perform deep sequential analysis of network traffic. Studies have shown that such hybrid models achieve higher detection accuracy, lower false positive rates, and improved scalability compared to standalone machine learning or deep learning systems.

Despite significant progress, several challenges remain in real-time anomaly detection. Many existing models require substantial computational resources and may struggle to process high-speed network traffic efficiently. Additionally, maintaining detection accuracy while minimizing false alarms remains a critical concern. The emergence of encrypted traffic, IoT devices, cloud computing environments, and sophisticated attack techniques further complicates anomaly detection tasks. Therefore, there is a continuing need for intelligent, scalable, and adaptive solutions capable of operating effectively in dynamic network environments.

3. PROPOSED HYBRID AI FRAMEWORK

The proposed Hybrid AI Framework is designed to provide accurate and real-time anomaly detection in network traffic by integrating the strengths of Machine Learning and Deep Learning techniques. Modern network environments generate large volumes of traffic data that contain complex patterns and behaviors. Traditional intrusion detection methods often struggle to identify unknown attacks and adapt to evolving cyber threats. To address these limitations, the proposed framework combines Random Forest and Long Short-Term Memory (LSTM) models to improve detection accuracy, reduce false positives, and enable timely threat identification.

The framework begins with the collection of network traffic data from network monitoring tools and benchmark cybersecurity datasets. The collected data contain information related to packet transmission, protocol usage, connection duration, source and destination addresses, and traffic flow characteristics. Since raw network data may contain missing values, noise, and redundant information, a preprocessing stage is applied. This stage includes data cleaning, normalization, encoding of categorical features, and removal of irrelevant records to ensure data quality and consistency.

After preprocessing, feature extraction is performed to identify important traffic characteristics that can distinguish normal behavior from malicious activities. Features such as packet size, flow duration, protocol type, connection frequency, and traffic volume are extracted from the dataset. To further enhance computational efficiency, the framework employs the Random Forest algorithm for feature selection. Random Forest evaluates the importance of each feature and selects the most relevant attributes, thereby reducing dimensionality and eliminating redundant information. This process improves model performance while decreasing training time and computational overhead.

The selected features are then provided to the LSTM network for deep learning-based analysis. LSTM is particularly suitable for network traffic anomaly detection because it can capture temporal dependencies and sequential patterns present in traffic data. By analyzing traffic behavior over time, the LSTM model can identify subtle anomalies and detect sophisticated attacks that may not be recognized through conventional methods. The deep learning component continuously learns traffic patterns and improves its detection capability through training.

The outputs generated by the Random Forest classifier and the LSTM model are integrated within a Hybrid Decision Engine. This component combines the predictions from both models to produce a final classification result. The decision engine evaluates whether a network activity is normal or anomalous based on the confidence levels and outputs of the individual models. This hybrid approach leverages the strengths of machine learning in feature optimization and deep learning in pattern recognition, resulting in improved detection accuracy and robustness.

Once an anomaly is detected, the system generates real-time alerts and notifications for network administrators. These alerts facilitate rapid response and mitigation of potential cyber threats before significant damage occurs. The framework is designed to support real-time deployment in enterprise networks, cloud environments, and IoT ecosystems.

4. METHODOLOGY

This study adopts a systematic methodology to develop and evaluate a Hybrid Artificial Intelligence (AI) framework for real-time anomaly detection in network traffic. The methodology consists of dataset selection, data collection, preprocessing, feature extraction, hybrid model development, performance evaluation, and experimental implementation. The proposed framework integrates Machine Learning and Deep Learning techniques to improve the detection of malicious activities while maintaining high accuracy and low false positive rates.

4.1 Dataset Description

To evaluate the effectiveness of the proposed framework, benchmark cybersecurity datasets commonly used in intrusion detection research are considered. The NSL-KDD dataset is an improved version of the KDD Cup 1999 dataset and contains various attack categories such as denial-of-service, probing, user-to-root, and remote-to-local attacks. The CICIDS2017 dataset provides realistic network traffic and includes modern attack scenarios such as brute-force attacks, botnets, and distributed denial-of-service attacks. The UNSW-NB15 dataset contains contemporary network traffic records generated using realistic network environments and includes both normal and malicious activities. The CSE-CIC-IDS2018 dataset offers a comprehensive collection of network traffic representing multiple attack types and real-world network behaviors. These datasets provide a reliable foundation for training and testing anomaly detection models.

4.2 Data Collection

The data collection process involves gathering network traffic information from the selected datasets and network monitoring environments. Packet capture techniques are used to record network communications and collect detailed traffic information. Flow generation methods transform raw packet data into network flow records by grouping packets with similar characteristics. Traffic aggregation is then performed to organize and summarize network activities, enabling efficient analysis and processing. The collected data represent both normal network behavior and various cyberattack scenarios.

4.3 Data Preprocessing

Data preprocessing is an essential step to improve the quality and usability of the collected network traffic data. Initially, missing values and incomplete records are identified and removed to prevent inaccuracies during model training. Data normalization is then applied to scale numerical features into

a consistent range, ensuring that no single feature dominates the learning process. Since network datasets often contain categorical attributes such as protocol types and service categories, encoding techniques are employed to convert these attributes into numerical representations suitable for machine learning and deep learning algorithms. The preprocessing stage also includes noise reduction and duplicate record removal.

4.4 Feature Extraction

Feature extraction aims to identify the most informative attributes from network traffic data. Several traffic characteristics are extracted, including packet size, flow duration, protocol type, source and destination port numbers, connection frequency, traffic volume, and transmission statistics. These features provide valuable insights into network behavior and help distinguish legitimate activities from malicious actions. Effective feature extraction enhances model performance and reduces computational complexity.

4.5 Hybrid AI Model Development

The proposed Hybrid AI framework consists of three major stages. In the first stage, the Random Forest algorithm is employed for feature importance ranking and dimensionality reduction. Random Forest identifies the most significant features that contribute to anomaly detection while eliminating redundant and irrelevant attributes.

In the second stage, the selected features are supplied to a Long Short-Term Memory (LSTM) network. The LSTM model performs sequence learning by analyzing temporal dependencies within network traffic. This enables the system to identify unusual traffic patterns and detect anomalies that evolve over time.

In the third stage, a Hybrid Decision Layer combines the outputs generated by the Random Forest and LSTM models. The integrated predictions are evaluated to produce a final classification result, categorizing network activities as either normal or anomalous. This hybrid approach improves detection accuracy and reliability.

4.6 Evaluation Metrics

The performance of the proposed framework is evaluated using standard classification metrics. Accuracy measures the overall correctness of the model's predictions. Precision evaluates the proportion of correctly identified anomalies among all detected anomalies. Recall measures the ability of the system to identify actual attack instances. The F1-Score provides a balanced assessment of precision and recall. Detection Rate indicates the percentage of successfully detected attacks, while False Positive Rate measures the frequency of incorrect anomaly alerts. Receiver Operating Characteristic–Area Under Curve (ROC-AUC) is also used to assess the model's classification capability across different threshold settings.

4.7 Experimental Setup

The experimental implementation is conducted using a Python-based development environment. TensorFlow and Keras libraries are utilized for designing and training the LSTM deep learning model, while Scikit-learn is employed for Random Forest implementation and data preprocessing tasks. GPU acceleration is used to improve training efficiency and reduce computation time. The experiments are performed within a network simulation environment that enables realistic traffic analysis and performance evaluation. The proposed framework is tested under various attack scenarios to assess its effectiveness in real-time anomaly detection and cybersecurity applications.

5. RESULTS AND DISCUSSION

The proposed Hybrid AI framework was evaluated using benchmark network traffic datasets and compared with conventional machine learning and deep learning models. Performance assessment

was conducted using standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, Detection Rate, and False Positive Rate. The experimental results demonstrate that the proposed approach significantly improves anomaly detection performance while maintaining low false alarm rates and real-time processing capabilities.

5.1 Performance Comparison

Table 1 presents the comparative performance of the proposed Hybrid AI model against Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) models.

Table 1. Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	90.2	89.4	88.7	89
Random Forest	94.1	93.5	92.8	93.1
LSTM	96.4	95.9	95.2	95.5
Proposed Hybrid AI	98.7	98.1	97.9	98

The results indicate that the Hybrid AI model achieved the highest performance among all evaluated approaches. The proposed framework obtained an accuracy of 98.7%, outperforming SVM by 8.5%, Random Forest by 4.6%, and LSTM by 2.3%. Similarly, precision, recall, and F1-score values were consistently higher for the Hybrid AI model, demonstrating its superior ability to correctly identify anomalous traffic while minimizing classification errors.

5.2 Detection Performance

The effectiveness of the proposed framework was further analyzed by evaluating its ability to detect different categories of cyberattacks.

Table 2. Detection Rate for Various Attack Types

Attack Type	Detection Rate (%)
DoS	99.1
DDoS	98.8
Probe	97.5
Brute Force	98.3
Botnet	97.9

The detection results reveal that the proposed model successfully identified a wide range of network attacks with high accuracy. Denial-of-Service (DoS) attacks achieved the highest detection rate of 99.1%, while Distributed Denial-of-Service (DDoS) attacks were detected with an accuracy of 98.8%. The framework also demonstrated strong performance against Probe, Brute Force, and Botnet attacks, highlighting its ability to handle diverse threat scenarios in real-time network environments.

5.3 False Positive Analysis

False positive rate is a critical metric in anomaly detection because excessive false alerts can overwhelm security administrators and reduce system effectiveness.

The Hybrid AI framework achieved the lowest false positive rate of 1.9%, significantly outperforming the comparison models. The integration of Random Forest feature selection and LSTM sequence learning enabled the framework to distinguish normal traffic patterns from malicious activities more accurately. This reduction in false alarms improves operational efficiency and enhances trust in automated detection systems.

Table 3. False Positive Rate Comparison

Model	False Positive Rate (%)
SVM	8.5
Random Forest	5.2
LSTM	3.8
Hybrid AI	1.9

5.4 Discussion

The experimental findings demonstrate the effectiveness of the proposed Hybrid AI framework for real-time network anomaly detection. By combining the strengths of machine learning and deep learning techniques, the system achieved superior classification performance compared to standalone approaches. The Random Forest component effectively selected the most relevant traffic features, reducing data complexity and improving model efficiency. Simultaneously, the LSTM network successfully captured temporal dependencies and behavioral patterns within network traffic, enabling the detection of sophisticated and previously unseen attacks.

Another significant advantage of the proposed framework is its ability to reduce false alarms while maintaining high detection rates. Lower false positive rates are essential in practical cybersecurity environments because they minimize unnecessary investigations and allow security teams to focus on genuine threats. The framework also demonstrated strong performance in detecting multiple attack categories, including DoS, DDoS, Botnet, Probe, and Brute Force attacks, confirming its adaptability across diverse threat landscapes.

Furthermore, the real-time processing capability of the Hybrid AI model makes it suitable for deployment in enterprise networks, cloud infrastructures, and Internet of Things (IoT) environments. Its scalable architecture enables efficient handling of large-scale traffic data without significant degradation in performance. Overall, the results confirm that the proposed Hybrid AI framework provides a reliable, intelligent, and scalable solution for modern network security and anomaly detection applications.

6. SECURITY IMPLICATIONS

The increasing sophistication of cyber threats has created a pressing need for intelligent security mechanisms capable of detecting and mitigating attacks in real time. The proposed Hybrid AI framework offers significant security benefits by enhancing the ability of organizations to identify, analyze, and respond to malicious activities within network environments. By integrating Machine Learning and Deep Learning techniques, the framework strengthens cybersecurity defenses and provides proactive protection against both known and unknown threats.

One of the major security implications of the proposed system is its ability to improve threat detection accuracy. Traditional intrusion detection systems often rely on predefined attack signatures, making them ineffective against emerging and previously unseen attacks. The Hybrid AI model addresses this limitation by learning normal network behavior and identifying deviations that may indicate malicious activity. This capability enables organizations to detect zero-day attacks, advanced persistent threats (APTs), and sophisticated cyber intrusions before they cause significant damage.

The framework also contributes to faster incident response and threat mitigation. Real-time anomaly detection allows security teams to receive immediate alerts whenever suspicious network activities are identified. Early detection reduces the time available for attackers to exploit system vulnerabilities, steal sensitive information, or disrupt critical services. Consequently, organizations can implement

timely countermeasures, minimizing the overall impact of cyberattacks and reducing operational downtime.

Another important implication is the reduction of false positive alerts. Security analysts often face alert fatigue due to the large number of notifications generated by conventional monitoring systems. Excessive false alarms can lead to delayed responses and overlooked threats. The proposed Hybrid AI model significantly reduces false positive rates through advanced feature selection and temporal pattern analysis. This improvement allows security personnel to focus on genuine security incidents, enhancing the efficiency and effectiveness of cybersecurity operations.

The proposed framework also supports security in modern computing environments, including cloud computing platforms, enterprise networks, and Internet of Things (IoT) ecosystems. These environments generate massive volumes of dynamic network traffic that require continuous monitoring and intelligent analysis. The scalability of the Hybrid AI approach enables it to process large datasets efficiently while maintaining high detection performance. This capability is particularly valuable for organizations managing distributed infrastructures and complex digital ecosystems.

Furthermore, the framework strengthens organizational resilience against evolving cyber threats. Cybercriminals continuously develop new attack strategies to bypass traditional security controls. By employing adaptive learning mechanisms, the Hybrid AI model can recognize changing attack patterns and update its detection capabilities accordingly. This adaptability ensures long-term effectiveness and supports the development of more resilient cybersecurity architectures.

7. FUTURE WORK

Although the proposed Hybrid AI framework demonstrates high accuracy and effectiveness in real-time network anomaly detection, several opportunities exist for further enhancement and research. Future developments can focus on improving detection capabilities, scalability, interpretability, and adaptability to emerging cybersecurity challenges.

One potential direction is the integration of Federated Learning techniques into the anomaly detection framework. Traditional machine learning models require centralized data collection, which may raise privacy and security concerns. Federated Learning enables multiple organizations or devices to collaboratively train AI models without sharing sensitive data. This approach can improve model generalization while preserving data privacy, making it particularly suitable for cloud computing and distributed network environments.

Another important area for future research is the incorporation of Explainable Artificial Intelligence (XAI) methods. While deep learning models such as LSTM provide excellent detection performance, they often function as "black-box" systems whose decision-making processes are difficult to interpret. XAI techniques can provide transparency by explaining why specific network activities are classified as anomalous. Improved interpretability would increase user trust, support security investigations, and facilitate regulatory compliance in critical sectors.

The rapid growth of the Internet of Things (IoT) presents additional challenges for cybersecurity. Future work may focus on adapting the proposed framework for resource-constrained IoT devices and edge computing environments. Edge-based anomaly detection can process data closer to the source, reducing latency and enabling faster threat detection. Such an approach would be particularly beneficial for smart cities, healthcare systems, industrial automation, and connected transportation networks.

Future research can also explore the use of advanced deep learning architectures, including Transformer Networks**,** Graph Neural Networks (GNNs)**,** and Attention-Based Models. These techniques have shown promising results in handling large-scale and complex data structures and may further enhance anomaly detection performance in highly dynamic network environments.

Another promising direction involves the development of self-learning and adaptive security systems. Cyber threats continuously evolve, and static models may become less effective over time. Incorporating online learning and reinforcement learning mechanisms would allow the framework to automatically update its knowledge and adapt to newly emerging attack patterns without requiring complete retraining.

The framework may also be extended to support multi-class attack classification, enabling the identification of specific attack categories rather than simply distinguishing between normal and anomalous traffic. This enhancement would provide more detailed threat intelligence and assist security teams in implementing targeted mitigation strategies.

8. CONCLUSION

The rapid expansion of digital communication networks, cloud computing platforms, and Internet of Things (IoT) technologies has significantly increased the complexity of modern network environments. While these advancements have improved connectivity and operational efficiency, they have also created new opportunities for cybercriminals to exploit vulnerabilities and launch sophisticated attacks. Traditional intrusion detection systems often struggle to identify unknown threats and adapt to the constantly evolving cybersecurity landscape. As a result, there is a growing need for intelligent, adaptive, and real-time security solutions capable of detecting malicious activities before they cause significant damage. This research addressed these challenges by proposing a Hybrid Artificial Intelligence (AI) framework for real-time anomaly detection in network traffic.

The proposed framework combines the strengths of Machine Learning and Deep Learning techniques to enhance network security performance. Specifically, the Random Forest algorithm was utilized for feature selection and dimensionality reduction, while the Long Short-Term Memory (LSTM) network was employed to capture temporal dependencies and sequential patterns within network traffic data. By integrating these complementary approaches, the framework was able to effectively distinguish between normal and anomalous network activities. The hybrid architecture leveraged the efficiency of machine learning in identifying relevant features and the advanced pattern recognition capabilities of deep learning to achieve superior detection performance.

The methodology involved the use of benchmark cybersecurity datasets, including NSL-KDD, CICIDS2017, UNSW-NB15, and CSE-CIC-IDS2018, which contain diverse attack scenarios and realistic network traffic patterns. Data preprocessing techniques such as normalization, missing value removal, and categorical feature encoding were applied to improve data quality and model performance. The extracted traffic features were then processed through the proposed hybrid framework, and the results were evaluated using widely accepted performance metrics such as accuracy, precision, recall, F1-score, detection rate, false positive rate, and ROC-AUC.

Experimental results demonstrated the effectiveness of the proposed Hybrid AI model in detecting network anomalies. The framework achieved an accuracy of 98.7%, outperforming traditional machine learning models such as Support Vector Machines and standalone Random Forest classifiers, as well as deep learning-based LSTM models. Furthermore, the system successfully detected various cyberattacks, including Denial-of-Service (DoS), Distributed Denial-of-Service (DDoS), Probe, Brute Force, and Botnet attacks with high detection rates. One of the most significant achievements of the framework was its ability to maintain a low false positive rate of 1.9%, which is essential for reducing alert fatigue and improving the efficiency of security operations.

The findings of this study confirm that hybrid AI-based approaches offer substantial advantages over conventional anomaly detection techniques. The proposed framework not only improves detection accuracy but also enhances scalability, adaptability, and real-time operational performance. Its ability to identify both known and unknown attacks makes it particularly valuable in modern cybersecurity environments where threats evolve rapidly and continuously. Moreover, the framework can be

deployed across enterprise networks, cloud infrastructures, and IoT ecosystems to provide continuous monitoring and proactive threat detection.

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