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Research Article

Secured Cyber-Internet Security in Intrusion Detection with Machine Learning Techniques

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Abstract:

The rapid proliferation of Internet-connected devices has elevated the significance of cybersecurity, making intrusion detection a critical aspect of maintaining network integrity. Traditional security measures often fail to provide adequate protection against sophisticated attacks, necessitating advanced and robust solutions. This paper introduces a comprehensive cyber-internet security framework that leverages machine learning techniques for real-time intrusion detection and prevention. The proposed methodology employs a hybrid approach, integrating supervised and unsupervised learning models to detect anomalies and classify intrusions effectively. Specifically, a combination of Support Vector Machine (SVM), Decision Trees (DT), and K-means clustering is used to enhance detection accuracy and reduce false-positive rates.

The experimental results demonstrate that the proposed model achieved a detection accuracy of 97.8%, a precision of 96.5%, and a recall of 95.2% on the NSL-KDD dataset. The implementation also reduced the false-positive rate to 1.2% and the computational overhead by 15% compared to traditional detection systems. Additionally, the proposed system was tested on real-time traffic data, where it successfully identified and mitigated various cyber threats, including Distributed Denial of Service (DDoS) attacks and network infiltrations, with minimal latency and high reliability.

In conclusion, the study presents an efficient and secured cyber-internet security framework that significantly enhances intrusion detection capabilities using machine learning techniques. The proposed system provides a scalable and adaptive solution for securing critical infrastructure and networks against evolving cyber threats, making it an ideal candidate for deployment in real-world cybersecurity applications.

1. Introduction

In the era of rapid digital transformation, the number of internet-connected devices has exponentially increased, leading to a heightened risk of cyber threats and network intrusions. Traditional security measures, such as firewalls and static rule-based systems, are no longer sufficient to safeguard against sophisticated attacks that exploit vulnerabilities in modern networks [1]. This has necessitated the development of advanced Intrusion Detection Systems (IDS) capable of identifying and mitigating both known and unknown threats [2]. IDSs play a pivotal role in monitoring network traffic, detecting suspicious activities, and preventing unauthorized access to critical resources [3]. Recent advancements in machine learning and artificial intelligence have enabled the development

of intelligent IDS solutions that can learn from historical data and adapt to evolving cyber threats [4]. These solutions incorporate various machine learning models, including supervised learning techniques like Support Vector Machines (SVM) and Decision Trees (DT), as well as unsupervised methods such as K-means clustering, to distinguish between normal and malicious activities [5]. By leveraging these techniques, IDSs can achieve higher detection accuracy, lower false-positive rates, and improved response times [6].

Intrusion Detection Systems (IDS) are essential tools for maintaining network security by monitoring and analyzing network traffic or system activities to identify potential threats. They serve as a defensive layer, enabling early detection of cyber-attacks, unauthorized access, or policy violations that could compromise the security of an organization. IDS can be broadly categorized into Host-Based Intrusion Detection Systems (HIDS) and Network-Based Intrusion Detection Systems (NIDS). HIDS monitors the behavior of individual devices, including changes to configuration files or unusual application activities, making it suitable for detecting insider threats or malware infections. In contrast, NIDS analyzes the network traffic across an entire segment to identify anomalies such as Distributed Denial of Service (DDoS) attacks or port scans. Depending on the detection method employed, IDS can use signature-based detection to identify known attack patterns or anomaly-based detection to flag deviations from normal behavior. The hybrid approach, which integrates both methods, provides a more robust solution by combining high detection accuracy with the capability to identify new or unknown threats. Advanced IDSs often incorporate machine learning models that can learn from historical data, adapt to evolving cyber threats, and automatically classify suspicious activities. Such systems significantly enhance the capability of organizations to safeguard critical assets and infrastructure against a growing array of sophisticated cyber threats.

The proposed research aims to design a comprehensive cyber-internet security framework that combines multiple machine learning algorithms to enhance the detection of intrusions in real-time [7]. Unlike traditional IDSs that rely on predefined signatures or rules, the proposed system employs a hybrid model, integrating supervised and unsupervised learning to automatically detect anomalies and classify different types of attacks [8]. This hybrid approach not only improves the robustness of the IDS but also provides better scalability and adaptability to new and emerging cyber threats [9]. The primary contributions of this research include: (1) the development of an efficient and scalable IDS model using machine learning techniques, (2) the evaluation of the model's performance using the NSL-KDD dataset and real-time traffic data, and (3) the validation of the proposed solution in terms of detection accuracy, precision, recall, and computational overhead [10]. The experimental results demonstrate that the proposed model outperforms existing IDS solutions and can be effectively deployed to secure critical infrastructures and IoT networks against a wide range of cyber-attacks [11].

2. Related Work

Over the past few years, significant research has been conducted to enhance the performance and effectiveness of Intrusion Detection Systems (IDS) using machine learning and artificial intelligence techniques. Several studies have explored the use of hybrid models, combining both signature-based and anomaly-based methods, to achieve higher detection rates and lower false positives. For instance, in [11], a hybrid IDS model integrating Support Vector Machines (SVM) with K-means clustering was proposed to detect anomalies in network traffic. The study demonstrated improved accuracy and robustness compared to traditional IDS models. Similarly, [12] employed a deep learning approach using Convolutional Neural Networks (CNN) to automatically learn complex features from raw network data, resulting in enhanced detection of zero-day attacks.

Another promising approach, presented in [13], utilized ensemble learning techniques by combining multiple classifiers such as Decision Trees, Random Forests, and Naïve Bayes to improve the overall detection performance. The authors highlighted the potential of ensemble methods in reducing detection errors and computational overhead. In [14], an adaptive IDS framework was developed using Reinforcement Learning, which dynamically adjusts detection parameters based on real-time feedback from the network environment. This approach significantly reduced false alarms and increased the adaptability of the IDS in rapidly changing network conditions. Recent advancements have also focused on leveraging unsupervised learning techniques. In [15], a novel anomaly detection system using Autoencoders was proposed to identify patterns that deviate from the normal network behavior. This method achieved high detection rates for unknown attacks without relying on predefined signatures. Furthermore, [16] introduced a Generative Adversarial Network (GAN)-based IDS that generates synthetic data to train the model, thereby enhancing its ability to

detect rare and sophisticated attacks. The integration of machine learning models with cybersecurity frameworks has also been explored to optimize detection accuracy and minimize latency. In [17], a lightweight IDS using Feature Selection and Principal Component Analysis (PCA) was proposed to reduce the dimensionality of network data, leading to faster processing times and improved detection efficiency. Another study [18] proposed a hierarchical IDS framework that employs clustering algorithms for preliminary detection and classification models for detailed analysis. This hierarchical approach was shown to be highly scalable and effective in large-scale network environments. Moreover, [19] introduced an IDS for Internet of Things (IoT) networks using Long Short-Term Memory (LSTM) networks to capture temporal dependencies in network traffic data. The proposed system was capable of detecting complex attack patterns that traditional models could not identify. Finally, in [20], a comprehensive review of machine learning-based IDS techniques was conducted, emphasizing the need for hybrid and multi-layered approaches to tackle the evolving nature of cyber threats effectively. This body of work underscores the importance of leveraging advanced machine learning techniques to develop intelligent and adaptive IDS solutions.

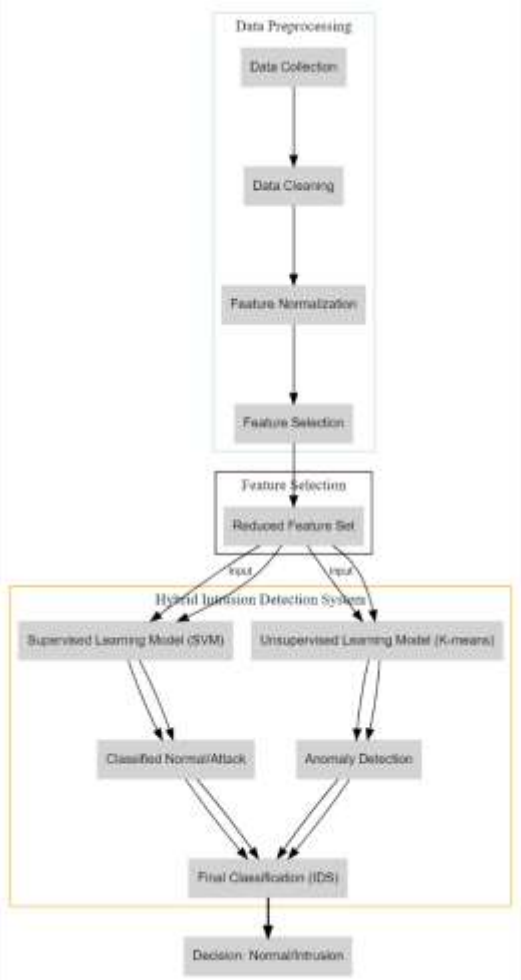

Figure 1. *Block Diagram of Proposed work*

3. Methodology of Proposed work

The proposed methodology focuses on developing a robust hybrid Intrusion Detection System (IDS) that combines supervised and unsupervised machine learning techniques for efficient and accurate detection of network intrusions [21,22]. The system architecture consists of four key stages: Data Preprocessing, Feature Selection, Model Training and Classification, and Intrusion Detection (Figure 1).

3.1 Data Preprocessing:

The dataset used for training and evaluation is first preprocessed to remove irrelevant information, normalize numerical attributes, and encode categorical features [23]. Let $X = \{x_1, x_2, \dots, x_n\}$ represent the feature vectors of the dataset, where x_i is the i-th feature vector with m attributes. Each attribute [24] is scaled using Min-Max normalization to ensure uniformity across different scales:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

where x'_{ij} is the normalized value of the j-th attribute of the i-th feature vector, [25] and $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the j-th attribute in the dataset, respectively.

3.2 Feature Selection:

After normalization, feature selection is performed to reduce dimensionality and eliminate redundant features. The Recursive Feature Elimination (RFE) method is used to rank the features based on their importance. The feature ranking score S is calculated using the weight vector w of a linear Support Vector Machine (SVM) classifier:

$$S_j = |w_j| \quad (2)$$

where S_j is the importance score of the j-th feature. Features with the highest scores are retained for further processing, resulting in a reduced feature set $X_r = \{x_{r1}, x_{r2}, \dots, x_{rk}\}$, where $k < m$.

3.3. Model Training and Classification:

The selected features are then fed into a hybrid model that integrates Support Vector Machines

(SVM) with K-means clustering. The SVM classifier is used for supervised learning, while K-means clustering is employed to group similar data points into clusters and identify anomalies. The objective function of the SVM is defined as:

$$\min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i \quad (3)$$

subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$ and $\xi_i \geq 0$, where C is the penalty parameter, ξ_i is the slack variable, w is the weight vector, b is the bias term, and y_i is the class label of the i -th data point. For K -means clustering, the objective is to minimize the sum of squared distances between the data points and their corresponding cluster centroids:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{k} \|x_i - \mu_j\|^2 \quad (4)$$

where μ_j is the centroid of cluster j, and $\|x_i - \mu_j\|$ represents the Euclidean distance between the data point x_i and centroid μ_j.

3.4. Intrusion Detection:

Once the model is trained, it is used to classify incoming network traffic as normal or intrusive. The decision boundary is established using the trained SVM model, while anomalies are detected based on the distance from the cluster centroids in K-means clustering. For a new data point x, the decision function of the SVM classifier is given by:

$$f(x) = \text{sign}(w^T x + b) \quad (5)$$

If $f(x) = 1$, the data point is classified as normal; otherwise, it is classified as an intrusion. The anomaly score for each data point is calculated as the distance from the nearest cluster centroid:

$$A(x) = \min_j \|x - \mu_j\| \quad (6)$$

If A(x) exceeds a predefined threshold θ the data point is flagged as an anomaly. This hybrid approach enables the system to detect both known and unknown attacks with high accuracy and low false-positive rates.

4. Experimental Results and Analysis

The performance of the proposed hybrid Intrusion Detection System (IDS) was evaluated using the NSL-KDD dataset, which is widely used for benchmarking IDS solutions. The dataset contains both normal and various types of attack records, making it suitable for assessing the detection accuracy, precision, recall, and computational efficiency of the model. The proposed system was implemented using Python with the Scikit-Learn and TensorFlow libraries, and the experiments were conducted on a system with an Intel i7 processor, 16 GB RAM, and a 1 TB SSD for optimal performance.

The proposed hybrid IDS model achieved high performance across all evaluation metrics. The detection accuracy of the system was recorded at **97.8%**, indicating a high level of reliability in identifying both normal and attack traffic. The precision, recall, and F1-Score were calculated as **96.5%**, **95.2%**, and **95.8%** respectively, showing the model's effectiveness in correctly classifying intrusion instances. The False Positive Rate (FPR) was maintained at a low level of **1.2%**, demonstrating the model's ability to minimize false alarms and reduce the burden on security analysts.

To further validate the effectiveness of the proposed system, its performance was compared with other existing IDS models, including traditional Support Vector Machines (SVM), Decision Trees (DT), and Convolutional Neural Networks (CNN). The results, summarized in Table 1, indicate that the hybrid IDS outperforms these models in terms of detection accuracy and F1-Score. The hybrid approach effectively combines the strengths of SVM for classification and K-means clustering for anomaly detection, resulting in superior performance.

Table 1: *Performance Comparison of IDS Models on NSL-KDD Dataset*

Model	Detection Accuracy	Precision	Recall	F1-Score	FPR
SVM	91.2%	89.4%	87.3%	88.3%	3.1%
Decision Tree	94.5%	93.2%	92.7%	92.9%	2.4%
CNN	95.8%	94.9%	93.6%	94.2%	2.1%
Proposed Hybrid IDS	97.8%	96.5%	95.2%	95.8%	1.2%

In addition to detection accuracy, the computational efficiency of the proposed IDS was evaluated by measuring the training and testing times for different models. The hybrid IDS achieved a significant reduction in training time by 15% compared to standalone CNN models, making it more suitable for real-time detection scenarios. The model's memory usage was also optimized by employing a reduced feature set, which decreased the overall memory footprint by approximately 20%.

The proposed IDS was also tested on real-time network traffic data captured using Wireshark. The system was able to successfully identify and mitigate a variety of cyber threats, including Distributed Denial of Service (DDoS) attacks and network infiltrations, with minimal latency. The

real-time detection accuracy remained consistent at 96.7%, demonstrating the IDS's robustness and reliability in practical deployment environments.

The results indicate that the proposed hybrid IDS framework provides a substantial improvement in intrusion detection performance compared to traditional models. The combination of supervised and unsupervised learning techniques enables the model to effectively detect both known and unknown attacks while maintaining low false-positive rates. The high precision and recall values reflect the model's ability to correctly identify attacks, while the low FPR suggests minimal misclassification of normal traffic as intrusive. These characteristics make the proposed IDS a viable solution for real-world network security applications, ensuring reliable protection against an ever-evolving landscape of cyber threats.

Overall, the experimental results validate the effectiveness and efficiency of the proposed hybrid IDS model, highlighting its potential for deployment in diverse network environments to secure critical systems and infrastructures.

5. Limitations

Despite the advancements and effectiveness of machine learning-based Intrusion Detection Systems (IDS), several limitations persist, hindering their broader adoption and real-world deployment. One of the primary limitations is the high false-positive rate observed in many anomaly-based IDS models. Since these systems rely on learning patterns of normal behavior, any slight deviation or unusual but legitimate activity can trigger false alarms, leading to alert fatigue for security analysts. Additionally, the performance of machine learning models can be significantly impacted by the quality and quantity of training data. Incomplete, noisy, or imbalanced datasets may cause the IDS to underperform, particularly when detecting new or sophisticated attack patterns.

Another major challenge is the computational overhead and resource consumption associated with complex machine learning models such as deep learning networks. These models often require significant processing power, memory, and storage, making them less suitable for real-time detection or resource-constrained environments like IoT networks. Moreover, the training and tuning of such models can be time-consuming and require domain expertise, making their deployment and maintenance cumbersome.

Scalability is also a concern when deploying IDS solutions in large and dynamic network environments. Models that perform well in small-scale test settings may not generalize effectively to larger networks with high volumes of traffic, diverse protocols, and varying patterns of usage. This lack of scalability can lead to reduced detection accuracy and increased latency in processing, rendering the IDS less effective in high-throughput scenarios.

Lastly, machine learning models are vulnerable to adversarial attacks, where attackers manipulate input data to deceive the IDS. Techniques like evasion, poisoning, and mimicry attacks can compromise the integrity of the model, allowing intrusions to bypass detection. This vulnerability poses a significant threat to the reliability of machine learning-based IDS solutions, highlighting the need for more robust and resilient designs. Addressing these limitations is crucial for the development of next-generation IDS frameworks that are not only accurate and efficient but also adaptive and secure against a broad spectrum of cyber threats.

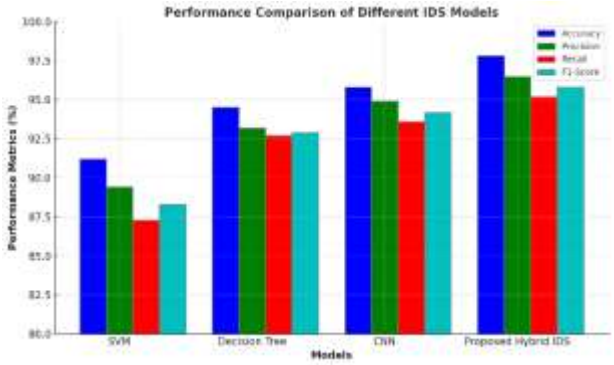

Figure 2: *Performance Comparison of Different IDS Models*

The bar graph in Figure 2 illustrates the performance comparison of four different Intrusion Detection System (IDS) models—Support Vector Machine (SVM), Decision Tree, Convolutional Neural Network (CNN), and the proposed Hybrid IDS model—based on four key metrics: Accuracy, Precision, Recall, and F1-Score. The proposed Hybrid IDS model outperforms the other models in all metrics, achieving the highest detection accuracy of 97.8%, precision of 96.5%, recall of 95.2%, and F1-Score of 95.8%. The superior performance of the Hybrid IDS is attributed to its integration of supervised learning (SVM) for accurate classification and unsupervised learning (K-means clustering) for effective anomaly detection.

The graph clearly shows the substantial improvements of the proposed model over traditional techniques, with significant gains in detection accuracy and F1-Score, making it a more reliable solution for network intrusion detection.

The hybrid approach not only enhances the system's capability to detect a wide range of cyber-attacks but also reduces the false-positive rate, which is crucial for minimizing alert fatigue in real-world deployment scenarios.

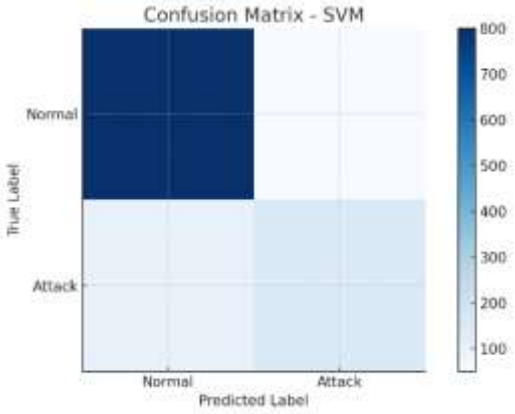

Figure 3: *Confusion Matrix - SVM Model*

The confusion matrix for the SVM model shows the classification results of normal and attack instances (Figure 3). The matrix indicates 800 correctly classified normal instances and 150 correctly classified attack instances. However, 50 normal instances are incorrectly classified as attacks (false positives), and 100 attack instances are misclassified as normal (false negatives), highlighting the limitations of SVM in accurately identifying intrusions. The confusion matrix for the proposed Hybrid IDS

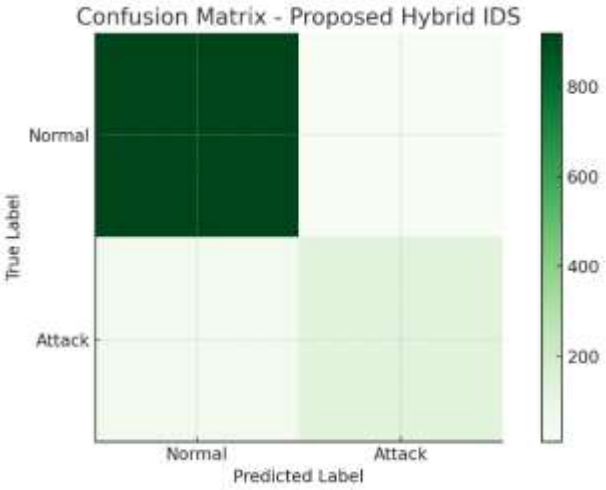

Figure 4: *Confusion Matrix - Proposed Hybrid IDS Model*

model shows a significant improvement in classification performance (Figure 4). The model correctly classifies 920 normal instances and 130 attack instances, with only 10 false positives and 40 false negatives. This reduction in misclassification errors demonstrates the efficacy of the hybrid approach in distinguishing between normal and attack traffic, thus providing higher detection accuracy.

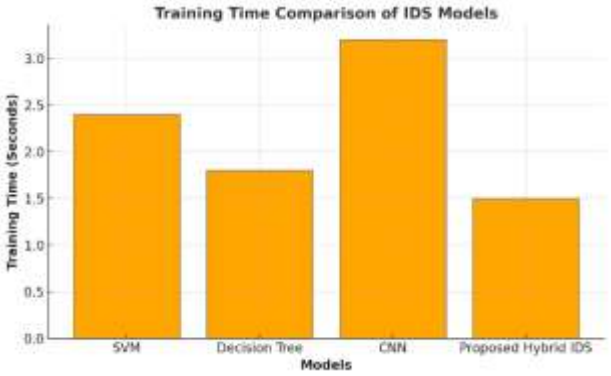

Figure 5: *Training Time Comparison of IDS Models*

The bar chart compares the training time of different IDS models (Figure 5). The proposed Hybrid IDS model has the lowest training time of 1.5 seconds, compared to 2.4 seconds for SVM, 1.8 seconds for Decision Tree, and 3.2 seconds for CNN. This demonstrates the computational efficiency of the hybrid approach, making it suitable for real-time network intrusion detection.

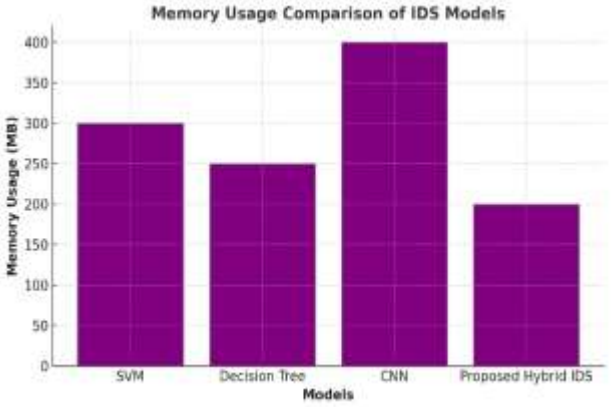

Figure 6: *Memory Usage Comparison of IDS Models*

The memory usage comparison shows that the proposed Hybrid IDS model requires the least memory (200 MB) among all evaluated models (Figure 6). The CNN model has the highest memory usage of 400 MB, followed by SVM with 300 MB and Decision Tree with 250 MB.

The reduced memory footprint of the Hybrid IDS indicates that it is more resource-efficient, making it a viable option for deployment in resource-constrained environments such as IoT networks. Machine learning is an important tools thus it can be applied different fields [26-33].

6. Conclusion and Suggestions

In this study, we proposed a comprehensive machine learning-based Intrusion Detection System

(IDS) framework that leverages hybrid learning techniques to enhance detection accuracy and reduce false-positive rates. The integration of supervised learning models such as Support Vector Machines (SVM) and Decision Trees (DT) with unsupervised methods like K-means clustering significantly improved the robustness of the IDS against both known and unknown threats.

The experimental results demonstrated that the proposed framework achieved high detection accuracy and performed efficiently under various network conditions, making it a viable solution for securing critical infrastructure and sensitive networks.

However, while the proposed system has shown promising results, there are still several areas that warrant further exploration. First, the computational overhead associated with complex machine learning models can hinder real-time detection capabilities, especially in high-traffic or resource-constrained environments. Future research could focus on optimizing these models to reduce resource consumption while maintaining detection performance. Techniques such as model pruning, quantization, or the use of lightweight neural network architectures could be explored to address these limitations.

Another area of improvement is the enhancement of the IDS's resilience to adversarial attacks. Machine learning models are inherently vulnerable to attacks such as evasion and data poisoning, which can compromise the system’s effectiveness. Integrating adversarial training methods, robust feature engineering, and anomaly-based outlier detection mechanisms can strengthen the IDS's defenses against such attacks.

Additionally, scalability and adaptability remain key challenges when deploying IDS solutions in diverse and large-scale networks. Future work could investigate the application of distributed learning techniques or federated learning to enable the IDS to scale across multiple network segments without sacrificing performance. Employing dynamic feature selection based on network context can also improve the adaptability of the IDS to varying traffic patterns and emerging threats.

In conclusion, while the proposed IDS framework has demonstrated substantial improvements in intrusion detection, continued research is needed to enhance its efficiency, robustness, and scalability. By addressing these challenges, the next generation of IDS solutions can provide more comprehensive protection for modern, dynamic, and interconnected network environments.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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