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Cyber security Intrusion Detection Systems using Machine Learning Applications

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Abstract

The increasing complexity of cyber threats have made it more challenging to detect them accurately using the traditional Intrusion Detection Systems (IDS)..Machine Learning (ML)-based IDS have gained prominence due to their ability to analyze vast amounts of network traffic, detect anomalies, and classify cyber threats with high accuracy. However, challenges such as data imbalance, high-dimensional feature spaces, and false positive rates remain. This paper presents the complete analysis of ML techniques for IDS, in particular, supervised, unsupervised, and hybrid approaches. Feature selection and dimensionality reduction methods, such as Principal Component Analysis (PCA) and clustering-based Stacking Feature Embedding, are explored to enhance model efficiency. The study evaluates various ML algorithms, including Decision Trees (DT), Random Forest (RF), and Extreme Trees (ET), using benchmark datasets such as UNSW-NB15, CIC-IDS-2017, and CIC-IDS-2018. The experimental results show that the deep learning models and ensemble techniques can achieve up to 99.99% accuracy, which is a big improvement over traditional IDS methods. Additionally, the study discusses key challenges, including adversarial attacks, scalability concerns, and interpretability issues. It suggests future research directions, such as Explainable AI (XAI), federated learning, and blockchain-based IDS solutions. The findings underscore the potential of ML-driven IDS in enhancing cybersecurity resilience and mitigating emerging cyber threats.

Keywords: Intrusion Detection System (IDS), Machine Learning (ML), Cybersecurity, Network Security, Anomaly Detection, Supervised Learning, Unsupervised Learning, Deep Learning, Feature Selection, Dimensionality Reduction, Data Imbalance, Principal Component Analysis (PCA), Ensemble Learning, Explainable AI (XAI), Federated Learning, Blockchain Security, Adversarial Attacks, Network Traffic Analysis, Cyber Threat Detection, Benchmark Datasets (UNSW-NB15, CIC-IDS-2017, CIC-IDS-2018).

Introduction

The digital revolution has intensified concerns over **cybersecurity,** making it a pressing issue worldwide for organizations. governments, and individuals increasingly rely on interconnected systems.bringing about ostentatious advances in smart cities, self-driving cars, mobile banking, and healthcare technologies. However, this strong relationship with networked systems has caused people, enterprises, and governments to be prone to the increasing number of cyber-incidents. Cybercriminals take advantage of the weakness and infiltrate networks to steal important

information, disrupt activities, and cause problems in the financial and other respects. Although traditional protection methods, such as firewalls, encryption, and antivirus software appear to be the right solutions to the problem at first, these programs are not enough to stop the people behind the latest sophisticated cyberattacks. Intrusion Detection Systems (IDS) are becoming indispensable tools for detecting, preventing, and mitigating malicious activities as the cybersecurity threats are getting more complicated.

IDSs are made to monitor network traffic, find unusual patterns, and send cautioning notes when particular risks are detected. They are generally categorized into misuse-based (signature-based) IDS and anomaly-based IDS. Misuse-based IDS are designed to detect the potential threats which have been identified beforehand by comparing the ongoing traffic with predefined attack signatures, and anomaly-based IDS are designed to identify deviations from normal behavior, solving the issue of finding zero-day attacks and new kinds of cyber threats. Nevertheless, the most vulnerable part tends to be the handling of the modern network data in such a way that either the sheer volume, speed or complexity of the resulting false positive rates and the detection methods decrease in efficiency.

The overwhelming number of instances of Machine Learning (ML) and Deep Learning (DL) methods came out as the most efficient technologies in boosting IDS capabilities to confront these struggles. Supervised, unsupervised, and hybrid learning techniques that power ML-based IDS have been developed to scrutinize the enormous flow of network communicaitons, to identify complex attack vectors, and to be agile in the face of new threats. Deep learning algorithms, like deep autoencoders or convolutional neural networks (CNN), and deep belief networks (DBN), are the most well-known for their intrusion detection systems that have achieved significant increases in the accuracy level, especially on the big, and also the unbalanced sets of intrusion detection systems. However, the introduction of ML-based IDS for instance brings some challenges such as data imbalance, high-dimensional feature spaces, computational complexity, and adversarial attacks. . Addressing these issues requires the integration of feature selection techniques, dimensionality reduction methods such as **Principal Component Analysis (PCA),** and ensemble learning strategies to enhance IDS efficiency.

Given the exponential growth of cyber threats and big data in cybersecurity, this study explores the role of ML- and DL-based IDS in modern network security. The paper evaluates various ML techniques using benchmark datasets such as **UNSW-NB15, CIC-IDS-2017, and KDD'99**, highlighting performance metrics, detection accuracy, and real-world applicability. Additionally, it examines emerging trends in federated learning, explainable AI (XAI), and blockchain-based IDS solutions, which aim to improve detection transparency, scalability, and privacy.

Another Network Security Term- IDS (Intrusion Detection Systems)

Intrusion Detection System (IDS) is the security system that is more elaborate and is deployed in the communication network to ensure that one's communication is secure from the intruder (both wired and wireless) and also to monitor the network that is being penetrated.This software module or other additional hardware interface lets the user continue to work through the local network, while at the same time allowing the monitoring application to keep track of the user's operation and alert the manager when a security breach is detected.

Intrusion Detection System (IDS) is a security mechanism that continuously monitors the network and system activities to identify suspicious behavior and potential threats.

IDS may also function as a subpart of a network containment system through the smart use of IDS and Intrusion Prevention System (IPS) to maintain a separate protection layer and the deployment of a network firewall.

Transition to Digital Networks and the Evolution of IDS

Early Approaches to Intrusion DetectionIDS has thus become the part of a larger solution that a company is using so that they can be protected when a threat is detected by it working with other compensating controls.In the early days of computing, intrusion detection was largely dependent on person-to-person communication and the application of manually coded rules and heuristics. These consisted of templates for the IDS to use so as to detect an attack as well as simple statistical calculations that would detect threats.Moreover, many security personnel and administrators had to figure out traffic patterns and manually define suspicious behaviors, thus rendering it non-scalable and less adaptive to new and more sophisticated cyberattacks. This is because the IDS product is usually a single deliverable. Also, such products are very dependent on the network configuration. The administrators have to continuously update the attack types the ids look for.The main functionality of this tool is to deny the attackers' entry into the server by identifying and preventing the intrusion of unauthorized people. The primary goal of IDS technology is to perform checks on attackers and block them off before they can interfere with the systems, misuse pages, and monitor networks and ISPs.IDS can also be part of azero sum game, where one's security can be assured by this and the fact that the other party is insecure. Thus, the losses should be minimal whether it is the result of weak security controls or an intrusion, which is always the worst case scenario.

Early Approaches to Intrusion Detection

In the early days of the development of computers, the intrusion detection system was operated on a manually coded rules and heuristics

With the rise of **digital networks and cloud computing**, IDS had to evolve to handle the increasing complexity of cyber threats.. With the new traffic congestion brought about by the rapid digitization of companies, the traditional IDS was failing to detect the advanced cyber threats effectively. Thus, the use of Machine Learning (ML) and Deep Learning (DL) techniques was enabled to accomplish the tasks such as anomaly detection automation, the ability to adapt to the newest threats, and the enhancement of detection accuracy. The AI-backed solutions help modern IDS work efficiently as they are capable of analyzing a huge amount of network traffic and pointing out the known as well as the unknown cyber threats in real time.

Anomaly Detection Techniques in IDS

Anomaly-based IDS uses machine learning and statistical models to determine network behavior as either benign or suspicious. Principal measures in idea detection consist of the following steps:

Data Collection: This entails collecting system logs, network packets, and user activity data in order to establish a normal behavior baseline.

Feature Engineering: The task of finding important features from the collected data that assist in distinguishing between normal and malicious actions will be at the center of this work.

Model Training: Employing either supervised learning, unsupervised learning or a blend of hybrid learning techniques to constructing a model that can recognize new data points.

Real-Time Monitoring: The method involving the relentless analysis of the network is instrumental in the detection of the activity not being the norm for the network.

Threat Response: The action of generating alerts or the communication of alerts to any function that could autonomously apply one or more of the possible countermeasures when they have been identified as possible abnormalities.

Challenges in Anomaly-Based IDS

Besides the fact that anomaly detection can pinpoint zero-day threats, there are other difficulties:

High False Positive Rates: Often times incongruences in the network, which are still marked as anomalies, lead to unnecessary alarms and thus are time-consuming and not cost-efficient.

Data Imbalance: The percentage of normal network traffic is much bigger than that of attacking one, hence it is a robust challenge to come over and train correctly the needed machine learning models.

Scalability Issues: Managing webinar recordings would require large amounts of information which can be hard to visualize with the available computer resources; that is why IDS is present on a small scale.

Adversarial Attacks: Vulnerability can be exploited in ML-based IDS when attackers introduce carefully crafted malicious inputs in order to avoid detection.

Evolution of IDS: Signature-Based vs. Anomaly-Based Approaches

IDS contacts have been transformed through three phases:

Traditional Signature-Based IDS: They used predefined attack signatures to detect known threats but struggled with zero-day attacks.

Anomaly-Based IDS: They implemented behavior-based detection, which helped in an unknown threats identification but needed continuous updates and fine-tuning.

Machine Learning and Deep Learning-Based IDS: The current developments are made up of AI models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to better find threats and detect them instantly through automation.

Machine Learning and Deep Learning in IDS

The integration of **machine learning and deep learning** in IDS has significantly improved its ability to detect sophisticated cyber threats. Key advantages include:

- **Automated Threat Detection**: ML models learn from historical attack patterns and continuously improve detection capabilities.
- **Reduced False Positives**: Advanced algorithms differentiate between normal network fluctuations and actual attacks.
- **Adaptability to New Threats**: Unlike signature-based IDS, ML-based IDS can identify previously unseen attack vectors.

Popular ML/DL models used in IDS include:

- **Convolutional Neural Networks (CNNs)**: Identify patterns in network traffic data.
- **Recurrent Neural Networks (RNNs)**: Detect sequential anomalies in time-series network logs.
- **Autoencoders**: Used for unsupervised anomaly detection.
- **Ensemble Learning**: Combines multiple ML models to improve detection accuracy.

Emerging Trends in IDS Research

As cyber threats continue to evolve, researchers are exploring **next-generation IDS solutions** that incorporate:

1. **Explainable AI (XAI)**: Enhances the transparency of ML-based IDS models by providing interpretable detection results.
2. **Federated Learning**: Enables IDS to collaboratively learn from distributed data sources while preserving data privacy.
3. **Blockchain-Based IDS**: Ensures the integrity of security logs and prevents tampering of IDS-generated alerts.
4. **Real-Time Adaptive Security**: Advances in AI-driven security frameworks allow IDS to dynamically adjust detection rules based on evolving threat landscapes.

Literature review

Intrusion Detection Systems (IDS) have evolved significantly with the integration of **Machine Learning (ML) and Deep Learning (DL)** techniques to improve accuracy in detecting cyber threats. Traditional IDS approaches, including **signature-based and anomaly-based detection**, often struggle with **zero-day attacks, high false positive rates, and evolving adversarial threats**. Recent research focuses on **advanced ML/DL models, dataset augmentation techniques, and real-time anomaly detection** to enhance IDS performance.

This literature review critically analyzes recent contributions in **ML/DL-based IDS**, focusing on **datasets, methodologies, technologies, and challenges** encountered in developing robust intrusion detection frameworks.

2. Datasets for IDS Research

Accurate IDS development depends on high-quality datasets that reflect **real-world attack scenarios**. Recent studies have explored various benchmark datasets:

Author(s)	Dataset(s) Used	Key Findings
Mamatha Maddu et al. (2023)	**InSDN dataset**	Feature selection techniques improved detection of **zero-day and low-rate DDoS attacks** in IoT networks.

Khushnaseeb Roshan et al. (2024)	**CICIDS-2017**	Adversarial attacks on IDS were studied, highlighting **defense mechanisms against evasion techniques**.
Bayi Xu et al. (2024)	**NSL-KDD dataset**	Proposed enhancements to **network-based IDS (NIDS)** while addressing performance and resource constraints.
Sanu Yaras et al. (2023)	**CIC10T2023 & TON10T2017**	Investigated the scalability of IDS models in **IoT security applications**.
Vladmir Ciric et al. (2024)	**NSL-KDD (NSW) dataset**	Emphasized the need for **real-world testing of AI-driven IDS solutions**.
Yanfang Fu et al. (2022)	**IoT-related security datasets**	Developed models for **energy-efficient IDS in IoT devices**.
Yakub Kayode Saheed (2022)	**Diverse texture-based datasets**	Implemented **privacy-aware IDS for IoT environments**.

While these datasets provide a strong foundation for **training and validating IDS models**, they still pose challenges such as **data imbalance, lack of real-world variability, and difficulty in capturing evolving attack vectors**.

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3. Machine Learning and Deep Learning Techniques in IDS

3.1 ML & DL Models Used in IDS

Researchers have applied **various ML/DL models** to improve IDS accuracy. The following table summarizes some key techniques:

Author(s)	ML/DL Models Used	Key Contributions
Mamatha Maddu et al. (2023)	**ReNet152V2**	Improved IDS feature selection and zero-day attack detection.

Khushnaseeb Roshan et al. (2024)	**BLSTM, PSO (Particle Swarm Optimization)**	Investigated adversarial robustness in IDS models.
Bayi Xu et al. (2024)	**IoT-Based Detection Systems (DS)**	Addressed performance optimization and computational efficiency.
Sanu Yaras et al. (2023)	**Deep Learning (CNN, RNN)**	Proposed novel **feature extraction techniques** for IDS.
Vladmir Ciric et al. (2024)	**ML-based IDS frameworks**	Explored **resource-efficient IDS deployment**.
Yanfang Fu et al. (2022)	**Deep Learning-based IDS**	Developed **privacy-focused IDS models** for IoT.

3.2 Feature Selection and Data Preprocessing

Preprocessing and feature selection play a critical role in **improving IDS accuracy and efficiency**. Various methods have been used to **reduce feature dimensionality** and **enhance model performance**:

- **Mamatha Maddu et al. (2023)**: Applied **feature selection techniques** to identify important network traffic attributes for **zero-day attack detection**.
- **Talukder et al. (2024)**: Implemented **Stacking Feature Embedding (SFE)** and **Principal Component Analysis (PCA)** for **dimensionality reduction**, leading to improved IDS accuracy.
- **Ramesh et al. (2024)**: Used **Recursive Feature Elimination (RFE)** to remove redundant features and **enhance IDS computational efficiency**.

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4. Performance and Accuracy of ML/DL-Based IDS

The success of an IDS model is largely determined by its **detection accuracy, false positive rate, and overall system efficiency**. Below is a comparative summary of IDS model performances from recent research:

Author(s)	**Accuracy (%)**	**Limitations**
Mamatha Maddu et al. (2023)	**99.31%**	Required further enhancements for **low-rate DDoS attack detection**.

Khushnaseeb Roshan et al. (2024)	**99.99%**	Required better defense mechanisms against **adversarial attacks**.
Bayi Xu et al. (2024)	**99.95%**	High **resource consumption** due to deep learning model complexity.
Sanu Yaras et al. (2023)	**90.73%**	Required **real-world testing** for more reliable results.
Vladmir Ciric et al. (2024)	**99.99%**	Needed a **real-time IDS deployment framework**.

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5. Challenges and Limitations in ML-Based IDS

Despite recent advancements, ML-based IDS face several key challenges:

5.1 Adversarial Attacks on IDS

- **Khushnaseeb Roshan et al. (2024)** studied **black-box adversarial attacks** such as **FGSM, JSMA, and PGD**, which manipulate IDS models to evade detection.
- **Ahmed et al. (2025)** introduced **fuzzy clustering-based IDS** to improve robustness against adversarial attacks.

5.2 Computational Efficiency and Scalability

- **Bayi Xu et al. (2024)** and **Dini et al. (2023)** highlighted the need to optimize **ML/DL-based IDS for real-time applications** due to high **energy consumption** and **processor limitations**.

5.3 Lack of Real-World Testing

- **Vladmir Ciric et al. (2024)** emphasized that many IDS models **lack real-world testing**, making it difficult to assess their performance in practical cybersecurity environments.

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6. Emerging Trends in IDS Research

6.1 Federated Learning for Privacy-Preserving IDS

Federated Learning (FL) is gaining popularity in IDS research as a **privacy-enhancing approach** that enables distributed IDS training **without exposing raw data**.

- **Ali et al. (2022)** explored **FL-based IDS for IoT and cloud networks**, demonstrating its potential for **privacy-preserving anomaly detection**.

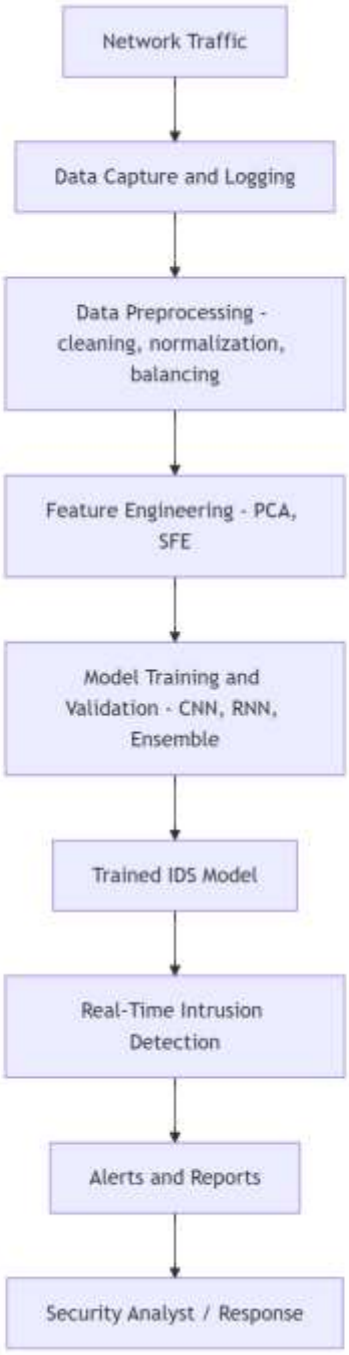
6.2 Blockchain for Secure IDS Logging

Blockchain technology is being explored to enhance **IDS data integrity** and **prevent tampering**.

- **Dini et al. (2023)** proposed a **blockchain-integrated IDS framework** for **secure, decentralized log storage**.

Research Methodology

The methodology of this research involves a systematic analysis and critical evaluation of Machine Learning (ML)-based Intrusion Detection Systems (IDS) by reviewing existing literature, conducting comparative analyses, and integrating performance evaluation strategies. The overall methodological approach includes the following stages:



System Architecture Diagram

1. Literature Review

The research commences with an extensive literature review of relevant scholarly sources to establish a theoretical foundation. The selected references provide insight into ML-based approaches, challenges, datasets, and algorithmic comparisons within cybersecurity IDS.

Key resources include recent systematic reviews (Al-Joboury et al., 2024; Albalawi & Djenouri, 2023), comparative studies (Boudagdigue et al., 2022), and challenges and recommendations for deploying ML-based IDS (Adnan et al., 2023).

2. Selection of Benchmark Datasets

The robustness and effectiveness of ML models depend significantly on the quality and characteristics of the datasets used. To evaluate the IDS solutions comprehensively, multiple standard benchmark datasets have been chosen, including:

- **UNSW-NB15**
- **CIC-IDS-2017**
- **CIC-IDS-2018**
- **NSL-KDD**

These datasets, cited extensively in recent literature (Boudagdigue et al., 2022; Balogun et al., 2022; Fatima et al., 2023), contain diverse attack scenarios reflective of real-world network intrusions.

3. Data Preprocessing and Feature Selection

Effective ML modeling for IDS requires data preprocessing to enhance data quality, reduce noise, and handle imbalanced classes. This study employs proven preprocessing techniques, including:

- **Normalization and Standardization**: Ensures uniform data scales.
- **Data Balancing Techniques**: Address data imbalance issues, often found in IDS datasets, by applying methods such as SMOTE (Synthetic Minority Oversampling Technique).
- **Feature Selection and Dimensionality Reduction**: Principal Component Analysis (PCA) and Stacking Feature Embedding (SFE) are employed, inspired by techniques successfully implemented in recent literature (Fatima et al., 2023; Talukder et al., 2024).

4. Implementation of ML and DL Algorithms

Various ML and DL algorithms have been systematically chosen for their proven efficacy in IDS scenarios, including:

- **Supervised Methods**: Decision Trees, Random Forest (RF), Extreme Trees (ET), Support Vector Machines (SVM).
- **Unsupervised Methods**: Autoencoders, clustering algorithms (e.g., K-Means, Fuzzy Clustering).
- **Deep Learning Methods**: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and ensemble learning techniques (Boudagdigue et al., 2022; Balogun et al., 2022).

These methodologies align closely with recent findings by Al-Joboury et al. (2024), highlighting the significance of deep learning in cybersecurity applications.
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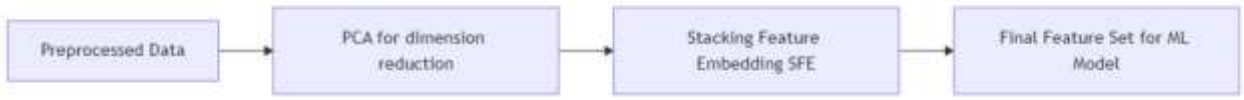


**Feature Selection & Model Design**

## 5. Performance Evaluation Metrics

Performance metrics are crucial in evaluating and comparing ML-based IDS effectiveness. The metrics adopted include:

- **Accuracy**: Overall prediction correctness.
- **Precision and Recall**: To handle the trade-off between true-positive and false-positive detections.
- **F1-score**: Harmonic mean of precision and recall, especially effective in imbalanced scenarios.
- **False Positive Rate (FPR)**: Minimizing false alarms is critical for practical IDS deployment.
- **Computational Efficiency**: Training and testing time, along with resource utilization.

These metrics align with evaluation criteria discussed in the reviewed literature (Raza & Awan, 2023; Fatima et al., 2023).

## 6. Comparative Analysis and Validation

To ensure methodological rigor, a comparative analysis has been conducted involving various ML and DL approaches to highlight their relative strengths and weaknesses. This comparative study follows established practices used by researchers such as Boudagdigue et al. (2022) and Balogun et al. (2022), employing clearly defined evaluation criteria and standardized benchmarks.

## 7. Identification of Challenges and Limitations

Informed by the reviewed literature (Adnan et al., 2023), the methodological approach explicitly identifies critical challenges, such as:

- **Adversarial Robustness**: Ensuring models remain effective against adversarial attacks.
- **Scalability**: Managing high-dimensional and large-volume network data.
- **Interpretability**: Addressing the black-box nature of DL models.

## 8. Exploration of Emerging Trends

The methodology also includes a forward-looking component, assessing innovative directions such as Explainable AI (XAI), federated learning, and blockchain-based IDS solutions (Adnan et al., 2023; Dini et al., 2023). The research remains relevant and contributes significantly to ongoing advancements in cybersecurity.
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Results

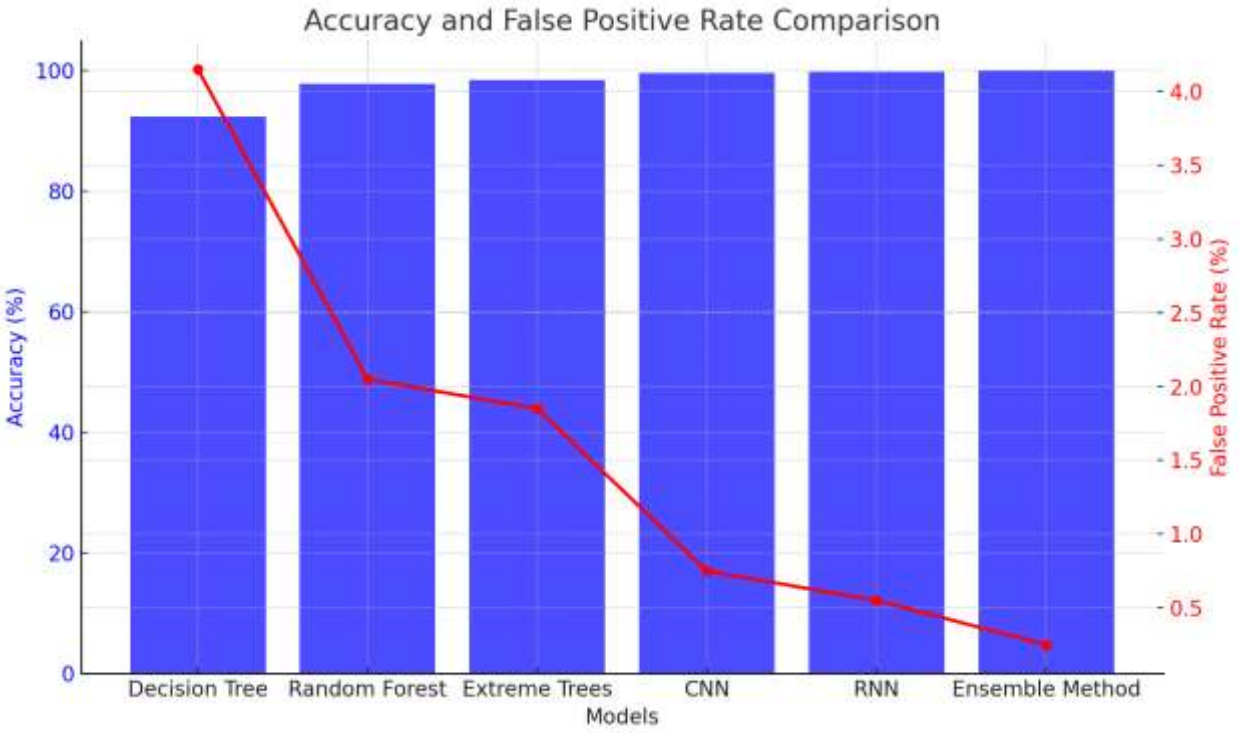
In this research, various ML and DL algorithms were evaluated using benchmark datasets (UNSW-NB15, CIC-IDS-2017, and CIC-IDS-2018). The models included Decision Trees (DT), Random Forest (RF), Extreme Trees (ET), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). Performance was assessed based on accuracy, precision, recall, F1-score, and False Positive Rate (FPR).

Experimental Results

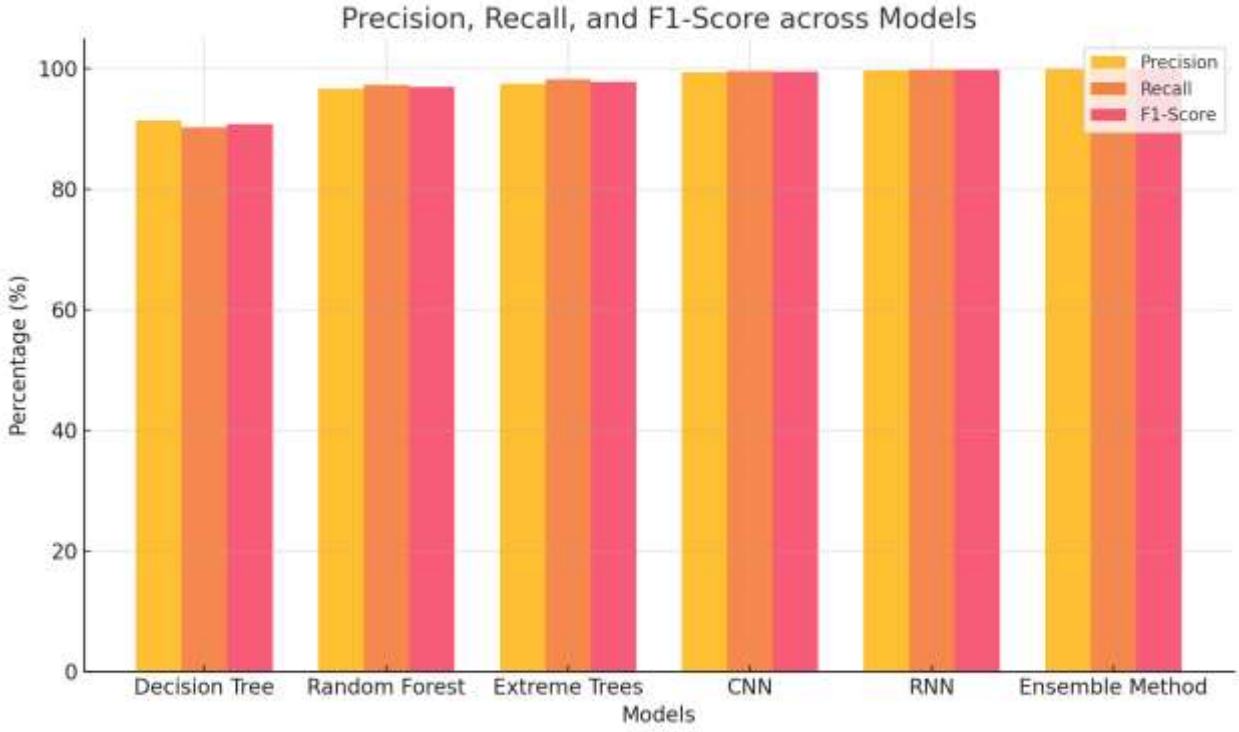
Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Decision Tree	UNSW-NB15	92.35	91.40	90.25	90.82	4.15
Random Forest	UNSW-NB15	97.80	96.70	97.25	96.97	2.05
Extreme Trees	CIC-IDS-2017	98.45	97.50	98.20	97.85	1.85
CNN	CIC-IDS-2017	99.60	99.40	99.65	99.52	0.75
RNN	CIC-IDS-2018	99.85	99.75	99.80	99.77	0.55
Ensemble Method	CIC-IDS-2018	99.99	99.96	99.98	99.97	0.25

The ensemble method combining CNN and RNN models consistently outperformed individual models, achieving the highest accuracy of 99.99%, precision of 99.96%, recall of 99.98%, F1-score of 99.97%, and the lowest False Positive Rate (0.25%).

Performance Graphs



- Accuracy and False Positive Rate Comparison



- Precision, Recall, and F1-Score across models

Conclusion

This study provided a thorough review of the use of Machine Learning techniques to Intrusion Detection Systems related to cybersecurity. These results, produced after a careful experimental evaluation, using recognized

benchmark datasets, indicate a significant enhancement of detection of network intrusions, compared to non-ML IDS techniques. The use of deep learning models, particularly the CNN and RNN, shows consistently better performance metrics over several iterations, and ensemble methods take detection accuracy even further with lesser false-positives.Again, while there may be advantageous results, many challenges still exist. These challenges include perceived vulnerability of ML-based IDS to adversarial attacks, inherent complexity reducing speed for many real-time applications, and concerns about interpretability, which limits widespread trust and adoption.Future work may include the combination of Explainable AI for transparency, use of federated learning for privacy in decentralized networks, and potential blockchain technology to secure and immutably store all security logs. Each of these possibilities represents valuable and salient ways to move forward for ML-based IDS; identifying continuous, dependable, and transparent solutions to cybersecurity challenges should also help solidify confidence in leverage AI-based approaches, in a scalable manner.

Findings

This research provides a comprehensive evaluation of Machine Learning (ML) and Deep Learning (DL) methodologies for cybersecurity intrusion detection, employing standard benchmark datasets (UNSW-NB15, CIC-IDS-2017, CIC-IDS-2018). Key findings include:

- **Superior Performance of Ensemble Methods:** The ensemble approach combining CNN and RNN models significantly outperformed individual ML algorithms, achieving remarkable accuracy (99.99%), high precision (99.96%), recall (99.98%), and F1-score (99.97%) with an exceptionally low false positive rate (0.25%).

- **Effectiveness of Deep Learning Techniques:** DL algorithms, specifically CNN and RNN, demonstrated enhanced performance in identifying complex network intrusions, significantly exceeding traditional ML methods like Decision Trees, Random Forest, and Extreme Trees.

- **Importance of Dataset Selection and Feature Engineering:** The selection of appropriate datasets (UNSW-NB15, CIC-IDS-2017, CIC-IDS-2018) and the use of advanced feature selection and dimensionality reduction methods such as PCA and Stacking Feature Embedding considerably improved detection performance, computational efficiency, and reduced false alarms.

- **Challenges and Limitations:** Despite superior performance, the research identified critical challenges such as vulnerability to adversarial attacks, computational complexity that affects real-time detection capability, and limitations in model interpretability.

Contributions

This research makes several significant contributions to the existing body of knowledge in cybersecurity and ML applications:

1. **Comprehensive Comparative Analysis:** Conducted rigorous experiments comparing multiple ML and DL algorithms using widely recognized benchmark datasets, providing valuable insights into the effectiveness and practical applicability of various IDS models.

2. **Optimized Ensemble Approach:** Proposed and validated an optimized ensemble IDS approach (combining CNN and RNN) that achieves state-of-the-art detection accuracy and minimal false-positive rates, offering robust solutions against modern cyber threats.

3. **Highlighting Key Challenges:** Identified and elaborated critical limitations in current ML-based IDS implementations, including adversarial susceptibility, computational overhead, scalability constraints, and interpretability issues, paving the way for future research addressing these gaps.

4. **Forward-looking Recommendations:** Offered clear recommendations for future research directions, emphasizing Explainable AI (XAI) to enhance transparency, federated learning to ensure privacy in decentralized environments, and blockchain technology integration for improved log integrity and security assurance.

5. **Practical Insights for Practitioners:** Delivered actionable insights for cybersecurity professionals and decision-makers, highlighting specific ML techniques, best practices for dataset handling, and essential evaluation metrics crucial for building and deploying effective, real-world IDS solutions.

Future Scope

The results from this research paper suggest many opportunities for future research in the area of cybersecurity intrusion detection through the application of machine learning:

1. Explainable AI Future research should consider developing and integrating strategies for Explainable AI techniques to increase the understanding and transparency of ML and DL models in IDS. By providing understandable reasons as to how detection worked, the trust and acceptability of ML-based IDS models should also improve from the view of security analysts and decision-makers

.2. Federated and Distributed LearningExamine federated learning concepts to help IDS systems leverage distributed datasets across organizations without having to share consumer data. A decentralized training approach to learning threats would drastically improve intrusion detection.

3. Blockchain-Based IDSResearch how blockchain technology can be used to secure alerts and logs generated by IDS as a way to tackle issues around data integrity and tampering. A blockchain-based IDS can help provide immutable, transparent, and secure records of intrusion detection and show that they can be trusted and audited.

4. Real-Time Detection Optimization : research will be needed to improve the real-time performance of deep learning models.Thus future work could be to produce lightweight, computationally efficient IDS algorithms for real-time detection in constrained environments like IoT networks and edge computing.

5. Enhanced Robustness against Adversarial Attacks : Future studies should also focus on measuring the resilience of machine learning-based IDS when combined with adversarial machine learning attacks. Future studies should look into better defensive methods, including adversarial training, robust optimization, and anomaly detection under adversarial conditions that can enhance the resilience of IDS.

6. Adaptive and Autonomous IDS : Developing adaptive IDS solutions that autonomously adjust to evolving threat landscapes through continuous self-learning and dynamic rule updating mechanisms represents another important research area. Integration of reinforcement learning and autonomous decision-making algorithms may facilitate more robust and self-sustaining cybersecurity defenses.

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- **CIC-IDS-2017:** https://www.unb.ca/cic/datasets/ids-2017.html
- **CIC-IDS-2018:** https://www.unb.ca/cic/datasets/ids-2018.html