Hybrid Machine Learning Models for Enhancing Cybersecurity in Smart Grid Infrastructures

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ABSTRACT

The increasing reliance of smart grid infrastructures on digital communication networks has made them highly vulnerable to cyber threats, particularly Distributed Denial-of-Service (DDoS) attacks. Traditional security mechanisms often struggle to detect and mitigate these sophisticated, evolving threats. This study proposes a hybrid machine learning model that enhances cybersecurity in smart grids by improving the accuracy and efficiency of DDoS attack detection and mitigation. The proposed model integrates supervised and unsupervised learning techniques, leveraging deep learning-based anomaly detection and ensemble classification algorithms to differentiate between normal and malicious network traffic in real-time. A comparative analysis of multiple machines learning classifiers, including Random Forest, Support Vector Machine (SVM), and Neural Networks, is conducted to assess performance in terms of detection accuracy, false positive rates, and computational efficiency. The model is evaluated using real-world and simulated datasets, demonstrating its ability to detect various types of DDoS attacks with high precision and minimal false alarms. By incorporating adaptive learning techniques, the model dynamically evolves to counter emerging cyber threats, ensuring robust security for smart grid communication networks. The results highlight the potential of hybrid machine learning approaches in reinforcing the resilience of next-generation smart grid infrastructures against cyber-attacks, thereby enhancing system reliability and stability.

Keywords: Smart Grid Security, Hybrid Machine Learning, DDoS Detection, Cybersecurity, Anomaly Detection, Intrusion Prevention

INTRODUCTION

Background to the Study

According to Tang et al., 2025, the rapid digital transformation of critical infrastructure, particularly in power distribution networks, has led to the emergence of smart grids, which integrate advanced communication networks, automation systems, and Internet of Things (IoT) technologies to enhance operational efficiency and reliability. Unlike traditional power grids that rely on one-way energy flow, smart grids employ bi-directional communication between energy providers and consumers, enabling real-time monitoring, demand response, and adaptive control of electricity distribution (Makhmudov et al., 2025). This shift towards intelligent, automated grid systems has revolutionized power management but has also exposed the grid to significant cybersecurity threats.

Among the most pressing cyber threats facing smart grids today are Distributed Denial-of-Service (DDoS) attacks. These attacks involve flooding network resources with excessive traffic, disrupting communication channels, and potentially causing large-scale power outages. Smart grids, being highly dependent on interconnected communication protocols, cloud computing, and IoT-based technologies, present a broad attack surface that adversaries can exploit to launch DDoS attacks. These attacks not only threaten the availability and reliability of energy services but also pose risks to grid stability and consumer data security (Saad et al., 2025).

To address these challenges, researchers and industry professionals have explored the potential of machine learning (ML) and artificial intelligence (AI) to detect, mitigate, and prevent cyber threats in smart grid environments. Traditional rule-based security solutions struggle to adapt to evolving attack patterns, making ML-based anomaly detection models a promising alternative. However, single-model machine learning approaches often exhibit limitations in accuracy, adaptability, and computational efficiency. Hence, hybrid machine learning models, which combine the strengths of multiple algorithms, have gained traction as an effective solution for real-time DDoS detection and mitigation in smart grids.

Problem Statement

Despite advancements in cybersecurity measures, smart grids remain highly susceptible to sophisticated DDoS attacks due to the following challenges:

a) High Attack Complexity – DDoS attacks in smart grids are becoming more complex, employing botnets, spoofing techniques, and polymorphic attack patterns that evade traditional security measures.
b) Lack of Adaptive Security Solutions – Existing intrusion detection systems (IDS) often rely on static rules or signature-based detection, making them ineffective against zero-day attacks and dynamically evolving threats.
c) High False Positive and False Negative Rates – Many conventional ML models exhibit poor detection accuracy, leading to false alarms that compromise the efficiency of cybersecurity measures.
d) Scalability and Computational Constraints – The vast amounts of real-time data generated by smart grid sensors and communication networks demand highly scalable and computationally efficient solutions to prevent latency issues.
e) To bridge these gaps, this study proposes a hybrid machine learning-based approach for enhanced cybersecurity in smart grid infrastructures, leveraging the strengths of multiple ML models to improve accuracy, adaptability, and detection efficiency.

Research Aim and Objectives

The primary aim of this study is to develop a hybrid machine learning model for real-time DDoS attack detection and mitigation in smart grid infrastructures. To achieve this, the following objectives are pursued:

a) To develop a robust hybrid machine learning model that integrates anomaly detection techniques with classification-based approaches for improved accuracy in detecting DDoS attacks.
b) To evaluate and compare multiple ML algorithms (e.g., Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN)) in detecting and mitigating cyber threats in smart grids.
c) To analyse real-world and simulated datasets to assess the effectiveness of the proposed model in detecting various forms of DDoS attacks.
d) To optimize computational efficiency and scalability of the model for real-time implementation in smart grid environments.

Significance of the Study

The findings of this study will have significant implications for smart grid cybersecurity, power system resilience, and machine learning-based intrusion detection systems. The proposed hybrid machine learning model will enhance smart grid security by improving cyber resilience against DDoS attacks, ensuring stable and uninterrupted energy distribution. By integrating multiple machine learning techniques, this study aims to reduce false positive rates, improve detection accuracy, and enhance the reliability of DDoS mitigation mechanisms. Furthermore, the research will contribute to ongoing advancements in AI-driven cybersecurity solutions, providing a comprehensive analysis of hybrid ML models for cyber threat detection. This study will also have practical applications in energy systems, aiding grid operators, policymakers, and cybersecurity experts in deploying effective security frameworks for modern power grids. Ultimately, the findings will support the development of AI-driven security solutions that can adapt to evolving cyber threats, ensuring a more secure and resilient energy infrastructure.

Scope of the Study

This research focuses on the development and evaluation of a hybrid machine learning model for detecting and mitigating DDoS attacks in smart grid environments. The study encompasses an analysis of different types of DDoS attacks, including volumetric attacks, protocol-based attacks, and application-layer attacks, which specifically target smart grid communication networks. It explores the application of both supervised and unsupervised learning techniques to effectively detect and mitigate these cyber threats. Additionally, the study evaluates the performance of various machine learning models using both real-world and simulated datasets to determine their effectiveness in identifying and mitigating attacks. Furthermore, it investigates the scalability and computational efficiency of the proposed model to ensure its feasibility for real-time deployment in smart grid infrastructures. However, this study does not focus on hardware-level cybersecurity measures, cryptographic protocols, or non-ML-based detection approaches.

Limitations of the Study

While the research provides valuable insights into hybrid ML-based cybersecurity solutions, it is subject to the following limitations:

a) Dataset Availability – Real-world smart grid cyberattack datasets are limited, which may require reliance on simulated attack scenarios.
b) Computational Constraints – Machine learning models require high computational power for training and optimization, which may limit real-time performance testing.
c) Dynamic Attack Evolution – Cybercriminals continuously develop new attack strategies, requiring continuous model retraining to maintain detection effectiveness.

LITERATURE REVIEW

According to Liu et al. (2025), the increasing adoption of smart grid systems has brought about significant advancements in electricity distribution, real-time monitoring, and automation. However, the reliance on digital communication networks and IoT-based infrastructure has also introduced critical cybersecurity vulnerabilities, particularly Distributed Denial-of-Service (DDoS) attacks. These attacks target smart grid communication channels, disrupting energy distribution and posing significant threats to grid stability. To mitigate these risks, researchers have explored various machine learning (ML)-based techniques for intrusion detection and prevention. This literature review explores the nature of DDoS attacks in smart grids, existing detection and mitigation strategies, and the role of machine learning in improving smart grid cybersecurity.

Cybersecurity in Smart Grid Systems

Smart grids integrate bi-directional communication, sensors, and IoT technologies to optimize electricity generation, distribution, and consumption. However, this increased connectivity also exposes the grid to various cyber threats, including malware infections, unauthorized access, and network-based attacks. Among these, DDoS attacks are particularly challenging due to their distributed nature, high attack volume, and ability to bypass traditional security mechanisms (Albaseer et al., 2024).

Cyber-physical attacks on smart grids can lead to energy theft, system failures, financial losses, and even large-scale blackouts. Attackers leverage vulnerabilities in communication protocols, cloud-based storage, and IoT devices to launch sophisticated cyberattacks. Studies by Chikouche et al. (2024) highlight the increasing number of DDoS-for-hire services, which have significantly lowered the barrier for launching large-scale cyberattacks on smart grids. Given these challenges, researchers have proposed AI-driven solutions, particularly machine learning models, to enhance smart grid resilience against cyber threats.

Distributed Denial-of-Service (DDoS) Attacks in Smart Grids Nature and Impact of DDoS Attacks

Qi (2023) said that DDoS attacks overwhelm a network or service by flooding it with illegitimate traffic, preventing legitimate users from accessing critical services. In smart grids, attackers exploit vulnerabilities in

IoT devices, communication protocols, and cloud-based services to disrupt grid stability. According to Shukla et al. (2023), DDoS attacks can deplete computing resources and network bandwidth within minutes, causing severe operational failures.

DDoS attacks on smart grids can be categorized into:

1. Volumetric Attacks – Overload the grid's bandwidth with massive amounts of fake requests.
2. Protocol-Based Attacks – Exploit weaknesses in network protocols (TCP, UDP, ICMP) to disrupt smart grid communication.
3. Application-Layer Attacks – Target web-based services to disable energy management systems.

Studies by Prasad et al. (2019) emphasize that traditional firewall and intrusion detection systems are ineffective against advanced botnet-driven DDoS attacks, necessitating adaptive, AI-based solutions.

Traditional Approaches to DDoS Detection and Their Limitations

Signature-Based and Rule-Based Detection Systems

Conventional DDoS detection methods rely on signature-based and rule-based intrusion detection systems (IDS). These systems compare incoming network traffic against a database of known attack patterns. However, research by Sardar et al. (2024) highlights the ineffectiveness of signature-based IDS against zero-day attacks, as they fail to detect unknown or evolving attack patterns.

Statistical and Anomaly-Based Detection

Anomaly-based detection methods use statistical thresholds to identify unusual traffic patterns. While this approach can detect unknown threats, studies by Praveen et al. (2024) reveal that high false positive rates make it unreliable for real-time smart grid security.

Limitations of Traditional Security Approaches

1. Lack of Adaptability – Rule-based systems cannot handle evolving attack tactics.
2. High False Positives – Anomaly-based detection methods often misclassify legitimate traffic as malicious.
3. Scalability Issues – Large-scale smart grids generate massive amounts of network traffic, making real-time analysis difficult.

These limitations underscore the need for AI-driven, machine learning-based solutions that can dynamically learn and adapt to evolving threats.

Machine Learning for DDoS Detection in Smart Grids

Machine learning has emerged as a powerful tool for cybersecurity, enabling adaptive, real-time detection of

complex attack patterns. Unlike traditional methods, ML models learn from historical data, allowing them to identify anomalies, classify attack types, and enhance threat mitigation.

Supervised Machine Learning Models

Supervised learning involves training classification algorithms using labelled datasets to distinguish between benign and malicious traffic. Studies by Yang et al. (2025) show that Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers achieve high accuracy in detecting network anomalies. However, these models struggle with zero-day attacks and high-dimensional data.

Unsupervised Machine Learning Models

Unsupervised learning models, such as K-Means Clustering and Autoencoders, detect unknown attack patterns by identifying deviations from normal traffic behaviour. Research by Chaudhary et al. (2025) highlights the effectiveness of unsupervised anomaly detection models, though they require extensive fine-tuning to minimize false positives.

Hybrid Machine Learning Models

Hybrid models combine multiple ML approaches to improve detection accuracy and reduce false positives. Combined with traditional classifiers, deep learning-based anomaly detection can significantly enhance smart grid cybersecurity. According to Liu et al. (2025), hybrid models integrating Convolutional Neural Networks (CNNs) with traditional ML classifiers outperform standalone models in detecting DDoS attacks in IoT networks.

Comparative Analysis of Existing DDoS Detection Techniques

Approach	Advantages	Limitations
Rule-Based IDS	Easy to implement	Cannot detect unknown attacks
Anomaly Detection	Identifies zero-day threats	High false positive rates
Supervised ML	High accuracy in known threats	Requires labelled datasets
Unsupervised ML	Detects unknown attack patterns	Requires feature engineering
Hybrid ML Models	Improves detection accuracy and reduces false positives	Higher computational complexity

As seen in the table above, hybrid ML models offer a balance between accuracy, adaptability, and efficiency, making them a promising approach for smart grid cybersecurity.

Summary and Research Gap

The literature highlights the growing cybersecurity challenges in smart grid systems, particularly DDoS attacks targeting network communication infrastructure. While traditional security mechanisms such as firewalls and IDS provide basic protection, they are insufficient against evolving attack strategies. Machine learning-based techniques offer enhanced threat detection capabilities, yet single-model approaches suffer from false positives, scalability issues, and adaptation limitations. The need for hybrid ML models that integrate anomaly detection, supervised learning, and deep learning techniques remains a critical research gap.

This study aims to bridge this gap by developing a hybrid machine-learning model for real-time DDoS attack detection and mitigation in smart grids. By combining multiple ML algorithms, this approach will improve accuracy, reduce false positives, and enhance grid security, ensuring a resilient and secure smart grid infrastructure.

METHODOLOGY

Research Design

This study adopts an experimental research design to develop and evaluate a hybrid machine learning model for detecting and mitigating DDoS attacks in smart grid infrastructures. The methodology involves integrating supervised and unsupervised learning techniques to analyse network traffic and identify anomalies indicative of cyber-attacks.

Data Collection and Preprocessing

To ensure robust model training and evaluation, both real-world and simulated datasets were utilized. The CICDDoS2019 dataset, which provides labelled network traffic data representing various DDoS attack types,

was selected for its relevance and comprehensiveness. The dataset was preprocessed by removing redundant features, handling missing values, normalizing numerical attributes, and encoding categorical variables.

Hybrid Model Architecture

The proposed hybrid model integrates an Autoencoder (for unsupervised anomaly detection) with an ensemble classifier comprising Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANNs).

- The autoencoder identifies deviations from normal traffic patterns.
- Traffic flagged as anomalous is passed to the ensemble classifier for final attack classification.
- A weighted majority voting mechanism determines the final label (benign or malicious).

Model Training and Evaluation

Each classifier was trained on 80% of the labelled data and validated on the remaining 20%. Cross-validation (5-fold) was employed to reduce overfitting. Evaluation metrics included:

- Accuracy
- Precision
- Recall
- F1-score
- False Positive Rate (FPR)
- Area Under Curve (AUC)

All models were implemented in Python using Scikit-learn, TensorFlow, and Keras libraries. Training was performed on a high-performance computing environment with GPU acceleration to simulate real-time detection capabilities.

RESULTS AND DISCUSSION

Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	FPR	AUC
Random Forest	96.8%	95.3%	96.0%	95.6%	2.3%	0.97
SVM	94.1%	93.5%	92.8%	93.1%	4.8%	0.95
ANN	95.4%	94.7%	94.2%	94.4%	3.6%	0.96
Hybrid Model	98.2%	97.8%	97.5%	97.6%	1.4%	0.99

Discussion

The results indicate that the hybrid model significantly outperforms individual classifiers in terms of accuracy and false positive rate. The Autoencoder effectively identified anomalous traffic, while the ensemble classifier refined detection by reducing misclassifications. The model's high AUC suggests robust performance across various DDoS attack types.

The hybrid approach also demonstrated strong adaptability to new attack patterns during real-time testing, validating its suitability for dynamic smart grid environments. However, training time and computational resources were higher due to the layered structure of the hybrid model.

CONCLUSION

This study introduces a hybrid machine learning model designed to enhance cybersecurity in smart grid infrastructures, specifically for detecting and mitigating DDoS attacks. By combining an Autoencoder for

anomaly detection with an ensemble of classifiers—Random Forest, SVM, and ANN—the model achieves high accuracy and low false positive rates across various attack scenarios.

The results demonstrate that the hybrid approach outperforms traditional and single-model methods in both effectiveness and adaptability, making it suitable for real-time deployment in smart grid environments. Its ability to detect complex and evolving threats highlights its value as a practical solution for improving grid resilience and operational security. The proposed model contributes to advancing AI-driven cybersecurity in critical infrastructure and provides a scalable foundation for future smart grid protection strategies.

RECOMMENDATIONS AND FUTURE WORK

Future studies should explore:

a) Integration with real-time smart grid systems to test deployment feasibility.
b) Lightweight model variants for deployment in edge devices with limited processing power.
c) Expansion to other cyber threats, such as data exfiltration or ransomware.
d) Reinforcement learning for automated response mechanisms post-attack detection.
e) Federated learning architectures to preserve data privacy across distributed grid systems.

Additionally, collaboration with industry stakeholders will help validate the model in real operational contexts.

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