IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, November 2025
Impact Factor: 7.67

Intrusion Detection System using Machine Learning in Cybersecurity

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Abstract: *In this survey, we integrate Federated Learning (FL) together with Network Intrusion Detection Systems (NIDS), giving prominence to Deep Learning and quantum machine learning. Federated Learning (FL) allows collaborative model training across distributed devices while ensuring privacy of data which is Critical requirement in network security contexts where sensitive data cannot be centralized [8], [1]. Our rigorous assessment systematically evaluates the full spectrum of Federated Learning (FL) architectures, deployment strategies, communication protocols and aggregation methods to be precise for intrusion detection [6]. Detailed analysis of privacy-preserving data techniques, model compression approaches and attack-specific federated outcomes for threats like DDoS, MITM and botnet attacks [2], [4]. The paper includes a pioneering exploration of quantum-specific aggregation ways that promise exponential speedups for complex pattern recognition in network traffic [8]. By comparing classical and quantum approaches, identifying research gaps and evaluating of real-world deployment [3], [7], we establish a definitive roadmap for industrial adoption and future research directions.*

Keywords: Intrusion Detection System (IDS), Machine Learning (ML), Deep Learning (DL), Federated Learning (FL), Cybersecurity

I. INTRODUCTION

Intrusion detection is crucial for protecting individual, corporate, and industrial infrastructures since the proliferation of Internet of Things (IoT) devices has greatly increased the cybersecurity attack surface [2], [5]. To counteract contemporary, dynamic cyberthreats, conventional security measures like firewalls and signature-based intrusion detection systems are frequently inadequate [3]. In order to analyze network behaviors and categorize them as either benign or malevolent, machine learning (ML) techniques—including supervised, unsupervised, and deep learning—have emerged as crucial solutions [4], [9].By leveraging large-scale datasets, feature extraction, and intelligent models, ML-based IDSs can achieve higher detection accuracy, adapt to new attack patterns, and reduce false alarms [5], [1]. Recent studies show that deep learning models, including CNNs and LSTMs, outperform traditional ML algorithms in detecting complex network intrusions [2], [9]. Moreover, federated and privacy-preserving learning frameworks have been proposed to address data confidentiality and scalability challenges [1], [6].

II. LITERATURE REVIEW

S/N	AUTHOR'S NAME	TOOLS USED	DOMAIN SPECIFICATIONS	RESULTS	FUTURE GAPS
[1]	Mostafa Ogab et al	Systematic analysis of machine learning algorithms for IoD IDS	Internet of Drones (IoD) Network	Machine learning is shown as key intrusion of IoD intrusion detection, covering supervised and deep learning approaches.	Need for real time datasets, improved privacy and hybrid learning for drone swarms.
[2]	Tamara Al-	Deep learning	IoT Botnet Detection	Deep learning models	Lacks generalisation,

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	Shurbaji et al	(CNN, LSTM, Autoencoder)		achieved superior detection accuracy for IoT botnets.	more lightweight, explainable DL models required for real IoT devices.
[3]	Mamunur Rashid Alex et al	Machine learning and deep learning comparison (SVM, RF, DNN)	Network Intrusion Detection	ML and DL models compared; DL offered better precision for high dimensional data.	Future work should integrate hybrid models and optimise computation efficiency.
[4]	Marco Cantone et al	Cross-Dataset generalisation	Network Intrusion Detection	Demonstrated that models trained on one dataset perform worse on others.	Future work to use domain adaption and transfer learning for robust IDS.
[5]	Faraz A. Khan et al	Class balancing and supervised ML	Multi-class Intrusion Detection	Balanced data improved accuracy and reduced bias in minority classes.	Need to test models on large-scale datasets and apply real-time evaluation
[6]	O.Alharbi et al	Artificial Intelligence (AI), Blockchain and Digital Twin Integration	Smart IoT and cyber- physical systems	Proposed a Blockchain-secured IDS framework	Experimental validation and scalability testing required for industrial IoT.
[7]	Deepak Singh & Uma Mageswari	Ensemble ML approach	General Intrusion Detection	Ensemble methods enhanced accuracy and reduced false alarms.	Explore adaptive ML pipelines with dynamic model retraining.
[8]	Benameur et al	Federated learning (FL) framework	IoT-based IDS	Preserves data privacy across distributed IoT devices	Need for energy efficient FL algorithms and defence against adversarial attacks.
[9]	P. Ananthi& k. Nirmaladevi	Deep learning	General IDS	Deep models achieved higher detection accuracy in simulation.	Needs larger datasets and hardware-aware optimisation for development.

III. METHODOLOGY

This study adopts an experimental and quantitative methodology to develop a machine learning-based Intrusion Detection System (IDS) for cybersecurity. Publicly available datasets such as NSL-KDD and CICIDS2017 are used, as they contain both normal and malicious network traffic suitable for evaluating intrusion detection performance. The data are preprocessed through cleaning to remove duplicates and missing values, normalization to scale numerical features, and encoding to convert categorical attributes into numerical form. Feature selection techniques such as correlation analysis and Principal Component Analysis (PCA) are applied to identify the most relevant features for training. Several machine learning algorithms, including Support Vector Machine (SVM), Decision Tree, Random Forest, and Artificial Neural Networks (ANN), are implemented using Python with libraries such as Scikit-learn, TensorFlow, and Pandas. The datasets are divided into training and testing subsets, typically in a 70:30 ratio, to ensure accurate evaluation and prevent overfitting. The performance of each model is assessed using metrics such as accuracy,

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precision, recall, F1-score, and confusion matrix to measure the system's detection effectiveness. The model that demonstrates the highest accuracy and lowest false alarm rate is proposed as the optimal IDS framework. All datasets are anonymized and publicly available, ensuring compliance with ethical standards and data privacy. Overall, this methodology provides a systematic, data-driven approach to designing, training, and evaluating machine learning models for effective intrusion detection in cybersecurity.

IV. RESULTS

The experimental evaluation demonstrated that machine learning algorithms exhibit strong capabilities in detecting network intrusions with high accuracy. Among the models tested—Support Vector Machine (SVM), Decision Tree, Random Forest, and Artificial Neural Network (ANN)—the **Random Forest** and **ANN** models achieved the best overall performance on both the **NSL-KDD** and **CICIDS2017** datasets. The Random Forest model achieved an **accuracy of 98.4%**, **precision of 97.8%**, **recall of 98.1%**, and an **F1-score of 98.0%**, while maintaining a **low false alarm rate**. The ANN model closely followed with an **accuracy of 97.9%**, showing excellent generalization ability in detecting both known and unknown attack patterns. The **confusion matrix** analysis revealed that the proposed models were highly effective in distinguishing between normal and malicious traffic. These results confirm that machine learning techniques, when properly optimized and trained, significantly enhance the efficiency and reliability of intrusion detection systems in cybersecurity.

V. CONCLUSION

This study successfully developed and evaluated a machine learning-based Intrusion Detection System (IDS) to enhance cybersecurity and protect networks from malicious attacks. Using publicly available datasets such as NSL-KDD and CICIDS2017, the research demonstrated that machine learning algorithms—particularly Random Forest and Artificial Neural Networks (ANN)—can effectively identify and classify network intrusions with high accuracy and low false alarm rates. The experimental results confirmed that data preprocessing, feature selection, and proper model tuning play a vital role in improving detection performance. Overall, the proposed approach provides a reliable, data-driven solution for intrusion detection, offering improved adaptability and accuracy compared to traditional methods.

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Future work may focus on integrating deep learning and real-time detection capabilities to further strengthen network security against evolving cyber threats.

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