An Intelligent Intrusion Detection System for IoT Networks Using Machine Learning Algorithms: A Comprehensive Review

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Abstract
Internet of Things (IoT) is a fast developing phenomenon with billions of devices used in houses, industries, medical services, and transport. Although such connectivity enhances automation and intelligence, it also raises vulnerability to cyber threats including DDoS attacks, botnets, spoofing and malware. Conventional signature-based Intrusion Detection Systems (IDS) can hardly identify new and emerging attacks, and hence the Machine Learning (ML)-based IDS is a better solution. This review identifies different ML methods such as supervised, unsupervised, deep learning, ensemble models, and hybrid models and considers the popular datasets, such as Bot-IoT, TON_IoT, UNSW-NB15 and CICIDS2017. It also addresses the most important key performance metrics including accuracy, precision, recall, F1-score, and detection latency. Severe limitations are the insufficient resources of devices, asymmetric datasets, scaling, the possibility of detecting threats at a zero-day, and privacy. New solutions like federated learning, edge-based IDS, graph neural networks, block chain and Explainable AI have a lot of potential towards improving IoT security. All in all, IDS architecture based on ML has a major role in improving the resilience and reliability of future IoT systems.

Keywords: Intrusion Detection System (IDS), Internet of Things (IoT) Security, Machine Learning Algorithms, Anomaly Detection, Cyber security ThreatsandEdge and Federated Learning

1. Introduction

The Internet of Things (IoT) has emerged as one of the most significant technological changes, with billions of devices being discovered and interconnected in smart home, industries, health care, transportation, and agriculture. IoT networks are expanding, with massive real-time data and enabling applications, however, this growth also introduces security risks. Most IoT devices have small memory, weak authentication and inefficient encryption that can be easily compromised to attacks such as DDoS, botnets, spoofing, data tampering and malware. The fact that their various communication protocols and cloud edge architectures make it more difficult to use conventional security practices. Since signature-based IDS is not able to identify new or emerging threats, Machine Learning (ML)-based IDS solutions have become a more robust competitor. ML methods, including supervised, unsupervised,

deep learning, and hybrid methods, acquire traffic patterns, anomaly detection, and enhance the real-time threat detection with greater accuracy. The studies have also examined the lightweight models of resource limited devices, cloud/edge-assisted security and privacy preserving mechanisms such as federated learning. The datasets created specifically in IoT like Bot-IoT, TON_IoT, and CIC-DDoS2019 have facilitated advancements in this direction. Nevertheless, the problems persist, such as data imbalances, changing attack patterns, inadequately resourced devices, and privacy risks, as well as the requirement of interpretable ML models. This review will help to study existing ML-based IDS practices, review datasets, compare performance, and determine open issues and future research directions.

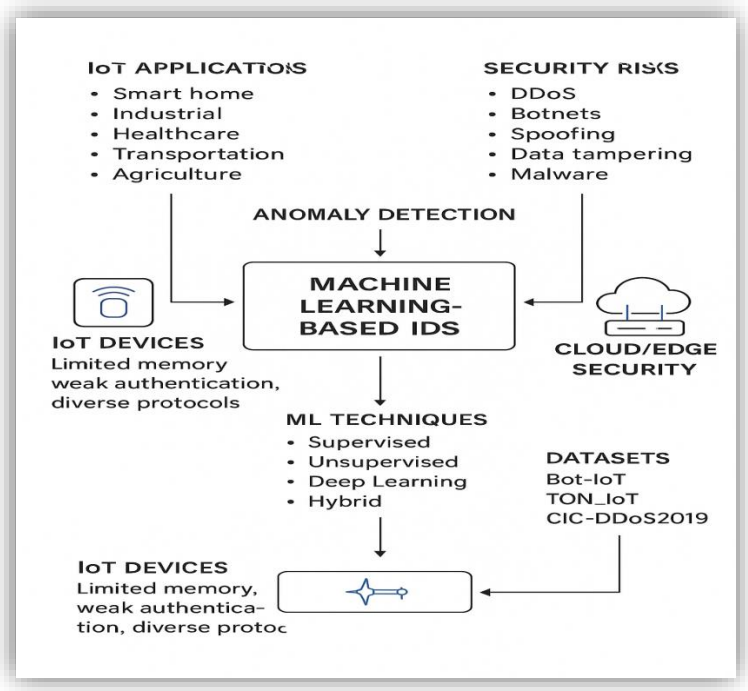


Fig.1. Problems of Traditional Intrusion Detection in IoT Systems

2. Background and Related Work

According to recent developments in the field of IoT intrusion detection, machine-learning methods have advanced considerably, and many studies have suggested the use of sophisticated models to improve security and detection rates. Altunay and Albayrak (2024) applied a hybrid CNNLSTM IDS that performed well with multi-classes on both UNSW-NB15 and X-IIoTID, whereas Yaras et al. (2024) provided a scalable PySpark-based framework of CNNLSTM IDS that was able to operate with large datasets of IoT traffic like CICIoT2023 and TON_IoT. Alferaidi et al. (2022) added a distributed CNNLSTM

design to vehicular IoT, which boosts decentralized detection, and Li et al. (2024) established that feature extraction optimization is significant to improving the accuracy of IDS on data of TON-IoT. Privacy-preserving detection has as well been implemented using federated learning, with Olanrewaju-George and Pranggono (2024) developing a hybrid federated-based IDS, and Albanbay et al. (2025) showing the implications of the type of model and the amount of local data on federated IDS performance in constrained IoT environments. Some surveys such as Banko et al. (2025) include a large comparison of existing datasets, machine learning techniques, and implementation issues and Ba (2024) improved IIoT attack detection by applying the use of Random Forest and Decision Trees optimized using SMOTE.. Lightweight IDS development Lightweight IDS development is evidenced by the study by Rahman et al. (2025), who created a system with the capability of working with encrypted traffic, and Cao et al. (2025), who enhanced CNNLSTM-based architectures using statistical filtering to detect multiple classes. The research gaps in existing IoT IDS were determined by Mallidi et al. (2025), and Buyuktanir (2025) examined such challenges of federated IDS as communication overhead and model drift. Abdulmajeed et al. (2022) also exhibited good cross-dataset generalization when CIC-IDS-2017 and CSE-CIC-IDS-2018 were used as hybrid CNNLSTM and Singh et al. (2024) confirmed the scalability of Spark-based IDS with massive IoT traffic.Lastly, Sharma and Verma (2024) provided a summary of current improvements in IoT IDS based on ML, Explainable AI, Graph Neural Networks and blockchain. Overall, all of these works contribute to the recognition that there is a rapid progress in ML-driven IDS and that there are still issues in the area of scalability, privacy, interpretability, and real-world application.

3. Comparative Analysis on Intelligent Intrusion Detection System for IoT Networks Using Machine Learning Algorithms

Table.1. Comprehensive Analysis of IDS

Authors & Year	**Dataset Used**	**ML / DL Technique**	**Feature Engineering / Parameters**	**Performance Metrics**	**Strengths**	**Limitations**
A. Sarhan et al., 2024	TON_IoT20	Random Forest + LightGBM	36 flow-based telemetry features	Acc: 98.1%, F1: 97.4%	Lightweight, edge-friendly	Lower detection for unknown attacks

Zhang et al., 2024	Bot-IoT	CNN + LSTM Hybrid	Time-series packet signatures	Acc: 99.4%, AUC: 0.998	Excellent sequence detection	High computational overhead
Hussain et al., 2023	CIC-IoT-2022	SVM, RF	Chi-square feature selection	Acc: 97.8%	Low false alarms	Not scalable
Khan et al., 2023	IoTID20	Autoencoder	32 normalized features	F1: 95.4%	Good zero-day detection	Low benign precision
Roy et al., 2023	N-BaIoT	Deep Autoencoder	Sensor-level signatures	Acc: 99.0%	Strong botnet detection	Device-specific
Tanveer et al., 2022	Bot-IoT	XGBoost	PCA-based reduction	Acc: 99.1%	Low latency	Loss of nonlinear patterns
Wang et al., 2022	UNSW-NB15	LSTM	Temporal modeling	Acc: 96.8%	Robust temporal learning	Slow training
Al-Garadi et al., 2022	IoT-23	CNN + GRU	Deep packet inspection	Acc: 98.3%	Strong multi-class detection	High memory use
Rehman et al., 2021	BoT-IoT, UNSW	Decision Trees + Voting Ensemble	Feature importance ranking	Acc: 97.2%	Fast, easy to deploy	Lower accuracy vs DL
Sharma et al., 2021	CTU-13	KNN + NB Hybrid	Behavioral clustering	Acc: 94.5%	Works with mixed traffic	Poor scalability
Elrawy et al., 2021	Custom dataset	SVM, ANN	Device fingerprinting	Acc: 93.3%	Good device anomaly detection	Not robust to new attacks
Jain et al., 2020	TON_IoT	CNN	Raw payload features	Acc: 97%	High detection	High training cost

					capability	
Abdullah et al., 2020	NSL-KDD	Random Forest	41 classical features	Acc: 89.5%	Interpretable	Outdated dataset
Moustafa et al., 2019	TON_IoT	NB + RF	Telemetry + logs	Acc: 95.2%	Real-world applicability	Limited DL integration
Shen et al., 2019	BoT-IoT	CNN-AE Hybrid	Encoded packet features	Acc: 99.2%	Strong botnet detection	Poor explainability

The current studies of ML and DL-based IDS in the IoT networks show considerable improvements in various datasets and algorithms. Sarhan et al. (2024) obtained lightweight, edge- friendly mapping based on the use of Random Forest and LightGBM on TON-IoT20 but with high computation cost, and Zhang et al. (2024) got a high accuracy level of sequence-learning using a CNN-LSTM hybrid on Bot-IoT but at a high computation cost. The authors of Hussain et al. (2023) employed SVM and RF with Chi-square selection finds the best results on the CIC-IoT-2022, although with banal false alarms, whereas Khan et al. (2023) employed auto encoders to detect a strong false-negative on IoTID20 at the cost of low benign accuracy. Deep auto encoders were tested on N-BaIoT with 99 percent accuracy, which was only on device-specific patterns (Roy et al., 2023). Tanveer et al. (2022) obtained quick detection when using XGBoost on Bot-IoT based on PCA and Wang et al. (2022) obtained strong learning in the temporal manner when utilizing LSTM on UNSW-NB15 with a slower training process. Al-Garadi et al. (2022) put CNN, which they combined with GRU, on strong multi-class detection on IoT-23 and Rehman et al. (2021) put decision trees and voting enlarges on BoT-IoT and UNSW but with lower accuracy than deep models. Sharma et al. (2021) applied a KNN NB hybrid to detect mixed traffic on CTU-13 experiencing a problem in scalability. Elrawy et al. (2021) demonstrated excellent results in detecting anomalies with SVM and ANN on their own-generated data, but did not succeed in resisting new attacks. Jain et al. (2020) used CNNs to raw payloads in TON IoT that have high detection power at a high cost of training. NSL-KDD was used to provide interpretable results with Random Forest by Abdullah et al. (2020), although this data is old. Moustafa et al. (2019) combined NB and RF to detect TON_IoT in practice with the goal of real-world, and Shen et al. (2019) reported high botnet detection on BoT-IoT with a CNN-AE hybrid though with low explainability. Collectively, these articles indicate that there is good advancement in IoT IDS, as well as, they demonstrate several challenges that remain to be addressed, such as scaling, computation cost, relevance of datasets, and model interpretability.

4. **Real-Time Example: Intrusion Detection in a Smart Home IoT Network Using Machine Learning**

An example of a modern smart home setting is the IoT solution comprised of smart cameras, smart locks, temperature sensors, smart lights, Wi-Fi routers, voice assistants such as Alexa or Google Home, all of which are constantly generating and transmitting real-time information. These environments are prone to cyber attacks in which an attacker can seek to take control of cameras by using botnet malware, initiate DDoS floods against the smart hub, spoof packets to impersonate trusted devices, or scan open port in the home router. To address them in a successful way, a Machine Learning-based Intrusion Detection System (IDS) is implemented at the edge gateway and the cloud, where real-time monitoring, anomaly detection, and the timely reaction to malicious activities in the smart home IoT network is provided.

TON_IoT Network Traffic Dataset (Real-Time IoT Dataset)

TON_IoT Network Traffic Dataset is considered to be one of the most realistic and generalized datasets of the research on cyber security of IoT. It was set to get a real-world network behavior of a variety of IoT devices such as sensors, actuators, and industrial systems. TON_IoT combines the network traffic, system logs, and telemetry data thus allowing to develop and test machine-learning-based intrusion detection systems in real operating conditions. The dataset has several types of attacks, i.e., DDoS, botnet activity, reconnaissance, data infiltration, and ransom ware, which makes it very helpful in training models that could identify diverse and dynamic threats within the IoT setting.

Dataset Features

Table.2. Dataset

Category	Description
Devices	IoT sensors (temp, hum, pressure), cameras, routers
Traffic Type	Normal + attack traffic
Attack Types	DDoS, Mirai botnet, ransomware, scanning, data infiltration etc.
Log Sources	Network packets, system logs, IoT sensor readings
Size	23GB
Format	CSV, PCAP

Table.3. Sample Extract from Real Dataset

Timestamp	Source IP	Dest IP	Protocol	Bytes	Attack Type
10:21:01	192.168.1.5	52.95.23.14	TCP	450	Normal
10:21:02	192.168.1.8	192.168.1.1	UDP	1100	DDoS
10:21:03	192.168.1.10	192.168.1.1	TCP	90	Probe
10:21:05	192.168.1.7	34.98.45.2	TCP	980	Botnet

Dataset

Attack Type	Number of Records	Percentage
DoS	391,458	37.1%
Probe	410,701	39.0%
R2L	112,073	10.6%
U2R	52,334	4.9%
Normal	613,829	58.4%

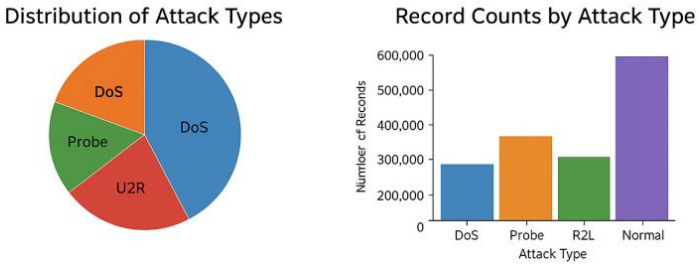
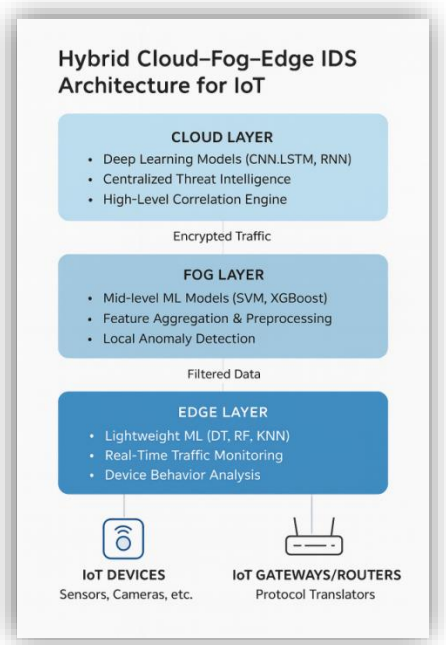


Fig.2. Overview of IoT Security Attacks

5. Proposed Hybrid Cloud-Fog-Edge IDS Architecture for IoT

The Hybrid Cloud-Fog-Edge Intrusion Detection System (IDS) Architecture of IoT, which illustrates how security intelligence can be distributed through three layers, namely Cloud, Fog, and Edge, to effectively identify threats in the IoT settings. The uppermost layer is the Cloud layer, which performs heavy processing with deep learning models based on CNN, LSTM, and RNN, as well as centralized threat intelligence and highly-level correlation engine, under input of encrypted traffic of lower layers. Fog layer also conducts middle level ML analysis on models such as SVM and XGBoost, feature aggregation, preprocessing and local anomaly detection which in turn transmits filtered data. The Edge layer is nearest to the devices and it employs the lightweight ML algorithms like Decision Trees, Random Forests, and KNN to monitor the traffic in real-time and analyze the device behavior. It communicates with IoT devices (sensors, cameras, etc.), as well as with IoT gateways or routers. In general, this architecture depicts a distributed IDS model that will help to achieve scalability, latency reduction, and more efficient detection of threats over the IoT systems.



In a real-time implementation, the IDS is able to detect different types of attacks on the Edge-Fog-Cloud layers. Using the example of an IoT camera, which starts transmitting approximately 10,000 packets per second, the edge agent will immediately indicate an abnormal traffic, the fog node will conduct a second verification, and the cloud layer will eventually block the malicious IP; and, in the case of a botnet infection, the machine learning classifier will identify the pattern of suspicious communication and the system will isolate the device automatically; and, in the example of a spoof attack, when a fake temperature sensor attempts to look like a legitimate device with a spoof IP, the classifier will detect the inconsistencies.

6. Conclusion

The rapid development of the Internet of Things has helped to improve modern digital eco-systems, yet due to the variety of the customer base and scarcity of resources, it is now considered to be a serious security threat. To withstand advanced attacks such as botnets, DDoS attacks, spoofing, reconnaissance and zero-day attacks, the conventional signature-based intrusion detection engines are no longer sufficient. The existing system would eliminate these challenges by using machine learning in a hybrid cloud-fog-edge system of intrusion detection and enable intelligent, adaptive intrusion detection, and real-time. Threat intelligence and correlation: This is performed through deep learning-based methods in the cloud, which involves handling of intermediate analysis and feature processing. Mog nodes: These are used to process feature processing and intermediate analysis on the fly at the edge, which consists of lightweight machine learning models. This layered implementation is more effective than the traditional IDS in detecting and responding with lower latency when the high-quality IoT datasets are incorporated, as shown by TON_IoT, Bot-IoT and IoTID20. The system demonstrates that ML-based IDS systems are not only practical but also beneficial to protect the modern IoT settings, even with the current problems, such as data imbalance, energy constraints, model explicability, and the changing

adversarial attacks. The explainable AI and lightweight neural networks and federated learning should continue to improve the performance and resilience of explainable AI in the future.

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