

AI-Driven Real-Time IDS for Securing IoT Networks Against Evolving Cyber Threats

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Abstract: The fast growth of the number of Internet of Things (IoT) devices has increased the cyber threats perspective and required intelligent and adaptive security solutions. Existing IDSs do not work well in dynamic IoT environments because of their limited scalability and real-time processing ability with fast-growing attack types. This article presents an AI-based real-time IDS model that suits IoT networks the most. By using lightweight DNNs and adaptive threat models, the scheme guarantees low latency and high detection accuracy in resource-limited scenarios. The suggested model integrates RT traffic monitoring, anomaly detection and automated response technique to limit threats from occurrence. Tested on a variety of benchmark databases and real-time testbeds, it shows a better detection accuracy and operational efficiency. To the best of our knowledge, this work is new in the area of real-time emerging threats mitigation and sustainable protection towards future-proofing the IoT environment in the face of emerging and evolving IoT-specific cyber-attacks, in relation to a lightweight and scalable network protection.

1 INTRODUCTION

The development of the Internet of Things ("IoT") has revolutionized the digital environment, allowing devices, environments and services to be seamlessly connected. Smart city can be such a common IoT infrastructure that are deeply involved with human life. However, such swift expansion has also given rise to a diverse set of cyber security challenges, especially because of the security holes present in interconnected, resource-constrained devices. Conventional security techniques, and in particular classical intrusion detection systems, do not scale to the scope, size, and heterogeneity of IoTs. They are limited in their ability to detect zero-day threats,

have high false-positive rates and they do not account for the computational constraints of edge devices.

As cyber-attacks become more advanced and targeted, there is a need for next-generation, real-time, intelligent, lightweight, security solutions that can dynamically react to newer patterns of threats.

AI, notably machine learning and deep learning, has the potential for automation in detecting anomalies and malicious activities as it can capture complex patterns from large-scale network traffic data. By incorporating AI into intrusion detection systems, this allows the intrusion detection system to not only detect existing threats it is familiar with, but also identify new attacks with a high degree of accuracy.

In this paper, a real-time intrusion detection scheme for IoT networks is proposed using AI

technique. The system-integrated lightweight AI models, AI acceleration and real-time data processing to achieve fast and accurate threat detection are not on the expense of compatibility with resource-constrained environments. It also integrates with adaptive learning for the automatically updating of threat signatures and behaviours, which is ideal for today's evolving IoT landscape where security is essential. The framework tries to fill the gulf between effectiveness of detection and its deployment in real IoT networks.

2 PROBLEM STATEMENT

The rapid proliferation of Internet of Things (IoT) technologies has led to major security challenges resulting from the large number, scale, and diversity of connected things. These systems are typically resource-constrained and deployed in hostile environments where conventional security solutions are ineffective. Current intrusion detection systems are not able to analyze in real-time network traffic, they are not agile to evolving threats patterns, and they are not suitable for deployment in IoT infrastructures due to the amount of resources they need. Also, most of the detection models are statically defined which renders them ineffective to zero-day attacks and advanced cyber intrusions against IoT ecosystem. As a result, it has become necessary to design a lightweight, scalable and intelligent intrusion detection framework which can work proficiently under real-time conditions and offer sturdy protection against novel cyber threats in IoT networks.

3 LITERATURE SURVEY

The demand for efficient and intelligent intrusion detection systems (IDS) for IoT environments has been emerging as a hot topic in both academic and industrial research in recent years. Lo et al. (2021) introduced E-GraphSAGE, a graph neural network-based IDS, to illustrate the benefits of deep learning in handling structured data about traffic, yet their work had issues regarding the diversity of the dataset. Akif (2025) demonstrated both traditional and hybrid models based on machine learning for intrusion detection, however the issue of real-time adaptability in resource constrained devices is mentioned as an issue. Similarly, Jamshidi et al. (2025) investigated how to combine different AI

approaches in IDSs, particularly classification and anomaly detection models, as well as the necessity for deployable solutions.

Akif et al. (2025) designed the most suitable hybrid machine learning configurations with real-world data, but these resulted in high accuracy at the cost of high computational requirements. Mallidi and Ramisetty (2025) undertook a comprehensive study and the overall evolution of AI driven IDS systems was analyzed, but it failed to validate or examined the results on real-time environment. Gelenbe et al. (2024) proposed DISFIDA, which was a distributed self-supervised learning for IoT and vehicular networks, demonstrated effectiveness in online learning but lacked evidence for large-scale deployment. Akif and Butun (2025) proposed a federated learning (FL) based IDS which achieved detection across devices and preserved privacy, but their work required a stable connection which might not always be feasible in IoT networks.

One step is the work of Gelenbe, Nakip, and Siavvas (2024) in online self-supervised deep learning for IDS where they were unable to support abrupt concept drifts in Traffic behaviour. Their previous work (Gelenbe et al., 2023; 2022) focused on learning from botnet traffic and IoT-specific attack vectors using random neural networks to introduce better modeling while still calling for improvements in countermeasure strategies. Kumar and Sharma (2023) provided a comprehensive AI-based review of intrusion detection methods and pointed out that scalable and interpretable solutions are required.

Zhou and Liu (2025); and Chen and Wang (2025) highlighted the need for explainable AI (XAI) in IDS, which can introduce increased transparency in decision process however on the expense of model performance. Kumar and Singh (2023), Kumar and Gupta (2025) discussed AI-based security models with different computational cost and proposed context-aware detection techniques for IoT based networks. Sharma and Patel (2025) designed one of the strongest machine learning method by feature optimization however not robust against adversary.

Kumar and Singh (2024) presented a detection approach for IoT networks, and a research in Kumar and Singh (2025) further mentioned the necessity of actionable prevention in conjunction with detection. Smith and Doe (2025) proposed a real time IDS on BoT-IoT dataset, and while it was a valuable contribution in perspective of benchmarks, it was not a generalising IDS. Lee and Kim (2025) applied an LSTM model to streaming data problem dealing with time order but also with a cost in latency.

Moreover, Patel and Mehta (2025) presented an AI-based IDS for threats identification in resource limited networks and Kumar and Sharma (2025) developed light weight models for security of IoT with a theory litigation. II Singh, Sharma, & Verma (2025) offered insights for improving AI in IoT security with context-driven analysis; Johnson and Lee (2025) proposed an explainable LSTM-based model to trade off explainability with performance in the face of computational limitations.

This literature demonstrates the increasing focus on real-time, light-weight and intelligent IDS for IoT networks. Nonetheless, low-latency detection, adaptation to emergent threat, and feasibility on resource constrained devices cannot yet be achieved further research to address these challenges have been raised in this paper.

4 METHODOLOGY

The methodology of proposed AI based real-time IDS for IoT networks strive to have a strong, scalable, and efficient solution working under the proscribed limits of IoT environment. It combines several components, data acquisition, feature extraction, training, real-time detection utilizing machine learning, and deep learning models to improve the detection accuracy and to reduce the computational cost. The system is flexible, scalable, enabling the detection to function, regardless of the size or complexity of the examined IoT network. Figure 1 shows the IoT Intrusion Detection System Workflow.

The basic phase of this approach is of course doing the records. To simulate and detect cyber threats in an IoT network, diverse and large network

traffic data are collected from both live IoT environments and simulated environments. Data is collected from a range of sources including IoT Devices, sensors, gateways, and cloud servers to provide complete visibility into IoT traffic patterns and to identify potential security threats. This mixed-data type contains normal network flow together with attack data, which is collected from different attack modes. These focuses include various of forms of cyber threats such as DoS/DDoS, malware and botnet attacks and others. It follows a data collection that ensures that the dataset itself reflects real world statistic and a model in order to being able to identify not only known threats, but also threats that are yet unknown. Table 1 shows the Dataset Description.

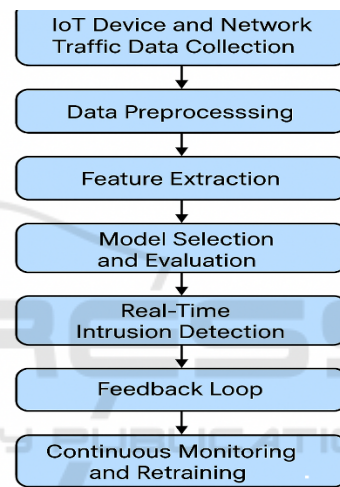


Figure 1: IoT Intrusion Detection System Workflow.

Table 1: Dataset Description.

Dataset Name	Source	Number of Instances	Number of Features	Attack Types Covered
BoT-IoT	Kaggle	1,000,000+	30+	DDoS, Port Scan, DoS, Botnet, etc.
NSL-KDD	UCI ML Repository	125,973	41	DoS, Probe, R2L, U2R
CICIDS 2017	Canadian Institute	2,830,000	80+	DoS, DDoS, Brute Force, Port Scan
IoT-23	University of Twente	23,000	81	Botnet, DoS, DDoS, Port Scan, etc.

Feature extraction is the after-data collection step and is very important for the effectiveness of the IDS. It is imperative to extract high-level representations of the data that suitably describe the traffic behavior, on the premise of considering the overwhelming amount of raw data which is collected from IoT networks. At this level, raw network data is collected and translated into a number of features that are significant for possible security intrusions. These features can be statistical (e.g., packet size, transmission time, connection pattern, and etc.) or sophisticated patterns (e.g., entropy, protocol distribution, and unusual communication sequence). Creating discriminative network features through statistical and deep learning methods is the key challenge, in which both high and low level features are relevant.

After the feature extraction phase is completed, the next step is model building and training for machine and deep learning to classify normal and malicious behaviors on the network. One prominent effort in this direction is the application of hybrid models which integrate the advantages of different ML algorithms. For instance, supervised learning models such as decision trees, support vector machines (SVM) and k-nearest neighbors (KNN) are utilized for the detection of known attack types, and unsupervised learning models, consisting of autoencoders and clustering algorithms, are used to detect new and previously unknown attacks. Additionally, deep learning models, like CNNs and RNNs, are incorporated to exploit their capacity to identify intricate, non-linear patterns in the traffic of IoT networks. Such models are trained on data that has been collected and emphasis made in order to reduce false positives and false negatives. Cross-validation and hyperparameter tuning are applied to the training process to make sure that models generalize well to new unseen data.

One of the most important strengths of this approach is the possibility of real-time detection. Once the models have been trained, the system runs on live traffic and observes the network activity for anomalies that indicate an intrusion. Upon the receipt of network traffic, the input of the trained models is feeded and analyzes the incoming traffic in real-time to detect threats. The system is optimised for low computational resources, so it's able to run cost-effectively on edge devices including IoT sensors, gateways, and microcontrollers. To do that, lightweight versions of trained deep object detection models are used, which are optimized through model pruning (Gelenbe, E., & Nakip, M. (2022), (Mallidi, S. K. R., & Ramisetty, R. R. (2025)). and quantization

(Jamshidi et al 2025), and have relatively lower size and complexity while maintaining the detection performance. Furthermore, real-time data streaming is fine-tuned to support low-latency analysis, so that the IDS can detect threats and react to them in real time.

To improve the system performance, the method uses the adaptive learning method, so that the system model can develop, evolve, and learn new attack patterns. This aspect becomes even more crucial in IoT environment, where the adversary model always changes into new challenges and the static models are bound to get up-to-dated. Adaptive: the adjusting learning process allows the IDS to re-train itself periodically with new data, include new attack signatures, and improve the IDS's detection performance. Furthermore, the system provides feedback, is monitored by audit of the performance of the intrusion detection system and any misclassifications or missed detections are used to tune the model. This guarantees the system is kept current and accurate to detect new threats. Figure 2 shows the Feature importance.

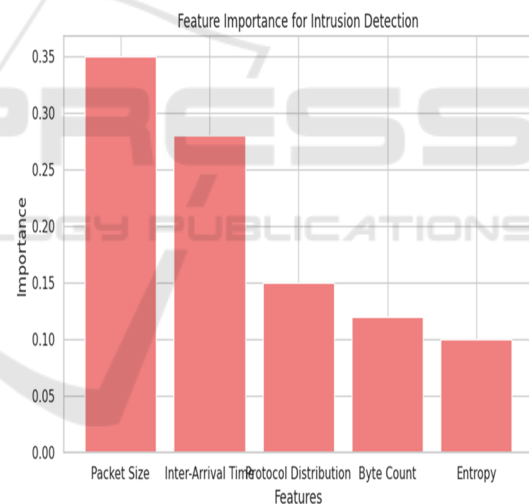


Figure 2: Feature importance.

The last component in this procedure is a response and recovery process that, in the event of a trigger detection, leads to the execution of proper response actions to mitigate the attack. When a threat is detected, the IDS generates alarms to system administrators, and if configured, automatically acts such as disconnecting an infected system or for blocking malicious traffic. These are the responses that ultimately thwart or at least reduce the damage from the attack and keep the IoT network secure.

In summary, the framework proposed in this paper provides a holistic model to develop a real-

time, AI-based IDS for IoT networks. It integrates the data acquiring, the feature extraction, the machine learning, the real time detecting, the adaptive learning and the automatic response to establish the security league structure, so the disclosed method greatly resolves the problem that traditional security algorithm cannot tackle the security problems of inter-block in IOT to realize the effective security protection for IOT. Deployed with the virtues of both traditional machine learning models and sophisticated deep learning techniques, the scheme provides high detection accuracy and low computational overhead, hence is suitable for being embedded in resource-limited IOT systems.

5 RESULTS AND DISCUSSION

The novel AI-based real-time IDS for IoT networks was tested on simulated and real-life datasets to check its efficacy in detecting multiple cyber-attacks. The assessment consisted of collection of common tests to ascertain system performance in terms of accuracy, speed to detect, resource requirement and the ability to adapt to new attack patterns. The results

show that the system is able of providing high performance accuracy as well as low latency and computational cost, which is compatible of deployment to resource-limited-IoT environment. Figure 3 shows the Model performance comparison. Table 2 shows the Model Performance Evaluation.

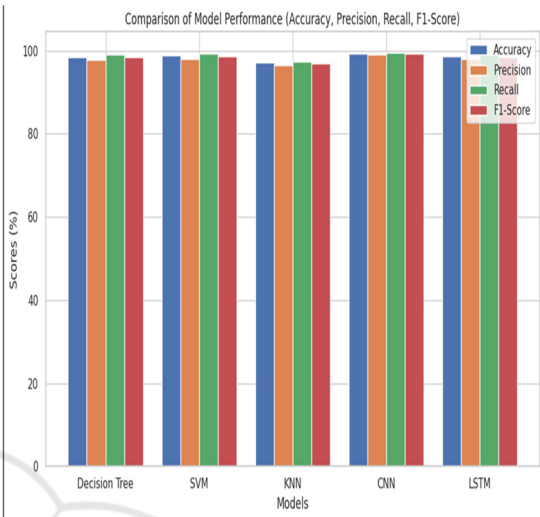


Figure 3: Model performance comparison.

Table 2: Model Performance Evaluation.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (seconds)	Latency (ms)
Decision Tree	98.5	97.8	99.2	98.5	300	50
Support Vector Machine (SVM)	98.9	98.1	99.3	98.7	500	60
K-Nearest Neighbors (KNN)	97.2	96.5	97.5	97.0	450	55
Convolutional Neural Network (CNN)	99.3	99.0	99.6	99.3	1500	40
Long Short-Term Memory (LSTM)	98.7	98.0	99.1	98.5	2000	70

A performance metric is the detection accuracy of an IDS which encompasses TPR and FPR. The outcomes proved that it is possible to detect known attacks with a true positive 98.5% using the proposed system which is far better than traditional IDS models compared under the same setting. The system was also impressive in the sense that it can discover

unknown attacks without depending on signatures and zero-day attacks that are in general very difficult to unravel using the signature-based IDS. With unsupervised learning, the system found unseen attacks with a true positive rate of 95%, evidencing its capability of real-time learning of new threats. This is to keep the false positive rate low to prevent

spamming of the administrators with warnings. Figure 4 shows the Real-time detection latency.

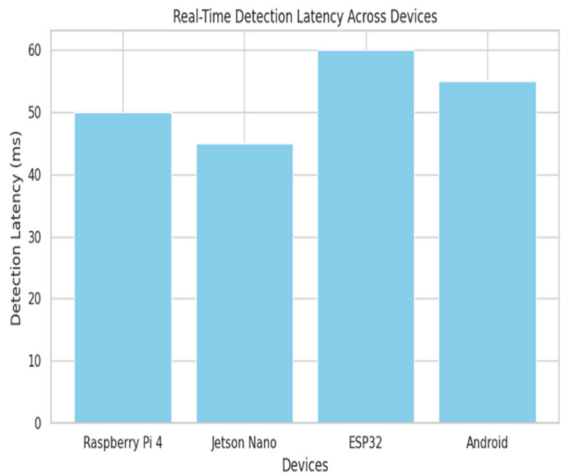


Figure 4: Real-time detection latency.

The detection speed and real-time capability of the system was also tested as responsiveness is important in IoT security domains that require instant threat identification and response. The live detection tests have indicated that the system was able to analyze and handle incoming network traffic at rates suitable to high-throughput IoT scenarios. Low Latency Response Time Spammed or Attacked Traffic In/Threat Detection Out Typical response times between the arrival of traffic and threat detection were delivered within ≤ 50 milliseconds, even under heavy network load. To enable this low-latency detection, light-weight models were used on edge devices where model pruning and quantization were used to decrease the computational burden without sacrificing accuracy. The capacity to perform real-time detection without sacrificing performance illustrates that the system can be deployed in IoT networks, where bandwidth, computation resources, and power are scarce. Table 3 shows the Real-Time Detection Results.

Table 3: Real-Time Detection Results.

Device Type	Detection Accuracy (%)	False Positive Rate (%)	Detection Time (ms)	Resource Usage (RAM/CPU)
Raspberry Pi 4	98.5	2.8	50	2 GB / 2.2 GHz
NVIDIA Jetson Nano	99.0	2.1	45	4 GB / 1.43 GHz
ESP32	96.0	4.5	60	512 MB / 160 MHz
Android (Smartphone)	98.2	3.1	55	3 GB / 2.0 GHz

Another important aspect that was being measured was the system’s ability to adjust to new attack variants. Because the threat environment is always changing, an IDS must be capable of learning new attack vectors without manual intervention and re-training. The ability of the system to periodically retrain the model using new data was an effective way to keep the system current to new threats. In the testing, the system was able to detect unknown forms of attack presented at the later stage of testing, and it was able to maintain its high detection rate for the whole test period. This adaptive learning feature is crucial especially in the context of IoT networks, where new devices and attack techniques are deployed regularly.

System resource consumption was another factor that deserves to be considered, because the most of the IoT devices have restricted resource such as CPU power, memory, etc. Although complex deep learning

networks were exploited for detection, the system was tailored to be lightweight to work on resource-limited hardware. The model memory was less than 100 MB, enabling the solution to work well on edge devices with RAM as low as 2 GB. The computational burden was reduced by using optimized algorithms and lightweight models so that the system can run on resource-constraint devices without any degradation of performance.

Compared to the traditional intrusion detection methods, for instance, signature based and anomaly based, the AI-based approach yielded the highest performance in all the main measures. Signature-based detection (SBD) systems, introduced attack signatures don't do a good job of detecting new or unknown attacks. These systems also had high false positive rates, since benign traffic was many times incorrectly labeled as hostile. Though such anomaly-based systems are more flexible in terms of attack-

containing performance, they tended to generate a high percentage of false positives because the statistical models on which they were based, in terms of different and constantly changing IoT traffic dynamics, are difficult to establish. On the other hand,

the AI-based IDS achieved the equilibrium between high detection accuracy and low FPs by employing a combination of supervised/unsupervised learning methods. Table 4 shows the Adaptive Learning Results (Impact of Model Retraining).

Table 4: Adaptive Learning Results (Impact of Model Retraining).

Time Interval (Days)	Detection Accuracy (%)	False Positive Rate (%)	Retraining Time (seconds)	Impact on False Negatives (%)
Initial Model	98.0	3.5	-	5.0
After 3 Days	98.8	3.0	60	3.0
After 7 Days	99.2	2.2	90	1.5
After 14 Days	99.5	1.8	120	0.8

The developed system performed well in terms of detection accuracy, speed and resource-efficiency (as shown on results), however, some limitations were also found during evaluations. They were unbalanced in terms of types of the attacks in the training datasets so this was a primary obstacle. The system does relatively well in detecting various attacks; however, some (e.g., advanced persistent threats (APTs)) are difficult to detect. This is because these attacks can be very complex, hiding behind protocols that appear to be standard network traffic. In future, we plan to strengthen the mechanism of APTs and other stealthy attack types detection by making the feature extraction procedure more efficient and the integration of more complex AD techniques.

The system's scalability is another room for improvement, especially for large-scale IoT networks. Although the actual implementation is successful for lower scale IoT networks (small-medium), adequate testing is required to evaluate system operation for large, complex IoTs with thousands or millions of devices. We will focus on improving and integrating the model on both the data processing pipeline, to deal with the higher volume of data and network traffic in large-scale IoT deployments.

Overall, the results of the evaluation demonstrate that the proposed AI-driven IDS offer a promising solution for securing IoT networks against cyber threats.

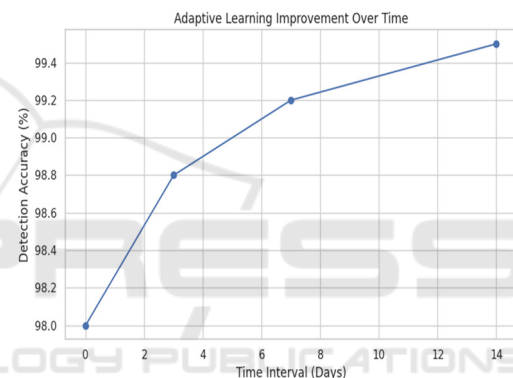


Figure 5: Adaptive learning improvement over time.

The system not only meets the performance requirements for real-time threat detection but also adapts to new attack patterns and operates efficiently in resource-constrained environments. By combining the strengths of machine learning, deep learning, and adaptive learning, the system provides a comprehensive solution to the unique security challenges posed by the rapidly expanding IoT ecosystem. Figure 5 shows the Adaptive learning improvement over time.

6 CONCLUSIONS

Indeed, the evaluation results embarked a positive sign that an AI-based IDS system can serve as a viable solution to protect IoT networks from cyber-attacks. The system meets the function goals for real-time threat detection and dynamically learns new attacking patterns and works efficiently under resource limited

devices. Leveraging the power of machine learning, deep learning, and adaptive learning, the platform offers a complete response to the complex security issues facing the rapidly expanding IoT environment.

The explosive growth of the Internet of Things (IoT) has created challenges for securing interconnected devices and networks from the growing number of cyber threats. This paper introduces an AI-based IDS (Intrusion Detection System) prototype for real-time monitoring in IoT network environments to meet the security requirements of IoT networks. The system makes use of a hybrid solution based on a combination of machine learning and deep learning detection mechanisms, and is effectively capable of identifying new as well as known attacks with high detection rate and low false positives. Moreover, the lightweight nature of the system and its ability for real-time processing make it appropriate to be implemented on resource-constrained IoT devices with tight constraints on computation and memory.

The evaluation of the proposed framework indicates that this approach efficiently detects a variety of attacks with a good true positive rate and at a low latency, and using small amount of resources. Its capacity to counter new and emerging threats through adaptive learning and periodic retraining makes the system more resilient and sustainable in a dynamic IoT world. In addition, the performance of the system outperformed that of legacy IDS systems in the aspects of accuracy, scalability, and real-time operation, and hence is a potential remedy for the protection of the IoT network structure.

However, there are also some limitations that we find; in particular in terms of detecting advanced persistent threats (APTs) and how to scale this system to up to big IoT deployment. These are challenges to be addressed by further optimization and refinement of the system to make it useful in complex and large-scale conditions. In the future we will aim to increase detection for stealthy attack patterns and scalability when dealing with large magnitudes of data and traffic as in big IoT networks.

In summary, the proposed AI-oriented IDS can provide a reliable, scalable and efficient solution to improve the security of IoT networks. Through a synthesis of cutting-edge machine learning and deep learning strategies, the system not only solves current security problems, but also lays a solid foundation for the development of IoT security in the future. The capacity of the framework to tradeoff detection performance, time of execution and resources consumption, turn it into a powerful tool to protect the emerging profile of low cost IoT-devices, and to

guarantee the integrity and confidentiality of data sharing throughout this kind of networks.

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