Alkadhim Journal for Computer Science, Vol. 4, No. 2 (2025)

Open Access ISSN: 3007-1437 (Online), ISSN: 3007-1429 (Print)

IRAQI Academic Scientific Journals

Alkadhim Journal for Computer Science (KJCS)

Journal Homepage: https://alkadhum-col.edu.iq/JKCEAS

KJCS ALKADHIM JOURNAL FOR COMPUTER SCIENCE

A Comprehensive Review of Intrusion Detection Systems in IoT Networks Using ML and DL Techniques

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Article information

Article history:
Received: May, 24, 2025
Accepted: June,19, 2025
Available June,25, 2025

Keywords:
IoT, Intrusion Detection System, Machine learning (ML), Deep learning (DL).

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DOI:
To be assigned

Abstract

The Internet of Things (IoT) is growing at an extremely rapid rate, impacting all aspects of our lives and extending to various fields, including wearable technology, smart sensors, and home appliances. However, the rapid growth is coupled with serious security concerns that render these technologies vulnerable to hacking opportunities and erode user privacy, as well as data protection, especially as cyber-attacks become more complex. Intrusion detection is a crucial aspect for tracking and thwarting such attacks. Machine learning (ML) and deep learning (DL) algorithms have ever-increasing efficiency in automating procedures like these. This study aims to provide researchers with a comprehensive overview of contemporary Intrusion Detection System (IDS) techniques employed in the IoT environment, highlighting strengths and weaknesses. It also gives direction to future research by suggesting that more adaptive, lightweight, and efficient intrusion detection systems can be developed to address the unique constraints of IoT networks.

1. Introduction

The Internet of Things (IoT) has emerged as the next significant technological revolution in computing, impacting all aspects of human existence [1]. The increasing network of interconnected Internet-enabled devices encompasses IoT applications in connected autos, smart homes, smart retail, supply chain management, urban environments, educational institutions, industrial facilities, organizations, agricultural settings, and healthcare centres [2]. The term IoT refers to a category of computing systems that facilitate the collection, transmission, and interconnection of devices, as well as the real-time management of data and applications [3]. Nonetheless, this rapid growth and the incorporation of electronics into everyday life present numerous concerns, especially those related to security [4].

Constructing resilient IoT networks presents various challenges, including constrained resources, inadequate energy efficiency, device heterogeneity, managing substantial data volumes, ensuring high-bandwidth data transmission, scalability, and, crucially, safeguarding user data and privacy [5, 6]. The extensive array of

linked devices creates a significant attack surface, rendering them potential access points for malevolent entities. Furthermore, the absence of standards, inherent unsafe configurations, and restricted processing capacity in numerous IoT devices exacerbate these security issues. Strong security solutions are therefore essential to protecting the constantly changing IoT environment [7]. Resolving these security issues is crucial to ensuring that the Internet of Things reaches its full potential without jeopardizing user safety and confidence [8]. Network Intrusion Detection Systems (NIDS) have become a crucial component of cybersecurity protection strategies. These technologies detect and notify security administrators of anomalous activity that could compromise the network's integrity [9]. Artificial intelligence and machine learning-based intrusion detection systems have been increasingly employed in the Internet of Things (IoT). These systems can automatically learn and recognize typical network behaviour patterns to detect unusual activity efficiently. IDSs can prevent intrusions and notify IoT devices of unusual activity before attackers can compromise the network. Therefore, for IDS to perform well, it must meet the requirements of time efficiency, high accuracy, and low complexity. Compared to traditional IDSs, data mining exhibits more robust behaviour and helps achieve improved accuracy in novel types of intrusion through knowledge discovery [10].

Our contributions to this work are the following:

• We survey previous studies of NIDS that use AI techniques.

• We compare the performance of different models with different datasets and IoT.

2. Relevant Terms

This section introduces the two primary concepts of this paper: intrusion detection systems and the Internet of Things.

2.1. Internet of Things

IoT has undergone exponential growth over the years [11]. IoT is a network of interconnected devices that can communicate and share data without human intervention, and is utilized in various applications. These gadgets can learn and adapt to user preferences by analysing past data, enhancing prediction capabilities, and improving user experience. IoT devices connect to the Internet directly or indirectly, enabling the sharing of information and facilitating user interaction. In a nutshell, IoT establishes a unified network of physical devices that combine software applications, allowing users to access and operate their gadgets from practically anywhere via Internet-connected devices [12].

This architecture is composed of three layers. The first is the perception layer, sometimes known as the physical layer. It has sensors that detect and collect information about the surroundings. It senses specific physical factors or recognizes other intelligent objects in its environment [13]. Second Network Layer: It serves as a connection between the perception and network layers. It sends the data recorded by the preceding layer to multiple devices, hubs, or servers on the Internet via any communication medium, whether it's wired or wireless [14]. The third is the application layer, which provides end users with application-specific services while maintaining the confidentiality, integrity, and authenticity [15]**.** As shown in Figure 1.

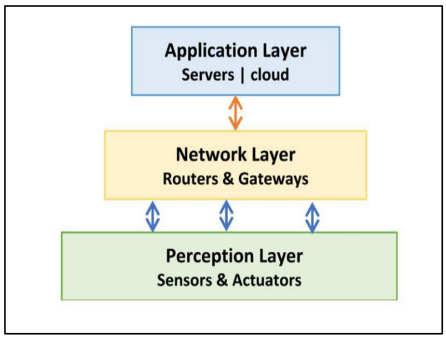

Figure (1): Layer architecture of IoT [15]

The Confidentiality, Integrity, and Availability (CIA) triangle is a fundamental concept in cybersecurity, although little research has directly linked it to IoT. In addition to the CIA trinity, recent research highlights the importance of elements such as identification and verification, privacy, and trust. The Open Web Application Security Project (OWASP) identifies IoT Attack Surface Areas that manufacturers, developers, researchers, and organizations deploying IoT technologies must be aware of. Security issues arise at several stages of the IoT architecture, each exposing distinct weaknesses and potential attacks: The perception layer, which is responsible for data collecting, faces issues such as data fraud and device destruction. Attacks include node acquisition, malicious code injection, fake data injection, replay or freshness concerns, cryptanalysis, eavesdropping, interference, and sleep deprivation. The network layer is responsible for data transmission, and its security issues centre on the availability of network resources. Common threats include denial-of-service (DoS) attacks, spoofing, sinkholes, wormholes, man-in-the-middle (MITM) attacks, routing information manipulation, Sybil attacks, and unauthorized access. The application layer provides user-requested services and is primarily vulnerable to software-related attacks, such as phishing, malicious viruses and worms, and dangerous scripts. Overall, a thorough knowledge of these problems is required [16,17].

2.2 Intrusion Detection System (IDS)

Intrusion is defined as any illegal activity that causes damage to an information system. Any attack threatening confidentiality, integrity, or availability will be considered an incursion. For example, behaviours that render computer services unusable to legitimate users are termed intrusions. IDS is a software or hardware device that detects harmful activity on computer systems and maintains system security. An IDS aims to detect many types of malicious network traffic and computer activities that a typical firewall cannot detect. This is crucial for ensuring robust protection against actions that compromise the availability, integrity, or confidentiality of computer systems [18]. Individual IDSs consist of both network-based and host-based IDS [19]. A NIDS monitors network traffic for network device security and analyses the protocols (network, application, transport, etc.) utilized to detect suspicious behaviours. HIDS monitors a host's properties and activities to detect potential threats. A host-based intrusion detection system monitors data, including traffic information, system logs, file access, and file modifications [20]. IDS systems are classified into two main categories: signature-based intrusion detection systems (SIDS) and anomaly-based intrusion detection systems (AIDS).

A. Signature-based Intrusion Detection System (SIDS): a typical method for detecting cyberattacks that uses pattern matching to identify known threats from a database of predefined attack signatures [19,20]. These systems perform well in identifying previously published assaults, but they struggle with zero-day attacks and advanced threats such as polymorphic malware. However, the rising complexity of modern attacks shows the limitations of SIDS. It emphasizes the need for alternative approaches, such as AI-based Detection Systems, to boost the efficiency of identifying emerging and advanced threats [21].

B. Anomaly-Based Intrusion Detection System (AIDS): This approach has garnered significant interest due to its ability to overcome the limitations of SIDS. AIDS uses machine learning, statistical analysis, and knowledge-based techniques to build a model of typical system functioning. Any significant variation from this expected behaviour is recorded as an anomaly, which could indicate an intrusion. Unlike SIDS, AIDS can detect zero-day assaults since it does not rely on pre-existing signature databases. AIDS development is divided into two phases: training, which builds a model of normal behaviour, and testing, which evaluates the system on new data [22].

AIDS provides various benefits, including the ability to identify previously unknown intrusions and internal harmful activity. For example, an alarm is raised if an intruder performs unusual actions within a stolen account. Furthermore, the system's reliance on specific behavioural profiles makes it difficult for attackers to avoid discovery. However, one significant weakness of AIDS is its sensitivity to large false positive rates, as new, normal activities may be misclassified as anomalies. AIDS methods are categorized into various groups, including statistics-based, pattern-based, rule-based, state-based, and heuristic-based approaches, which make them adaptable but challenging to standardize [23].

3. AI Methods for NIDS

This section provides an overview of the AI-based NIDS technique, along with specifics on the most commonly used machine learning (ML) and deep learning (DL) algorithms for designing an efficient NIDS. Machine and deep learning are widely classed as supervised and unsupervised algorithms. Unsupervised algorithms use unlabelled data to extract useful features and information, whereas supervised algorithms derive usable information from labelled data [24].

3.1. A general AI-based IDS methodology

A NIDS is generated using ML and DL approaches and typically consists of three key processes, as shown in Figure 2: (i) data pre-processing, (ii) training, and (iii) testing. All the recommended solutions begin with pre-processing the dataset to convert it into a format the algorithm can use. This stage usually includes encoding and normalization. The dataset may occasionally require cleaning, such as deleting missing data and duplicate entries, which is also conducted during this step. The pre-processed data is randomly separated into two sets: the training and testing datasets. Typically, the training dataset accounts for nearly 80% of the original dataset size, with the remaining 20% being the testing dataset. The training dataset is then used to train the machine learning (ML) or deep learning (DL) algorithm. The time required for the method to learn is determined by the size of the dataset and the complexity of the proposed model. Typically, the training period for the DL model necessitates deep and complicated structures. Once the model has been trained, predictions are made. In NIDS models, network traffic instances are expected to be either benign (standard) or belong to an attack class [25]. The following section presents a detailed review of commonly used machine learning (ML) and deep learning (DL) methods for NID systems.

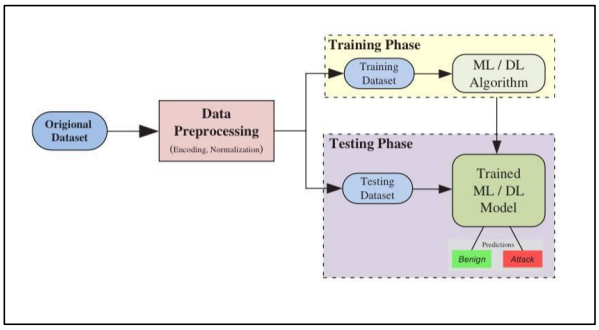

Figure (2): Generalized ML\DL-based NIDS [25]

3.2.ML algorithms

Machine Learning (ML) is a subfield of AI that focuses on creating methods and algorithms that enable computers to learn from data and make judgments or predictions without explicit programming [26]. It is used for large-scale data processing and is ideal for complex datasets with many variables and characteristics. The ML process begins with receiving training data and making observations on data through direct experience or by instruction, which results in output values. Algorithm selection should be appropriate for observing data trends, improving analytic and predictive power, and making better selections in future training data. Machine learning approaches are primarily classified into three categories: supervised, unsupervised, and reinforcement learning [27].

The following subsection provides a brief review of some of the most commonly used machine learning (ML) techniques for network intrusion detection.

3.2.1 Decision Tree (DT): Decision trees are popular for IDS because they are intuitive and easy to read. They classify data by dividing it into subgroups according to the value of the input attributes. Each node represents a feature, and each branch represents a decision rule, with leaf nodes indicating the class name [28].

3.2.2 K-Nearest Neighbour (KNN): is a basic supervised machine learning approach that uses "feature similarity" to classify data samples. By computing distances between points, KNN identifies the class of a new data point based on the majority vote of its k-nearest neighbours, with the parameter k determining

model performance. The model risks overfitting when k is too small, whereas a huge k can result in misclassification. KNN is a popular and straightforward strategy for machine learning classification jobs due to its simplicity, ease of implementation, and ability to learn complex functions [29].

3.2.3 Support vector machine (SVM): is a supervised machine learning technique based on the concept of a maximum margin separation hyperplane in n-dimensional feature space. It solves linear and nonlinear problems. Kernels are used to solve nonlinear issues. A dimensional input vector is initially mapped and allowed into a high-dimensional feature space using the kernel function. The support vectors are then used to compute an optimal maximum marginal hyperplane, which serves as a decision boundary. The SVM method can enhance the efficiency and accuracy of NIDS by accurately predicting normal and malicious classes [30].

3.2.4 K-means clustering: It divides data points into clusters based on similarity. In IDS, regular traffic forms distinct clusters, whereas abnormalities appear as outliers or establish their own clusters. This strategy effectively detects fresh dangers, although the number of clusters must be carefully tuned. To enhance performance, the authors proposed integrating data transformation (DT) with k-means clustering for anomaly detection in Internet of Things (IoT) networks [31].

3.2.5 Ensemble methods: The main idea behind ensemble methods is to profit from the many classifiers by learning in an ensemble manner. Each classifier has various advantages and disadvantages. Some individuals may excel in identifying specific types of attacks while performing poorly on others. The ensemble approach combines weak classifiers by training several classifiers and then generating a stronger classifier using a vote algorithm [32].

3.3. Deep learning algorithms

DL is a subtype of ML that uses multiple hidden layers to obtain the features of a deep network [33]. This section describes the DL methodologies used to propose DL-based NIDS solutions in their published works.

3.3.1. Recurrent Neural Networks (RNNs): are neural network structures that process sequential data, such as time series or textual data. Its mechanism cycles information throughout the network, allowing it to save contextual knowledge from prior inputs and apply it to the present input [34]. A form of neural network with sequential modelling capacity is commonly employed in intrusion detection. Unlike CNNs, RNNs can handle sequential input and capture temporal correlations by recalling prior information. As a result, RNNs can be used to improve the detection capabilities of intrusion detection models, particularly for intrusion behaviours with temporal characteristics [35].

3.3.2. Autoencoder (AE): is an unsupervised machine learning approach for learning compact features or data representations. It consists of two basic components: an encoder and a decoder. The data is encoded into a low-dimensional representation, which the decoder remaps into a data reconstruction. The AE is mainly utilized for data dimensionality reduction and feature extraction. As a result, AE and machine learning are frequently combined in IDS to construct novel deep-learning models.AE handles feature extraction and data dimensionality reduction, whereas machine learning handles classification [36].

3.3.3. Deep Neural Network (DNN): is a robust neural network structure, built as a feed-forward neural network (FNN) to eliminate recursive connections. Its most prominent characteristic is the ability to contain numerous hidden layers, significantly impacting learning. Each hidden layer comprises multiple neurons that receive and process the output of the previous layer. These neurons can capture the intricate and delicate correlations in the data by applying a nonlinear adjustment to the activation function. The layered structure of hidden layers in a DNN facilitates the learning of complex nonlinear patterns and the extraction of highly abstract and meaningful features from the input [37].

3.3.4. Deep Belief Network (DBN): The DBN is a deep generative model that utilize**s** multilayer Restricted Boltzmann Machines (RBMs) [38]. The primary purpose of DBN is to understand the underlying distribution of data and generate unique samples. Its distinctive characteristic is the multi-layer architecture, with each layer including an RBM. The RBM is a probabilistic model that uses an energy-based method with visible and hidden layers to efficiently simulate the joint distribution of data by altering weighting parameters. DBNs are trained using a layer-by-layer approach, combining pre-training and fine-tuning. They have many uses, including feature learning, data generation, migration learning, and unsupervised pre-training. DBN can build data, scale it down, and extract useful feature representations with excellent performance and generalization capabilities [39].

3.3.5. Convolutional Neural Network (CNN): The CNN is a novel network topology that replaces matrix multiplication with convolution calculations, distinguishing it from previous artificial neural networks. This convolutional procedure gives CNNs a distinct property that enhances data processing performance [40]. CNNs are characterized by their ability to utilize the two-dimensional properties of the input data fully. CNNs have been shown to outperform other deep learning frameworks in terms of voice and picture recognition. CNNs have three major layers. The convolutional layer is primarily responsible for feature extraction, which involves capturing significant input data elements via convolutional algorithms. The pooling layer is accountable for feature selection, which minimizes parameter complexity by reducing the number of features. The collected features are mapped to specific classes using a fully linked layer in the final classification task. The result is a hierarchy that enables the CNN to perform outstanding feature extraction and classification tasks [41].

4. Intrusion Detection System in the Internet of Things

In this section, a collection of previous studies on intrusion detection in Internet of Things networks using machine learning and deep learning techniques will be presented. To facilitate the comparison of several studies, highlight the most prominent methods used and their results, and identify the strengths and limitations of each study, a table (4.1) has been prepared to summarize these studies.

In 2021, Kasongo, S. M., et al. [42] developed an advanced IDS for Industrial Internet of Things (IIoT) networks using the Genetic Algorithm (GA) for feature selection using the Random forest RF model within the fitness function and used several classifier including Decision trees, Extra tree, XGBoost, and logistic Regression were evaluated on the UNSW-NB15 dataset, which represents complex network traffic patterns. The results demonstrated a classification accuracy of 87.61% in binary classification with an AUC score of 0.98

In 2022, Disha & Waheed. [43] Analysed the performance of IDS using modern machine learning techniques such as Decision Trees, Gradient Boosting Trees, and neural networks regarding feature selection by using the Gini Impurity Weighted Random Forest technique for reducing data dimensions. The study utilized newer datasets, such as UNSW-NB 15 and Ton_IoT, which demonstrated exemplary performance. The DT model achieved an accuracy of 93.01% and an F1 score of 93.72% on the UNSW-NB15 dataset after feature selection. In contrast, the Gradient Boosting Tree model reached an accuracy of 99.98% on the Ton_IoT dataset. Feature selection also aided in improving the F1 score and reducing the false positive rate, thereby enhancing the effectiveness of IDS in detecting modern threats.

In 2023, Altunay, H. C., et al. [44] proposed a combination model that integrates Convolutional Neural Networks and Long Short-Term Memory networks for intrusion detection in IIoT. The model was validated on the UNSW-NB15 and X-IIoTID datasets for binary and multi-classification experiments. The hybrid model outperformed other approaches, achieving 93.21% and 92.9% accuracy for binary and multi-class classification, respectively, on the UNSW-NB15 dataset. Additionally, it gained 99.84% and 99.80% accuracy, with an F1 score of 99.60% in binary classification and 90.54% in multi-class classification for the X-IIoTID dataset. This result demonstrates significant improvements in intrusion detection systems and underscores the necessity of utilizing deep learning techniques to manage complex and large datasets in Industrial Internet of Things configurations.

In 2023, Bakhsh et al. [45] conducted research aimed at enhancing the security of IoT networks using an IDS based on deep learning methods, such as Feed Forward Neural Networks (FFNN), Long Short-Term Memory (LSTM), and Random Forest Neural Networks (RF and NN). The study utilized the CIC-IoT22 dataset to develop models that efficiently detect cybersecurity attacks, including Denial-of-Service (DoS) attacks and flooding attacks. the FFNN achieved the maximum accuracy of 99.93%, precision of 99.93%, recall of 99.93%, and F1-score of 99.93%. and achieved an accuracy of 99.85% using LSTM, suggesting the proposed approach's ability to improve intrusion detection in IoT networks.

In 2023, Awotunde et al. [46] conducted an extensive review for enhancing the Intrusion Detection System (IDS) performance on IIoT networks. The study utilized the Ton_IoT dataset, which comprises real-time telemetry data from IIoT appliances, including refrigerators, thermostats, and motion sensors. It used the Chi-Square feature selection approach to minimize data complexity and improve model efficiency. Different ensemble methods were applied, including XGBoost, Random Forest, and AdaBoost, with the results indicating that XGBoost achieved optimal performance, detecting attacks such as DDoS, Ransomware, and

Injection with an accuracy 100%, Recall 99.79%, precision 99.95% and Recall 99.75% The study recommended data-balancing techniques and deep learning approaches as further steps toward performance optimization, hence serving as a suitable reference point for constructing successful IDS solutions for IIoT networks.

In 2023, Le et al. [47] proposed A fusion Model to enhance the performance of intrusion detection systems in IoT networks. The authors utilized state-of-the-art methods, such as Mean Decrease in Impurity (MDI), to select the most relevant features. Explainable AI methods, including LIME and Counterfactual, were employed to interpret and analyse the model's decisions. The process was tested on two extensive datasets, CICIoT2023, achieving detection accuracies of 99.5%, precision of 98.51%, recall of 99.63%, and an F1 score of 99.07%. Additionally, IoTID20 achieved 100% results across all scales. The results demonstrated significant advancements in capability explanation and clear definitions of classification boundaries for various attack categories, highlighting the benefits of integrating state-of-the-art and explainable AI techniques for improved IoT security.

In 2023, Sayed, N., et al. [48] introduced two novel CNN models for identifying nine attacks from the NF-UNSW-NB15-v2 dataset. Accuracy levels were established at 99% detection of the largest share of the attack classes, indicating the model's efficacy in classifying categories. The study was hindered by the imbalanced classes in the dataset, which necessitated the use of resampling and cost-sensitive learning to optimize model performance. This study makes a significant contribution to the field of intrusion detection systems in IoT settings, as it provides efficient solutions that are resource-intensive for devices.

In 2024, Sarhan et al. [49] conducted a study comparing the execution of intrusion detection frameworks in IoT systems using feature extraction techniques (PCA, LDA, Autoencoder) and six machine learning algorithms on three benchmark datasets (UNSW-NB15, Ton-IoT, CSE-CIC-IDS2018). The results indicated that the Autoencoder combined with the Decision Tree model achieved the highest performance on the Ton-IoT and CSE-CIC-IDS2018 datasets, with accuracies of 98.23% and 98.15%, respectively. In comparison, CNN attained the top performance on UNSW-NB15 with an accuracy of 98.16%. The study highlighted the importance of feature selection and dimensionality reduction, determining that 20 dimensions were optimal for enhancing performance, and recommended a standardized feature set to facilitate generalization and real-world applicability.

In 2024, Almotairi et al. [50] focused on enhancing the performance of intrusion detection systems in IoT networks using machine learning algorithms. The study utilized the Ton-IoT dataset and employed the K-Best algorithm to identify 15 key features. A Stack Classifier model was developed, an ensemble of several traditional algorithms, including Random Forest, Support Vector Machines, Naïve Bayes, and K-NN. The results indicated that the ensemble model outperformed individual models, achieving an impressive accuracy of 99.99%, precision of 99.98%, recall of 99.99%, and an F1 score of 99.99%. This is a testament to its effectiveness in detecting suspicious activity and minimizing false alarms in IoT networks.

In 2024, Inuwa & Das. [51] Compare the efficiency of machine learning models for anomaly detection in IoT networks using the Ton-IoT and BoT-IoT datasets. Five models were employed: Neural Networks, Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbours (KNN), and Logistic Regression. The results demonstrated that Neural Networks were more efficient than other models, achieving 99.99% accuracy. Therefore, they are the best to employ in cyber-attack detection. This study serves as a valuable reference for enhancing cybersecurity practices in IoT environments.

In 2024, Xiao et al. [52] were Interested in developing an effective intrusion detection system for IoT networks using Autoencoder technology. Traditional models were hindered by two fundamental challenges: limited computing power on edge devices and the need for improved accuracy in reduced models. To overcome these challenges, researchers used an Extreme Learning Machine to implement an Autoencoder, dividing data into various fields to maximize performance. Testing with the NSL-KDD dataset, improvements in accuracy and F1-score were observed to be 3.5% and 2.9%, respectively, without any loss in model lightness, rendering it suitable for deployment on resource-constrained edge devices.

In 2024, Li et al. [53] used the Ton-IoT dataset to compare Feature Selection (FS) and Feature Extraction (FE) techniques to improve the performance of IDS in IoT networks. Five machine learning algorithms were utilized in the experiment: Multi-Layer Perceptron, K-NN, RF, DT, and NB. FE outperformed FS, which achieved the highest accuracy of 86% when the Random Forest algorithm was applied to all 77 features and 89.1% when the k-Nearest Neighbours algorithm was used on 33 features. The study emphasizes the need to select a strategy that is most suitable for the system's requirements and available resources.

In 2024, Sayegh, H. R., et al. [54] proposed an intrusion detection system (IDS) based on a Long Short-Term Memory (LSTM) model to enhance the security level of IoT networks. SMOTE was utilized in this work to generate synthetic minority class samples, thereby overcoming the data imbalance issue. The proposed system outperformed other methods, achieving detection rates of 99.34% and 99.75% using the CICIDS2017 and NSL-KDD datasets, respectively. One of the difficulties emphasized was dealing with temporal data and precisely balancing classes in the datasets so that the system performs well.

Table 1: Comparison between different approaches to intrusion detection systems for IoT networks

Authors	Dataset	Methodology	Accuracy	Strengths	Limitation
[42]	UNSW-NB15	GA, RF, LR, NB, DT, ET, XG Boost	87.61%	Used GA to select an important feature	only used one dataset and a Low accuracy result
[43]	UNSW-NB15 and Ton-IoT	DT, RF, AdaBoost, GBT, MLP, LSTM, GRU	99.98%	Comprehensive performance and excels with high accuracy	high computation cost
[44]	UNSW-NB15 and X-IIoTID	CNN, LSTM	99.80%	Used deep learning techniques	a long-time detection and high computation cost
[45]	CIC-IoT22	FFNN, LSTM, RF, and NN.	99.85%	The ability to learn complex patterns	Complexity And needs a long time to train
[46]	Ton-IoT	XGBoost, RF, ET	99%	Used ensemble techniques to classify	only used one dataset
[47]	CICIoT2023 and IoTID20	Gradient Boosting, DT, RF, with LIME and Counterfactual	98.3%	Enhance generalization	High computation cost
[48]	NF-UNSW-NB15-v2	CNNs	99%	Used deep learning techniques	only used one dataset and a long-time detection
[49]	Ton-IoT, UNSW-NB15 And CSE-CIC-IDS2018	DT, LR, NB, RNN, CNN, DFF	98.33%	Used diverse techniques and evaluation methods across three datasets	Long-time detection and high computation cost
[50]	Ton-IoT	NB, RF, KNN, SVM	99.99%	Selecting the most important feature	only used one dataset The model lacks generalization
[51]	Ton-IoT and Bot-IoT	SVM, NN, KNN, DT, LR	99.99%	Comprehensive performance and excels with high accuracy	High computational cost
[52]	NSL-KDD	Autoencoder, ELM	94.32%	An accurate and lightweight model	only used one dataset
[53]	Ton-IoT	Multi-Layer Perceptron, K-NN, RF, DT, and NB.	89.1%	Focuses on feature education techniques	Low accuracy result, and only used one dataset

[54]	CICIDS2017 and NSL-KDD	LSTM	99.75%	Solved the imbalance problem and used LSTM	Long detection time

The reliability of research in the area of intrusion detection systems for IoT networks is influenced by several foundational factors. Most significant among them is dataset diversity and completeness, as research that utilizes varied and multiple datasets is more reliable than work based on a single dataset. Diversity provides generalizability and reduces bias in findings. Methodological comprehensiveness is the second aspect, where studies that employ an array of integrated methods and offer extensive comparisons between different methodologies are more insightful regarding the problem and yield more robust solutions. The third factor is the transparency of results and limitations. More reliable studies are those that openly acknowledge their limitations and challenges, such as high computational costs and difficulties in generalization, unlike studies that present idealized outcomes without declaring their limitations. The fourth factor is real-world issue management in the field, e.g., data imbalance and network complexity, where studies that address such practical challenges provide more applicable and implementable solutions. Finally, methodological innovation with assured results is regarded as a critical variable. An investigation that employs new techniques while achieving assured results in repetitive experiments is more credible than one that attains high accuracy in a single successful experiment.

5. Challenges of IDS in IoT networks

The field of intrusion detection in IoT networks faces several critical challenges that must be addressed to develop robust, efficient, and scalable solutions:

1. Data Imbalance and Diversity: Numerous devices, including sensors, cameras, and smart appliances, contribute to the vast amounts of heterogeneous data generated by IoT networks. This variability complicates the creation of uniform detection models. Additionally, unbalanced datasets, where attack data constitutes a small fraction of the total traffic, introduce biases towards majority classes that hinder the performance of machine learning models.

2. Resource Limitations: The processing power, memory, and energy resources of many IoT devices are constrained. Designing a lightweight IDS that can operate effectively under these limitations while maintaining high accuracy, particularly when utilizing sophisticated AI algorithms, can be challenging.

3. False Positives and Detection Accuracy: In AIDSs, high false-positive rates continue to be a significant problem. Misclassifying harmless activities as threats might result in resource waste and declining confidence in the IDS.

4. Zero-Day and Evolving Threats: A significant problem is the ever-changing nature of cyber threats, such as advanced persistent threats (APTs) and zero-day attacks.

5. Scalability and Real-Time Processing: IDS must be able to scale to manage enormous data volumes while offering real-time threat detection as the number of linked IoT devices increases.

6. Availability of datasets and benchmarking: Benchmarking model performance is restricted by the lack of realistic and comprehensive datasets for IoT-specific IDS testing. Most existing statistics do not accurately represent the complexity of IoT environments, which include a range of traffic patterns and types of attacks.

6. Conclusion

This research investigated the use of advanced artificial intelligence (AI) techniques to enhance Intrusion Detection Systems (IDS) for Internet of Things (IoT) networks, addressing some of the most pressing issues, including security vulnerabilities, false positives, and limited resources. By reviewing current approaches and combining state-of-the-art techniques, the research highlighted the importance of feature extraction, ensemble techniques, and testing on real-world datasets in designing effective intrusion detection system (IDS) solutions.

The results indicate that hybrid models and ensemble approaches can be integrated to enhance the detection rate while maintaining reduced computational complexity. Furthermore, a comparison with current literature

suggests that integrating feature optimization and deep learning techniques is crucial for achieving scalable and efficient IoT network security.

Future work should focus on surmounting other challenges, such as the diversity of data, real-time detection in resource-constrained environments, and integrating explainable AI techniques to enhance the interpretability and reliability of IDS solutions. Deploying these cutting-edge methods can secure the IoT ecosystem against future attacks, ensuring its sustainable growth and users' confidence.

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