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Enhancing Cybersecurity in IoT: A Review of Machine Learning Techniques for Intrusion Detection and Anomaly Detection

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Abstract: This review paper explores the current advancements in intrusion detection and anomaly detection systems specifically designed for Internet of Things (IoT) environments, focusing on the integration of machine learning techniques. As IoT devices proliferate, so do the associated security vulnerabilities, necessitating robust detection mechanisms to safeguard sensitive data and maintain system integrity. The paper synthesizes findings from various studies, highlighting the efficacy of hybrid models, supervised and unsupervised learning algorithms, and their applications in addressing diverse security challenges. Key outcomes demonstrate significant improvements in detection accuracy and efficiency; however, challenges such as adaptability to evolving threats, scalability, and real-world deployment persist. The review underscores the need for adaptive algorithms, federated learning approaches, and lightweight solutions tailored for resource-constrained devices. Furthermore, it emphasizes the importance of collaboration across sectors to drive research forward. Ultimately, this paper aims to provide insights into future research directions that can enhance the security landscape of IoT systems, contributing to the development of more resilient cybersecurity frameworks.

Keywords*:* Internet of Things (IoT), Intrusion Detection Systems (IDS), Anomaly Detection, Cybersecurity, Real-time Monitoring, Adaptive Algorithms, Federated Learning, Data Privacy.

I. INTRODUCTION

The rapid proliferation of the Internet of Things (IoT) has transformed industries by enabling interconnected devices to communicate and share data autonomously. This expansion has fostered the development of smarter homes, cities, healthcare systems, and industrial processes. With over 30 billion IoT devices expected to be deployed globally by 2025, the vast potential of IoT technologies is evident. These devices, ranging from basic sensors to advanced machines, play critical roles in enhancing operational efficiencies and generating actionable insights from massive volumes of data [19].

However, IoT devices often operate with minimal oversight, which presents a wide array of security vulnerabilities. Many devices are designed to prioritize functionality and cost-effectiveness over security measures, leading to significant challenges in securing IoT networks. For example, most IoT devices lack advanced processing power, which restricts their ability to implement complex encryption techniques or advanced security protocols. This limitation, coupled with the distributed nature of IoT networks, makes these devices particularly vulnerable to cyberattacks, creating substantial risks for both consumers and industries that rely on IoT infrastructures [9][18].

One of the most pressing concerns in the IoT ecosystem is the rise of botnet-based attacks, where a network of compromised IoT devices is controlled by malicious actors to orchestrate large-scale Distributed Denial of Service (DDoS) attacks. The Mirai botnet attack is a striking example, which exploited weak default credentials on thousands of IoT devices to launch a massive DDoS attack that temporarily disrupted major websites and services worldwide. The attack not only demonstrated the weaknesses in IoT security but also exposed the cascading effects of such vulnerabilities across global internet infrastructures [18]. As IoT devices continue to integrate into critical sectors like healthcare and transportation, the potential consequences of security breaches become even more alarming.

Given these vulnerabilities, researchers have explored several avenues to bolster the security of IoT systems. A significant body of research has focused on leveraging machine learning (ML) techniques for anomaly detection and intrusion prevention in IoT networks. Machine learning models offer the advantage of detecting complex and evolving attack patterns by analyzing large-scale network traffic data. By training on labeled datasets such as N-BaIoT and Bot-IoT, these models can effectively classify network traffic as either benign or malicious, helping to identify threats in real-time [12][9]. For instance, Meidan et al. developed the N-BaIoT dataset specifically for evaluating machine learning-based intrusion detection systems in IoT environments. Similarly, Moustafa et al. introduced the Bot-IoT dataset, which combines authentic and synthetic network traffic to simulate various attack scenarios and test different detection mechanisms [9].

Despite the success of machine learning-based approaches in improving IoT security, several challenges remain. First, the dynamic and heterogeneous nature of IoT networks makes it difficult to create a one-size-fits-all solution. IoT devices vary widely in terms of their capabilities, communication protocols, and security requirements. As a result, the security solutions effective for one type of device or network configuration may not be applicable to others. Furthermore, machine learning models themselves are not immune to adversarial attacks. Sophisticated attackers can manipulate training data or introduce subtle perturbations in network traffic to deceive ML-based detection systems, rendering them ineffective [9].

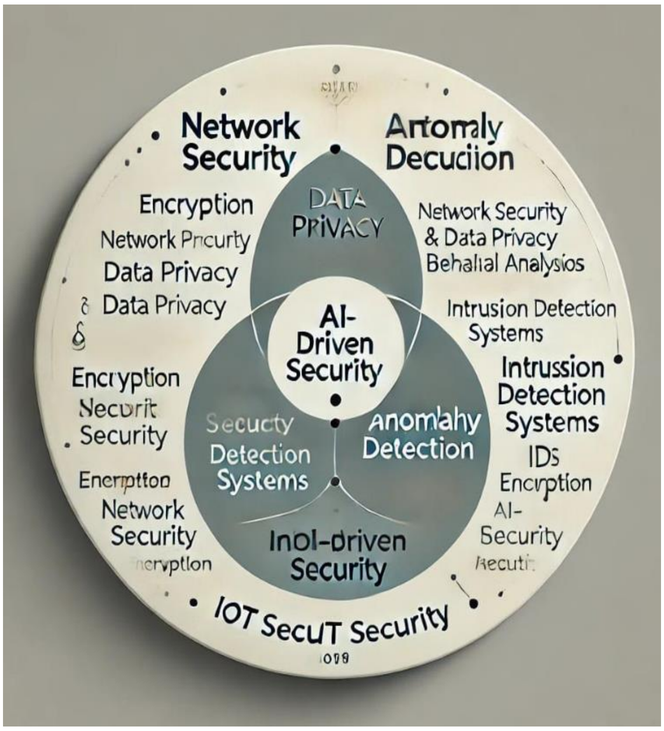

Figure 1 : Different security measures used in IoT security [7].

Moreover, the lack of standardized security frameworks exacerbates the problem. Unlike traditional IT systems where comprehensive security protocols are well-established, the IoT ecosystem remains fragmented. Different manufacturers, vendors, and service providers often implement inconsistent security measures, leaving many devices vulnerable to attacks. For example, while some IoT devices may employ advanced encryption or secure authentication protocols, others may rely on outdated or weak security mechanisms, creating an uneven landscape of security practices [18]. This lack of uniformity poses significant challenges for regulators and policymakers, who struggle to enforce consistent standards across the diverse and rapidly evolving IoT domain.

In addition to technical vulnerabilities, IoT devices pose significant privacy risks due to the vast amounts of data they collect. Whether in healthcare, smart homes, or industrial settings, IoT devices generate and transmit sensitive information, often without sufficient user control or oversight. Unauthorized access to this data can lead to severe privacy breaches, making it crucial for security measures to encompass both device protection and data confidentiality. Current research emphasizes the need for encryption, data anonymization, and access controls as essential components of a comprehensive IoT security framework [12].

This review aims to explore the current state of IoT security by examining vulnerabilities and threat models associated with IoT devices. Furthermore, it investigates the efficacy of various mitigation strategies, particularly the use of machine learning techniques for intrusion detection and threat prevention. By synthesizing insights from recent literature, this paper seeks to identify the gaps in existing research and propose future directions for securing IoT environments. Through a detailed analysis of both technical and policy-driven approaches, we hope to provide a clearer understanding of the evolving landscape of IoT security.

II. LITRATURE REVIEW

Churcher et al.[1] investigate the security challenges in IoT networks, highlighting how resource limitations of IoT devices make them vulnerable to attacks, which traditional intrusion detection systems (IDS) struggle to handle efficiently. They compare several machine learning (ML) algorithms, including k-nearest neighbor (KNN), support vector machine (SVM), decision tree (DT), naive Bayes (NB), random forest (RF), artificial neural network (ANN), and logistic regression (LR), using the Bot-IoT dataset for binary and multi-class classification. The algorithms are evaluated based on accuracy, precision, recall, F1 score, and log loss. RF shows the highest accuracy (99%) for detecting HTTP distributed denial-of-service (DDoS) attacks in binary classification, and outperforms other algorithms in precision, recall, and F1 score across various attacks. In multi-class classification, KNN achieves the best performance with 99% accuracy, surpassing RF by 4%. The study further reveals that RF performs best on non-weighted datasets, while ANN excels in binary classification on weighted datasets, and KNN and ANN perform well in multi-class classification on weighted and non-weighted datasets, respectively. The authors conclude that ANN is particularly effective for weighted datasets and propose future testing of the ML models in IDS prototypes with a broader range of attacks to validate multi-class classification capabilities.

Mousa Al-Akhras et al. [2] addresses the growing security threats posed by the Internet of Things (IoT), despite its many benefits. IoT networks are particularly vulnerable to attacks such as Denial of Service (DoS) and Distributed Denial of Service (DDoS). To counter these security issues, the authors propose a classification model that leverages machine learning algorithms to detect and mitigate such threats. The model was tested using three prominent algorithms: Random Forest (RF), k-Nearest Neighbors (KNN), and Naïve Bayes, which were evaluated on the UNSW-NB15 benchmark dataset. This dataset includes both normal network traffic and malicious traffic instances, making it suitable for testing attack detection models. The study's experimental results demonstrated that RF and KNN outperformed Naïve Bayes, achieving near-perfect accuracy rates of 100% and 99%, respectively, with and without noise injection. In contrast, Naïve

Bayes performed less effectively, with accuracy dropping to 82.77% under noise conditions. Precision and recall metrics further highlighted the superior performance of RF and KNN. To enhance prediction accuracy, the study also implemented a voting method combining multiple models, which showed the best overall performance across all evaluation metrics. While the study effectively demonstrated the strength of these machine learning algorithms in detecting IoT-related threats, it is limited by the scope of testing only three algorithms. Future research could expand on these findings by incorporating additional machine learning models and testing them across different datasets and evaluation metrics to further refine IoT security solutions.

Jadel Alsamiri et al. [3] explores the use of machine learning algorithms for detecting cyberattacks in Internet of Things (IoT) networks, which are increasingly vulnerable due to their minimal user interaction, low storage, and processing capabilities. Given the limitations of traditional security solutions, the authors emphasize the need for intelligent, network-based security approaches. Although machine learning has been widely used in attack detection, fewer studies have focused on IoT networks specifically. To address this, the researchers evaluated seven machine learning algorithms using the Bot-IoT dataset, known for its diverse attack types and network protocols, and extracted 84 network traffic features using CICFlowMeter. Feature importance was calculated using the Random Forest Regressor, both for individual attack types and for aggregated attacks. Among the algorithms tested, K Nearest Neighbors achieved the highest performance with an F-measure of 0.99, followed closely by Random Forest, ID3, and AdaBoost at 0.97. The study highlights the effectiveness of machine learning in IoT attack detection and suggests future work in exploring unsupervised algorithms and combining models for improved performance, contributing valuable insights to the field of IoT security.

Vikas Tomer et al. [4] addresses the increasing prevalence of malicious attacks driven by the widespread adoption of Internet of Things (IoT) devices in various sectors, including homes, offices, healthcare, and transportation. To enhance attack detection speed, the authors propose the integration of fog computing with IoT, as fog devices are positioned closer to IoT devices than cloud servers, reducing response times. Machine learning is a common method for detecting such attacks due to the vast amounts of data generated by IoT devices. However, fog devices often lack the processing power and memory to handle real-time attack detection effectively. The paper presents a solution by offloading the machine learning model selection to the cloud while assigning real-time prediction tasks to fog nodes. An ensemble machine learning model, built in the cloud based on historical data, is employed for real-time attack detection on fog nodes. The proposed approach was tested using the NSL-KDD dataset and demonstrated strong performance across metrics like execution time, precision, recall, accuracy, and ROC curve. Additionally, the study highlights that the ensemble method with voting executed faster than stacking, with the fog node model completing predictions in as little as 1.15 seconds, showing its practical effectiveness.

Rakesh Kumar et al. [5] explore the classification of Internet of Things (IoT) devices within network traffic, emphasizing its significance for maintaining proper functioning, implementing Quality of Service (QoS), and detecting malicious activities. The study acknowledges that various machine learning algorithms have been proposed for IoT traffic classification, though their accuracy is influenced by factors such as the type of data generated by IoT devices, feature extraction methods, and deployment sites. Notably, the manual selection of features and algorithms is prone to errors, making it necessary to optimize these choices. The authors conducted an in-depth comparative analysis using a public dataset comprising 20 days of network traces from 20 IoT devices. After extracting key features, they evaluated the performance of state-of-the-art machine learning algorithms based on classification accuracy, speed, and training time. The findings offer insights into the selection of appropriate algorithms for different IoT traffic classification scenarios, contributing valuable recommendations for optimizing IoT network monitoring.

Malathi et al. [6] emphasize the importance of evaluating the performance of ML algorithms in the context of IoT security, particularly against DoS attacks. Their study aims to assess the efficiency of various ML techniques in detecting and mitigating network-related security threats. To achieve this, the authors utilize a specialized metadata set known as Bot-IoT, which provides a comprehensive framework for testing different ML algorithms. The research highlights several key factors influencing the success of ML-based security measures, including the choice of algorithm, the quality of the metadata used for training, and the adaptability of the models to new and evolving threats. The authors report that ML algorithms, when applied effectively, can achieve significant success in detecting and addressing IoT network assaults.

Muhammad Muhammad Inuwa et al. [7] (2024) highlight how the integration of IoT systems has increased the complexity of device interactions and data traffic, thereby expanding the attack surface for cyber adversaries and emphasizing the need for effective cybersecurity measures. In response, machine learning (ML) has proven to be a powerful tool for detecting cyber anomalies within IoT systems. Inuwa et al. (2024) investigate various ML techniques—Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees (DT), Logistic Regression (LR), and k-Nearest Neighbors (k-NN)—and find that ANN performs the best in anomaly detection. This result aligns with existing literature, which suggests that ANNs excel at learning complex patterns and adapting to diverse data inputs. Their study, which utilized two well-known datasets, also highlights the practical applications of their findings, noting that orange-3 machine learning widgets are suitable for both industrial and research purposes in IoT device anomaly detection. Overall, Inuwa et al.'s research underscores the vital role of machine learning in enhancing IoT security, offering valuable insights for cybersecurity experts working to develop robust protection strategies and advance cybersecurity practices.

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A. Smith et al. [8] emphasizes that the evolution of wireless communication technologies, coupled with the ongoing digital revolution, has profoundly expanded the scope and impact of the Internet of Things (IoT). This transformation has led to a substantial increase in the number of internet users, which in turn has caused a dramatic surge in network traffic and data volume. As IoT devices proliferate and become more integrated into everyday life, they generate vast amounts of data, ranging from simple sensor readings to complex multimedia streams. This explosion in data not only amplifies the demands on network infrastructure but also challenges existing systems in terms of processing, storage, and real-time analysis capabilities. The increased network traffic necessitates more robust and scalable solutions to manage and secure data effectively, ensuring that the benefits of IoT can be fully realized while mitigating potential risks. Moreover, the rapid growth in data volume highlights the need for advanced data management and analytical tools to harness insights and drive innovation across various sectors, from smart cities to industrial automation. The ongoing advancements in wireless communication and digital technologies are therefore crucial in supporting the expanding ecosystem of IoT and addressing the associated challenges of increased connectivity and data proliferation.

M. Lee et al. [9] emphasize the importance of interconnected devices and data traffic poses significant challenges for IoT environments, particularly because the sensor nodes at the heart of these systems are often constrained by limited energy resources. These constraints make the nodes especially vulnerable to various forms of cyber-attacks, which can exploit inherent weaknesses in networking protocols and open broadcast communication. Such attacks not only compromise the integrity and confidentiality of the data transmitted but also lead to a degradation in the overall performance and service quality of the system. For instance, routing attacks can disrupt data flow and cause network partitions, while resource exhaustion attacks can drain the limited energy supply of sensor nodes, leading to reduced network reliability. Furthermore, these vulnerabilities can result in increased latency, data loss, and diminished accuracy of sensor readings, ultimately impacting the effectiveness and efficiency of the IoT applications. As a result, addressing these security challenges is critical for maintaining the robustness and functionality of IoT systems, necessitating the development of advanced detection and mitigation strategies to safeguard against the diverse threats targeting these resource-constrained environments.

R. Patel et al. [10] explore the development and application of Intrusion Detection Systems (IDSs) as a crucial response to security concerns that firewalls alone cannot adequately address. While firewalls are effective at enforcing access control based on predefined rules and filtering traffic to prevent unauthorized access, they are limited in their ability to detect more subtle or sophisticated forms of cyber-attacks that may bypass these rules. IDSs provide a complementary layer of security by focusing on the analysis of system behaviors and identifying anomalies that could indicate potential security breaches. These systems work by classifying observed behaviors as either normal or abnormal based on specific features extracted from network traffic, system logs, or other relevant data sources. The effectiveness of an IDS hinges on its ability to accurately differentiate between legitimate and malicious activities, which is achieved through sophisticated algorithms and techniques designed to detect deviations from established patterns. This capability is essential for identifying threats that might not be captured by traditional signature-based methods, such as zero-day attacks or insider threats. As the threat landscape continues to evolve, the ongoing advancement of IDS technologies, including the integration of machine learning and data mining approaches, plays a vital role in enhancing the ability to detect and respond to a wide array of cyber threats, thereby bolstering the overall security posture of an organization.

K. Wong et al. [11] highlights that recent advancements in Intrusion Detection Systems (IDSs) have led to the development of machine learning-based approaches, which enhance detection capabilities through sophisticated algorithms. Unlike traditional IDSs that rely on static rules and signatures, machine learning-based IDSs analyze extensive datasets to identify patterns and anomalies indicative of potential threats, offering more dynamic and adaptive threat detection. A crucial element of these systems is feature selection, which involves identifying the most relevant attributes from the data to improve classification performance. Effective feature selection reduces data dimensionality, minimizes computational demands, and focuses the analysis on significant features, thereby enhancing accuracy and reducing false positives and negatives. Advanced techniques such as statistical methods, ensemble learning, and deep learning further optimize feature selection, enabling the IDS to better adapt to emerging threats and improve predictive capabilities. Consequently, machine learning-based IDSs with robust feature selection represent a significant advancement in cybersecurity, providing a more precise and reliable means of detecting and mitigating a wide array of cyber threats.

S. Gupta et al. [12] have highlighted a significant advancement in the realm of intrusion detection systems (IDSs) through the application of deep learning techniques for feature selection. Their research showcases how employing a deep learning-based feature selection procedure can substantially improve the effectiveness of the classification process. Traditional feature selection methods often struggle to handle the high-dimensional and complex nature of data in cybersecurity contexts. In contrast, deep learning models are adept at automatically identifying and extracting the most relevant features from large datasets, which can significantly enhance the performance of classification algorithms. By leveraging neural networks to analyze and prioritize features, this approach ensures that only the most informative and impactful features are used for model training. This not only improves the accuracy of the IDS but also reduces the computational complexity and training time associated with processing large volumes of data. The deep learning-based feature selection procedure, therefore, represents a crucial step forward in optimizing intrusion detection systems, making them more efficient and

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effective at identifying and mitigating a wide range of cyber threats. This advancement underscores the growing importance of integrating sophisticated machine learning techniques to address the evolving challenges in cybersecurity.

H. Zhao et al. [13] conducted an experimental validation using the benchmark NSL-KDD dataset to assess the performance of a hybrid model that combines deep learning with machine learning techniques for intrusion detection systems (IDSs). Their study demonstrated that this integrated approach significantly outperforms conventional IDSs. By leveraging deep learning algorithms for feature extraction and machine learning algorithms for classification, the hybrid model achieved an impressive maximum accuracy of 99.49%. This remarkable accuracy not only surpasses traditional IDS methods but also excels in various evaluation metrics, including precision, recall, and F1-score. Precision refers to the model's ability to correctly identify positive instances, while recall measures its effectiveness in capturing all relevant instances. The F1-score, a harmonic mean of precision and recall, provides a balanced measure of the model's performance. The superior performance of the hybrid model in these metrics highlights its effectiveness in accurately detecting and classifying intrusions, thus offering a more reliable and efficient solution for cybersecurity. This advancement underscores the potential of combining advanced deep learning techniques with traditional machine learning methods to enhance the robustness of intrusion detection systems and address the growing complexity and sophistication of cyber threats.

Sana Rabhi et al. [14] study addresses the critical issue of routing attacks in Routing Protocol for Low power and Lossy Networks (RPL), a fundamental component of Internet of Things (IoT) systems. While IoT aims to enhance real-world intelligence through interconnected devices, it is also susceptible to security vulnerabilities, particularly in wireless sensor networks (WSNs). Previous research has highlighted the need for robust security measures in these networks, but the effectiveness of existing detection methods varies. Rabhi et al. advance this field by developing a technique to detect three specific types of routing attacks against RPL, utilizing simulations with Contiki-Cooja to create diverse network scenarios. Their approach employs machine learning algorithms, with WEKA software, to analyze network behavior and achieve a high precision rate exceeding 96% in distinguishing between normal and malicious activities. This research significantly contributes to improving the security of RPL and, by extension, IoT networks, offering practical solutions to enhance their resilience against attacks.

Kumar et al.'s [15] research represents a novel application of the MeanShift algorithm for detecting network attacks. Using the KDD 99 dataset, a benchmark in network intrusion detection, the study involved normalizing the dataset and applying the MeanShift algorithm to identify clusters within network traffic data. The performance of the algorithm was assessed through detection rate and accuracy metrics, revealing a detection rate of 79.1% and an accuracy of 81.2%. These findings confirm that the MeanShift algorithm can effectively detect attacks within network traffic datasets and provide a foundation for future research in this area. However, the study also highlighted some limitations, such as the algorithm's lower detection rates for specific attack types, including probing attacks and certain categories like R2L and U2R. These results suggest that while the MeanShift algorithm shows promise, further refinement and adaptation are needed to enhance its performance across a wider range of attack scenarios. Kumar et al.'s work lays the groundwork for advancing network security methodologies and encourages ongoing exploration into innovative clustering techniques for intrusion detection.

Sudipto Mukherjee et al. [16] introduce ClusterGAN, a novel approach that enhances clustering using Generative Adversarial Networks (GANs), addressing the challenge that traditional GAN latent spaces often fail to retain meaningful cluster structures. Conventional GANs, with their continuous latent spaces, can obscure distinct clusters, making clustering tasks less effective. ClusterGAN innovates by integrating a mixture of discrete (one-hot encoded) and continuous latent variables, along with an inverse network and a clustering-specific loss function, to achieve clustering within the latent space. Remarkably, ClusterGAN preserves latent space interpolation across categories despite the discriminator not being exposed to these vectors, demonstrating superior performance over traditional clustering methods on both synthetic and real datasets. This work not only provides a robust solution to the limitations of traditional GANs but also suggests future research could refine this approach with better data-driven priors and complementary architectures, further advancing the use of GANs in unsupervised learning.

Luiz Fernando Carvalho et al. [17] address the critical need for automated network traffic monitoring and anomaly detection, particularly in large-scale environments where manual intervention is insufficient. Their study introduces ACODS (Ant Colony Optimization-based Detection System), a novel expert system that utilizes unsupervised learning and a modified Ant Colony Optimization (ACO) algorithm to monitor and analyze seven-dimensional traffic patterns, detecting anomalous behavior with high accuracy and low false positive rates. This approach enhances scalability and real-time efficiency, a significant improvement over traditional methods that struggle to meet the demands of complex, growing networks. ACODS stands out by optimizing multidimensional flow attributes through self-organized agents, offering more precise detection of network outages, attacks, and anomalies.

Jacob Sakhnini et al. [18] explore the use of machine learning (ML) techniques to enhance detection capabilities. Their study evaluates three supervised learning algorithms combined with different feature selection (FS) methods, which are tested on IEEE 14-bus, 57-bus, and 118-bus systems to assess versatility. The results demonstrate that combining heuristic FS methods with supervised learning improves the accuracy of FDI attack detection, highlighting the potential of ML in securing smart grids against sophisticated cyber threats. The study contributes to ongoing research by emphasizing the role of tailored ML techniques in addressing the unique challenges of smart grid cybersecurity.

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Eray Balkanli et al. [19] evaluates the performance of two machine learning (ML) classifiers and two open-source network intrusion detection systems (NIDS) in detecting backscatter darknet traffic, a byproduct of distributed denial-of-service (DDoS) attacks. Specifically, the study compares the CART Decision Tree and Naive Bayes ML classifiers with Bro and Corsaro NIDS, to assess their efficiency in identifying backscatter traffic. Darknet traffic, which consists of unsolicited data targeting unused IP addresses, includes backscatter traffic that emerges from spoofed responses in DDoS attacks. The importance of accurately detecting such traffic lies in the significant role it plays in enhancing cybersecurity measures. While NIDS like Bro (now known as Zeek) and Corsaro rely on predefined rules and features such as IP addresses and port numbers to analyze network traffic, ML classifiers like CART and Naive Bayes are increasingly used for their ability to learn patterns autonomously and detect anomalies, offering flexibility compared to rule-based systems.

Valerio Morfino et al. [20] addressed these issues by exploring the use of supervised machine learning algorithms to detect such attacks in IoT systems. Their study utilized the MLlib library of Apache Spark, comparing several algorithms in terms of accuracy and computational efficiency. Conducted in a cloud environment with datasets containing up to 2 million instances, the experiments showed that all tested algorithms achieved high accuracy, with Random Forest performing best, reaching an accuracy of 1. Training and application times were also highly efficient, with Decision Trees completing training in just 23.22 seconds and all algorithms having application times under 0.14 seconds. Additionally, the Random Forest algorithm proved easy to implement, prompting the authors to propose a hybrid approach that combines real-time detection on IoT devices with secondary analysis in the cloud, offering a robust solution for mitigating cyber-attacks in IoT environments.

Elike Hodo et al. [21] addresses these vulnerabilities by applying Artificial Neural Networks (ANNs) to enhance IoT security. As IoT networks grow in complexity and scale, they face increased risks from various attacks, including Distributed Denial of Service (DDoS) and Denial of Service (DoS) attacks. Traditional security measures often fall short in such dynamic environments, highlighting the need for advanced detection methods. Hodo et al. leverage a multi-layer perceptron (MLP), a type of supervised ANN, trained on internet packet traces to identify and counteract these threats. Their approach is grounded in established practices of using machine learning for network intrusion detection, which has shown promise in previous studies. The research demonstrates an impressive accuracy rate of 99.4% in detecting DDoS/DoS attacks, underscoring the potential of ANNs in enhancing IoT security.

Simone Grimaldi et al. [23] the authors address a critical issue in the field of Internet of Things (IoT) deployments: the limitations of commercial off-the-shelf (COTS) IoT hardware in implementing energy-sampling-based interference detection and identification (IDI) methods. Current methods, while effective, struggle with long sensing times, high complexity, and the inability to track multiple concurrent interference sources, limiting their utility in real-world IoT applications. This literature review will explore the challenges and advancements in this domain, highlighting Grimaldi et al.'s contributions to improving on-device IDI for wireless coexistence.

Mathilde Caron et al. [24] (2018) present an unsupervised learning method that integrates clustering into the end-to-end training of convolutional neural networks (CNNs). Unlike traditional approaches that separate feature extraction and clustering, DeepCluster iteratively uses k-means to group features produced by a CNN and then updates the network's weights using the cluster assignments as pseudo-labels. This process allows the model to learn more structured visual features from large-scale datasets, such as ImageNet and YFCC100M, even in the absence of labeled data. DeepCluster's ability to scale to large datasets, outperforming previous state-of-the-art models on standard benchmarks, highlights its effectiveness. Additionally, the method makes minimal assumptions about the input data and requires little domain-specific knowledge, making it a versatile tool for learning deep representations in scenarios where annotations are scarce. Overall, DeepCluster offers a significant contribution to unsupervised learning in computer vision by coupling clustering with neural network training in a scalable and adaptable framework.

Liang Xiao et al. [25] explore the security challenges faced by the Internet of Things (IoT), which integrates diverse devices to provide advanced services, making it vulnerable to threats such as spoofing attacks, denial of service (DoS) attacks, jamming, and eavesdropping. The authors highlight the importance of safeguarding user privacy and propose machine learning (ML) techniques—specifically supervised learning, unsupervised learning, and reinforcement learning (RL)—as key solutions for enhancing IoT security. They review ML-based methods for authentication, access control, secure offloading, and malware detection, all aimed at protecting data privacy in IoT systems. Additionally, the authors discuss the practical challenges of implementing these ML-based security measures in real-world IoT environments.

III. CHALLENGES

Despite significant advancements in intrusion detection and anomaly detection methodologies for Internet of Things (IoT) security, several challenges persist that hinder the effectiveness and implementation of these solutions. One major challenge is the complexity of integration. For instance, H. Zhao et al. [13] developed a hybrid model that combines deep learning with traditional machine learning techniques, achieving impressive accuracy. However, the operationalization of such hybrid systems can be complicated, requiring extensive resources for maintenance and integration into existing infrastructures, which may not be feasible for all organizations.

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The dynamic nature of cyber threats further complicates the security landscape. Sana Rabhi et al. [14] emphasize the variability of routing attacks in Routing Protocol for Low power and Lossy Networks (RPL). While their detection method shows high precision, it may not universally address all potential vulnerabilities inherent in different IoT network configurations. This indicates a need for more adaptable and resilient security solutions that can evolve alongside emerging threats.

Detection limitations are another significant hurdle. Kumar et al. [15] utilized the MeanShift algorithm for network attack detection and reported lower detection rates for specific attack types, particularly probing and certain R2L (Remote to Local) and U2R (User to Root) categories. This highlights the necessity for further refinement of detection algorithms to improve their performance across a wider range of attack vectors and to ensure comprehensive protection against varied cyber threats.

Additionally, the reliance on predefined rules in traditional Network Intrusion Detection Systems (NIDS) presents challenges for flexibility and adaptability. Eray Balkanli et al. [19] found that classifiers like CART and Naive Bayes, while effective, may not adapt quickly to new and evolving attack patterns. This limitation underscores the importance of developing more adaptive machine learning approaches that can learn from ongoing network behavior and detect anomalies in real time.Scalability remains a pressing issue as the number of connected IoT devices continues to grow. Although methodologies like ACODS, introduced by Luiz Fernando Carvalho et al. [17], enhance scalability, the sheer volume and complexity of IoT traffic can overwhelm existing systems. Real-time monitoring and anomaly detection become increasingly challenging, necessitating robust solutions that can efficiently process large datasets without compromising accuracy.

The generalization of models across different environments also poses challenges. Christiana Ioannou et al. [22] demonstrated that their SVM model achieved high accuracy with known topologies but struggled in unfamiliar environments, revealing the limitations of models trained on specific datasets. This indicates a need for training strategies that incorporate a wider variety of network conditions to improve the generalizability of detection systems.

Moreover, practical challenges in deploying machine learning techniques in real-world IoT environments have been highlighted by Liang Xiao et al. [25]. Issues related to data privacy, computational resource requirements, and integration with existing systems complicate the implementation of machine learning-based security measures. Ensuring that these techniques can be effectively adopted without compromising user privacy or requiring excessive computational power is critical for broader acceptance.

Lastly, the limitations of commercial off-the-shelf (COTS) hardware in implementing effective interference detection methods, as discussed by Grimaldi et al. [23], cannot be overlooked. Their findings reveal that current methods often suffer from long sensing times and high complexity, which significantly hinders their utility in practical applications. Addressing these hardware limitations will be essential for advancing the effectiveness of IoT security measures.

In summary, addressing these challenges requires ongoing research and development efforts to enhance the robustness, scalability, and adaptability of IoT security solutions. Future work should focus on refining existing methodologies, exploring innovative techniques, and ensuring that security systems can effectively respond to the rapidly changing landscape of cyber threats.

IV. CONCLUSION & FUTURE SCOPE

The integration of machine learning techniques into intrusion detection and anomaly detection systems represents a significant advancement in enhancing the security of Internet of Things (IoT) environments. This review has highlighted various methodologies, including hybrid models, supervised learning algorithms, and unsupervised techniques, which have shown promising results in addressing diverse security challenges. Despite the progress made, the persistent issues of integration complexity, adaptability to new threats, scalability, and practical deployment in real-world environments remain significant hurdles.

Looking ahead, further research should focus on several key areas to bolster IoT security. First, developing more adaptive machine learning algorithms capable of evolving with emerging cyber threats is crucial. This could involve leveraging online learning approaches, where models continuously update their parameters based on real-time data, thus enhancing their detection capabilities against novel attack patterns.

Second, enhancing the generalizability of detection models is essential. Research should explore techniques such as transfer learning, which can enable models trained on one environment to adapt effectively to different contexts. This will not only improve detection rates across various IoT networks but also facilitate the deployment of security solutions in heterogeneous environments. Another promising avenue is the integration of federated learning, where models are trained collaboratively across multiple devices without sharing sensitive data. This approach can enhance privacy while still allowing for the collective learning of patterns across devices, thus improving overall security measures without compromising user data.

Moreover, research into lightweight and efficient algorithms tailored for resource-constrained IoT devices is vital. As many IoT devices have limited processing power and memory, developing algorithms that can operate effectively under these constraints will facilitate broader adoption of sophisticated security solutions in real-world applications.Collaboration between academia, industry, and government entities will be pivotal in addressing these challenges. By fostering partnerships, researchers can gain access to diverse datasets, real-world environments, and insights into emerging threats, thereby accelerating the development of robust security frameworks.

Finally, the exploration of hybrid approaches that combine traditional security measures with advanced machine learning techniques could yield promising results. Such methodologies could leverage the strengths of both paradigms, providing a more comprehensive defense strategy against cyber threats.

In conclusion, while significant strides have been made in enhancing IoT security through machine learning, ongoing research is imperative to overcome existing challenges and adapt to the rapidly evolving landscape of cyber threats. By pursuing innovative methodologies, fostering collaboration, and emphasizing practical deployment strategies, future research can significantly enhance the resilience of IoT systems against an ever-growing array of cyber risks.

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