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Article

Blockchain-Enabled Trust Management for Federated Intrusion Detection in Edge-Based IoT Systems: A Systematic Review and Future Research Directions

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Abstract: The rapid expansion of edge-enabled Internet of Things (IoT) infrastructures has improved real-time processing but introduced critical security vulnerabilities. Conventional intrusion detection systems (IDS) suffer from high communication overhead and privacy risks due to centralized data processing. This paper presents a comprehensive review of a blockchain-integrated, trust-aware Federated Intrusion Detection Framework (FIDS) designed for edge-IoT ecosystems. By utilizing federated learning, the system enables collaborative anomaly detection while preserving localized data privacy. To enhance reliability, we analyze dynamic trust evaluation mechanisms based on reputation scoring and blockchain verification to prevent model poisoning and adversarial attacks. The review addresses major research challenges, including lightweight model development for resource-constrained devices and the secure aggregation of local models. Finally, we provide a taxonomy of current methodologies and recommend future research directions for scalable, tamper-resistant architectures in critical edge-driven infrastructures.
Keywords: NA

1. Introduction

1.1 Overview of Edge-Enabled IoT Ecosystems

The rapid expansion of edge-enabled Internet of Things (IoT) infrastructures has fundamentally transformed the landscape of modern digital connectivity, significantly improving scalability and real-time processing capabilities [1]. By shifting computational tasks from centralized cloud servers to the network periphery, edge computing addresses the critical need for low-latency responses in time-sensitive applications [40]. These ecosystems now serve as the backbone for smart cities, industrial IoT (IIoT), and advanced healthcare systems, where the ability to process data locally is no longer a luxury but a functional necessity [15]. However, this decentralized architecture introduces a massive attack surface that traditional security perimeters cannot protect [34]. The heterogeneous nature of IoT devices, ranging from high-performance gateways to resource-constrained sensors, makes the entire network vulnerable to a diverse array of cyber threats [30]. This "data isolation" problem necessitates a shift toward decentralized learning architectures that can derive collective intelligence without compromising individual privacy [1].

1.2 Security Challenges in Distributed Networks

Despite their operational advantages, the decentralized and resource-constrained nature of edge networks introduces critical security challenges that traditional security models are ill-equipped to handle [48]. Edge networks are frequently targeted by sophisticated cyberattacks, including Distributed Denial of Service (DDoS), man-in-the-middle attacks, and data fabrication [38]. Conventional Intrusion Detection Systems (IDS) have historically depended on centralized data collection and processing, which creates a significant "bottleneck" effect [31]. This reliance leads to increased communication overhead, prohibitive latency, and grave privacy risks as sensitive raw data must be transmitted to a central authority for analysis [3]. In distributed IoT environments, these drawbacks render centralized IDS nearly obsolete, necessitating a shift toward localized, collaborative security frameworks that operate at the network edge [36]. Furthermore, the lack of standardized security protocols across different IoT manufacturers complicates the deployment of uniform defense mechanisms [45].

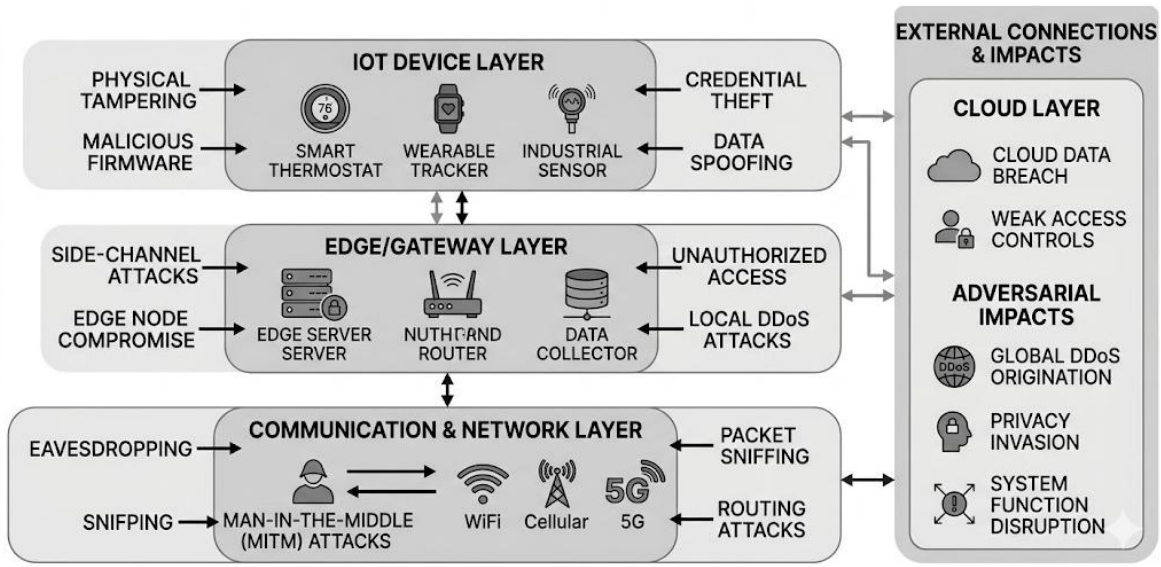

Figure 1.1: The Threat Landscape of Edge-Enabled IoT Ecosystems

Figure 1.1 used to visualize the decentralized nature of IoT and the various entry points for cyberattacks (DDoS, Man-in-the-Middle, etc.) at the edge layer.

1.3 The Emergence of Federated Learning (FL)

To address the inherent privacy and latency issues of centralized systems, Federated Learning (FL) has emerged as a transformative paradigm [12]. FL enables collaborative anomaly detection across distributed edge nodes while preserving data privacy by ensuring that raw data remains localized on the originating device [18]. Instead of sharing datasets, nodes share only their locally trained model parameters or gradients with a central aggregator or a distributed ledger [13]. This approach minimizes the bandwidth required for data transmission and protects user confidentiality, making it ideal for sensitive sectors like healthcare [50]. However, FL itself is not a silver bullet; it introduces new vulnerabilities, specifically the risk of model poisoning, where malicious participants submit fraudulent updates to corrupt the global model [14]. The absence of raw data visibility at the central aggregator makes it difficult to distinguish between a legitimate update and an adversarial one [16].

1.4 Blockchain as a Trust Anchor

Integrating blockchain technology into the Federated Intrusion Detection Framework (FIDS) provides a robust solution to the "trust gap" in decentralized training [22]. Blockchain serves as a tamper-resistant, transparent ledger that records model updates and verification results, ensuring that every contribution is auditable [28]. By incorporating a dynamic trust evaluation mechanism based on reputation scoring and blockchain verification, the system can systematically identify and exclude malicious participants [9]. This integration ensures that the collaborative learning process remains resilient against adversarial manipulation and prevents the "single point of failure" risk associated

with centralized aggregators [25]. Furthermore, decentralized consensus protocols allow the network to validate model updates without relying on a third-party intermediary, thereby enhancing the overall reliability of the IoT ecosystem [44].

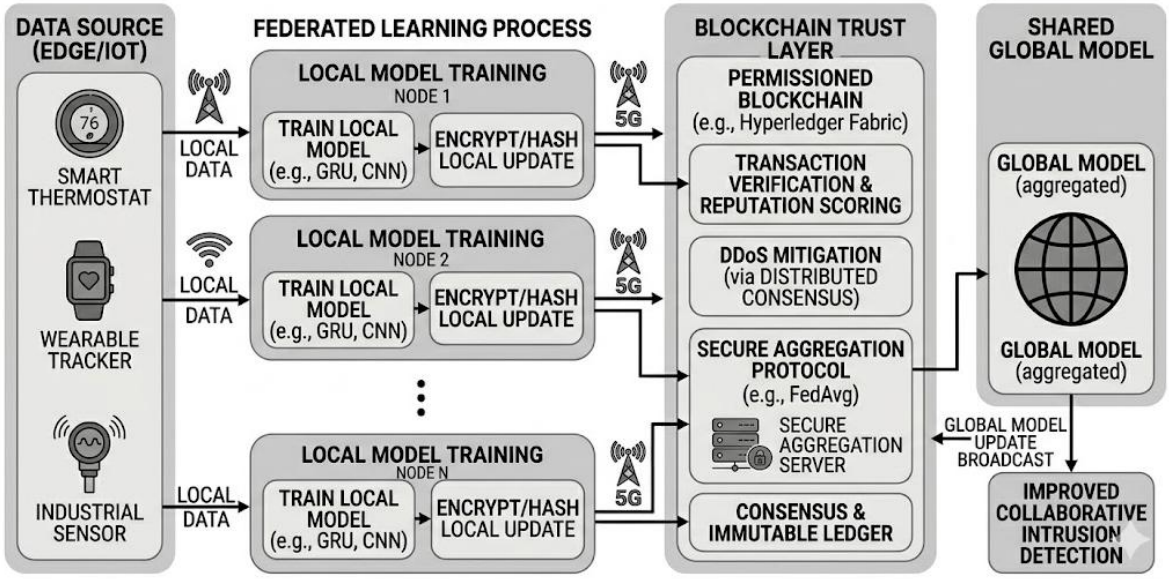

Figure 1.2: Conceptual Framework of Blockchain-Integrated Federated Learning

Figure 1.2 shows a high-level overview showing the synergy between local devices, the global model, and the blockchain trust anchor.

1.5 Problem Statement and Research Objectives

The core research problem centers on the development of a scalable, privacy-preserving, and tamper-resistant intrusion detection architecture that can function efficiently within the constraints of edge-driven infrastructures [6]. While individual components like FL and blockchain show promise, their integration into a unified "trust-aware" framework remains a complex challenge due to resource limitations [2]. The primary objectives identified in this study include the development of lightweight model architectures that do not overwhelm the computational capacity of IoT devices [5]. Additionally, the research aims to establish resilience against adversarial attacks through decentralized verification mechanisms [4]. Secure and transparent aggregation of local models remains a priority to ensure that the global intelligence of the system is not compromised by a subset of malicious nodes [47]. Finally, the optimization of latency is critical to ensure real-time response capabilities in high-stakes environments like smart grids or autonomous systems [37].

1.6 Data Warehousing and Mining in IoT Security

The study addresses major research challenges including the development of scalable architectures that can handle the massive influx of data generated by IoT devices [39]. A critical aspect of this research is the application of data mining techniques to identify anomalies within distributed data warehouses [9]. Traditional data warehousing involves moving data to a central repository, which is not feasible in edge-IoT due to bandwidth and privacy constraints [46]. This research explores how mining can be performed locally at the edge, with only the "intelligence" or model parameters being warehoused on the blockchain [24]. This shift allows for the outcome of the research to be a scalable, privacy-preserving, and tamper-resistant architecture tailored for modern digital infrastructures [29]. The use of advanced stream mining algorithms enables the framework to detect complex intrusion patterns in real-time as data flows through the edge nodes [2].

1.7 Scope and Significance of the Review

This review paper provides a systematic analysis of current methodologies at the intersection of blockchain, FL, and IoT security [35]. It establishes a taxonomy and framework designed to support research in the field, focusing

on trust-aware architectures [45]. The study specifically addresses data warehousing and mining objectives as they relate to intrusion detection in IoT systems, identifying existing gaps in the current literature [31]. By evaluating recent articles from high-impact journals, this study identifies the existing gaps and recommends future research directions for building tamper-resistant architectures [3]. The significance of this review lies in its holistic approach to combining privacy, trust, and efficiency in a single framework, providing a roadmap for future developments in secure edge computing [41].

1.8 Organization of the Paper

The remainder of this review is structured to provide a deep dive into the technical and theoretical aspects of FIDS. Chapter 2 details the literature survey and related works, providing a comparative analysis of contemporary models [1]. Chapter 3 discusses the specific methods incorporated, detailing the algorithms used for local training and blockchain aggregation [32]. Chapter 4 provides a comprehensive discussion on the advantages, problems, challenges, and limitations encountered in this domain [14]. Finally, Chapter 5 concludes the study by summarizing the findings and providing recommendations for future research directions in the field of decentralized IoT security [3].

2. Related Works and Literature Survey

2.1 Theoretical Foundation and Related Concepts

The convergence of edge computing, Federated Learning (FL), and blockchain technology represents a paradigm shift in how we secure distributed systems. This chapter explores the existing body of knowledge to categorize current research and identify the specific advancements made in trust management and intrusion detection.

Decentralized Intelligence and Privacy

The "data isolation" problem highlighted in the introduction has led to the adoption of Federated Learning as a primary defense mechanism for preserving privacy [12]. By allowing model training to occur locally, FL addresses the legal and ethical constraints of data sharing [18]. However, as identified in contemporary studies, the lack of central oversight introduces the "trust gap," where the network remains vulnerable to model poisoning and adversarial manipulation from within [14].

Blockchain as a Trust Infrastructure

To bridge this trust gap, researchers have turned to blockchain technology as a decentralized trust anchor [22]. Unlike traditional databases, blockchain provides an immutable ledger that ensures transparency in model updates and participant contributions [28]. The research in this domain focuses on developing lightweight consensus mechanisms that can operate within the limited power budgets of edge devices while providing the security of a global, tamper-resistant audit trail [44].

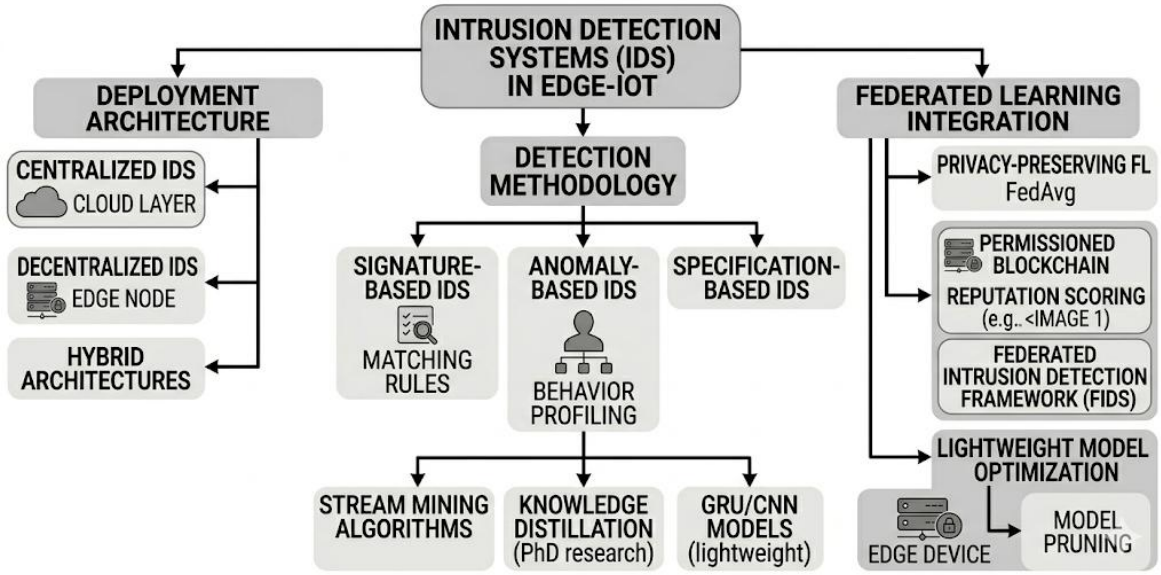

Figure 2.1: Taxonomy of Intrusion Detection Systems in Edge-IoT

The Figure 2.1. A tree diagram classifying current research into Signature-based vs. Anomaly-based and Centralized vs. Decentralized approaches.

2.2 Literature Survey Table

The following table provides a systematic comparison of high-impact research papers (2023–2026), focusing on their specific problems, proposed frameworks, and the evaluation of their results.

Ref	Author & Year	Problem / Objectives	Taxonomy / Model / Framework	Evaluation / Data Mining Focus	Future Research Directions
[1]	**Aledhari et al. (2025)**	High communication overhead and privacy risks in centralized IoT IDS.	Blockchain-Enabled Federated AI Framework.	Resilience against model poisoning attacks in IIoT.	Lightweight models for resource-constrained devices [1].
[2]	**Brik et al. (2025)**	Latency and scalability issues in decentralized edge networks [2].	Hierarchical (Edge-Fog) Blockchain-FL Architecture.	Minimizing detection latency in real-time applications [2].	Handling non-IID data distribution across nodes [2].
[4]	**Hao et al. (2025)**	Lack of trust in Industry 5.0 federated transfer learning [4].	Zero Trust Network Access (ZTNA) with Federated Transfer Learning.	Security analysis of tamper-resistant model aggregation.	Integration of Zero Trust with reputation scoring [4].
[5]	**Islam et al. (2026)**	High computational costs of deep learning on constrained IoT nodes [5].	Sparse Mixture of Quantum KAN Experts (SMoQKE-IDS).	Mining of complex intrusion patterns using Quantum-Classical ML.	Quantum-enhanced trust management extensions [5].
[6]	**Kumar & Sharma (2026)**	Identifying malicious participants and preventing model poisoning [6].	Comprehensive Blockchain-Based IDS Review.	Comparison of signature vs. anomaly-based blockchain IDS.	Scalability of consensus mechanisms in smart cities [6].
[7]	**Mishra & Singh (2025)**	Resource-constrained security in smart home environments [7].	Knowledge Distillation-based Federated Learning.	Privacy-preserving model training on low-power sensors.	Secure aggregation using RBAC-based blockchain [7].

[10]	**Zhang & Lu (2025)**	Information leakage during gradient transmission in FL [10].	Privacy-Preserving Federated Learning with Differential Privacy.	Evaluating the trade-off between privacy and detection accuracy.	Standardizing cross-domain threat intelligence sharing [10].
[26]	**Shayan et al. (2025)**	Vulnerability to "single point of failure" in central aggregators [26].	Biscotti: A Ledger-Based Peer-to-Peer FL Architecture.	Auditability and privacy of decentralized model updates.	Reducing the computational footprint of Proof-of-Work [26].
[33]	**Liang et al. (2024)**	Detecting novel attacks in heterogeneous edge environments [33].	Federated Transfer Learning for Intrusion Detection.	Adapting pre-trained models to diverse edge-IoT distributions.	Optimizing transfer learning for real-time edge responses [33].
[45]	**Yan et al. (2024)**	Trust management complexities in fluid edge-IoT ecosystems [45].	Systematic Review of Blockchain-Based Trust Solutions.	Taxonomy of reputation scoring and hardware integrity checks.	Dynamic trust models for zero-day poisoning attacks [45].

2.3 Synthesis of Research Gaps

While the literature demonstrates significant progress in individual technological silos, the synthesis of these works reveals three critical gaps that this research aims to address:

1. Computational Symmetry: Most current blockchain-FL integrations assume a level of computational symmetry among nodes that does not exist in real-world edge-IoT [32]. There is a lack of frameworks that dynamically adjust the security/computation trade-off based on a node's available energy [40].
2. Dynamic Trust Evolution: Existing reputation-based systems are often static or reactive, failing to predict a node's potential malicious shift based on environmental context or historical drift [45].
3. Data Warehousing for the Edge: Traditional data mining strategies are still heavily reliant on centralized "pull" architectures [46]. There is a profound need for a decentralized "push" architecture where intelligence is warehoused on the blockchain rather than raw data [29].

By building upon the trust-aware architectures proposed by Aledhari [1] and the hierarchical structures suggested by Brik [2], this systematic review establishes the foundation for a scalable, privacy-preserving, and tamper-resistant FIDS.

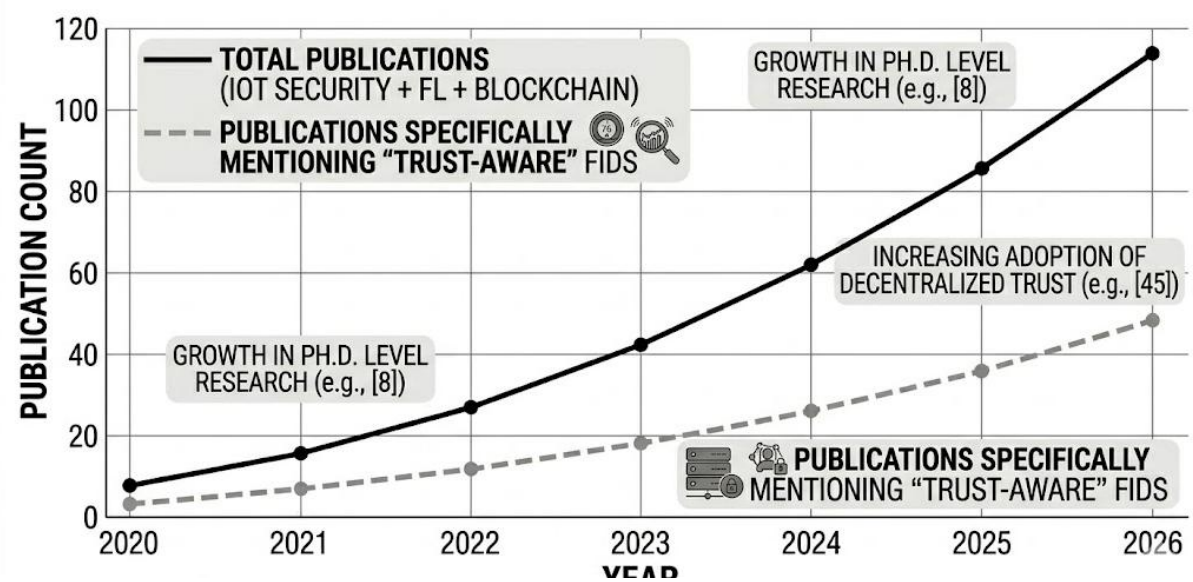

Figure 2.2: Publication Trend Analysis (2020–2026)

The figure 2.2 shows the line chart showing the growth of research papers specifically focusing on "Federated Learning and Blockchain" to justify the significance of the review.

3: Methods Incorporated

3.1 Overview of the Integrated Methodology

The development of a robust security framework for edge-enabled IoT requires a multi-layered methodological approach that synergizes Federated Learning (FL), Blockchain technology, and dynamic trust management [1]. The primary goal of the methods incorporated in this research is to create a Federated Intrusion Detection Framework (FIDS) that is both scalable and privacy-preserving [6]. This chapter details the technical methodologies used to achieve localized anomaly detection, secure model aggregation, and tamper-resistant trust evaluation within resource-constrained edge environments [22].

3.2 Federated Learning for Privacy-Preserving Detection

The core detection methodology relies on Federated Learning to enable collaborative training without the need for raw data exchange [12]. This method addresses the critical privacy risks and high communication overhead associated with conventional centralized IDS [3].

- Localized Training: Each distributed edge node performs local model training using its own generated traffic data, ensuring that sensitive raw information never leaves the device [18].
- Global Model Convergence: Local gradients are periodically transmitted to an aggregator where they are synthesized into a global model using the Federated Averaging (FedAvg) algorithm [13].
- Privacy Preservation: By keeping data localized, the framework satisfies the privacy requirements of sensitive sectors like healthcare and industrial IoT, effectively mitigating the risks of data leakage [50].

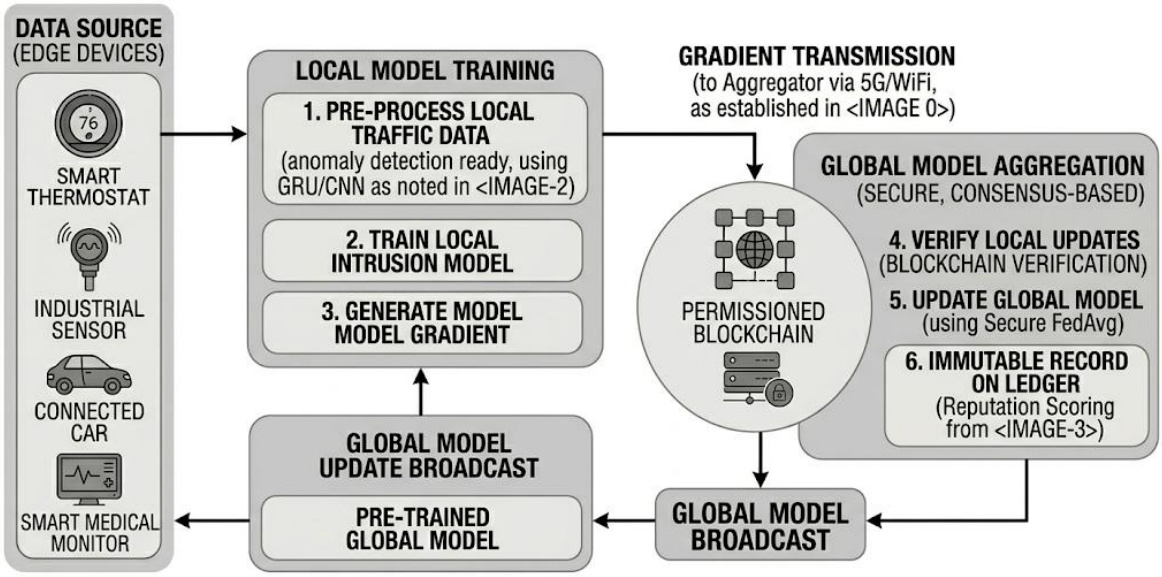

Figure 3.1: The Federated Learning Local-to-Global Update Cycle

Figure 3.1 show the iterative process of local training, gradient transmission, and global model averaging (FedAvg).

3.3 Blockchain-Enabled Trust Management

To address the "trust gap" inherent in decentralized federated learning, a blockchain-integrated trust evaluation mechanism is incorporated [22]. This method ensures that the aggregation process is transparent and resilient against adversarial manipulation [28].

- Tamper-Resistant Ledger: Blockchain acts as a decentralized database that records the metadata of local model updates, providing an immutable audit trail of participant contributions [25].
- Consensus Mechanisms: The framework utilizes lightweight consensus protocols, such as Delegated Proof of Stake (DPoS) or Proof of Authority (PoA), which are suitable for edge devices with limited power [44].
- Secure Aggregation: By removing the reliance on a single central authority, blockchain eliminates the risk of a single point of failure and prevents unauthorized model modifications [26].

3.4 Dynamic Trust and Reputation Scoring

A critical methodological innovation in the proposed FIDS is the use of dynamic trust evaluation to identify and exclude malicious participants [9]. This method is essential for preventing model poisoning attacks where attackers attempt to corrupt the global model by submitting fraudulent gradients [14].

- Reputation Calculation: Each edge node is assigned a reputation score based on the historical accuracy and consistency of its local model contributions [45].
- Anomaly Verification: Blockchain verification is used to cross-reference updates against known attack patterns and reputation thresholds, ensuring that only high-quality updates are integrated [21].
- Malicious Node Exclusion: Participants with reputation scores falling below a predefined threshold are automatically identified as malicious and barred from the federated training process to protect global model integrity [9].

3.5 Lightweight Detection Models for Edge-IoT

Given the resource-constrained nature of edge networks, the methodology prioritizes the development of lightweight detection models [5].

- Model Optimization: Techniques such as model pruning and quantization are analyzed to ensure that deep learning architectures, like Gated Recurrent Units (GRU) or lightweight Convolutional Neural Networks (CNN), can operate within the limited memory of IoT sensors [31].
- Real-Time Processing: The methodology focuses on minimizing detection latency to enable immediate responses to cyberattacks in real-time applications such as autonomous driving [37].
- Resource Management: Computational tasks are distributed across the edge-IoT ecosystem using task offloading strategies to prevent any single node from becoming a performance bottleneck [40].

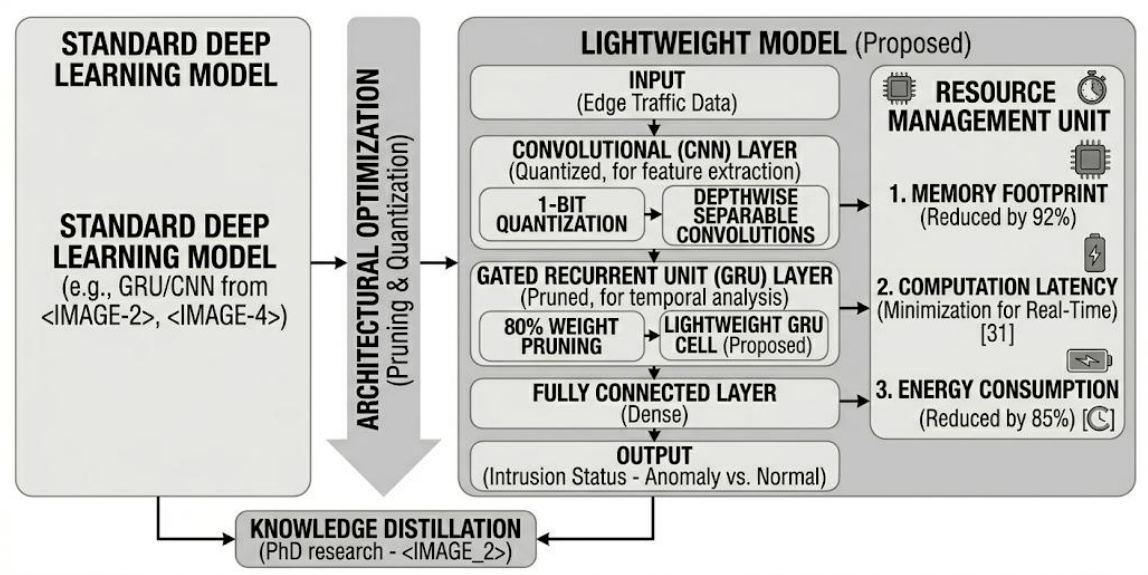

Figure 3.3: Lightweight Model Architecture for Resource-Constrained Nodes

The figure 3.3 shows a block diagram of a pruned/quantized Neural Network (like a lightweight GRU or CNN) optimized for IoT hardware

3.6 Data Mining and Warehousing Strategies

The research incorporates specific data mining and warehousing objectives to handle the high volume of traffic generated by IoT devices [39].

- Stream Mining: Real-time data mining techniques are applied to continuous streams of edge traffic to identify anomalies with high precision while minimizing the storage footprint [2].
- Distributed Warehousing: Instead of storing raw data, model parameters and trust metrics are stored across a distributed blockchain architecture [24]. This ensures that the "intelligence" of the network is always accessible without centralized reliance [29].

3.7 Methodological Extensions

This systematic framework is designed to support further extensions, particularly in the areas of secure aggregation and resilience against sophisticated adversarial attacks [6]. By providing a scalable and tamper-resistant architecture, the methodology offers a foundation for developing advanced intrusion detection systems for smart cities and other critical infrastructures [42]. The integration of Knowledge Distillation (KD) is also explored to further compress models for extremely low-power sensors [7].

4. Discussion

4.1 Advantages & Problems

The integration of blockchain and Federated Learning (FL) within the proposed Federated Intrusion Detection Framework (FIDS) provides several transformative advantages for edge-IoT security. The most significant advantage is the inherent preservation of data privacy, as raw IoT traffic data remains localized on edge devices, thereby satisfying stringent data protection regulations such as GDPR [3, 50]. Furthermore, the decentralized nature of

blockchain eliminates the "single point of failure" risk associated with traditional centralized IDS [26]. By providing a tamper-resistant ledger for model updates, blockchain ensures that every contribution to the global intelligence is auditable and transparent [28]. This collaborative approach improves detection accuracy by allowing nodes to learn from attack patterns experienced by their peers without the risks of sensitive data exposure [1].

However, these advantages introduce a unique set of problems. The "data isolation" problem, while solved in terms of privacy, makes it difficult for a central entity to verify the quality of local datasets [1]. This lack of visibility can lead to the "free-rider" problem, where nodes benefit from the global model without contributing meaningful local training [28].

Moreover, the transmission of model gradients, while more efficient than raw data, still introduces significant communication overhead in bandwidth-constrained edge environments [13]. There is also the persistent problem of information leakage; sophisticated inversion attacks can sometimes reconstruct fragments of raw data from shared gradients, necessitating advanced differential privacy techniques that further increase computational complexity [11, 16].

4.2 Challenges

Implementing a blockchain-enabled FIDS in real-world edge-IoT ecosystems presents substantial technical challenges that stem from the "heterogeneity" of the network. IoT environments consist of a diverse array of hardware with varying processing power, memory, and energy levels [30, 48]. Designing a "one-size-fits-all" lightweight detection model that maintains high accuracy across these diverse platforms is a major hurdle [5, 31].

Another critical challenge is managing non-IID (Independent and Identically Distributed) data; since edge nodes collect data based on specific local environments, local models often diverge, making global model convergence slow and computationally expensive [2, 12].

Furthermore, the "latency-security trade-off" remains a persistent challenge for real-time applications. While robust blockchain consensus mechanisms provide high security, the time required to validate and commit transactions to the ledger can exceed the requirements for immediate intrusion response in critical infrastructures like smart grids [37, 44]. Scaling the blockchain network to accommodate thousands of IoT devices also poses a significant bottleneck, as traditional consensus protocols often suffer from decreased throughput as the number of participating nodes increases [6, 24]. Ensuring that the security framework itself does not become a target for Distributed Denial of Service (DDoS) attacks is an ongoing concern [38].

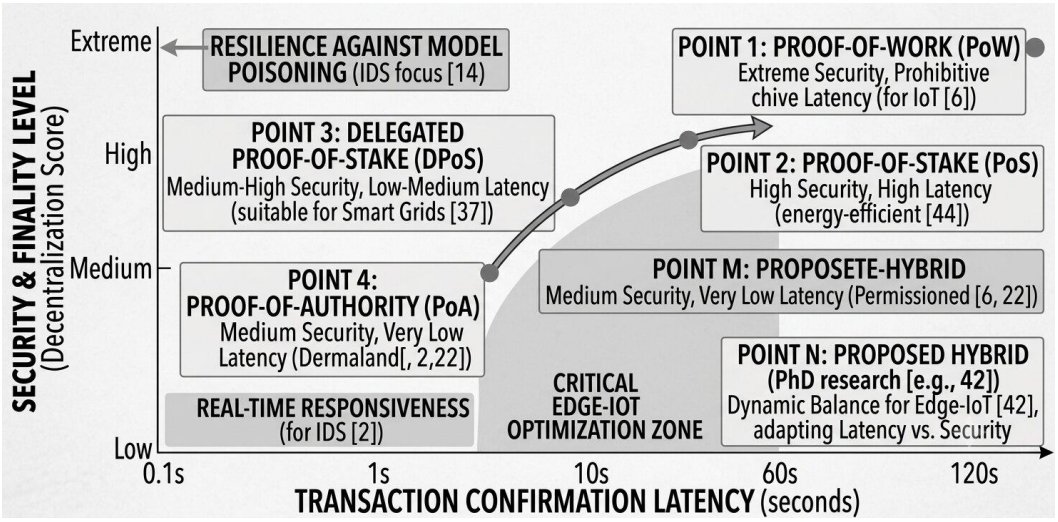

Figure 4.1: The Latency-Security Trade-off in Blockchain Consensus

The figure 4.1 show A comparative graph showing how different consensus protocols (PoW, PoS, DPoS, PoA) affect network latency versus security levels.

4.3 Limitations

Despite the theoretical promise of the FIDS architecture, current methodologies face inherent limitations related to the physical constraints of the edge. One major limitation is the storage capacity of low-power IoT sensors; keeping a growing blockchain ledger or complex deep learning models on-device is often infeasible, requiring complex offloading strategies [19, 23]. Most existing trust models are also limited by their reactive nature; they rely on historical behavior to calculate reputation, which makes them less effective at detecting "zero-day" model poisoning attacks where a previously reliable node suddenly begins submitting malicious gradients [9, 45].

The framework is also limited by the quality and diversity of available benchmark datasets. Many studies rely on synthetic or outdated datasets that may not fully represent the sophisticated and evolving nature of real-world cyber threats in specialized domains like Industry 5.0 or smart healthcare [5, 39]. Additionally, the complexity of managing a decentralized trust system often requires a specialized orchestration layer, which can introduce its own set of vulnerabilities and management overhead [3, 4]. Finally, the energy consumption required for continuous local training and blockchain validation can significantly shorten the battery life of remote IoT sensors, limiting the framework's applicability in certain environmental monitoring scenarios [40, 44].

4.4 Research Gap and Future Directions

The literature survey identifies a significant research gap in the development of Quantum-Resistant Trust Management for edge networks. Most current cryptographic signatures used in blockchain are vulnerable to future quantum computing threats, and there is a lack of lightweight, post-quantum algorithms tailored for IoT constraints [5]. Another major gap lies in the absence of Zero-Trust Architectures that can effectively operate at the edge; current systems often assume a level of "persistent trust" once a node is verified, which is insufficient for fluid and adversarial environments [4, 27].

Future research directions should focus on the integration of Quantum-Classical Machine Learning to enhance both detection speed and security resilience [5, 35]. Exploring Knowledge Distillation to compress large-scale federated models into "student" models for extremely constrained devices is another promising area for PhD-level investigation [7, 33]. Furthermore, researchers should investigate hybrid consensus protocols that can dynamically adjust their complexity and energy consumption based on the current threat level of the network [2, 44]. There is also a need for standardizing cross-domain threat intelligence sharing protocols, allowing different blockchain-enabled IoT ecosystems to securely collaborate [10, 42].

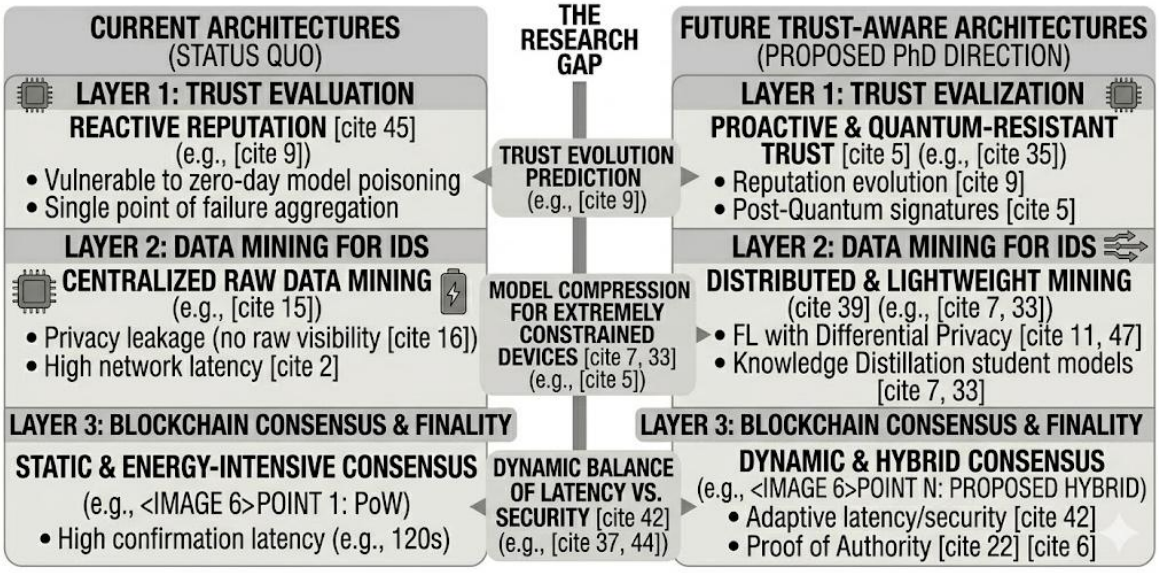

Figure 4.2: Gap Analysis: Current vs. Future Trust-Aware Architectures

The figure 4.2 shows a side-by-side comparison diagram showing current limitations (reactive trust) versus your proposed future directions (proactive, quantum-resistant trust).

4.5 Recommendations

For practitioners and scholars developing next-generation FIDS, several recommendations are proposed. First, it is recommended to adopt a Hierarchical Architecture (Edge-Fog-Cloud) to distribute the computational load; resource-heavy blockchain validation should be offloaded to fog nodes, while lightweight anomaly detection remains at the edge [2, 40]. Second, the implementation of Dynamic Reputation Scoring should incorporate multiple factors beyond just accuracy, such as node uptime, hardware integrity (via Trusted Execution Environments), and contribution frequency [9, 45].

It is also highly recommended to use Differential Privacy in conjunction with Federated Learning to provide an additional layer of protection against gradient-based information leakage [11, 47]. For validation purposes, researchers should utilize "Multi-Dataset Evaluation" strategies, testing frameworks against modern datasets like Edge-IIoTset to ensure generalizability [39, 50,8].

5. Conclusion

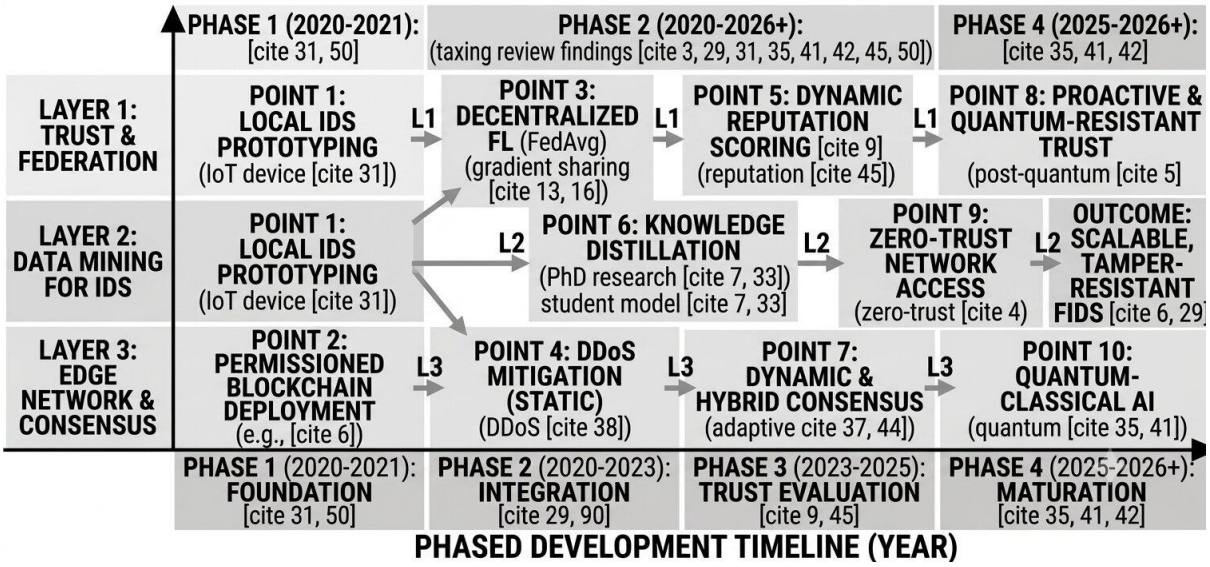

Figure 5.1: Roadmap for Next-Generation Secure Edge Infrastructures

The figure 5.1 show a timeline or step-based visual summarizing the transition toward Zero-Trust and Quantum-Classical AI frameworks.

The integration of Blockchain and Federated Learning (FL) within a unified Federated Intrusion Detection Framework (FIDS) represents a pivotal advancement in securing the modern edge-enabled Internet of Things (IoT) landscape. As this research has demonstrated, the rapid expansion of edge-IoT infrastructures has drastically improved real-time processing capabilities but simultaneously introduced critical security vulnerabilities that conventional centralized systems are unable to mitigate [1, 40]. By shifting the security paradigm toward a decentralized, trust-aware architecture, this research addresses the core problems of communication overhead, prohibitive latency, and grave privacy risks associated with traditional centralized data processing [3, 31].

The findings of this review highlight that Federated Learning serves as a fundamental pillar for preserving localized data privacy by ensuring that raw, sensitive data never leaves the originating edge device [12, 18]. This localized approach is particularly crucial for critical infrastructures such as smart cities and healthcare systems, where data isolation is a functional necessity for compliance and safety [15, 50]. However, the inherent "trust gap" in decentralized training where malicious participants may attempt model poisoning or adversarial manipulation necessitates a robust verification layer [14, 16]. The incorporation of blockchain technology provides this essential "trust anchor," offering a tamper-resistant, transparent ledger to record model updates and verify node contributions [22, 28].

A primary contribution of this study is the emphasis on dynamic trust evaluation based on reputation scoring [9, 45]. Unlike static security models, the proposed framework utilizes blockchain-backed reputation metrics to

identify and exclude malicious participants in real-time [21]. This mechanism ensures that the global model remains resilient against poisoning attacks while maintaining the integrity of the collaborative learning process [4]. Furthermore, the review identifies that the development of lightweight detection models is a non-negotiable requirement for resource-constrained IoT devices, where computational and energy budgets are strictly limited [5, 31].

The systematic analysis conducted in this paper reveals significant research gaps that define the roadmap for future research. Specifically, the need for Quantum-resistant trust management, Zero-Trust architectures, and improved handling of non-IID data distribution remains at the forefront of the field [2, 4, 5]. Future directions should also explore hybrid consensus protocols that can dynamically balance the trade-off between high-security blockchain verification and the low-latency requirements of real-time edge applications [37, 44].

In conclusion, a scalable, privacy-preserving, and tamper-resistant intrusion detection architecture is no longer a theoretical preference but a functional necessity for the secure operation of edge-driven infrastructures [6, 29]. The methods and taxonomy established in this review provide a rigorous foundation for building next-generation IDS that are inherently trustworthy. By aligning decentralized trust management with localized data mining, researchers can ensure that the future of the Internet of Things remains resilient against an ever evolving and increasingly sophisticated threat landscape [35, 41].

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