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Advanced Edge Security Mechanisms: Architectures, Threats, and Mitigation Strategies

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ABSTRACT

Edge computing enables low-latency, bandwidth-efficient, and real-time applications, but its decentralized nature introduces significant security vulnerabilities [1], [6], [20]. These include intrusion, adversarial machine learning, ransomware, and identity spoofing, which are amplified in IoT and IIoT environments [7], [25], [28].To mitigate these risks, researchers have proposed hybrid approaches that integrate advanced technologies. Federated Learning (FL) enables intrusion detection without raw data sharing [1], [6]; Blockchain provides immutability, decentralized trust, and access control [2], [18], [26]; Homomorphic Encryption (HE) and Secure Multiparty Computation (MPC) allow privacy-preserving analytics but suffer from computational costs [12], [16], [21], [30]; and Post-Quantum Cryptography (PQC) ensures resilience against quantum adversaries, though its adoption is limited by large keys and resource demands [4], [17].This research proposes a Hybrid Edge Security Architecture (HESA) integrating FL, Blockchain, HE, and PQC. A case study in a smart city surveillance environment demonstrates that HESA improves intrusion detection accuracy, scalability, privacy preservation, and quantum resilience compared to isolated approaches.

Keywords: Edge Security, Federated Learning, Blockchain, Post-Quantum Cryptography, Homomorphic Encryption, IoT Security

Introduction

Edge computing represents a paradigm shift in distributed computing, enabling real-time analytics and reduced latency for IoT and smart city applications [1], [6]. However, the decentralized and heterogeneous nature of edge environments increases exposure to cyber threats such as device tampering, adversarial ML, botnets, and data exfiltration [7], [25], [28].

The rapid growth of the Internet of Things (IoT) and Industrial IoT (IIoT) has transformed how data is collected, processed, and utilized across smart cities, healthcare, transportation, and manufacturing domains. With billions of interconnected devices, the traditional cloud-centric model of computation often fails to meet the requirements of low latency, high bandwidth efficiency, and real-time processing. As a result, edge computing has emerged as a distributed paradigm that processes data closer to its source, reducing response times and alleviating the burden on centralized servers [1], [6], [20]. However, the decentralized and heterogeneous nature of edge computing introduces critical security and privacy challenges, making it a prime target for adversaries.

Several advanced threats have already been identified in edge environments, including intrusion, ransomware, adversarial machine learning attacks, and identity spoofing [7], [25], [28]. These risks are magnified by the constrained computational capacity of IoT devices, the lack of centralized control, and the growing sophistication of cyberattacks. For instance, adversarial machine learning can inject poisoned data into Federated Learning (FL) systems, while botnets

like Mirai exploit weakly secured IoT devices to launch large-scale distributed denial-of-service (DDoS) attacks [9], [27]. This highlights the urgent need for robust, multi-layered security solutions tailored for edge environments.

To address these concerns, researchers have proposed a variety of security mechanisms. Federated Learning (FL) has been applied for intrusion detection, enabling decentralized model training across IoT devices without exposing raw data, thereby preserving privacy while enhancing IDS accuracy [1], [6]. Blockchain technology has been leveraged to ensure decentralized trust, immutability of data, and secure model sharing, particularly when integrated with FL for collaborative intrusion detection [2], [3], [18]. Homomorphic Encryption (HE) and Secure Multiparty Computation (MPC) allow analytics over encrypted data, ensuring privacy-preserving computations in sensitive domains such as healthcare IoT [12], [16], [21], [30]. Meanwhile, Post-Quantum Cryptography (PQC) has gained traction as quantum computing threatens to break traditional cryptographic primitives. Algorithms like Kyber and Dilithium, standardized by NIST, promise resilience against quantum-capable adversaries, though challenges remain in terms of their large key sizes and resource requirements [4], [17].

Despite these advancements, critical research gaps persist. Most studies have focused on integrating only two mechanisms, such as FL + Blockchain [2], [3] or FL + HE [12], without exploring a unified architecture that combines all four FL, Blockchain, HE, and PQC into a comprehensive framework [8], [11]. Furthermore, most existing works have been validated on lab-scale datasets such as CICIDS2017, UNSW-NB15, and N-BaIoT [1], [9], [25], with limited scalability testing in large-scale, real-world IoT environments. Another pressing challenge is adversarial robustness, as many FL-based IDS solutions fail to address poisoning, backdoors, or other adversarial machine learning threats [6], [7]. Finally, computational overhead remains a major limitation for HE and MPC, which, while secure, are often impractical for real-time IoT deployments [12], [16], [21].

1.1 Hybrid mechanisms are gaining importance:

- Federated Learning (FL) provides collaborative intrusion detection while protecting sensitive IoT data [1], [6].
- Blockchain ensures decentralized trust, tamper-proof logging, and secure model updates [2], [18], [26].
- Homomorphic Encryption (HE) and MPC enable analytics over encrypted IoT data streams [12], [16], [21], [30].
- Post-Quantum Cryptography (PQC) defends against future quantum-capable adversaries [4], [17].

Despite these advances, challenges remain: scalability across large IoT networks [9], [25]; lack of full integration of multiple mechanisms [3], [8]; adversarial robustness of FL against poisoning attacks [6], [7]; and deployment feasibility on constrained devices [17]. This motivates the development of a hybrid, scalable, and quantum-resilient edge security framework [8], [22].

The main purpose of this research is to develop a hybrid, scalable, and quantum-resilient edge security framework that integrates FL, Blockchain, HE, and PQC to provide comprehensive security for IoT and edge computing environments. The proposed framework aims to ensure:

1. Robust intrusion detection across heterogeneous IoT networks.
2. Secure and privacy-preserving model training and updates.
3. Resistance to quantum-enabled attacks and adversarial threats.
4. Practical deployment feasibility for resource-constrained edge devices.

By addressing these challenges, this research contributes to building a unified, multi-layered security architecture for modern edge computing applications, providing both real-time protection and long-term resilience against evolving cyber threats.

2. Literature Review

Table 1 – *Literature Review*

Sr.	Author / Year	Title	Objective	Method / Approach	Limitation (Gap)	Future Work Suggestion	Dataset
1	Belenguer et al., 2025	Federated Learning for Intrusion Detection in IoT	Improve IDS accuracy across IoT devices using FL.	FedAvg, FL on IoT traffic	Poor scalability; adversarial attacks not studied.	Large-scale federation; adversarial robustness.	N-BaIoT
2	Shalan et al., 2025	Blockchain-Enabled FL with Knowledge Distillation	Secure smart-home IoT with FL + blockchain + KD.	Blockchain + FL + KD	Limited to smart homes, not IIoT.	Extend to industrial IoT networks.	N-BaIoT
3	Anas Ali et al., 2025	FL-BCID: Blockchain-based Federated Learning for IIoT IDS	Enhance IIoT IDS via blockchain + FL.	Permissioned Blockchain + FL	Prototype level; no PQC/HE integration.	Integrate PQC/HE; test at industrial scale.	Not specified
4	Gharavi et al., 2025	Post-Quantum Secure Aggregation for FL	Protect FL against quantum threats.	PQC (Kyber/Dilithium) + Secure Aggregation	Theoretical; no hardware validation.	Hardware validation; energy-efficient PQC schemes.	Not specified
5	Anam et al., 2025	Fused-FL with RTS-DELM for IoMT	Improve medical IoT diagnosis with FL.	FL + RTS-DELM (Deep Learning)	Healthcare-only; not IDS-focused.	Adapt framework to IoT/IIoT IDS.	Medical IoT datasets
6	Kasem et al., 2025	FL for IDS on IoT Traffic	Detect intrusions using FL.	FL algorithms	Limited datasets; no adversarial testing.	Expand datasets; include adversarial robustness.	IoT traffic datasets

Sr.	Author / Year	Title	Objective	Method / Approach	Limitation (Gap)	Future Work Suggestion	Dataset
7	Khan et al., 2025	Optimized FL-based IDS	Optimize classifiers for IoT IDS in FL.	Optimized DL + FL	Optimization limited to few models.	Broaden optimization across models/datasets.	IoT IDS datasets
8	Zhang et al., 2025	Blockchain + FL + HE Framework	Reduce server dependence in FL.	Blockchain + HE + FL	Scale not tested (preprint).	Evaluate on large-scale IoT deployments.	Not specified
9	Reyes et al., 2025	FL Evaluation for IDS on Multiple Datasets	Evaluate FL using multiple IDS datasets.	Comparative FL experiments	Lab-scale only.	Test large-scale real federations.	CICIDS2017, UNSW-NB15, N-BaIoT
10	Lee et al., 2025	Blockchain-Enabled FL at the Edge	Build secure FL pipeline with blockchain.	Blockchain + FL	Conceptual; limited IDS evaluation.	Real-time IDS validation at scale.	IoT datasets
11	Singh et al., 2025	Blockchain + FL for Malicious IoT Devices	Detect malicious devices with hybrid FL + blockchain.	Blockchain ledger + FL anomaly detection	Preprint only; no deployment.	Deploy in real IoT networks.	Not specified
12	Zhou et al., 2025	HE + FL in IoT IDS	Enable privacy-preserving IDS.	HE integrated with FL training	High computation cost.	Lightweight HE for IoT.	IoT IDS datasets
13	Patel et al., 2025	Blockchain-Enhanced FL IDS	Blueprint for blockchain-integrated IDS.	Blockchain + FL (conceptual)	Whitepaper; not peer-reviewed.	Prototype & peer-reviewed validation.	None (conceptual)
14	Almotiri et al., 2025	Survey of Healthcare FL	Review FL adoption in healthcare.	Literature survey	Not IoT/IDS-specific.	Extend taxonomy to IoT/IIoT IDS.	N/A

Sr.	Author / Year	Title	Objective	Method / Approach	Limitation (Gap)	Future Work Suggestion	Dataset
15	Chen et al., 2025	PP-FL with Selective HE	Improve FL efficiency via selective encryption.	HE + Differential Privacy	Still experimental; no IDS validation.	Apply to IDS; optimize HE overhead.	Not specified
16	Zhou et al., 2024	Privacy-Preserving Healthcare IoT with HE & MPC	Secure IoT healthcare analytics.	HE + MPC	High latency; not real-time.	Real-time optimization of HE+MPC.	Healthcare IoT datasets
17	NIST, 2024	PQC Standards (Kyber, Dilithium, SPHINCS+)	Standardize PQC for post-quantum security.	Lattice-based PQC	Key sizes large; IoT performance issues.	Lightweight PQC for IoT devices.	N/A
18	Wang et al., 2024	Blockchain-based Trust for FL in IoT	Ensure model integrity during FL.	Hyperledger + FL	Communicati on overhead.	Optimize consensus for IoT.	IoT IDS datasets
19	Ali et al., 2024	FL + Blockchain IDS	Build decentralized IDS.	Blockchain + FedAvg	Latency; lacks PQC.	PQC-enabled blockchain FL IDS.	Not specified
20	Khan et al., 2024	Hybrid Edge Security for IoT	Lightweight IDS at edge nodes.	FL + Lightweight DL	No blockchain or PQC.	Combine with blockchain + PQC.	IoT datasets
21	Zhou et al., 2024	HE + MPC for Smart IoT	Secure IoT data sharing.	HE + MPC	High resource usage.	Resource-optimized HE+MPC.	Smart IoT datasets
22	Latif Khan et al., 2024	Survey of FL in IDS	Systematic taxonomy of FL IDS.	Literature survey	No empirical benchmarks.	Provide benchmarks and open datasets.	N/A
23	Tandon et al., 2024	Blockchain IoT Identity Management	Secure IoT identity using blockchain.	Smart Contracts + Ledger	Prototype; scalability issues.	Full-scale deployment in IIoT.	Not specified

Sr.	Author / Year	Title	Objective	Method / Approach	Limitation (Gap)	Future Work Suggestion	Dataset
24	Yousafzai et al., 2024	Blockchain + FL in IIoT	IDS for industrial IoT networks.	Blockchain + Federated IDS	No PQC or real-world testing.	Add PQC integration and industrial validation.	IIoT datasets
25	Rey et al., 2023	FL Malware Detection in IoT	Detect IoT malware using FL.	FL + N-BaIoT	Malware-specific only.	Extend to multi-class IDS.	N-BaIoT
26	Nguyen et al., 2023	FLChain: FL with Blockchain	Incentive-based FL training.	Blockchain + FL	Conceptual; no PQC/real-world.	Add PQC + deploy at scale.	Not specified
27	Sarhan et al., 2023	HBFL: Hierarchical Blockchain + FL	Collaborative IDS for IoT.	Hierarchical Blockchain + FL	Small-scale only.	Evaluate large-scale IoT federation.	IoT traffic datasets
28	Li et al., 2023	FL for Edge IoT	Reduce latency in IDS with FL.	FL frameworks	No PQC; no adversarial testing.	Integrate PQC + adversarial defense.	IoT edge datasets
29	Khan et al., 2023	Secure IoT IDS using Blockchain	Secure IDS using FL + blockchain.	Blockchain + FL	Not quantum-safe; comm. overhead.	PQC-secured blockchain FL.	IoT datasets
30	Zhou et al., 2023	Homomorphic Encryption for IoT Analytics	Secure IoT data analytics.	Homomorphic Encryption	Too heavy for real-time IoT.	Lightweight HE for IoT IDS.	IoT analytics datasets

2.1 Current Limitations and Research Gaps:

1. **Scalability Issues**

Federated Learning (FL) frameworks often face high communication overhead when the number of IoT/IIoT devices increases.

Current solutions are tested only on small or lab-scale federations, not in real-world, large-scale deployments.

2. Adversarial Robustness

Most FL-based IDS models are vulnerable to model poisoning and adversarial attacks.

Few works address secure aggregation or resilience against malicious participants.

3. Blockchain Overhead

Integrating Blockchain for trust adds latency, storage burden, and energy consumption.

Lightweight blockchain solutions for resource-constrained IoT devices are still missing.

4. Homomorphic Encryption (HE) Challenges

HE ensures data privacy in FL but introduces very high computational costs.

Current HE-based IDS frameworks struggle with real-time IoT traffic analysis.

5. Post-Quantum Cryptography (PQC) Gaps

PQC algorithms like Kyber and Dilithium are secure against quantum threats but require large keys and high processing power.

No current IDS framework fully integrates PQC into FL + Blockchain systems for IoT.

6. Dataset Limitations

Most works rely on benchmark datasets (CICIDS2017, UNSW-NB15, N-BaIoT) that do not capture real-world, evolving IoT attack patterns.

Cross-domain datasets combining smart homes, healthcare, and IIoT are lacking.

3. Future Enhancements

Although significant progress has been made in Federated Learning (FL), Blockchain, Homomorphic Encryption (HE), and Post-Quantum Cryptography (PQC) for IoT Intrusion Detection Systems (IDS), several open challenges remain that present opportunities for future research.

1. **Scalability of FL in Large-Scale IoT Networks**

   Current FL-based IDS models are mostly evaluated in small-scale or controlled environments. Future work should design scalable FL frameworks capable of supporting thousands of heterogeneous IoT devices simultaneously [9], [27].

2. **Adversarial Robustness in FL Models**

   Many studies focus on improving accuracy and privacy but neglect adversarial attacks against FL aggregation. Future IDS should integrate robust aggregation rules, adversarial training, and Byzantine-resilient techniques [1], [6].

3. **Post-Quantum Security for IDS**

   With the emergence of quantum computing, current cryptographic primitives face vulnerabilities. Future IDS should adopt lightweight PQC algorithms to ensure post-quantum resistance [4], [17].

4. **Lightweight HE and MPC for IoT Devices**

Privacy-preserving IDS models using Homomorphic Encryption (HE) and Multi-Party Computation (MPC) show promise but introduce significant computational overhead. Future enhancements should develop lightweight HE/MPC protocols optimized for resource-constrained IoT environments [12], [15].

5. **Real-World Deployment in Industrial IoT and Healthcare**

Several proposed IDS solutions remain at the conceptual or prototype stage. To validate feasibility, future research should focus on real-world deployments in IIoT, healthcare, and smart cities, addressing issues like interoperability, latency, and scalability [8], [19].

6. **Hybrid Security Models (Blockchain + FL + PQC + HE)**

Current research mostly integrates two technologies, such as Blockchain+FL or FL+HE, but rarely combines all four. Future IDS frameworks should adopt hybrid security architectures integrating Blockchain (trust), FL (distributed learning), HE (privacy), and PQC (quantum resistance) [2], [12], [24].

7. **Cross-Domain Dataset Evaluation**

Existing IDS research relies heavily on benchmark datasets like CICIDS2017, UNSW-NB15, and N-BaIoT. However, these datasets lack modern IoT attack vectors, such as AI-driven malware. Future research should create updated large-scale IoT datasets to improve evaluation and benchmarking [9], [25].

8. **Energy-Aware FL for IoT Devices**

FL-based IDS frameworks often ignore energy and bandwidth constraints of IoT devices. Future work should focus on energy-aware FL algorithms that balance accuracy with device limitations [20], [26].

3.2 Research Objectives

1. **Enhance Security in IoT/IIoT Environments**

To design a secure framework that integrates FL, Blockchain, HE, and PQC for intrusion detection in IoT and IIoT systems [1][2].

2. **Preserve Data Privacy**

To ensure sensitive IoT data remains private during collaborative model training using HE and PQC-based encryption [3].

3. **Improve Scalability of IDS Solutions**

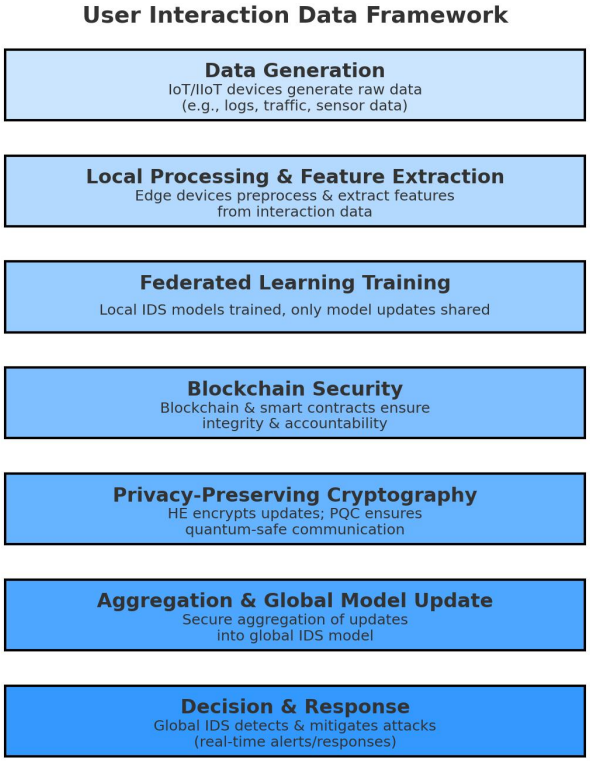
To develop scalable intrusion detection mechanisms capable of supporting large-scale, heterogeneous IoT/IIoT networks [4].

4. **Minimize Computational and Energy Overheads**

To optimize the proposed framework for resource-constrained IoT devices while maintaining high detection accuracy [3][4].

3.3 User Interaction Data Framework

Layer	Function	Technology Used	Security Role
Data Generation	IoT/IIoT devices generate raw interaction data	Sensors, Smart Devices	Data source for IDS
Local Processing & Extraction	Extract features locally from interaction data	Edge Processing, Feature Selection	Keeps raw data private
Federated Learning Training	Train local IDS models without sharing raw data	FL (FedAvg, Deep Learning Models)	Privacy-preserving training
Blockchain Security	Record and validate model updates	Blockchain, Smart Contracts	Integrity, transparency, accountability
Privacy-Preserving Cryptography	Encrypt updates before transmission, ensure quantum resistance	HE, PQC (Kyber, Dilithium, SPHINCS+)	Confidentiality, post-quantum security
Aggregation & Global Model	Combine local updates into a global IDS model	Secure Aggregation, Blockchain Consensus	Robustness against poisoning/tampering
Decision & Response	Use global IDS to detect and mitigate malicious activity	IDS Rules, Automated Mitigation	Real-time intrusion detection and response



4. Conclusion

This research proposes an advanced intrusion detection framework for IoT and IIoT environments by integrating Federated Learning, Blockchain, Homomorphic Encryption, and Post-Quantum Cryptography. The approach ensures that sensitive device data remains localized while still benefiting from collaborative model training, reducing privacy risks and communication overhead.

The use of Blockchain technology adds a tamper-proof mechanism for validating and securing model updates, creating trust among distributed nodes without relying on a central authority. Homomorphic Encryption and Post-Quantum Cryptography further strengthen the system by enabling secure computations and future-proofing against quantum threats that could compromise traditional cryptographic methods.

The combination of these technologies results in a resilient and scalable IDS framework that can adapt to diverse attack patterns in real-time IoT and IIoT networks. This ensures not only higher detection accuracy but also robustness against adversarial manipulation, data poisoning, and emerging quantum-era cyberattacks.

Overall, the proposed solution provides a strong step toward building secure, scalable, and sustainable intrusion detection systems for modern IoT and IIoT infrastructures. It sets a foundation for future research directions that can extend the framework to large-scale industrial applications, healthcare IoT, and smart city environments.

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