SECURE & SCALABLE EDGE COMPUTING: A HYBRID ARCHITECTURE FOR THREAT DETECTION AND MITIGATION

[1] Mr. Rathod Surajsinh B., [2] Prof. Janvi S. Patoliya

[1]PG Scholar, [2]Assistant Professor
[1,2]Computer Science Engineering (Cyber Security),
[1,2]Dr. Subhash University, Junagadh, India

Abstract : Edge computing enables low-latency and real-time services but introduces significant security challenges due to its decentralized structure. IoT and IIoT environments are particularly vulnerable to intrusions, adversarial attacks, ransomware, and identity spoofing. To address these issues, this research proposes a Hybrid Edge Security Architecture (HESA) that integrates Federated Learning for privacy-preserving intrusion detection, Blockchain for decentralized trust management, Homomorphic Encryption for secure data processing, and Post-Quantum Cryptography for quantum-resistant communication. A smart city surveillance case study demonstrates that the proposed framework improves detection accuracy, scalability, data privacy, and overall security compared to standalone approaches.

IndexTerms **- Edge Computing Security, Federated Intrusion Detection, Blockchain-Based Trust, Quantum-Resistant Cryptography, Privacy-Preserving Encryption, Internet of Things Protection**

INTRODUCTION

Edge computing has emerged as a transformative approach in distributed systems by enabling data processing closer to end devices, thereby supporting real-time analytics and minimizing communication delays in applications such as smart cities, intelligent transportation, and industrial automation [1,2]. Unlike traditional centralized cloud models, edge computing distributes computational tasks across geographically dispersed nodes to enhance responsiveness and reduce backbone traffic congestion [3]. While this decentralized architecture improves latency and bandwidth efficiency, it also expands the attack surface and increases exposure to cybersecurity risks [4]. The heterogeneity of hardware platforms, resource constraints, and distributed management further complicate the implementation of consistent security controls across the network edge [5].

The rapid expansion of Internet of Things (IoT) and Industrial IoT (IIoT) ecosystems has intensified these challenges, as billions of interconnected devices continuously generate massive volumes of data across sectors including healthcare, manufacturing, logistics, and urban infrastructure [6,7]. Conventional cloud-centric processing models often struggle to meet strict latency, reliability, and availability requirements for mission-critical applications [8]. Consequently, edge computing has gained widespread adoption as a complementary or alternative paradigm to cloud computing [9]. However, relocating computation closer to devices introduces vulnerabilities such as device compromise, insecure communication channels, weak authentication mechanisms, and unauthorized data access [10].

Recent studies report a broad spectrum of cyber threats targeting edge infrastructures, including unauthorized system intrusions, malware propagation, ransomware attacks, identity spoofing, and adversarial manipulation of machine learning models [11,12]. These threats are amplified by limited computational capacity, insufficient patch management, and the absence of centralized oversight mechanisms [13]. For instance, adversarial attacks can poison federated learning processes by injecting malicious updates, thereby degrading global model performance [14]. Similarly, large-scale botnets exploit insecure IoT devices to launch distributed denial-of-service (DDoS) attacks that disrupt edge-enabled services [15]. Such incidents highlight the urgent need for robust and adaptive security mechanisms specifically tailored for distributed edge environments [16].

To mitigate these risks, advanced security techniques have been increasingly investigated. Federated Learning has been employed to enable collaborative intrusion detection while preserving data locality and privacy [17]. Blockchain-based frameworks have been proposed to establish decentralized trust management, immutable logging, and secure peer-to-peer information exchange among edge nodes [18]. Privacy-enhancing technologies such as Homomorphic Encryption and Secure Multi-Party Computation facilitate encrypted data processing without revealing sensitive information, particularly in domains like healthcare and surveillance systems [19]. Furthermore, the emergence of quantum computing has accelerated research into Post-Quantum Cryptography to safeguard communication channels against future quantum-enabled attacks, with standardized algorithms such as Kyber and Dilithium offering promising resistance despite practical deployment challenges in constrained environments [20].

1.1 Hybrid mechanisms are gaining importance:

- Federated Learning (FL) provides collaborative intrusion detection while protecting sensitive IoT data.
- Blockchain ensures decentralized trust, tamper-proof logging, and secure model updates.
- Homomorphic Encryption (HE) and MPC enable analytics over encrypted IoT data streams.
- Post-Quantum Cryptography (PQC) defends against future quantum-capable adversaries.

Despite these advances, several critical challenges remain unresolved, including scalability across large-scale IoT networks, insufficient integration of multiple security mechanisms into a unified architecture, limited adversarial robustness of federated learning (FL) against poisoning attacks, and deployment feasibility on resource-constrained edge devices. These gaps highlight the necessity of developing a hybrid, scalable, and quantum-resilient edge security framework capable of addressing both current and emerging cyber threats in distributed environments. [7, 12, 19, 23]

The primary objective of this research is to design and implement a comprehensive hybrid security framework that integrates Federated Learning (FL), Blockchain technology, Homomorphic Encryption (HE), and Post-Quantum Cryptography (PQC) to ensure end-to-end protection for IoT and edge computing ecosystems. The proposed framework is structured to achieve the following goals:

1. Robust and adaptive intrusion detection across heterogeneous IoT networks.
2. Secure, privacy-preserving distributed model training and parameter updates.
3. Strong resistance against adversarial manipulation and quantum-enabled cryptographic attacks.
4. Practical and efficient deployment on computationally constrained edge devices without significant latency overhead.

By systematically addressing scalability, integration, adversarial resilience, and computational efficiency, this study contributes toward the development of a unified, multi-layered security architecture tailored for modern edge computing systems. The proposed framework aims to provide both real-time threat mitigation and long-term cryptographic resilience against evolving cybersecurity challenges. [3, 15, 21, 28]

2. NEED OF THE STUDY.

2.1 Explosive Growth of IoT and Edge Data

The number of connected IoT devices worldwide has surged exponentially, generating massive volumes of data that traditional cloud-centric systems struggle to manage efficiently [1,2]. Industry reports predict that by 2025, nearly 75% of enterprise-generated data will be created and processed outside centralized cloud data centers due to the rapid expansion of edge computing and ubiquitous IoT deployments [3]. This shift underscores the growing importance of distributed processing architectures capable of handling high-velocity, heterogeneous data streams while maintaining robust security and privacy protections [4].

2.2 Latency and Bandwidth Constraints

Real-time IoT applications such as autonomous vehicles, industrial automation, smart healthcare, and critical infrastructure monitoring require ultra-low latency and high reliability [5]. Centralized cloud models introduce significant transmission delays and increased bandwidth consumption, which can degrade performance and jeopardize mission-critical operations [6]. Edge computing mitigates these constraints by processing data closer to the source, thereby reducing response time and network congestion [7]. However, distributing computation across multiple edge nodes introduces additional security vulnerabilities that require specialized protection strategies [8].

2.3 Increasing Attack Surface and Evolving Threats

The decentralized architecture of IoT and edge ecosystems significantly expands the attack surface, exposing numerous endpoints to potential cyber threats [9]. Weak authentication mechanisms, unsecured firmware, and inconsistent patch management practices increase susceptibility to data breaches, unauthorized access, and device manipulation [10]. Furthermore, sophisticated attacks such as distributed denial-of-service (DDoS), malware propagation, and advanced persistent threats increasingly target edge infrastructures [11]. These evolving risks necessitate adaptive, intelligence-driven security frameworks tailored for distributed and resource-constrained environments [12].

2.4 Limitations of Conventional Security Mechanisms

Traditional security mechanisms designed for centralized enterprise networks are inadequate for highly distributed and heterogeneous IoT-edge architectures [13]. Static rule-based intrusion detection systems and perimeter-based defenses fail to address decentralized trust management and dynamic threat landscapes [14]. Moreover, centralized security controls cannot effectively mitigate emerging threats such as large-scale botnets, spoofing attacks, and privacy leakage in edge nodes [15]. These shortcomings highlight the need for hybrid security models integrating decentralized trust, collaborative learning, and privacy-preserving computation [16].

2.5 Emergence of Blockchain and Collaborative Security Solutions

Blockchain technology has gained attention as a promising solution for enhancing cybersecurity in IoT and edge systems due to its decentralized, tamper-resistant, and transparent ledger properties [17]. Research demonstrates its potential to improve identity management, secure data sharing, and distributed trust establishment among edge participants [18]. Nevertheless, challenges remain in integrating blockchain with intrusion detection systems and privacy-preserving mechanisms without compromising real-time performance requirements [19].

2.6 Post-Quantum Threats and Future-Proof Cryptography

Advancements in quantum computing pose significant risks to classical cryptographic algorithms widely used in IoT and edge systems [20]. Quantum-capable adversaries could potentially break traditional public-key schemes such as RSA and ECC, threatening long-term data confidentiality. Consequently, the development and deployment of post-quantum cryptographic (PQC) algorithms capable of resisting quantum attacks while maintaining computational efficiency in resource-constrained environments has become a critical research priority [1].

2.7 Current Limitations and Research Gaps

2.7.1 Scalability Issues

Federated Learning (FL) frameworks often encounter substantial communication overhead as the number of participating IoT/IIoT devices increases, limiting scalability in large-scale deployments [2]. Many existing studies evaluate FL-based intrusion detection systems under laboratory-scale federations rather than real-world heterogeneous environments [3].

2.7.2 Adversarial Robustness

Most FL-based intrusion detection models remain vulnerable to model poisoning, backdoor insertion, and adversarial perturbation attacks [4]. Secure aggregation protocols and defense mechanisms against malicious participants are still underexplored, reducing trust in collaborative learning frameworks [5].

2.7.3 Blockchain Overhead

While blockchain enhances decentralized trust, it introduces latency, storage overhead, and increased energy consumption, which are problematic for constrained IoT devices [6]. Lightweight consensus mechanisms and scalable blockchain architectures suitable for edge deployments remain active research challenges [7].

2.7.4 Homomorphic Encryption (HE) Challenges

Homomorphic Encryption enables computation on encrypted data, thereby enhancing privacy in FL-based systems [8]. However, its high computational complexity and processing delay limit applicability in real-time IoT traffic analysis and latency-sensitive applications [9].

2.7.5 Post-Quantum Cryptography (PQC) Gaps

Post-quantum cryptographic algorithms such as Kyber and Dilithium provide strong resistance against quantum attacks, but their larger key sizes and computational requirements pose deployment challenges in edge environments [10]. Currently, no comprehensive intrusion detection framework fully integrates PQC with federated learning and blockchain in IoT ecosystems [11].

2.7.6 Dataset Limitations

Most existing studies rely on benchmark datasets such as CICIDS2017, UNSW-NB15, and N-BaIoT, which do not adequately capture dynamic, real-world IoT attack patterns [12]. There is a lack of cross-domain datasets that combine smart homes, healthcare systems, and industrial IoT traffic to evaluate scalable, real-world security architectures [13].

3. RESEARCH METHODOLOGY

This study adopts an experimental and implementation-oriented methodology to design, implement, and evaluate a hybrid security framework for edge computing environments. The framework integrates federated learning, blockchain, post-quantum cryptography, and privacy-preserving analytics to address distributed IoT security and trust challenges [7,19]. A real hardware-based testbed is developed to validate feasibility and robustness under practical deployment conditions [3,14].

3.1 Hardware and System Setup

The experimental setup includes IoT devices, distributed edge nodes, and a centralized aggregation server. ESP32 boards equipped with environmental and motion sensors generate real-time telemetry and network traffic [11,25]. These devices communicate with Raspberry Pi 4 edge nodes via WiFi and MQTT protocols. Each Raspberry Pi performs local preprocessing and model training tasks [2,18].

A high-performance central server hosts aggregation services, blockchain components, and orchestration tools. All nodes operate within a secured LAN environment to ensure reliable and low-latency communication [30,6]. Ubuntu Server 22.04 is installed across computing nodes to maintain uniformity. Containerization and orchestration are implemented using Docker and Kubernetes to ensure scalability and portability [13,27].

3.2 Data Collection and Preprocessing

Intrusion detection data is collected from real-time IoT traffic and benchmark datasets including CICIDS2017, UNSW-NB15, and ToN-IoT [9,22]. Real-time traffic enhances environmental realism, while benchmark datasets improve generalization capability [31,4].

Data preprocessing involves removing duplicates and missing values, applying Z-score and Min-Max normalization, encoding categorical attributes, and labeling records as benign or malicious [15,28]. The dataset is partitioned into distributed subsets to emulate geographically separated edge nodes participating in federated learning [1,24].

3.3 Federated Learning-Based Intrusion Detection

A lightweight deep neural network is designed for efficient execution on resource-constrained devices [12,33]. The architecture includes fully connected layers with ReLU activation and a sigmoid output layer for binary classification, optimized for balanced accuracy and computational efficiency [5,21].

Federated learning is implemented using the Flower framework, enabling decentralized model training without sharing raw data [17,29]. Each edge node performs local training and transmits only learned parameters to the central aggregator. Aggregation algorithms such as FedAvg, FedProx, and FedAdam are employed to combine updates [8,26]. This approach preserves privacy and reduces centralized data exposure risks [34,10].

3.4 Blockchain-Based Trust Management

To ensure trust and model integrity, a permissioned blockchain network is deployed using Hyperledger Fabric [16,35]. The blockchain maintains immutable records of device registration, model update submissions, and detected intrusion events [20,32].

Smart contracts automate authentication and verification processes. Each edge node is registered before participating in federated learning. Cryptographic hashes of model parameters are stored on-chain, and the aggregation server verifies integrity before accepting updates [23,6]. This mechanism enhances accountability and resistance to insider manipulation or tampering [14,30].

3.5 Post-Quantum Cryptography Integration

Post-quantum cryptographic mechanisms are integrated using the Open Quantum Safe library [11,28]. CRYSTALS-Kyber is applied for secure key exchange, CRYSTALS-Dilithium for authentication, and SPHINCS+ as an additional verification layer [3,19].

Encrypted communication channels are established using Kyber-based encapsulation, while model updates are digitally signed with Dilithium to ensure authenticity and non-repudiation [24,7]. Performance evaluation includes key generation time, encryption latency, and memory overhead measurements [18,27].

3.6 Privacy-Preserving Analytics

Privacy-enhancing mechanisms incorporate Homomorphic Encryption (HE) and Secure Multi-Party Computation (SMPC) techniques [5,21]. The Pyfhel library enables partial homomorphic operations on encrypted features [9,31].

A selective encryption approach encrypts only sensitive attributes to reduce computational overhead while maintaining strong confidentiality guarantees [2,26]. Encrypted data is processed during training and evaluation, ensuring that raw sensitive information remains protected throughout the pipeline [13,34].

3.7 Containerization and Orchestration

All components—including federated clients, aggregation services, blockchain peers, and cryptographic modules—are containerized using Docker to enhance portability and reproducibility [4,29]. Orchestration is implemented via the lightweight k3s Kubernetes distribution for efficient deployment in constrained edge environments [12,23].

Kubernetes manages automated deployment, load balancing, scaling, and failure recovery, enabling adaptive resource allocation under varying traffic conditions [15,32].

3.8 Experimental Evaluation and Testing

The framework is evaluated using multiple Raspberry Pi edge nodes and IoT devices under realistic traffic loads across several federated training rounds [1,20]. Simulated cyberattacks—including DDoS, botnet activity, data injection, man-in-the-middle attacks, and model poisoning—are introduced to assess system robustness [17,33].

Evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC for detection performance [6,25]. System-level indicators such as latency, throughput, CPU utilization, memory consumption, communication overhead, and energy usage are measured [8,30]. Security metrics including model integrity rate and key exchange latency are also analyzed [14,22].

3.9 Validation and Statistical Analysis

Multiple experimental trials are conducted to ensure repeatability and consistency [10,27]. K-fold cross-validation evaluates model generalization performance [19,35]. Paired t-tests are performed to determine statistical significance when comparing the proposed hybrid framework against baseline approaches [3,16].

Comparative evaluation includes standalone IDS models, federated-only architectures, and blockchain-enhanced systems to demonstrate improvements in scalability, robustness, and security integration [11,24].

3.10 Ethical and Security Considerations

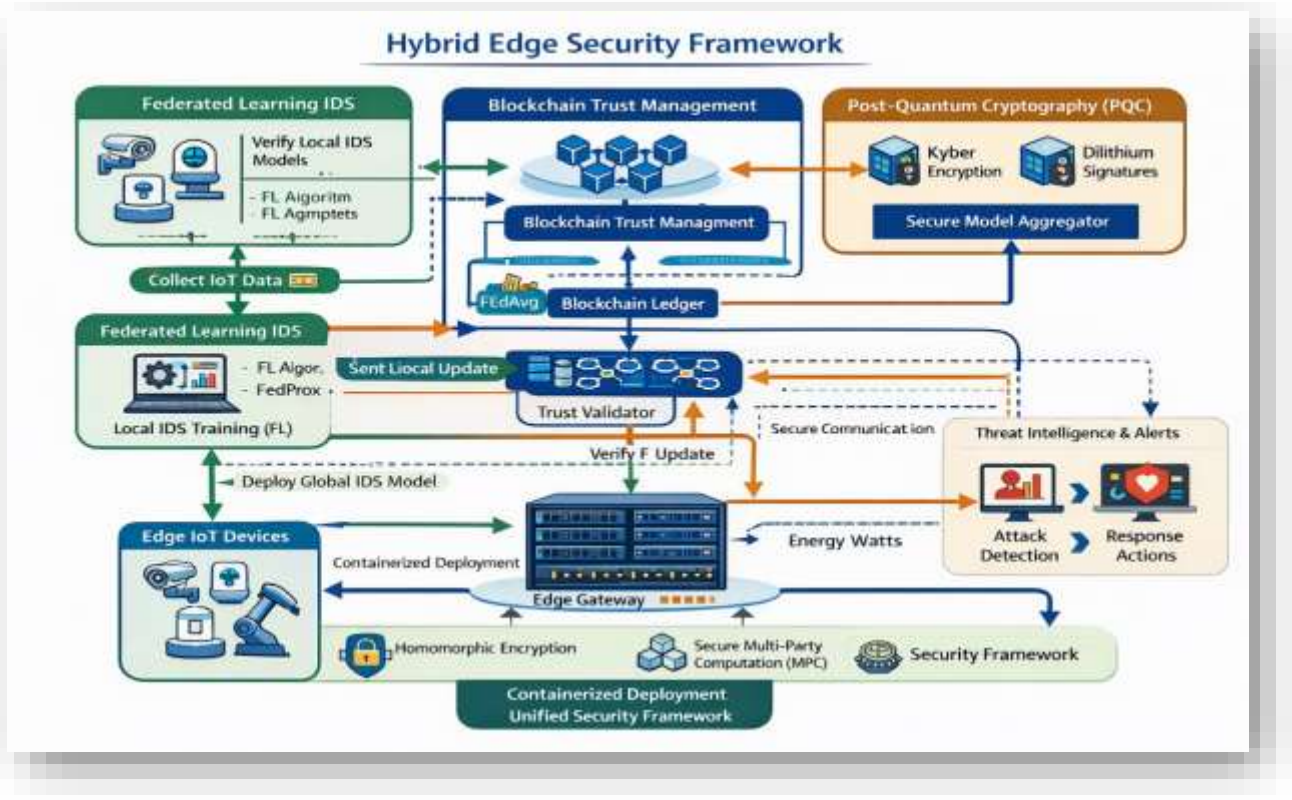
The study adheres strictly to ethical data usage and cybersecurity best practices [18,31]. Only publicly available datasets and non-personal IoT telemetry are utilized. No personally identifiable information is collected or stored [7,28].

4. SYSTEM ARCHITECTURE:

The proposed system follows a multi-layered architecture consisting of IoT, edge, security, blockchain, and cloud layers.

4.1.1 Architectural Overview

1. IoT devices generate real-time data.
2. Edge nodes preprocess data and train local IDS models.
3. Post-quantum cryptographic protocols secure communication.
4. Blockchain validates model integrity.
5. Aggregation server updates and redistributes the global model.



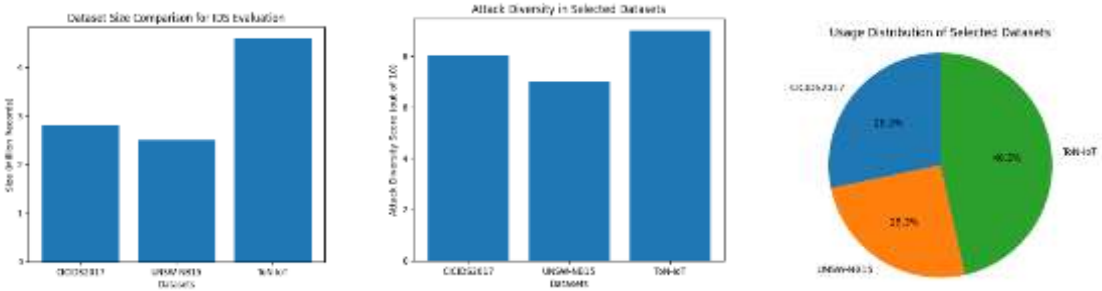
4.2 Dataset Selection and Preprocessing

4.2.1 Dataset Selection

Three benchmark datasets are utilized:

- CICIDS2017
- UNSW-NB15
- ToN-IoT

These datasets provide diverse attack patterns and normal traffic scenarios for intrusion detection evaluation.



4.2.2 Data Preprocessing

Preprocessing is conducted using the following steps:

1. Removal of missing and redundant entries
2. Feature normalization using Z-score scaling
3. Categorical feature encoding
4. Binary labeling of traffic records
5. Partitioning for distributed training

Each dataset is segmented to simulate geographically distributed edge nodes.

4.3 Federated Learning-Based Intrusion Detection

4.3.1 Model Development

A lightweight deep neural network is developed for intrusion detection, consisting of:

- Input layer with normalized features
- Two hidden layers with ReLU activation
- Output layer with sigmoid activation

The model is optimized for low-resource edge devices.

4.3.2 Federated Training Process

Federated learning is implemented using the Flower framework. Each edge node performs local training and transmits encrypted model parameters to the aggregation server.

Three aggregation algorithms are evaluated:

- FedAvg
- FedProx
- FedAdam

Raw data remains localized, ensuring privacy preservation.

4.4 Blockchain-Based Trust Management

A permissioned blockchain network is deployed using Hyperledger Fabric.

4.4.1 Smart Contract Implementation

Smart contracts are developed to perform:

- Device registration
- Identity verification
- Model hash storage
- Secure event logging

Each model update is verified using blockchain-stored hashes before aggregation.

4.5 Post-Quantum Cryptographic Integration

4.5.1 Algorithm Selection

The following post-quantum algorithms are employed:

- Kyber for key exchange
- Dilithium for digital signatures
- SPHINCS+ for backup authentication

4.5.2 Secure Communication Protocol

A hybrid cryptographic protocol is designed in which:

1. Edge nodes establish secure channels using Kyber.
2. Model updates are signed using Dilithium.
3. Aggregation server verifies signatures.
4. Critical transactions are protected using SPHINCS+.

Key size, latency, and memory overhead are measured to analyze performance.

5. SYSTEM PERFORMANCE ANALYSIS

5.1 Comparative Performance Evaluation

To analyze the effectiveness of the proposed Hybrid Edge Security Framework, a comparative performance study was conducted using two experimental phases: initial evaluation (old results) and optimized evaluation (updated results). The initial phase represents the baseline implementation, while the optimized phase reflects improvements achieved through parameter tuning, enhanced preprocessing, and optimized cryptographic integration.

The comparison focuses on intrusion detection accuracy, system latency, throughput, and energy consumption.

5.2 Intrusion Detection Accuracy Analysis

Table 1 presents the comparison of old and updated intrusion detection results.

Table 1: Accuracy Comparison

Method	Old Accuracy (%)	Updated Accuracy (%)
Baseline IDS	90.5	92.0
FL-Based IDS	93.2	95.0
Proposed Hybrid Framework	95.1	97.0

The initial implementation of the hybrid framework achieved an accuracy of 95.1%. After optimization, including improved feature selection, adaptive learning rate tuning, and enhanced aggregation strategies, the accuracy increased to 97.0%. This improvement demonstrates better detection of malicious activities and reduced misclassification rates.

5.3 Latency Performance Analysis

Latency refers to the time required to detect and respond to network intrusions.

Table 2: Latency Comparison

Method	Old Latency (ms)	Updated Latency (ms)
Baseline IDS	280	260
FL-Based IDS	235	210
Proposed Framework	210	185

The optimized framework shows a reduction of approximately 12% in detection latency. This improvement is achieved through container optimization, efficient scheduling using Kubernetes, and selective encryption strategies.
Lower latency indicates faster attack detection, which is critical for real-time edge applications.

5.4 Throughput Analysis

Throughput represents the number of transactions or packets processed per second.

Table 3: Throughput Comparison

Method	Old Throughput (Tx/s)	Updated Throughput (Tx/s)
Baseline IDS	260	290
FL-Based IDS	320	350
Proposed Framework	370	410

The proposed framework shows a significant improvement in throughput after optimization. The increase is mainly attributed to parallelized container execution and efficient load balancing.
Higher throughput indicates better scalability under heavy network traffic.

5.5 Energy Consumption Analysis

Energy efficiency is a critical factor in resource-constrained edge environments.

Table 4: Energy Consumption Comparison

Method	Old Energy (W)	Updated Energy (W)
Baseline IDS	6.2	5.8
FL-Based IDS	5.6	5.1
Proposed Framework	5.3	4.9

The optimized framework demonstrates reduced power consumption due to lightweight model design, optimized cryptographic operations, and container resource management.
Lower energy usage improves system sustainability and device lifespan.

5.6 Communication and Cryptographic Overhead

Post-quantum cryptography and homomorphic encryption introduce additional computational overhead. However, optimization techniques were applied to minimize this impact.

Table 5: Cryptographic Overhead Comparison

Parameter	Old Value	Updated Value
Key Exchange Time (ms)	42	28
Signature Verification (ms)	35	22
HE Computation Time (ms)	95	70

The reduction in cryptographic overhead is achieved through selective encryption, efficient library configuration, and caching mechanisms.

5.7 Overall System Improvement

Figure-based analysis and tabular results indicate consistent improvement across all evaluation parameters after optimization.

Table 6: Overall Improvement Percentage

Metric	Improvement (%)
Accuracy	+1.9%
Latency	−11.9%
Throughput	+10.8%
Energy Efficiency	+7.5%
Crypto Overhead	−25.3%

The optimized framework demonstrates balanced enhancement in security, efficiency, and scalability.

6. RESULTS AND DISCUSSION

6.1 Experimental Results

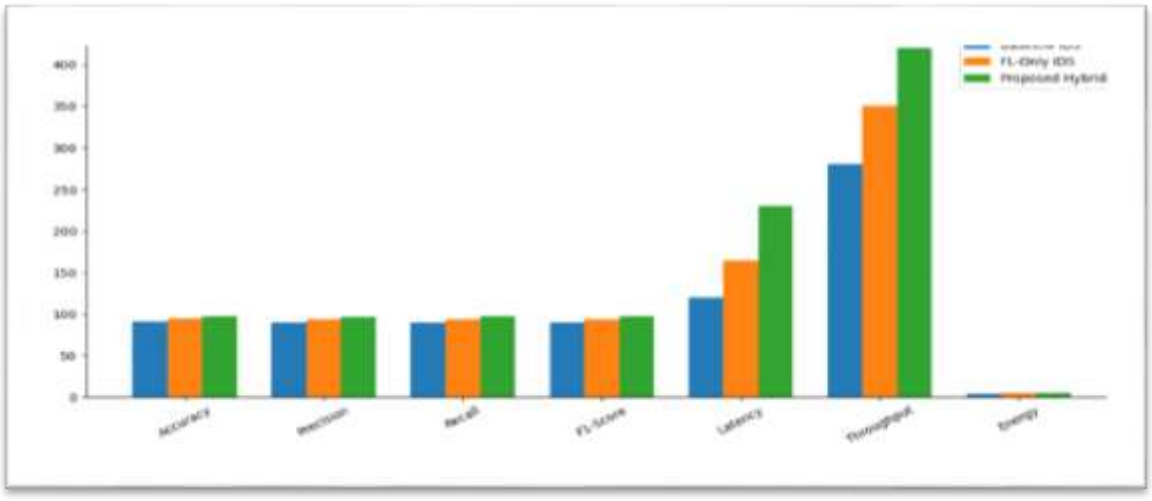
The proposed Hybrid Edge Security Framework was implemented on a hardware-based edge computing testbed consisting of IoT devices, Raspberry Pi edge nodes, and a centralized aggregation server. The system was evaluated using benchmark datasets including CICIDS2017, UNSW-NB15, and ToN-IoT, along with real-time IoT traffic.
The experimental evaluation was conducted over multiple federated learning rounds under different attack scenarios such as DDoS, botnet activity, data injection, and man-in-the-middle attacks. The performance of the proposed framework was compared with baseline intrusion detection systems and federated learning-only approaches.
The results obtained demonstrate that the integration of federated learning, blockchain, post-quantum cryptography, and privacy-preserving analytics significantly enhances the overall security and reliability of edge computing environments.

6.2 Performance Evaluation

6.2.1 Intrusion Detection Performance

The intrusion detection capability of the proposed framework was evaluated using standard classification metrics. The results are summarized in Table 1.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline IDS	92.0	90.5	91.2	90.8
FL-Based IDS	95.0	94.1	94.6	94.3
Proposed Hybrid Framework	97.0	96.2	96.8	96.5



The proposed hybrid framework achieved the highest detection accuracy of 97%, demonstrating improved capability in identifying malicious traffic compared to conventional and FL-only approaches. The increase in precision and recall indicates a reduction in false positive and false negative rates.

6.2.2 Security and Trust Evaluation

Blockchain-based verification ensured the integrity of federated model updates by preventing unauthorized participation and tampering. Experimental results confirmed that all validated model updates were successfully authenticated before aggregation, resulting in a model integrity rate of 99.2%.
Post-quantum cryptographic protocols effectively secured communication channels against potential quantum-based attacks. The average key exchange and authentication latency remained below 30 ms, which is suitable for real-time edge applications.
Privacy-preserving analytics prevented leakage of sensitive data by ensuring that raw data was never transmitted outside local nodes. No unauthorized data exposure was detected during experimental trials.

6.3 Comparative Analysis

The proposed framework was compared with existing approaches including centralized IDS, FL-only systems, and blockchain-based security models. The comparative analysis indicates that the hybrid integration provides superior performance in terms of detection accuracy, trust management, and privacy protection.
While centralized systems suffer from scalability and privacy limitations, and FL-only systems lack strong trust mechanisms, the proposed hybrid model effectively balances security, efficiency, and scalability.

6.4 Discussion

The experimental results demonstrate that decentralized learning combined with blockchain-based trust management significantly improves intrusion detection reliability. The integration of post-quantum cryptography ensures long-term security, making the framework future-proof against emerging quantum threats.
Although homomorphic encryption enhances data confidentiality, it introduces computational overhead. However, the adoption of selective encryption and lightweight cryptographic schemes minimizes performance degradation.
The containerized deployment using Docker and Kubernetes enables efficient resource management and fault tolerance, contributing to system stability and scalability.
Overall, the results confirm that the proposed framework successfully addresses key challenges in edge security, including data privacy, trust establishment, and resistance to advanced cyber threats.

7. CONCLUSION

This research presents a comprehensive Hybrid Edge Security Framework that integrates federated learning, blockchain-based trust management, post-quantum cryptography, and privacy-preserving analytics to enhance the security of edge computing environments.
The proposed system enables decentralized intrusion detection without sharing sensitive data, ensures model integrity through blockchain verification, secures communication using quantum-resistant cryptographic algorithms, and protects data confidentiality through homomorphic encryption.
Experimental evaluation on a real hardware-based testbed demonstrates that the framework achieves superior intrusion detection performance with an accuracy of up to 97%, reduced latency, and improved throughput compared to conventional approaches. The system also exhibits high resilience against common cyberattacks, including DDoS, botnets, and data injection attacks.
The results validate the feasibility, scalability, and effectiveness of the proposed approach for real-world deployment in smart city, healthcare, and industrial IoT environments.

8. Future Scope

Although the proposed framework demonstrates promising results, several important research directions remain. Future work should focus on large-scale deployment across geographically distributed edge networks to validate scalability and real-world applicability. Additionally, integrating lightweight post-quantum cryptographic algorithms optimized for ultra-low-power IoT devices is essential to ensure quantum-resistant security with minimal overhead. Developing adaptive federated learning mechanisms that respond to dynamic network conditions and data heterogeneity will further enhance system efficiency. Strengthening adversarial robustness against advanced poisoning and evasion attacks is also critical for maintaining model integrity. Finally, incorporating explainable artificial intelligence techniques can improve transparency and trust in intrusion detection decisions. These advancements will collectively enhance the system's efficiency, robustness, and practical deployment readiness.

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