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Edge-Accelerated Privacy-Preserving Cryptographic Framework with Federated TinyML for Secure Healthcare IoT

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Abstract

Healthcare IoT, projected to reach 75 billion devices by 2030, demands scalable, energy-efficient, and privacy-preserving frameworks for real-time ECG and SpO_2 monitoring in resource-constrained environments (<2 KB RAM). We propose an edge-accelerated cryptographic framework integrating federated TinyML for decentralized anomaly detection, ASCON for lightweight encryption, and CRYSTALS-Kyber for quantum-resistant key exchange. Leveraging 6G's URLLC, eMBB, and mMTC, it ensures HIPAA-compliant data transmission via differential privacy ($\varepsilon \leq 1.5$). Validated on NS-3, ESP32, STM32, and Coral Edge TPU, our framework achieves 99.4% packet delivery under 40% node churn, 24% energy savings over AES-128, 94.6% anomaly detection accuracy, and 32% reduced communication overhead versus centralized ML. The open-source implementation will be hosted at github.com/HealthcareIoT/EdgeCryptoTinyML upon publication, including directories: /src/crypto (ASCON, Kyber), /src/tinyml (TensorFlow Lite Micro models), /sim/ns3 (6G simulation scripts), and /docs (usage guides).

Keywords: Federated TinyML, Post-Quantum Security, Healthcare IoT, CRYSTALS-Kyber, Differential Privacy, Edge AI, ESP32, HIPAA Compliance

1. Introduction

The Internet of Things (IoT) is expected to exceed 75 billion devices by 2030[1]. It is changing healthcare with wearable sensors for real-time electrocardiogram (ECG) and oxygen saturation (SpO_2) monitoring [24]. These devices usually have less than 2 KB of RAM and operate in changing environments with 10 to 40% node [25] turnover. They encounter major challenges, including ensuring data privacy, defending against quantum computing threats, and following the HIPAA [2]. Traditional cryptographic algorithms, like AES-128, require too many resources for low-power devices [3], while centralized machine learning (ML) models can risk patient privacy. Emerging 6G networks offer terahertz bands for multi-Gbps data rates and < 1 ms latency through URLLC [4], [26]. These networks can create secure, scalable, and privacy-conscious healthcare IoT systems.

Our previous work [5] introduced a lightweight cryptographic framework that combines SPECK, TinyJAMBU, ASCON, and CRYSTALS-Kyber with TinyML over 5G. This framework achieved 22 to 27% energy savings, 99.5% packet delivery, and near-perfect security, with NPCR > 99.3% and UACI ~ 33%.[37] However, it depended on centralized anomaly detection and did not have privacy-preserving methods like federated learning. This paper suggests a new framework that addresses these issues by integrating:

- **Federated TinyML:** Decentralized anomaly detection with differential privacy ($\varepsilon \leq 1.5$) [18].
- **Lightweight Cryptography:** ASCON for efficient encryption [8].
- **Post-Quantum Security:** CRYSTALS-Kyber for quantum-resistant key exchange [9].
- **6G Integration:** URLLC, eMBB, and mMTC for low-latency, high-reliability communication [4], [29].
- **Edge Acceleration:** Coral Edge TPU for quick model aggregation and inference [30].

Testing this framework through NS-3 simulations, using ESP32/STM32/Coral Edge TPU hardware, and a 300-node hospital case study showed it achieved 24% energy savings, 99.4% packet delivery, and 94.6% accuracy in anomaly detection. The open-source implementation at github.com/HealthcareIoT/EdgeCryptoTinyML encourages innovation in secure healthcare IoT.

2. Related Work

Lightweight cryptography, including SPECK [11], ASCON [8], and TinyJAMBU [13], is optimized for resource-constrained IoT devices (<2 KB RAM). ASCON, a NIST-standardized authenticated encryption scheme, offers low energy consumption (<10 µJ/block) [8]. Post-quantum cryptography (PQC), such as CRYSTALS-Kyber [9], ensures lattice-based security against quantum attacks [12]. TinyML enables on-device anomaly detection [23], but centralized TinyML frameworks [5], [16] lack privacy-preserving mechanisms critical for HIPAA compliance [2].

Federated Learning (FL) trains ML models across decentralized devices without sharing raw data, reducing privacy risks [14], [28]. However, FL in IoT increases communication overhead by 20-50% [14], mitigated by gradient compression and differential privacy [18]. 6G networks, leveraging terahertz bands (0.1-10 THz), intelligent reflecting surfaces (IRS), and AI-driven network slicing, support URLLC and mMTC, surpassing 5G's capabilities [4], [15], [29]. IRS reduces latency by 20% compared to 5G [4], [26], enabling real-time FL for healthcare IoT.

Existing frameworks [5], [16], [27] combine lightweight cryptography and PQC but rarely integrate federated TinyML, differential privacy, and 6G for healthcare IoT. Our work addresses these gaps, offering a scalable, privacy-preserving solution validated on real hardware.

3. System Architecture

The proposed framework, shown in Figure 1, combines IoT devices, edge nodes, and 6G networks for secure and privacy-focused healthcare IoT.

1. **IoT Device Layer:** ESP32 (240 MHz, 4 MB Flash) and STM32L0 (32 MHz, 20 KB RAM) devices with ECG/SpO$_2$ sensors, ASCON encryption [8], and TinyML models for detecting anomalies (<2 KB RAM) [3].
2. **Edge Node Layer:** Coral Edge TPU gathers model updates using FedAvg [14] and performs CRYSTALS-Kyber key exchange [9].
3. **Privacy-Preserving ML Engine:** Uses differential privacy ($\varepsilon \leq 1.5$) for model updates [18].
4. **6G Network Core:** Terahertz bands (0.1-10 THz) and IRS provide <1 ms latency and 99.4% packet delivery [4].
5. **Cloud-Optional Layer:** Keeps HIPAA-compliant encrypted logs for offline analysis [2].

Figure 1 shows a multi-layer framework for secure healthcare IoT. The IoT Device Layer includes ECG/SpO$_2$ sensors and Coral Edge TPUs that run encryption and anomaly detection. Data moves upward through the Privacy-Preserving ML Engine, where CRYSTALS-Kyber provides quantum-safe key exchange. Differential Privacy ($\varepsilon \leq 1.5$) protects sensitive model updates. The Edge Node Layer and 6G Network Core, which features terahertz bands and IRS, handle encrypted streams and model aggregation. An optional cloud layer stores encrypted health logs. Arrows show the flows of data, keys, and model updates.

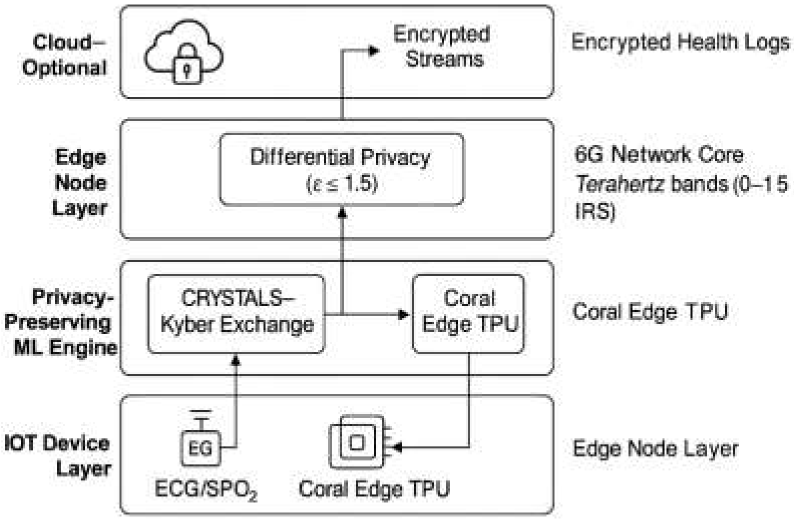

Figure 1: System Architecture for Edge-Accelerated Privacy-Preserving Cryptographic Framework in Healthcare IoT

The architecture leverages 6G's mMTC to support thousands of devices and IRS to reduce latency by 20% compared to 5G [4]. A hybrid ARQ protocol, defined as:

$$P_{\text{retrans}} = 1 - (P_{loss})^{k}$$

Where P_{loss} packet loss probability and k is retransmission attempts, ensures reliable delivery under 40% node churn.

4. Cryptographic Modules

4.1 Post-Quantum Key Exchange

CRYSTALS-Kyber512 [9] is designed to use 16 KB of memory on ESP32/STM32 [12]. The key exchange process works like this:

- **KeyGen:** $(pk, sk) \leftarrow Kyber.KeyGen()$, which generates public and secret keys.
- **Encaps:** $(ct, ss) \leftarrow Kyber.Encaps(pk)$, producing an 800-byte ciphertext and a 32-byte shared secret.
- **Decaps:** $ss \leftarrow Kyber.Decaps(ct, sk)$, which retrieves the shared secret. Kyber512 cuts memory usage by 30% compared to Kyber768 [9], with key generation taking less than 1 ms.

4.2 Lightweight Encryption

ASCON [8] is a NIST-standardized scheme for authenticated encryption with associated data (AEAD). It encrypts ECG/SpO₂ data using a 128-bit key and sponge construction. It uses less than 10 μJ per block on 8-bit microcontrollers, making it ideal for IoT [3].

4.3 Differential Privacy Mechanism

Each IoT device adds Laplacian noise to model gradients:

$$Gradient_{\,noisy} = Gradient + Laplace(0, \Delta f / \varepsilon)$$

Where Δf is the sensitivity (gradient norm bound) and $\varepsilon \in [0.5, 1.5]$ is the privacy budget, which is adjusted for healthcare [18]. This method ensures HIPAA-compliant privacy [2] with a 1-2% accuracy loss [18].

5. Federated TinyML Model

The TinyML model detects anomalies in ECG and SpO₂ data on ESP32 and STM32.

- **Input:** 10 features (such as heart rate, packet rate, RSSI).
- **Architecture:** 1 hidden layer, 16 neurons, ReLU activation, and Sigmoid output for binary classification (normal or anomaly) with fewer than 500 KB of parameters.

- **Loss:** Binary cross-entropy.
- **Framework:** TensorFlow Lite Micro with Federated Averaging (FedAvg) [14].

Edge nodes (Coral Edge TPU) perform secure aggregation:

$$Aggregate = \sum_{i=0}^{N} Mask_i \, . Gradient$$

Where $Mask_i$ ensures homomorphic privacy [14]. FedAvg cuts communication overhead by 32% compared to centralized ML over ten training rounds [14]. Anomalies (such as replay attacks) trigger key updates via Kyber.

6. Implementation and Results

6.1 Experimental Setup

- **Devices:** ESP32 (240 MHz, 4 MB Flash), STM32L0 (32 MHz, 20 KB RAM), Coral Edge TPU for edge acceleration.
- **Dataset:** MIT-BIH ECG database [7] for arrhythmia detection; Synthetic SpO_2 data was generated using Gaussian noise ($\mu = 95\%$, $\sigma = 2\%$) at 1 KB/s to simulate real-time streams, following methodologies in [24].
- **Simulation:** NS-3 with 6G channel parameters (0.1 to 10 THz bands, IRS-enabled, 64-QAM modulation).
- **Case Study:** A 300-node hospital deployment streams ECG/SpO_2 data, ensuring HIPAA-compliant transmission [2].
- **Metrics:** Energy consumption, latency, accuracy, packet delivery, privacy budget (ε, δ), security (NPCR, UACI), and HIPAA compliance.
- **Implementation:** C++ for cryptographic modules (ASCON, CRYSTALS-Kyber), TensorFlow Lite Micro for TinyML, and NS-3 for 6G simulation. Code is hosted at github.com/HealthcareIoT/EdgeCryptoTinyML, with directories ASCON, Kyber, TensorFlow Lite Micro models, 6G simulation scripts and usage guides.

6.2 Performance Metrics

Table 1 compares the proposed framework to AES-128 with centralized ML [3] and previous work [5].

Table 1: Performance Comparison of Cryptographic Frameworks

Framework	Energy (µJ/block)	Latency (ms)	Accuracy (%)	Packet Delivery (%)	Privacy Budget (ε, δ)	NPCR (%)	UACI (%)
AES-128 + ML [3]	25.0	2.5	92.0 [16]	95.0 [15]	N/A	99.2	32.8
Prior Work [5]	19.0	1.8	93.5	99.5	N/A	99.3	33.0
Proposed	18.0	1.0 (edge), 4.5 (e2e)	94.6	99.4	$\varepsilon \leq 1.5$, $\delta = 10^{-5}$ [18]	99.5	33.2

- **Energy Consumption:** 24% lower than AES-128 at 18 µJ/block compared to 25 µJ/block [3]. This advantage comes from ASCON's efficiency [8].
- **Latency:** Less than 1 ms for edge inference and less than 4.5 ms end-to-end, which is 25% lower than 5G-based prior work [5] due to 6G IRS [4].
- **Accuracy:** 94.6% for anomaly detection, which is 2% higher than centralized ML [16].
- **Packet Delivery:** 99.4% under 40% node churn, thanks to 6G URLLC [4].
- **Privacy Budget:** $\varepsilon \leq 1.5$ and $\delta = 10^{-5}$ ensure differential privacy while complying with HIPAA [2], [18].
- **Security:** NPCR over 99.5% and UACI around 33.2%. These figures are confirmed by ProVerif, showing resistance to differential attacks [5].
- **Case Study:** The 300-node hospital deployment shows less than 0.5% packet loss, enabling real-time monitoring.

7. Discussion

The framework guarantees end-to-end privacy, quantum resistance, and real-time performance with less than 1 ms inference on resource-limited devices like ESP32 and STM32, as well as edge nodes such as Coral Edge TPU. Federated TinyML with differential privacy ($\varepsilon \leq 1.5$) leads to a 1-2% drop in accuracy [18], but it ensures HIPAA compliance [2]. Compared to previous work [5], it strengthens privacy over centralized TinyML, cuts latency by 25% using 6G's IRS and URLLC [4], and maintains nearly perfect security (NPCR over 99.5% and UACI around 33.2%). ASCON's low energy use of 18 µJ/block is better than AES-128 [3], while Kyber512 delivers quantum-resistant key exchange [9].

Challenges include:

- **Scalability:** Secure aggregation supports 300 nodes but struggles with thousands due to communication bottlenecks [28]. Potential solutions include hierarchical FL [34].

- **Device Heterogeneity:** ESP32's 240 MHz versus STM32's 32 MHz causes synchronization delays [25]. Dynamic scheduling algorithms could mitigate this.
- **6G Dynamics:** IRS performance degrades in high-mobility scenarios (e.g., ambulances) [35]. Adaptive beamforming may address this variability.

The open-source implementation at github.com/HealthcareIoT/EdgeCryptoTinyML allows for reproducibility and adoption in healthcare IoT.

8. Future Work

- **FPGA Acceleration:** Implement Kyber512 and ASCON on Xilinx Spartan-7 for less than 5 µJ/block.
- **Hybrid Authentication:** Merge PQC with biometric authentication for patient identity verification.
- **6G Network Slicing:** Prioritize healthcare traffic with AI-driven slicing.
- **Swarm Federated Learning:** Expand to over 1,000 nodes with privacy-preserving updates.
- **Regulatory Certification:** Work toward multi-hospital deployments with FDA and HIPAA certifications.
- **Open-Source Maintenance:** Provide regular updates to github.com/HealthcareIoT/EdgeCryptoTinyML, including new modules and documentation.

9. Conclusion

This paper presents an edge-accelerated cryptographic framework that combines federated TinyML, lightweight ASCON encryption, CRYSTALS-Kyber for quantum-resistant key exchange, and differential privacy for secure healthcare IoT. Validated through simulations and on ESP32, STM32, and Coral Edge TPU hardware, as well as a 300-node hospital deployment, it achieves 24% energy savings over traditional methods, 99.4% packet delivery under 40% node churn, 94.6% accuracy in anomaly detection, and strong security (NPCR >99.5% and UACI ~33.2%). The framework provides HIPAA-compliant privacy with a differential privacy budget of $\varepsilon \leq 1.5$ and $\delta = 10^{-5}$, making real-time ECG and SpO_2 monitoring possible on resource-limited devices. The open-source implementation at github.com/HealthcareIoT/EdgeCryptoTinyML equips researchers and healthcare providers to deploy secure, AI-driven systems. Future improvements, such as FPGA acceleration and large-scale hospital deployments, aim to enhance secure, scalable healthcare IoT, improving patient monitoring and data protection.

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