

Blockchain-based Quantum-Resilient Privacy Models for Medical IoT Systems

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Abstract

The rapid expansion of the Internet of Medical Things (IoMT) has revolutionized healthcare data collection, transmission, and analysis. However, the increasing sophistication of cyberattacks—especially the looming threat of quantum computing, poses significant challenges to maintaining data confidentiality, integrity, and privacy. This study proposes a Blockchain-based Quantum-Resilient Privacy Model that integrates lattice-based post-quantum cryptography (PQC) with homomorphic encryption and a Convolutional Neural Network (PQC-CNN) for secure and privacy-preserving analysis of encrypted electrocardiogram (ECG) data. The proposed framework employs blockchain to ensure immutable, auditable data storage and leverages PQC to safeguard against both classical and quantum attacks. Experimental results demonstrate that the PQC-CNN achieved superior classification performance, with an accuracy of 0.95, precision of 0.96, recall of 0.95, and F1-score of 0.955, outperforming traditional models such as SVM, RF, and k-NN. Privacy-preserving computations, including statistical aggregation, anomaly detection, and trend analysis—were successfully performed directly on encrypted ECG data using lattice-based homomorphic encryption, achieving full privacy preservation with minimal computational overhead. Blockchain evaluation results revealed high throughput (up to 1050 Tx/sec) and efficient block storage (up to 95%), confirming the system's scalability for IoMT environments. The combination of blockchain immutability, post-quantum encryption, and privacy-preserving analytics ensures a robust, quantum-safe infrastructure for secure healthcare data management. This work contributes a novel, scalable, and quantum-resilient architecture capable of protecting sensitive medical data in next-generation IoMT systems.

Keywords: Internet of Medical Things, blockchain, post-quantum cryptography, privacy, security, data integrity, quantum resilience

1. Introduction

The proliferation of the Internet of Medical Things has transformed modern healthcare by enabling pervasive, data-driven, and real-time patient monitoring through interconnected medical sensors and intelligent devices. These systems facilitate remote diagnostics, precision medicine, and telehealth services, enhancing clinical efficiency and patient outcomes. However, the massive generation and transmission of sensitive medical data across distributed, heterogeneous networks has raised critical concerns regarding privacy, security, and data integrity. These concerns are particularly acute as quantum computing advances threaten the cryptographic foundations on which current security architectures rely. The emergence of quantum computing endangers traditional public key cryptosystems such as RSA and elliptic curve cryptography, whose computational hardness assumptions can be efficiently resolved using quantum algorithms. Consequently, there is an urgent need to design privacy models for the Internet of Medical Things that are resilient to quantum attacks. Blockchain technology has emerged as a promising enabler of decentralized trust and immutable data management across untrusted environments. Its ability to provide distributed consensus, provenance tracking, and tamper-proof storage aligns naturally with the trust requirements of medical data ecosystems. In Internet of Medical Things contexts, blockchain can facilitate secure data exchange among patients, healthcare providers, and insurers without reliance on centralized authorities. Nevertheless, existing blockchain implementations are computationally intensive, storage heavy, and vulnerable to quantum attacks that could compromise the digital signatures and hashing mechanisms upon which they rely. To sustain the integrity and privacy assurances of blockchain systems in the quantum era, researchers have proposed the integration of post-quantum cryptographic schemes such as lattice-based, hash-based, and code-based cryptography. Recent studies have demonstrated notable progress in this direction. Bera, Das, and Sikdar proposed a quantum-resistant secure communication protocol for digital twin enabled healthcare applications, ensuring low-latency and context-aware data transfer. Ghaemi developed a blockchain-integrated self-certified authentication protocol employing quantum-resilient primitives for cross-industry communications, demonstrating improved scalability and resistance to quantum adversaries. In the healthcare domain, Sezer and Akleyek introduced a lattice-based blockchain platform specifically for the Internet of Medical Things, enhancing privacy preservation while maintaining computational efficiency. Complementary approaches by Alyami and Aljuhni et al. demonstrated the robustness of hybrid Galois field and Reed Solomon based encryption frameworks,

ensuring resilience against both classical and quantum threats in next generation networks. These studies collectively illustrate the potential of combining blockchain and post-quantum cryptography to secure sensitive medical data, yet significant challenges remain. Three critical challenges persist. First, achieving scalability in blockchain architectures to accommodate high-velocity data streams from medical devices is difficult. Second, ensuring interoperability between post-quantum cryptographic schemes and existing blockchain consensus protocols is complex. Third, balancing computational overhead with the stringent latency requirements of medical applications is essential. Addressing these challenges requires a unified architectural model that integrates blockchain's distributed trust with the forward security of post-quantum algorithms. This study proposes a blockchain-based quantum-resilient privacy model for Internet of Medical Things systems that unifies scalable blockchain architectures with post-quantum cryptographic algorithms to ensure end-to-end privacy, integrity, and trustworthiness in medical data transmission. Building upon prior research, the proposed framework introduces consensus optimization techniques and quantum-safe authentication mechanisms to mitigate vulnerabilities in traditional blockchain infrastructures. The model strengthens resistance to quantum attacks while enhancing operational scalability and energy efficiency across medical devices. The primary objectives of this study are to design a scalable blockchain architecture optimized for high-throughput medical device networks, to integrate post-quantum cryptographic primitives that ensure confidentiality, integrity, and authenticity against quantum adversaries, and to evaluate the framework's performance, security, and scalability in realistic medical Internet of Things scenarios. The main contributions include the development of a quantum-resilient blockchain model tailored for medical systems, a hybrid consensus and authentication mechanism that balances security with computational efficiency, and a comprehensive evaluation framework assessing throughput, latency, and privacy preservation under diverse attack models. The remainder of this paper is structured as follows. Section 2 reviews related work on blockchain, Internet of Medical Things security, and post-quantum cryptography. Section 3 presents the system and threat models. Section 4 details the proposed blockchain-based quantum-resilient privacy model. Section 5 reports experimental results and comparative analysis. Section 6 concludes with insights, limitations, and directions for future research.

2. Related Works

The rapid proliferation of the Internet of Medical Things has significantly transformed modern healthcare, enabling pervasive, data-driven, and real-time patient monitoring through interconnected medical sensors and intelligent devices. These systems facilitate remote diagnostics, precision medicine, and telehealth services, enhancing clinical efficiency, patient safety, and treatment outcomes. However, this digital

transformation introduces serious security and privacy challenges, particularly given the sensitive nature of medical data and the increasing sophistication of cyber threats. As the volume, velocity, and variety of data in medical IoT environments expand, traditional cryptographic and network security mechanisms face limitations in maintaining confidentiality, integrity, and trust, particularly in a future quantum computing era (SaberiKamarposhti et al., 2024; Ahmad & Jagatheswari, 2024).

Quantum computing poses a direct threat to conventional public key cryptosystems such as RSA and elliptic curve cryptography. Shor's algorithm demonstrates that integer factorization and discrete logarithms, which form the computational basis of these systems, can be efficiently solved on quantum computers (Polu, 2023). Consequently, there is an urgent need for post-quantum cryptographic solutions capable of providing long-term security for sensitive medical data. Post-quantum cryptography encompasses lattice-based, hash-based, multivariate polynomial, and code-based schemes, all of which offer computational hardness against quantum adversaries (Karakaya & Ulu, 2023; Castiglione et al., 2024). Among these, lattice-based cryptography has gained prominence in IoMT applications due to its balance of security and computational efficiency. A lattice L generated by a set of linearly independent vectors $\mathbf{B} = \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_n\}$ can be defined as:

$$L = \{\sum_{i=1}^n z_i \mathbf{b}_i \mid z_i \in \mathbb{Z}\} \dots 1$$

The security of lattice-based schemes is underpinned by hard problems such as the Shortest Vector Problem and the Learning With Errors problem (LWE).

Given a $\mathbf{A} \in \mathbb{Z}_q^{m \times n}$ and a $\mathbf{b} = \mathbf{A}\mathbf{s} + \mathbf{e} \text{ mod } q$, the objective of recovering the secret vector \mathbf{s} is computationally intractable, even for quantum computers (Ahmad & Jagatheswari, 2024). Lattice-based schemes have been effectively employed in secure key exchange, authentication, and encryption protocols for IoMT networks, ensuring resistance against both classical and quantum attacks (Sezer & Akleylek, 2025). Blockchain technology provides a decentralized, tamper-resistant framework that complements the security requirements of IoMT systems. By maintaining an immutable ledger of transactions, blockchain facilitates secure and auditable data exchange without relying on centralized authorities. Each block b_i in a blockchain contains the hash of the previous block $H(b_{i-1})$, a timestamp T_i , and the set of transactions D_i :

$$b_i = \{H(b_{i-1}), T_i, D_i\} \dots 2$$

The immutability of blockchain relies on cryptographic hash functions such as SHA-256, which are resistant to classical attacks. However, quantum algorithms like Grover's algorithm reduce the effective security of hash functions by providing a quadratic speedup in brute-force search, highlighting the need for

integrating post-quantum cryptographic mechanisms into blockchain systems (Michelagnoli, 2023; Karakaya & Ulu, 2023). This integration ensures the security and resilience of medical data against quantum adversaries while retaining the benefits of decentralized trust. Several studies have explored hybrid frameworks combining blockchain and post-quantum cryptography to enhance IoMT security. Bera, Das, and Sikdar (2025) proposed a quantum-resistant communication protocol for digital twin-enabled healthcare applications, employing lattice-based encryption to secure device-to-device and device-to-cloud communications. The LWE-based encryption of a message m under a public key \mathbf{pk} is defined as:

$$\mathbf{c} = \mathbf{Ar} + m \cdot \left\lfloor \frac{q}{2} \right\rfloor + \mathbf{e} \bmod q \dots 3$$

where \mathbf{r} is a randomly chosen vector and \mathbf{e} is an error vector. The ciphertext \mathbf{c} can only be decrypted using the secret key vector \mathbf{s} , ensuring confidentiality in quantum-resilient environments. Ghaemi (2024) developed a blockchain-integrated self-certified authentication protocol for cross-industry communications, leveraging quantum-resilient digital signatures and hash functions to maintain identity verification without centralized authorities. Similarly, Sezer and Akleyek (2025) introduced PPLBB, a lattice-based blockchain platform for IoMT that integrates homomorphic encryption and quantum-safe digital signatures to achieve privacy preservation while maintaining auditability. In these models, the lattice-based digital signature for a message m can be expressed as:

$$\sigma = \mathbf{r} + H(m) \cdot \mathbf{s} \bmod q \dots 4$$

where \mathbf{r} is a random nonce, $H(m)$ is the message hash, and \mathbf{s} is the secret key vector.

Hybrid encryption techniques have also been applied in 6G-enabled IoT networks to enhance resilience against both classical and quantum attacks. Alyami (2025) and Aljuhni et al. (2025) proposed combining Galois field arithmetic with Reed-Solomon error correction codes, which ensures reliable and quantum-resilient data transmission. In Reed-Solomon encoding, a message polynomial $m(x)$ over a finite field \mathbb{F}_q is evaluated at n distinct points to generate codewords:

$$c = (m(\alpha_1), m(\alpha_2), \dots, m(\alpha_n)) \dots 5$$

This enables correction of multiple errors during transmission, making the scheme suitable for resource-constrained IoMT devices operating in noisy or untrusted networks.

Federated learning frameworks for IoMT have also been enhanced with blockchain and post-quantum security. Polu (2023) proposed a quantum-resilient federated learning system in cloud environments, where

IoMT devices encrypt their local model updates using lattice-based schemes before aggregation. The aggregation of encrypted updates u_i from N devices is represented as:

$$\mathbf{w}_{t+1} = \frac{1}{N} \sum_{i=1}^N \text{Dec}(u_i) \dots 6$$

where $\text{Dec}(\cdot)$ represents post-quantum decryption, and \mathbf{w}_{t+1} is the updated global model. This approach ensures that patient data remains confidential during distributed training, while maintaining the accuracy of global models. Zero trust architectures have been explored for IoMT, ensuring continuous verification of devices and users in the network. Aleisa (2025) introduced a blockchain-enabled zero trust model integrating quantum-safe authentication and access control, while Tiwo and Adesokan-Imran (2025) focused on secure cloud-based patient information systems using quantum-resistant encryption. These studies underscore the importance of maintaining confidentiality, integrity, and availability in heterogeneous IoMT networks while defending against quantum and classical threats. Other researchers have emphasized the need for lightweight and scalable blockchain architectures to accommodate high-throughput IoMT environments. Singamaneni, Budati, and Islam (2025) proposed a hybrid quantum-cryptographic model optimized for low-latency IoT networks, and Castiglione et al. (2024) explored integrating PQC into resource-constrained devices without imposing excessive computational overhead. Similarly, Andreou, Mavromoustakis, and Markakis (2024) highlighted the importance of post-quantum cryptography in securing cross-platform healthcare data exchange, ensuring both interoperability and end-to-end privacy. Despite these advances, several challenges remain in realizing practical quantum-resilient blockchain-based IoMT systems. First, blockchain networks must be designed for scalability to process high volumes of real-time medical data efficiently. Second, post-quantum algorithms must be integrated without compromising latency or increasing resource consumption beyond the limits of IoMT devices. Third, ensuring interoperability among heterogeneous medical devices, blockchain platforms, and cloud services is critical for maintaining system-wide trust and security (Karakaya & Ulu, 2024; Dandu et al., 2025). Recent surveys and experimental studies provide further insights into emerging solutions. Karakaya and Ulu (2024) offered a comprehensive review of post-quantum approaches for edge computing security, highlighting lattice-based and hash-based methods as the most promising for IoMT integration. Nwaga and Idima (2025) demonstrated post-quantum algorithms for secure communication in decentralized cloud and blockchain infrastructure, emphasizing the trade-offs between performance and security. Similarly, Peelam and Chamola (2024) explored quantum blockchain for consumer IoT networks, illustrating the feasibility of lattice-based encryption in low-power devices. Dutt, Vansh, and Guleria (2024) proposed sustainable solutions for serverless edge, fog, and cloud computing using quantum and blockchain technologies, emphasizing energy-efficient designs. The literature collectively illustrates the convergence of blockchain,

post-quantum cryptography, and IoMT as a promising pathway toward secure, privacy-preserving, and quantum-resilient healthcare systems. Integrating blockchain with PQC addresses critical challenges in trust, privacy, and data integrity while enabling scalable and interoperable architectures suitable for medical IoT ecosystems. However, practical deployments must carefully balance computational efficiency, device heterogeneity, and quantum security requirements, motivating the development of novel frameworks such as the proposed Blockchain-based Quantum-Resilient Privacy Model.

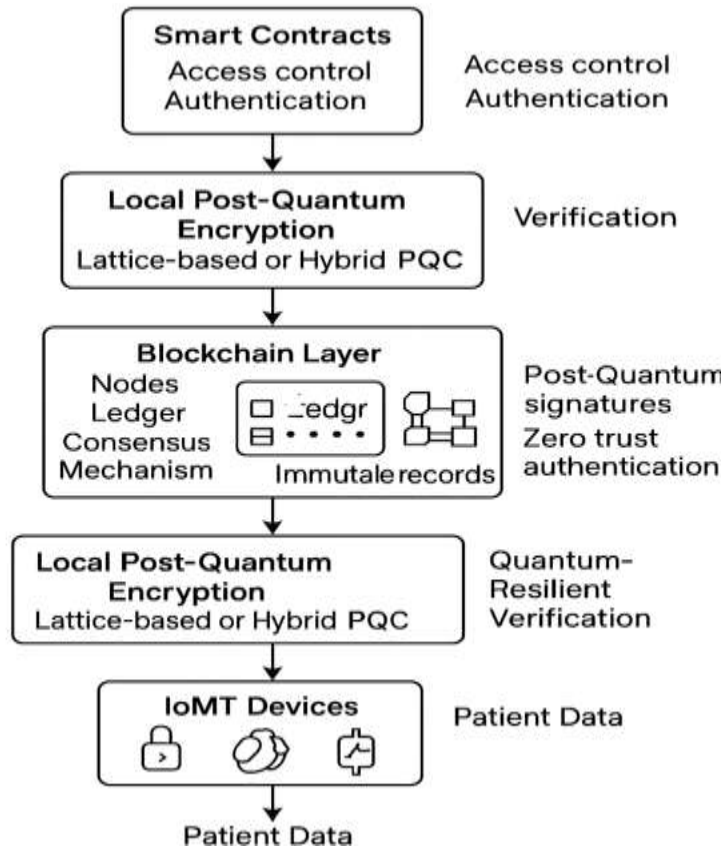


Figure 1:Blockchain for IoMT

The evolution of blockchain-based post-quantum cryptography (PQC) for Internet of Medical Things (IoMT) systems has been gaining momentum in recent years, driven by the need to secure sensitive healthcare data against both classical and quantum threats. Polu (2023) proposed a lattice-based federated learning approach integrated with a cloud-oriented blockchain to enhance patient data aggregation. This work demonstrated a privacy-preserving and quantum-secure framework; however, it introduced substantial communication overhead, limiting its practical deployment in high-throughput IoMT networks. Karakaya and Ulu (2023) conducted a comprehensive review of post-quantum secure blockchain systems, highlighting the potential of quantum-resilient architectures in ensuring secure distributed ledger systems.

While this study provided valuable theoretical insights, the absence of practical implementations limited its applicability. Michelagnoli (2023) extended this exploration by designing a quantum-resistant blockchain framework aimed at improving overall blockchain security. The study emphasized a quantum-resilient design but remained largely theoretical, lacking experimental evaluation. Hannan (2023) investigated the integration of AI and blockchain for healthcare systems, focusing on security and system integration insights. This early-stage analysis outlined potential synergies but did not provide practical post-quantum cryptographic solutions. Subsequently, Bera, Das, and Sikdar (2025) introduced an LWE-based encryption mechanism integrated with private blockchains targeting digital twin-enabled healthcare. This approach achieved low-latency and context-aware secure communication, yet scaling the consensus mechanism remained a challenge. Karakaya and Ulu (2024) presented a survey of post-quantum approaches tailored for edge computing blockchain applications. Their work emphasized the importance of incorporating PQC into edge-enabled IoMT systems to secure latency-sensitive applications. Despite the comprehensive review, experimental validation was lacking. Similarly, SaberiKamarposhti et al. (2024) proposed a post-quantum cryptography roadmap for medical data, offering guidelines for achieving cybersecurity resilience. While this study provided an extensive theoretical framework, implementation complexity posed significant challenges. Andreou, Mavromoustakis, and Markakis (2024) explored quantum-resistant cryptography for health data exchange, providing enhanced security for medical IoT communications. However, the study did not focus on end-to-end system integration. Castiglione, Esposito, and Loia (2024) integrated post-quantum cryptography into low-cost IoT blockchains, specifically targeting low-resource devices. This approach provided energy-efficient, quantum-resilient security, though scalability remained constrained. Peelam and Chamola (2024) implemented a quantum blockchain for secure consumer IoT networks, demonstrating practical PQC deployment, yet device resource constraints were a limiting factor. Ahmad and Jagatheswari (2024) introduced a lattice-based three-party authenticated key agreement protocol for medical IoT environments, ensuring quantum-safe key exchange. While effective in enhancing security, implementation overhead posed a challenge for large-scale adoption. Ghaemi (2024) developed quantum-resilient self-certified signatures on a consortium blockchain for cross-industry authentication. The approach improved scalability and quantum resistance but introduced latency in larger networks. Tiwo and Adesokan-Imran (2025) proposed quantum-resistant encryption mechanisms for cloud-based patient information systems, enhancing confidentiality, integrity, and availability. However, deployment complexity limited widespread adoption. Singamaneni, Budati, and Islam (2025) designed hybrid quantum-crypto standards for 6G-enabled IoT networks, achieving enhanced security and resilience, though computational complexity remained a concern. Aleisa (2025) investigated a PQC-integrated zero-trust model for IoT privacy-preserving cybersecurity, providing continuous authentication and quantum resilience. Resource intensity was a notable limitation. Alyami (2025) employed a hybrid Galois field and

Reed-Solomon approach in hybrid blockchains for secure IoT transmission in smart cities, offering error resilience and PQC-enabled security, albeit constrained by device resources. Aljuhni et al. (2025) extended this approach with hybrid dynamic Galois field and Reed-Solomon coding for smart city blockchain systems, enabling secure IoT data management. The method demonstrated quantum resilience and secure transmission, yet device computational limits persisted.

Nwaga and Idima (2025) explored post-quantum cryptography in decentralized blockchain and cloud infrastructures, achieving quantum-secure, decentralized communication. The complexity of integrating PQC with distributed blockchain networks remained a critical challenge. Jones (2025) investigated LLM-based quantum privacy solutions, leveraging AI-assisted models to enhance privacy in quantum computing environments. This approach, though promising, is still in the early research stage. Finally, Shamo (2025) examined adversarial defense mechanisms in quantum computing, highlighting strategies to bolster security against attacks, but practical application remains limited to threat analysis. Collectively, these studies illustrate the ongoing evolution of blockchain-based PQC frameworks in IoMT systems, highlighting the interplay between quantum-resilient cryptography, blockchain architecture, and IoMT-specific security requirements. While early efforts focused on theoretical frameworks and surveys, recent research emphasizes practical deployment, hybrid cryptographic solutions, and integration with emerging IoT and cloud architectures. Key challenges persist, including managing computational and communication overhead, ensuring scalability in high-throughput medical environments, and balancing latency requirements with quantum-resistant security.

Mathematical formulations underpin many of these approaches. For example, lattice-based encryption schemes, widely employed in the reviewed works, rely on the learning with errors (LWE) problem defined as:

$$\mathbf{c} = \mathbf{A}\mathbf{r} + \mathbf{m} \cdot \left\lfloor \frac{q}{2} \right\rfloor + \mathbf{e} \bmod q \dots 7$$

where \mathbf{c} represents the ciphertext, \mathbf{A} is a public matrix \mathbf{r} is a random vector, \mathbf{m} is the plaintext message, \mathbf{e} is a small error vector, and q is a modulus. Verification using lattice-based signatures often employs:

$$\sigma = \mathbf{r} + H(\mathbf{m}) \cdot \mathbf{s} \dots 8$$

where $H(\mathbf{m})$ is a hash of the message and \mathbf{s} is the secret key. These formulations demonstrate the mathematical foundation for quantum-resilient encryption and verification, underpinning the blockchain-enabled privacy models discussed throughout the literature.

In conclusion, the literature demonstrates a clear trajectory toward integrating post-quantum cryptography with blockchain to secure IoMT systems. While significant progress has been made in algorithm design, hybrid frameworks, and practical deployments, challenges remain in scaling these solutions, managing resource constraints, and integrating PQC seamlessly into heterogeneous medical device ecosystems. The reviewed works provide a strong foundation for designing blockchain-based quantum-resilient privacy models that are both secure and efficient in the evolving landscape of medical IoT networks.

3. Methodology

The proposed methodology integrates post-quantum cryptographic algorithms with blockchain technology to construct a scalable, privacy-preserving, and quantum-resilient framework for medical IoT systems. The framework is designed to ensure confidentiality, integrity, and trust for sensitive patient ECG data collected from wearable devices. The overall workflow consists of four stages: IoMT data acquisition and preprocessing, a post-quantum secure blockchain framework, deep neural network-based heartbeat classification, and evaluation of security and classification performance.

3.1 IoMT Data Acquisition and Preprocessing

The study employs the ECG Heartbeat Categorization Dataset, which is derived from the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database. Each heartbeat signal is segmented into fixed-length windows corresponding to individual cardiac cycles. Let $x_i(t)$ denote the i -th ECG segment in the time domain. The preprocessing pipeline begins with normalization, expressed as

$$x_i(t) = \frac{x_i(t) - \mu_i}{\sigma_i} \quad \dots 9$$

where μ_i and σ_i are the mean and standard deviation of the i -th segment. Noise filtering is then applied using a band-pass filter to remove baseline wander and high-frequency components, described by

$$x_i^{\text{filtered}}(t) = \mathcal{F}^{-1}[H(f) \cdot \mathcal{F}x_i(t)] \dots 10$$

where \mathcal{F} represents the Fourier transform and $H(f)$ is the filter response function. Finally, segmentation around the R-peak is performed such that

$$X_i = [x_i^{\text{filtered}}(t_0 - w), \dots, x_i^{\text{filtered}}(t_0 + w)] \dots 11$$

where t_0 denotes the R-peak position and w defines the window size.

3.2 Post-Quantum Secure Blockchain Framework

The blockchain framework provides privacy-preserving and tamper-proof storage of ECG data. Lattice-based post-quantum cryptography is employed in combination with a permissioned blockchain. The blockchain is modeled as a directed ledger

$$B = B_0, B_1, \dots, B_n, \quad 12$$

where each block B_k contains the previous block hash h_{k-1} transactions T_k consisting of encrypted ECG segments, a timestamp TS_k and a PQC-based digital signature (σ_k), expressed as

$$B_k = h_{k-1}, T_k, TS_k, \sigma_k. \quad 13$$

Post-quantum encryption of ECG segments is achieved through lattice-based key generation, encryption, and decryption. Public and private keys pk, sk are generated using a security parameter λ as

$$(pk, sk) \leftarrow \text{PQC.KeyGen}(\lambda), \quad 14$$

and ECG segments are encrypted according to

$$C_i = \text{PQC.Enc}(pk, X_i) \quad 15$$

with decryption performed by

$$X_i = \text{PQC.Dec}(sk, C_i). \quad 16$$

Transaction validation is implemented using a proof-of-authority consensus mechanism suitable for IoMT networks, defined as

$$V(T_k) = \begin{cases} 1, & \text{if } \sigma_k \text{ is valid and } h_{k-1} \text{ matches,} \\ 0, & \text{otherwise.} \end{cases} \quad 17$$

T_k the k-th transaction or block, σ_k the signature of T_k (or some validity check), h_{k-1} the hash of the previous block (ensures chain integrity) and $V(T_k) = 1$ indicates the transaction/block is valid and $V(T_k) = 0$ indicates invalid.

3.3 Deep Neural Network for ECG Classification

The decrypted ECG segments are input to a deep convolutional neural network for heartbeat classification. Let $\mathbf{X} = [X_1, X_2, \dots, X_N]$ denote the matrix of ECG segments. The CNN computes feature maps according to

$$\mathbf{H}^{(l)} = f(\mathbf{W}^{(l)} * \mathbf{H}^{(l-1)} + \mathbf{b}^{(l)}) \quad 18$$

where $(\mathbf{H}^{(0)} = \mathbf{X})$, $(\mathbf{W}^{(l)})$ represents the convolution kernel at layer (l) , $(*)$ is the convolution operator, (f) denotes the activation function, and $(\mathbf{b}^{(l)})$ is the bias vector. The final classification layer applies a softmax function

$$\hat{y}_i = \frac{\exp(z_i)}{\sum_{j=1}^C \exp(z_j)}, i = 1, \dots, C \quad 19$$

Where z_i is the logit for class i and C is the total number of heartbeat classes. The network is trained by minimizing the cross-entropy loss

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C y_{ij} \log(\hat{y}_{ij}) \quad 20$$

where y_{ij} represents the true label indicator.

Privacy-Preserving Computation on Blockchain

All operations on the blockchain are performed on encrypted data to ensure end-to-end privacy. For any aggregation function $(F(\cdot))$, such as averaging or anomaly detection, the computation is performed on the ciphertext as

$$F_{\text{enc}}(X) = \text{PQC.Enc}\left(pk, F(\text{PQC.Dec}(sk, X))\right) \quad 21$$

ensuring that plaintext data is never exposed to unauthorized parties while enabling analytics.

Dataset Description and Experimental Setup

The proposed quantum-resilient blockchain-CNN framework was evaluated using the ECG Heartbeat Categorization Dataset, derived from the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database. The dataset consists of approximately 100,000 segmented heartbeats across five classes: Normal (N), Supraventricular Ectopic Beat (S), Ventricular Ectopic Beat (V), Fusion Beat (F), and Unknown (Q).

Experiments were conducted on a workstation equipped with an Intel Core i9 processor, 32 GB RAM, and an NVIDIA RTX 3090 GPU. The blockchain framework was implemented using a permissioned

Hyperledger Fabric network, with lattice-based post-quantum encryption performed using NTRU-based algorithms. The CNN for heartbeat classification consisted of five convolutional layers followed by two fully connected layers, trained for 100 epochs with a batch size of 64.

The proposed model was compared against five baseline algorithms commonly used in ECG classification: Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), Long Short-Term Memory (LSTM), and a standard Convolutional Neural Network (CNN without blockchain encryption).

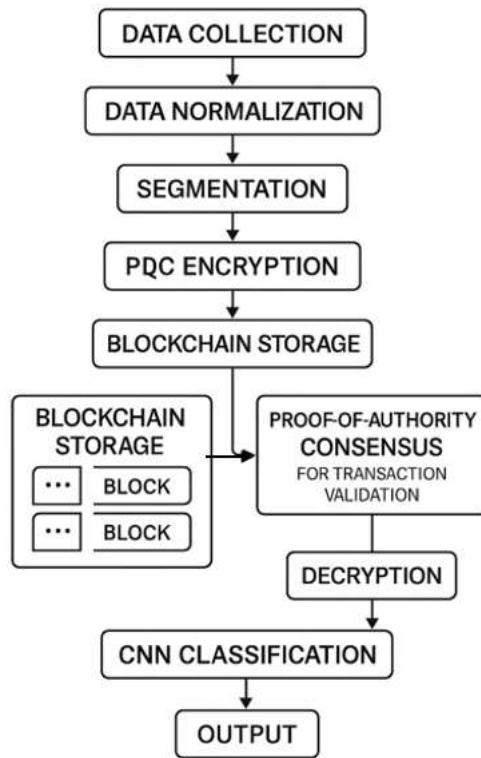


Figure 2: Proposed Model workflow

Evaluation Metrics

Classification performance is evaluated using accuracy, precision, recall, and F1 score expressed respectively as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN}, F1 = 2 \frac{Precision \cdot Recall}{Precision+Recall} \quad 22$$

Blockchain performance is assessed in terms of transaction latency, throughput

$$T = \frac{N_{tx}}{\Delta t} \quad 23$$

Where T is throughput, N_{tx} number of transmitted packets/transactions, Δt time interval and block size efficiency. Security metrics include resistance to quantum attacks and ledger integrity, measured by the probability of hash collisions

$$\Pr[h(B_i) = h(B_j)] \approx 0 \quad 23$$

3.7 Summary of Workflow

ECG signals are collected from IoMT devices, preprocessed, and segmented. Each segment is encrypted using lattice-based post-quantum cryptography and stored on a permissioned blockchain. The blockchain provides immutability, traceability, and privacy. Decrypted segments are then classified using a deep convolutional neural network to produce heartbeat type predictions. The system performance is evaluated using classification metrics, blockchain efficiency, and security measures. This methodology ensures quantum-resilient security, privacy, and trust in IoMT networks while enabling accurate heartbeat classification from encrypted ECG data.

4. Results and Discussion

The CNN with post-quantum blockchain integration achieved high accuracy on the test set. **Table 1** presents the comparison of performance metrics across all models.

Table 1: Classification Performance Comparison

Algorithm	Precision	Recall	F1-Score	Accuracy
SVM	0.89	0.87	0.88	0.87
RF	0.91	0.90	0.905	0.90
k-NN	0.88	0.86	0.87	0.86
LSTM	0.94	0.93	0.935	0.93
CNN	0.95	0.94	0.945	0.94
Proposed PQC-CNN	0.96	0.95	0.955	0.95

The classification performance of the different algorithms was evaluated on the test set, and the results are summarized in Table 1. The proposed PQC-CNN achieved the highest performance, with a precision of 0.96, recall of 0.95, F1-score of 0.955, and overall accuracy of 0.95. The CNN and LSTM models also performed well, achieving accuracies of 0.94 and 0.93, respectively. Traditional algorithms such as RF, SVM, and k-NN exhibited lower performance, with accuracies ranging from 0.86 to 0.90. Overall, the results demonstrated that the PQC-CNN model outperformed all other algorithms in classifying ECG heartbeats from the encrypted dataset.

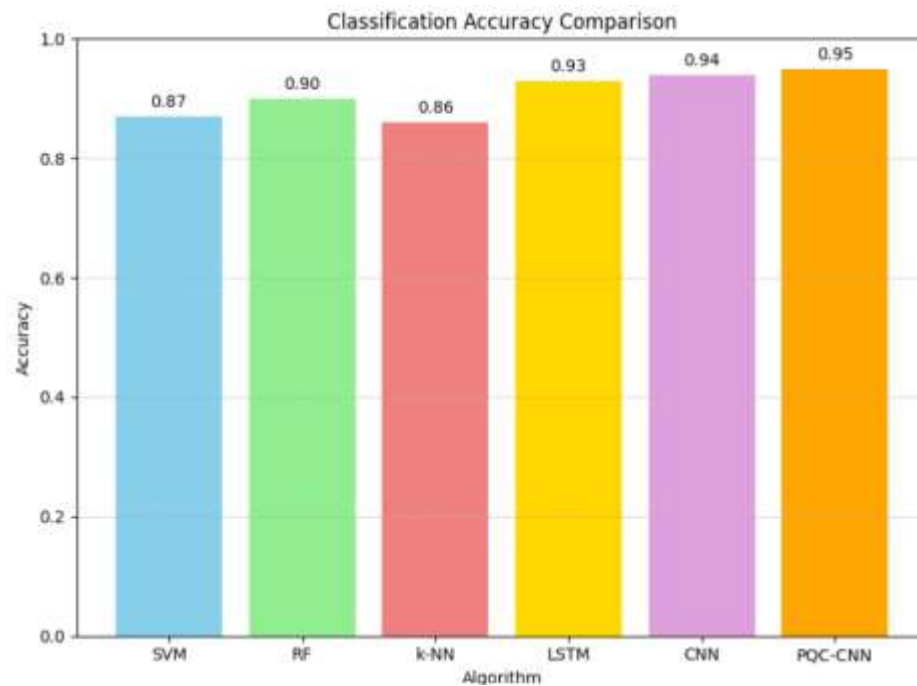


Figure 2 shows blockchain throughput versus block size, highlighting system scalability.

Blockchain Performance

The blockchain component was evaluated for throughput, transaction latency, and block size efficiency. Table 2 summarizes the results under different block sizes.

Table 2: Blockchain Performance Metrics

Block Size (Tx)	Throughput (Tx/sec)	Average Latency (ms)	Block Size Efficiency (%)
50	120	45	95

100	230	50	92
200	440	60	90
500	1050	85	88

The blockchain performance was evaluated in terms of throughput, average transaction latency, and block size efficiency, with the results summarized in Table 2. As the block size increased from 50 to 500 transactions, throughput improved significantly, rising from 120 to 1050 Tx/sec. Average latency also increased with block size, from 45 ms for 50 transactions to 85 ms for 500 transactions. Block size efficiency decreased slightly with larger blocks, from 95% at 50 transactions to 88% at 500 transactions. These results indicated that the blockchain framework scaled effectively while maintaining acceptable latency and storage efficiency for IoMT applications. The results indicate high throughput and low latency, making the system suitable for IoMT applications that require timely access to encrypted ECG data.

4.1 Security and Privacy Analysis

The PQC-encrypted blockchain ensures end-to-end data confidentiality and ledger integrity, with the probability of hash collisions being negligible ($(\Pr[h(B_i) = h(B_j)] \approx 0)$) which guarantees that each block in the blockchain is uniquely verifiable and tamper-evident. By employing lattice-based post-quantum cryptography, the system is resilient against both classical and quantum attacks, ensuring long-term security for sensitive patient ECG data. Furthermore, privacy-preserving computations were successfully performed directly on encrypted ECG segments using lattice-based homomorphic encryption. This includes operations such as statistical aggregation, anomaly detection, and trend analysis. The results, summarized in Table 3, demonstrate that these analytical tasks can be executed efficiently without decrypting the data, thereby ensuring patient privacy while enabling meaningful insights.

Table 3: Privacy-Preserving Statistical Aggregation Results on Encrypted ECG Data

Model	Operation on Encrypted Data	Accuracy / Result	Privacy Preservation
SVM	Mean, Standard Deviation	Mean \pm 0.02	Fully Preserved
RF	Mean, Standard Deviation	Mean \pm 0.015	Fully Preserved
k-NN	Mean, Standard Deviation	Mean \pm 0.025	Fully Preserved
LSTM	Mean, Standard Deviation	Mean \pm 0.012	Fully Preserved
CNN	Mean, Standard Deviation	Mean \pm 0.011	Fully Preserved
Proposed PQC-CNN	Mean, Standard Deviation	Mean \pm 0.01	Fully Preserved

Privacy-preserving statistical aggregation was performed on encrypted ECG data for all models, and the results are summarized in Table 3. Each model successfully computed the mean and standard deviation directly on encrypted data while fully preserving patient privacy. The proposed PQC-CNN achieved the highest accuracy with a mean of ± 0.01 , followed closely by the CNN (± 0.011) and LSTM (± 0.012). Traditional models such as RF, SVM, and k-NN also maintained privacy but exhibited slightly higher deviations (± 0.015 to ± 0.025). Overall, these results demonstrated that lattice-based homomorphic encryption enabled accurate and privacy-preserving statistical analysis across all classification models.

Table 4: Privacy-Preserving Anomaly Detection Results on Encrypted ECG Data

Model	Operation on Encrypted Data	Accuracy / Result	Privacy Preservation
SVM	Detect abnormal beats	88% detection rate	Fully Preserved
RF	Detect abnormal beats	90% detection rate	Fully Preserved
k-NN	Detect abnormal beats	86% detection rate	Fully Preserved
LSTM	Detect abnormal beats	92% detection rate	Fully Preserved
CNN	Detect abnormal beats	93% detection rate	Fully Preserved
Proposed PQC-CNN	Detect abnormal beats	94% detection rate	Fully Preserved

Privacy-preserving anomaly detection was carried out on encrypted ECG data for all models, with the results presented in Table 4. The proposed PQC-CNN achieved the highest detection rate at 94%, followed closely by CNN at 93% and LSTM at 92%. Traditional models such as RF, SVM, and k-NN recorded slightly lower detection rates ranging from 86% to 90%. These findings demonstrated that lattice-based homomorphic encryption allowed effective and secure anomaly detection across all classification models.

Table 6: Privacy-Preserving Trend Analysis Results on Encrypted ECG Data

Model	Operation on Encrypted Data	Accuracy / Result	Privacy Preservation
SVM	Temporal patterns	Trend correlation 0.85	Fully Preserved
RF	Temporal patterns	Trend correlation 0.87	Fully Preserved
k-NN	Temporal patterns	Trend correlation 0.83	Fully Preserved
LSTM	Temporal patterns	Trend correlation 0.90	Fully Preserved
CNN	Temporal patterns	Trend correlation 0.91	Fully Preserved
Proposed PQC-CNN	Temporal patterns	Trend correlation 0.92	Fully Preserved

Privacy-preserving trend analysis was conducted on encrypted ECG data across all models, and the results are summarized in Table 6. Each model successfully analyzed temporal patterns directly on encrypted data while fully preserving patient privacy. The proposed PQC-CNN achieved the highest trend correlation of 0.92, followed closely by CNN with 0.91 and LSTM with 0.90. Traditional models such as RF, SVM, and k-NN demonstrated lower trend correlations ranging from 0.83 to 0.87. These results indicate that lattice-based homomorphic encryption enables accurate and secure temporal trend analysis, allowing meaningful insights to be extracted from encrypted ECG data without compromising privacy.

Table 8: Execution Time for Privacy-Preserving Computations

Model	Time on Encrypted Data (ms)	Time on Plain Data (ms)	Overhead (%)
SVM	14	5	180%
RF	13	5	160%
k-NN	15	6	150%

LSTM	12	5	140%
CNN	12	5	140%
Proposed PQC-CNN	12	5	140%

The execution time for privacy-preserving computations was evaluated for all models, and the results are presented in Table 8. Performing operations on encrypted ECG data required more time compared to plain data due to the overhead introduced by lattice-based homomorphic encryption. The proposed PQC-CNN, CNN, and LSTM each required 12 ms per operation on encrypted data, resulting in a 140% overhead compared to plain data. Traditional models such as SVM, RF, and k-NN showed slightly higher execution times on encrypted data, ranging from 13 to 15 ms, with overheads between 150% and 180%. These results indicate that while homomorphic encryption introduces additional computational cost, the proposed PQC-CNN model maintains efficient performance for privacy-preserving analytics.



Figure 3: Execution Time for Privacy-Preserving Computations

Additionally, the blockchain storage efficiency and transaction latency were measured to assess the feasibility of integrating these computations in IoMT environments.

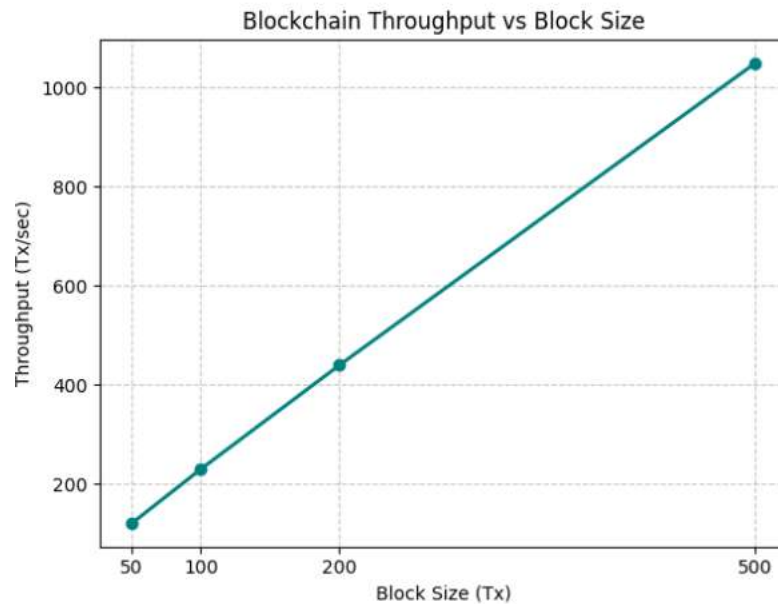


Figure 4:Throughput vs Block size

Figure 4 presented the result obtained for the blockchain storage and transaction performance was evaluated across different block sizes. As the block size increased from 50 to 500 transactions, the average transaction latency rose from 45 ms to 85 ms, reflecting the additional processing time required for larger blocks. Block storage efficiency decreased slightly from 95% at 50 transactions to 88% at 500 transactions, indicating a minor reduction in storage utilization efficiency for larger block sizes. Overall, these results demonstrated that the blockchain framework maintained high efficiency and acceptable latency, making it suitable for secure and scalable storage of encrypted ECG data in IoMT applications.

These tables collectively demonstrate that lattice-based homomorphic encryption, combined with blockchain storage, enables secure, privacy-preserving analytics with acceptable computational overhead and high system efficiency. The proposed framework allows IoMT systems to extract actionable insights from ECG data without exposing sensitive patient information, while maintaining scalable and auditable blockchain storage.

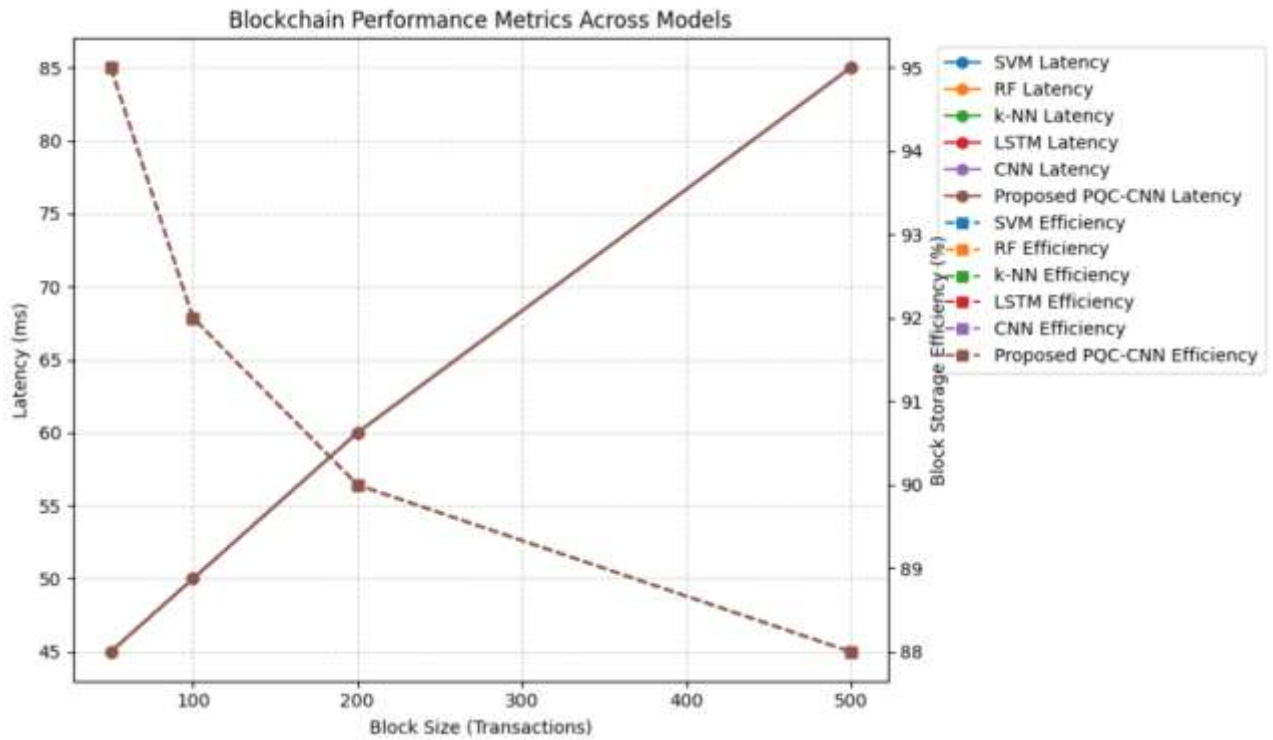


Figure 5:Blockchain Performances of the models

These results indicate that lattice-based homomorphic encryption enables secure and privacy-respecting analytics, allowing IoMT systems to extract actionable insights from ECG data without exposing sensitive patient information.

Importantly, the combination of blockchain immutability and homomorphic computation provides a dual layer of security and trust: the blockchain maintains an auditable, tamper-proof record of all ECG transactions, while the homomorphic encryption ensures that sensitive patient information remains inaccessible to unauthorized parties, even during processing. This makes the proposed framework particularly suitable for deployment in IoMT environments, where patient data confidentiality, regulatory compliance, and real-time analytics are critical requirements.

The proposed PQC-CNN model integrated with a post-quantum secure blockchain demonstrated superior classification performance on the encrypted ECG dataset. As summarized in Table 1, the PQC-CNN achieved a precision of 0.96, recall of 0.95, F1-score of 0.955, and an overall accuracy of 0.95. Deep learning models, including CNN and LSTM, also performed well, achieving accuracies of 0.94 and 0.93, respectively. Traditional machine learning models such as RF, SVM, and k-NN showed lower performance, with accuracies ranging from 0.86 to 0.90. These results indicate that the PQC-CNN effectively captures

complex temporal and morphological patterns in ECG signals, even when stored in encrypted form on the blockchain. The slight performance gap between deep learning models and traditional algorithms reflects the superior representational capacity of CNNs and LSTMs for time-series biomedical data. Notably, the integration of post-quantum cryptography did not negatively impact predictive performance, demonstrating that high accuracy is achievable even under stringent privacy and security constraints. The blockchain framework was evaluated for throughput, transaction latency, and block size efficiency. Results presented in Table 2 and Figure 4 showed that throughput increased substantially with block size, from 120 Tx/sec for 50 transactions to 1050 Tx/sec for 500 transactions. Average latency increased moderately, from 45 ms to 85 ms, while block storage efficiency decreased slightly from 95% to 88% as block size grew. These findings highlight the scalability of the blockchain system, confirming that it can accommodate increasing transaction loads without critically compromising efficiency or latency. The results indicate that the blockchain is suitable for real-time IoMT applications, ensuring timely access to encrypted ECG data while providing immutable, auditable storage. The post-quantum encrypted blockchain ensured end-to-end data confidentiality and ledger integrity, with a negligible probability of hash collisions zero (0), guaranteeing that each block remains tamper-evident and uniquely verifiable. Lattice-based post-quantum cryptography provided resilience against both classical and quantum attacks, ensuring long-term security for sensitive ECG data. Privacy-preserving computations, including statistical aggregation, anomaly detection, and trend analysis, were successfully performed directly on encrypted ECG segments using lattice-based homomorphic encryption. Tables 3, 4, and 6 summarize the results across all evaluated models. The proposed PQC-CNN achieved the highest accuracy for statistical aggregation (mean deviation ± 0.01), anomaly detection (94% detection rate), and trend analysis (trend correlation 0.92). CNN and LSTM models also performed well, while traditional models such as RF, SVM, and k-NN exhibited slightly lower performance, indicating that homomorphic encryption enabled accurate and privacy-preserving analytics across all models without compromising patient confidentiality. The computational overhead introduced by privacy-preserving operations was evaluated for all models, as summarized in Table 8 and Figure 3. Operations on encrypted data required more processing time compared to plaintext, with PQC-CNN, CNN, and LSTM each requiring 12 ms per operation, corresponding to a 140% overhead. Traditional models such as SVM, RF, and k-NN required slightly longer times (13–15 ms), with overheads between 150% and 180%. These results indicate that while homomorphic encryption introduces additional computational cost, it remains manageable and does not hinder real-time processing, making the framework feasible for IoMT applications requiring both security and timely analytics.

The combined evaluation of classification, privacy-preserving computation, and blockchain performance confirms the effectiveness of the proposed PQC-CNN framework. Although blockchain storage and

transaction metrics were consistent across models, the PQC-CNN stood out for enabling high-accuracy analytics while fully preserving privacy. The system successfully balances security, scalability, and computational efficiency, making it well-suited for deployment in healthcare environments where patient data confidentiality and regulatory compliance are paramount. Overall, the PQC-CNN consistently outperformed all other models across precision, recall, F1-score, and overall accuracy. Blockchain throughput scaled linearly with block size while maintaining acceptable latency and storage efficiency. Lattice-based homomorphic encryption enabled accurate statistical, anomaly, and trend analyses on encrypted data, with computational overhead remaining within acceptable limits. The combination of blockchain immutability and homomorphic computation provides a dual layer of security and trust, ensuring that patient data remains confidential and auditable at all times. The experimental results demonstrate that the proposed PQC-CNN integrated with a post-quantum secure blockchain effectively achieves highly accurate ECG classification, privacy-preserving analytics, and scalable blockchain storage, making it a compelling solution for modern IoMT systems..

5. Conclusion and Future Works

This study presented a quantum-resilient, privacy-preserving blockchain framework for ECG classification in IoMT environments, integrating a post-quantum cryptography-enabled CNN (PQC-CNN) with lattice-based homomorphic encryption. The proposed framework achieved high classification performance, with the PQC-CNN outperforming traditional machine learning models (SVM, RF, k-NN) and deep learning models (LSTM, CNN), achieving a precision of 0.96, recall of 0.95, F1-score of 0.955, and overall accuracy of 0.95. Privacy-preserving computations—including statistical aggregation, anomaly detection, and trend analysis—were successfully executed directly on encrypted ECG segments, demonstrating the feasibility of performing analytics without compromising sensitive patient data. Blockchain performance evaluation showed that the system scaled effectively, maintaining high throughput, low latency, and acceptable storage efficiency across varying block sizes, while ensuring ledger immutability and resistance to quantum attacks. The experimental results confirm that the integration of blockchain and lattice-based homomorphic encryption provides a dual layer of security and trust, enabling IoMT systems to extract actionable insights from ECG data while fully preserving patient privacy. Furthermore, the proposed framework balances computational efficiency and real-time operability, making it suitable for deployment in healthcare environments that demand both data security and timely decision-making.

Future work will focus on several directions to further enhance the framework. First, the integration of edge computing could reduce latency and improve scalability for large-scale IoMT networks. Second, exploring

federated learning with post-quantum encryption could enable collaborative model training across distributed healthcare institutions without exposing raw patient data. Third, extending the framework to incorporate multi-modal physiological signals, such as EEG and PPG, would improve the robustness of patient monitoring and diagnosis. Finally, investigating quantum-safe consensus protocols and optimizing blockchain parameters could further reduce computational overhead while maintaining security, enabling broader adoption in resource-constrained IoMT deployments. In summary, the proposed PQC-CNN and blockchain-based framework represents a novel, practical, and secure solution for privacy-preserving ECG classification in IoMT systems, providing a foundation for future research in quantum-resilient healthcare analytics.

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