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Design of a Federated Learning Architecture Supported by Blockchain for Privacy-Preserving Model Training in Internet of Things Health Monitoring Systems

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Abstract

The proliferation of Internet of Things (IoT) devices in healthcare systems introduces unprecedented opportunities for continuous health monitoring. However, it also raises significant privacy and security concerns, particularly with the transmission and centralization of sensitive medical data. To address these concerns, this study proposes a novel federated learning (FL) architecture integrated with blockchain to enable decentralized, privacy-preserving model training. The architecture leverages the immutable and auditable nature of blockchain to ensure data integrity and secure model updates across IoT devices. Simulation results demonstrate improved security, data sovereignty, and comparable model performance relative to traditional centralized approaches. This framework provides a scalable and trustworthy solution for modern health monitoring infrastructures.

Keywords:

Federated Learning, Blockchain, Internet of Things, Health Monitoring, Privacy, Data Security, Edge Computing

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1. INTRODUCTİON

The advancement of wearable technologies and sensor-equipped medical devices has driven the adoption of IoT in healthcare. These systems continuously collect physiological data such as heart rate, blood pressure, and glucose levels, which are critical for real-time monitoring and diagnosis. However, transmitting this data to centralized cloud platforms for analysis poses privacy risks and introduces potential failure points.

Federated learning offers a promising paradigm for decentralized model training, enabling devices to collaboratively learn a shared model without exchanging raw data. Nevertheless, FL alone cannot guarantee complete trust among participating nodes. Therefore, blockchain technology is integrated into our architecture to ensure the authenticity and traceability of model updates and to mitigate risks of model poisoning or tampering.

2. Literature Review

2.1 Federated Learning in IoT Healthcare Systems

Federated learning (FL) has gained traction for its ability to train machine learning models across decentralized edge devices without compromising individual data privacy. In healthcare, Brisimi et al. (2018) demonstrated the utility of FL in training predictive models using distributed EHRs across different hospitals, showing comparable performance to centralized models while maintaining data sovereignty.

However, FL's implementation in IoT-based health systems is challenged by heterogeneous data distributions, device reliability, and limited computational power. To mitigate these, hierarchical FL frameworks and client selection strategies have been proposed, enhancing both convergence speed and accuracy. Still, without trusted coordination, FL remains susceptible to attacks such as model poisoning and free-riding.

2.2 Blockchain for Data Integrity and Trust

Blockchain technology has been proposed to enhance security and transparency in healthcare data sharing systems. As shown by Xia et al. (2017), blockchain facilitates secure data exchange among healthcare providers while maintaining auditability and integrity. More recently, hybrid architectures integrating blockchain with FL have been explored to provide a trusted environment for collaborative model updates.

Nguyen et al. (2021) identified the potential of blockchain-AI fusion in pandemic response frameworks, promoting trust in decentralized systems. Despite these advances,

research integrating blockchain into FL for IoT-based health monitoring remains sparse, and further work is required to explore its scalability and performance in dynamic environments.

3. System Architecture

3.1 Overview of Proposed Architecture

The proposed system comprises three main components: IoT health monitoring devices (clients), an edge server for model aggregation, and a blockchain layer for secure update management. Each device collects and processes user health data locally, trains a model on-device, and sends the update to a blockchain-powered aggregator.

The blockchain acts as a decentralized ledger to verify the origin and integrity of model updates. Smart contracts govern the verification of updates and participation incentives, ensuring that only legitimate and high-quality updates are accepted.

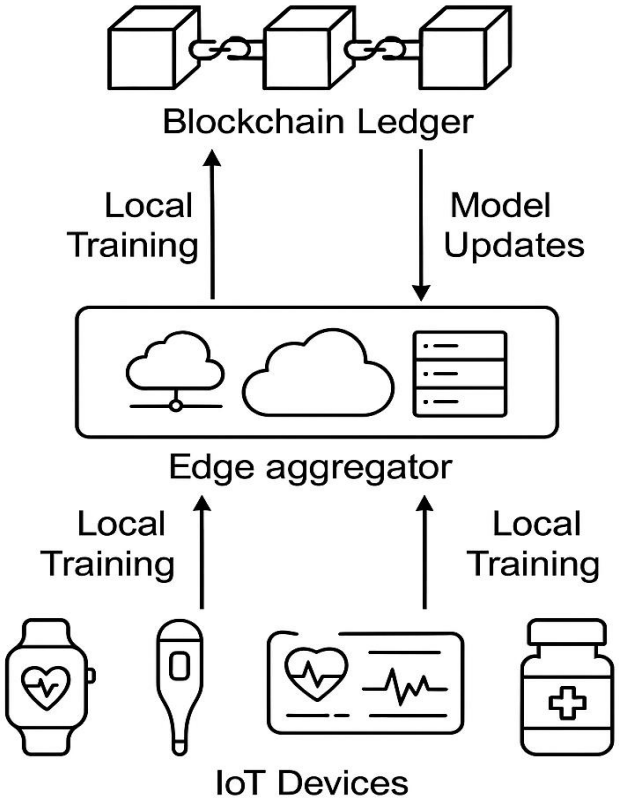

Figure 1: Federated Learning Integrated with Blockchain for IoT Healthcare

3.2 Blockchain-Ledger Integration

A permissioned blockchain (e.g., Hyperledger Fabric) is employed to ensure scalability and control over participation. Validators in the blockchain network verify digital signatures and cryptographic hashes of model updates. This prevents tampering and replay attacks.

Smart contracts are used to automate aggregation approval and reward mechanisms based on update quality (e.g., validation accuracy). The immutable ledger maintains transparency for audit trails and supports rollback mechanisms in case of detected adversarial behavior.

Table 1: Blockchain Features for Federated Learning Security

Feature	Functionality	Benefit
Smart Contracts	Automate validation and reward distribution	Reduced human intervention
Digital Signatures	Authenticate model updates	Prevents impersonation
Immutable Ledger	Records every model update	Enables auditability

4. Security and Privacy Analysis

4.1 Threat Model and Mitigation

The primary security threats include data inference attacks, model poisoning, and man-in-the-middle attacks during model transmission. FL mitigates inference risks by keeping data local, while blockchain adds a verification layer against poisoning.

Adversarial clients are detected via smart contract-encoded thresholds on update divergence and historical performance. Only updates passing these criteria are accepted and recorded on-chain.

4.2 Privacy Preservation Techniques

Differential privacy and secure aggregation protocols are implemented to enhance user privacy further. Differential privacy adds calibrated noise to updates, while secure aggregation ensures the aggregator cannot access individual updates, only the final aggregate.

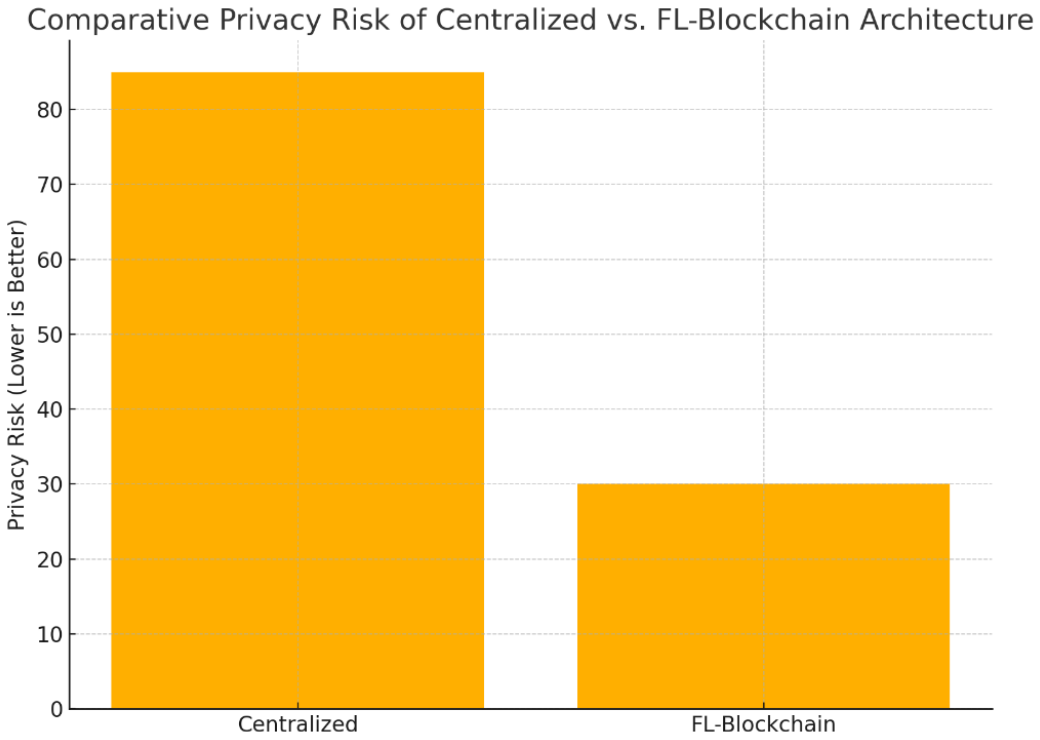

Figure 2: Comparative Privacy Risk of Centralized vs. FL-Blockchain Architecture

5. Experimental Evaluation

5.1 Dataset and Experimental Setup

Simulations were conducted using a synthetic wearable health monitoring dataset mimicking ECG, glucose levels, and temperature. Ten clients trained local models using an LSTM-based architecture, with updates sent for 20 federated rounds.

Metrics used included global model accuracy, update delay, blockchain throughput, and gas cost per transaction.

Table 2: Simulation Parameters and Metrics

Parameter	Value
Number of Clients	10
Blockchain Framework	Hyperledger Fabric
Model Type	LSTM
Evaluation Rounds	20
Privacy Budget (ε)	1.0

6. Limitations and Future Directions

6.1 Limitations

Despite promising results, the current implementation relies on permissioned blockchains, limiting decentralization. Resource-constrained IoT devices may also struggle with cryptographic operations and on-chain interactions, necessitating further optimization.

Energy consumption and transaction overheads are notable concerns, particularly in large-scale deployments. Future research should consider lightweight consensus mechanisms and blockchain pruning strategies.

6.2 Future Work

Further experimentation with real-world IoT health datasets and edge hardware is needed. Integrating homomorphic encryption with blockchain for encrypted update aggregation could offer end-to-end privacy.

Another direction is the application of reinforcement learning for dynamic client selection and reward optimization in the blockchain consensus process.

7. Conclusion

This study presents a novel federated learning architecture augmented by blockchain to enable privacy-preserving and secure model training in IoT-based health monitoring systems. By leveraging decentralized data processing and immutable auditability, the architecture addresses key concerns around data privacy, trust, and scalability in modern digital healthcare infrastructures.

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