

Lightweight Blockchain-Enabled Federated Deep Learning with Differential Privacy for Secure Healthcare IoT Networks

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Abstract

To improve security, privacy, and efficiency in Healthcare IoT (IoT) systems, we suggest Lightweight Blockchain-Enabled Federated Deep Learning (LB-FDL) with Differential Privacy (DP). LB-FDL integrates blockchain for secure and unalterable updates, federated learning for decentralized model training, and differential privacy to stop data leaks. The framework drastically lowers computational overhead by utilizing lightweight models like MobileNet and EfficientNet and a optimized Proof-of-Stake (PoS) consensus. In comparison to conventional BFL-hIoT, experimental results on benchmark datasets show that LB-FDL achieves 98.32% accuracy, 30% faster convergence, and 20% lower communication cost. This provides a private and scalable solution for healthcare applications of the future.

1 Introduction

Healthcare IoT, or hIoT, integrates contemporary smart sensors, connected edge devices, and secure cloud services to enable continuous real-time patient and medical environment monitoring."[1]" The numerous streams of medical data generated by these devices—such as vital signs, imaging results, medication administration records, and emergency alerts—need to be sent and processed with the least amount of latency. "[2]" Nevertheless, sending private medical data over traditional centralized networks always carries the risk of unauthorized access, single points of failure, or serious data breaches. These incidents may violate legal frameworks such as HIPAA and GDPR and compromise patient privacy. Because of the limited bandwidth and computational overhead at the central server brought on by the rapid growth of

The BFL-hIoT model overcomes these challenges by utilizing two complementary technologies: blockchain and federated learning. Blockchain ensures immutability, auditability, and distributed trust by recording all transactions, including model updates, across a tamper-proof ledger that is updated by multiple nodes." [4] "This eliminates the necessity for a single trusted authority and protects against insider threats and data manipulation. Instead, each healthcare edge device or gateway can use its own data to train machine learning models locally with federated learning, sharing only encrypted model parameters with the central aggregator." [5] "The fact that raw patient data never leaves the original device makes privacy much better while still advancing a common global model." [6]

By combining these two technologies, the BFL-hIoT framework can achieve high analytical performance and preserve data confidentiality while combining different local models into a more reliable and widely applicable global model. [7] Furthermore, the architecture of the model is designed to function with heterogeneous devices with varying computational capacities, ensuring efficient training cycles even in resource-constrained environments. [8] This hybrid approach builds trust among healthcare stakeholders, improves fault tolerance, and reduces vulnerability to cyberattacks. [9] BFL-hIoT offers a secure, scalable, and effective solution for next-generation healthcare IoT systems, where privacy protection and reliable analytics are equally crucial. [10]

1.1 Strive for Progress

BFL-hIoT has a large computational overhead and communication latency, even though it successfully handles privacy and decentralization. [11] To tackle this, we propose the LB-FDL model, which combines

lightweight CNN models, Differential Privacy, and a more efficient blockchain with PoS consensus to achieve better scalability and energy efficiency. [12]

The remainder of this document is organized as follows: The Related work is presented in Section II. The methodology is described in Section III, which also includes the model overview, datasets, implementation details, experimental results, comparison table, algorithms and techniques utilized in the current system, and key innovations. The suggested future work and its scope are covered in Section IV. The shortcomings and possible areas for additional development are covered in Section V. Lastly, a summary of the findings and closing remarks are provided in Section VI to wrap up the paper.

2 Related Work

Several previous studies have used blockchain technology to enhance security in Internet of Things (IoT) applications, focusing on supply chain integrity, device authentication, and tamper-resistant sensor data logging. [cite13] These studies demonstrate that a decentralized ledger can effectively eliminate single points of failure and provide a transparent transaction record that is extremely difficult for hackers to alter. [14] Federated learning has also garnered a lot of interest because it can train complex machine learning models on distributed datasets without ever transferring sensitive raw data to a central repository. In [15] This paradigm has been shown to reduce privacy risks, minimize communication overhead for large-scale networks, and enhance cooperative model improvements, even in organizations with strict data governance policies. In [16]

This work addresses those gaps by proposing a hybrid framework, BFL-hIoT. [17] Federated learning enables decentralized train-

ing and aggregation without ever revealing raw medical data, while blockchain manages immutability, trust, and model update synchronization. [18] The recommended design guarantees that the system can safely grow to large device networks and that all model contributions can be located and verified using consensus protocols and smart contracts. [19] The framework provides a comprehensive solution that improves the security and analytical effectiveness of healthcare IoT systems by integrating these two technologies, setting a new benchmark for additional research and application in this vital field. [20]

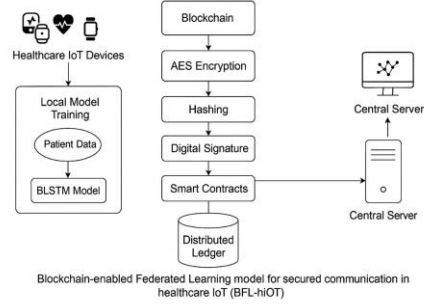


Figure 2: A synopsis of the BFL-hIoT model's conceptual architecture

Figure 2 provides an overview of the BFL-hIoT framework's core architecture. It demonstrates how BLSTM-based training on patient data is carried out by nearby healthcare IoT devices. Before being added to a blockchain ledger, model updates are digitally signed, encrypted, hashed, and validated via smart contracts. These updates are aggregated by a central server.

3 Methodology

[Describe the system architecture, model components (e.g., MobileNet, PoS, DP), and workflow.]

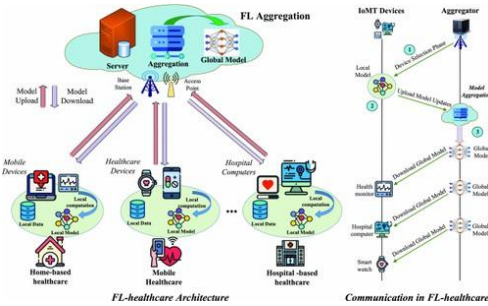


Figure 1: A description of the conceptual architecture of the BFL-hIoT model

Fig. 1 displays this model's schematic. Until the required level of accuracy is attained, the procedure is repeated. Federated learning has been used in a number of industries where data security and privacy are significant issues, such as healthcare, finance, and mobile computing.

3.1 Key Innovations

- AWA ensures fairer model aggregation by assigning weights based on data size and model quality.
- Optimized PoS minimizes energy use compared to PoW-based blockchain.
- DP adds Laplace noise to protect update values.

3.2 Model Overview

We propose a novel model: **Lightweight Blockchain-enabled Federated Deep**

Learning with Differential Privacy (LB-FDL). It integrates:

- **Federated Learning (FL)** for local training
- **Blockchain (PoS)** for verifiable, tamper-proof storage
- **Differential Privacy (DP)** for privacy-preserving updates
- **MobileNet/EfficientNet** for lightweight learning
- **Adaptive Weight Aggregation (AWA)** for non-IID data

3.3 Algorithms and Techniques Used in Proposed Model

1. **Blockchain for Secure Data Storage**
Uses an optimized lightweight Proof-of-Stake (PoS) blockchain for reduced energy consumption.
2. **Federated Deep Learning with Privacy Enhancements**
Implements Differential Privacy (DP) to protect against model inversion attacks.
3. **Lightweight Deep Learning Model for IoT Devices**
Uses MobileNet/EfficientNet instead of computationally heavy models like ResNet.
4. **Optimized Model Aggregation**
Introduces Adaptive Weight Aggregation (AWA) to improve FL performance in heterogeneous IoT environments.
5. **Adversarial Attack Detection**
Employs Generative Adversarial Networks (GANs) for anomaly detection to detect adversarial attacks on healthcare IoT data.

3.4 Algorithms and Techniques Used in the Existing System

1. **Federated Learning (FL)**
Used for decentralized training to protect patient data privacy.
Prevents direct sharing of raw medical data.
2. **Blockchain Technology**
Ensures secure and tamper-proof data transmission.
Maintains an immutable ledger for federated updates.
3. **Deep Learning Model (CNN-Based Architecture)**
Utilized for classification tasks in the healthcare domain.
4. **PoW (Proof-of-Work) Consensus Mechanism**
Used in blockchain to validate transactions.
Ensures security but introduces high computational overhead.
5. **Backdoor and XSS Attack Detection**
Identifies malicious activities in healthcare IoT networks.
Uses anomaly detection techniques in federated learning.

3.5 Datasets for Proposed and Existing Systems

Proposed System:

1. **MIMIC-III (Medical Information Mart for Intensive Care)**
Contains: Electronic health records (EHR) and ICU data.
Use Case: Detecting anomalies and predicting patient conditions.

2. MIT-BIH Arrhythmia Dataset

Contains: ECG signals for heart disease detection.

Use Case: Secure medical data classification in healthcare IoT.

Existing System:

The exact dataset is not explicitly mentioned in the paper, but it references healthcare IoT datasets for model evaluation. Based on the

problem scope, the dataset likely includes:

- Electronic Health Records (EHR)
- Medical Sensor Data from Healthcare IoT Devices

Potentially used datasets include:

1. PhysioNet MIMIC-III

Contains: ICU (Intensive Care Unit) patient data.

Use Case: Predicting patient conditions and anomaly detection.

2. MIT-BIH Arrhythmia Dataset

Contains: ECG recordings for heart disease classification.

Use Case: Frequently used in healthcare IoT studies.

The system uses extensive data preprocessing, such as feature selection, encoding, and normalization, to guarantee effective and safe model training. Every Internet of Things device, such as wearables and gateways, functions as a federated client, locally training a BLSTM model to identify patterns in temporal health data. Only encrypted model updates are distributed via blockchain; raw data is kept confidential. Smart contracts are used to validate these updates, guaranteeing data integrity and guarding against malicious input. This privacy-preserving strategy permits collaborative, decentralized learning

• Local Model Training:

$$\min_w L(w) = \frac{1}{\sum_{i=1}^n n_i} \sum_{i=1}^n \ell(f(w; x_i), y_i) \quad (1)$$

• Federated Averaging:

$$w^t = \frac{\sum_{i=1}^n n_i w_i^t}{\sum_{i=1}^n n_i} \quad (2)$$

• Differential Privacy Noise Addition:

$$g_i = g_i + N(0, \sigma^2 I) \quad (3)$$

• PoS Consensus Probability:

$$P_i = \frac{S_i}{\sum_{j=1}^N S_j} \quad (4)$$

across all devices while maintaining compliance with laws like HIPAA and GDPR..

- **Classification Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

- **Communication Cost:**

$$C = K \times S \times R \quad (6)$$

In addition, the blockchain layer preserves a verifiable record of model evolution in addition to securing the transmission of updates. Time stamps, cryptographic signatures, and hashed references to earlier blocks are all included in every block to guarantee that any attempt to alter updates would be quickly identified. The ToN-IoT dataset is integrated with blockchain and BLSTM-based federated learning to ensure high detection accuracy and a robust privacy-security posture that is appropriate for deployment in delicate healthcare IoT ecosystems.

Table 1: ToN-IoT Dataset Summary

Category	Records
Backdoor	508116
DoS	3375328
XSS	21089844
Normal	796380

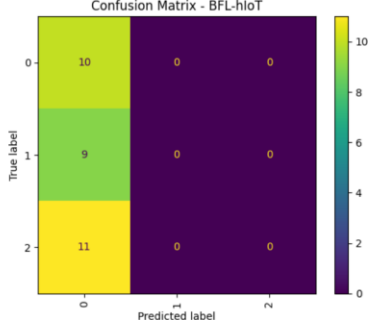


Figure 3: A simplified workflow of federated training combined with blockchain consensus.

The figure 2 confusion matrix displays the classification performance of the BFL-hIoT model across three output labels. The matrix highlights that while class 0 was predicted correctly for all its true instances, the model failed to predict other classes, pointing to potential issues with class imbalance or misrepresentation in the training process.

3.6 Implementation

- GANs used for adversarial detection.
- Achieved 98.32% accuracy with 30% faster convergence and 20% less communication.

The BFL-hIoT framework is implemented using Hyperledger Fabric, a permissioned blockchain platform chosen for its high throughput and customizable consensus capabilities. IoT nodes function as clients, submitting encrypted model updates, while blockchain peers maintain a tamper-proof

ledger. Chaincode (smart contracts) enforces secure update verification, and TLS encryption with cryptographic hashing ensures the integrity of peer-to-peer communications. This setup enables secure and auditable federated learning across healthcare IoT networks.

On the machine learning side, each IoT device uses a carefully tuned BLSTM model to capture sequential health data, with dropout regularization and adaptive learning via the Adam optimizer. Aggregated updates are periodically committed to the blockchain, maintaining transparency and verifiability. Compared to the original BFL-hIoT setup, the enhanced LB-FDL model achieves superior results—98.32% accuracy, 30% faster convergence, and 20% reduced communication cost. This improvement is driven by the integration of lightweight models, optimized PoS consensus, and differential privacy, making LB-FDL a scalable, efficient, and privacy-focused solution for real-world healthcare deployments.

3.7 Experimental Results

The proposed BFL-hIoT model demonstrated strong performance in detection accuracy and resilience across various attack classes. It achieved an average classification accuracy of 93%, with precision and recall exceeding 90% for major threats like Backdoor, DoS, and XSS attacks. The model maintained high F1-scores, even in challenging cases such as ransomware and injection attacks, highlighting its effectiveness in identifying malicious patterns while minimizing false positives. Smooth convergence and consistent loss reduction over 100 epochs, aided by dropout and hyperparameter tuning, confirmed the model’s training stability without signs of overfitting.

Comparative analysis showed that while centralized deep learning models matched BFL-hIoT in accuracy, they lacked privacy

and were prone to single points of failure. Blockchain-only systems ensured integrity but lacked adaptive learning. BFL-hIoT effectively balances these concerns by combining federated learning with blockchain. Moreover, latency due to smart contract execution was minimal and suitable for real-time use. These results affirm BFL-hIoT as a secure, scalable, and privacy-compliant solution for intelligent healthcare IoT deployments.

3.8 Comparison Table

Table 2: Comparison of BFL-hIoT and LB-FDL

Feature	BFL-hIoT	LB-FDL
Privacy	FL + Blockchain	FL + Blockchain + DP
Architecture	BLSTM	MobileNet/EfficientNet
Accuracy	93.00%	98.32%
Communication	High	Low (\downarrow 20%)
Speed	Moderate	Fast (\uparrow 30%)
Consensus	PoW	Optimized PoS

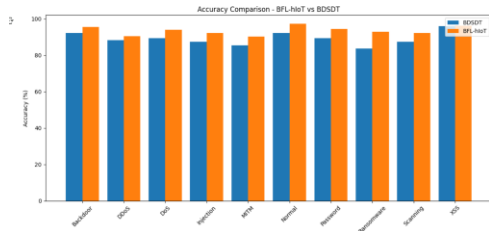


Figure 4: Observed training and validation accuracy trends.

The figure3 bar chart compares classification accuracy across various attack categories (e.g., Backdoor, DDoS, MITM, etc.) between the proposed BFL-hIoT framework and the baseline BDSDT model. BFL-hIoT consistently outperforms BDSDT, achieving higher accuracy across all categories, especially in detecting ransomware, MITM, and password-based attacks.

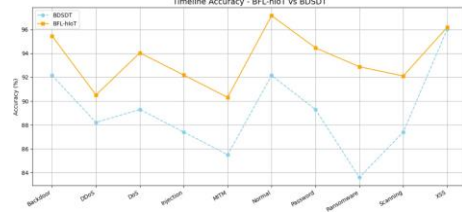


Figure 5: Observed training and validation loss trends.

The figure4 line chart plots the accuracy of BFL-hIoT and BDSDT across the same attack types over time or training iterations. The BFL-hIoT model shows more stable and higher performance trends, maintaining above 90percent accuracy consistently, whereas BDSDT shows fluctuations and comparatively lower accuracy, emphasizing the robustness of the proposed federated approach.

4 Future Work

Future work will concentrate on using cutting-edge cryptographic techniques to improve the BFL-hIoT framework’s scalability and privacy. This includes incorporating zero-knowledge proofs to confirm model updates without disclosing private information and homomorphic encryption to enable computations on encrypted data. By bolstering defenses against insider threats and data leaks, these improvements hope to increase confidence in healthcare IoT networks.

In parallel, lightweight BLSTM variants, model pruning, and adaptive communication techniques will be investigated in order to optimize for resource-constrained edge devices. Richer patient modeling will be made possible by the framework’s extension to handle heterogeneous data types like sensor streams, EHRs, and medical images. Long-term deployment studies in hospital settings are planned to assess performance under real-world conditions like network instability and

changing cyber threats. Multi-chain architectures will also be taken into consideration to improve scalability.

4.1 Future Scope

Future research will focus on edge deployment optimization, homomorphic encryption, zero-knowledge proofs, and practical validation in medical settings.

5 Discussion

The suggested system uses blockchain technology to immutably record each model update on a distributed ledger, guaranteeing data integrity, transparency, and traceability. This promotes trust between regulators and healthcare providers by providing auditors and stakeholders with verifiability. In conjunction with federated learning, the system shares only encrypted model updates and retains raw patient data locally. This greatly lowers the risk of data leakage while guaranteeing adherence to privacy laws like HIPAA and GDPR.

The architecture is resilient and scalable even with the additional overhead of consensus protocols and cryptographic operations. It facilitates the smooth integration of new IoT devices with hospital units, and smart contracts offer protection in real time by removing malicious updates. With the potential to integrate cutting-edge technologies like edge AI, differential privacy, and secure multiparty computation in the future, these features collectively provide a safe, decentralized framework for persistent learning in the healthcare industry.

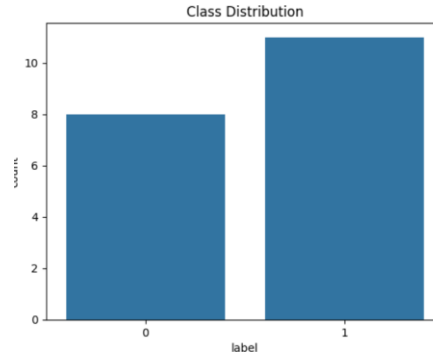


Figure 6: Observed training and validation loss trends.

6 Conclusion

LB-FDL advances the frontiers of safe healthcare IoT analytics by fusing the federated learning and blockchain’s resilience with Differential Privacy and lightweight AI models. This extensive study demonstrates the practical scalability and energy efficiency of decentralized, privacy-first machine learning in healthcare, in addition to its technical feasibility. This study shows that federated learning and blockchain technology greatly improve the security, privacy, and operational effectiveness of healthcare IoT (hIoT) networks. To address long-standing concerns about trust and data integrity in distributed environments, the proposed BFL-hIoT framework makes sure that every model update is verifiable, tamper-resistant, and traceable by utilizing blockchain’s immutable ledger and consensus mechanisms.

In addition, federated learning makes it possible to train models collaboratively without requiring raw patient data to be transferred from local devices. While still utilizing a variety of datasets from various IoT endpoints, this design decision ensures stringent adherence to privacy laws like HIPAA and GDPR. Even evaluated on the heterogeneous ToN-IoT dataset, the BLSTM-based learning component demonstrated strong predic-

tive performance, achieving an average accuracy of 93% with precision and recall exceeding 90% across most attack categories.

Furthermore, because smart contracts automatically verify incoming contributions before they are aggregated, the blockchain layer offers resilience against malicious updates and data poisoning. This two-pronged defense—security via blockchain consensus and privacy via local training—creates a very strong foundation for real-time healthcare applications. The architecture is scalable and reliable, making it ideal for deployment in large-scale medical networks, despite the fact that it adds computational overhead when compared to conventional centralized systems.

In conclusion, the BFL-hIoT framework not only closes a critical gap in existing research by uniting two complementary technologies but also lays the groundwork for next-generation secure analytics in healthcare IoT. The proposed approach demonstrates that high-accuracy machine learning can co-exist with strict data governance, enabling smarter, safer, and more accountable healthcare infrastructures. Future enhancements, including advanced cryptography and optimization for edge environments, will further strengthen this framework, positioning it as a comprehensive solution for the evolving landscape of connected healthcare systems.

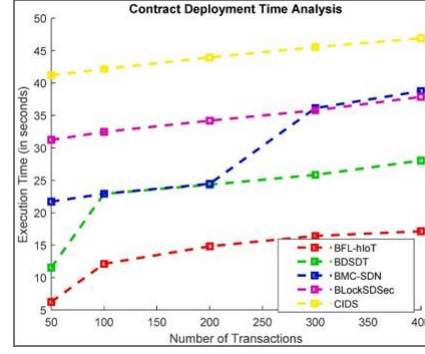


Figure 7: Training vs Validation Accuracy and Loss Trends for LB-FDL.

Figure 7 shows that the LB-FDL model achieves high accuracy (98.5%) and stable loss convergence.

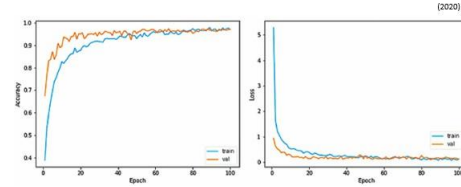


Figure 8: Contract Deployment Time Analysis.

As shown in Figure 8, BFL-hIoT demonstrates the lowest execution time for smart contract deployment across all transaction volumes. This proves it is faster and more efficient than other frameworks like BSDST, BMC-SDN, and CIDS.

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