SHIELD-Health: Secure Healthcare IoT with Energy-efficient Ledger-based Distributed Federated Learning

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ABSTRACT

Healthcare Internet of Things (HIoT) has revolutionized patient care through continuous monitoring and personalized treatment, but it introduces critical challenges in privacy protection, data security, and resource management across heterogeneous devices. Traditional centralized machine learning (ML) approaches face significant limitations due to privacy regulations and security concerns, leading to the emergence of federated learning (FL) and blockchain (BC) as complementary solutions. While FL enables collaborative model training without sharing raw data, and BC provides immutable verification and secure record management. We present SHIELD-Health, a novel framework that synergistically integrates these technologies to create a comprehensive solution for secure analytics in healthcare environments, featuring four key innovations: (1) resource-aware computation that dynamically adapts to device capabilities (2) a multi-layered privacy architecture designed for differential privacy and secure aggregation (3) Byzantine-robust aggregation ensuring model integrity under adversarial conditions, and (4) healthcare-specific optimizations including temporal attention mechanisms for physiological time-series data. Extensive evaluation demonstrates exceptional performance across multiple dimensions, maintaining high accuracy while achieving substantial communication efficiency and energy savings for resource-constrained devices. The framework also shows remarkable resilience against poisoning attacks, and robust performance under challenging non-independent and identically distributed (IID) data distributions common in healthcare scenarios. It represents a significant advancement in privacy-preserving collaborative analytics for sensitive medical applications where security, privacy, and resource constraints are paramount considerations.

1 Introduction

The proliferation of Internet of Things (IoT) devices in healthcare has revolutionized patient monitoring, treatment, and care delivery. From wearable sensors and implantable devices to stationary monitoring equipment, healthcare IoT (HIoT) systems continuously generate vast amounts of sensitive patient data that offer unprecedented opportunities for advancing medical research, improving diagnostic accuracy, and enabling personalized healthcare interventions[1]. However, this wealth of health data presents significant challenges in terms of privacy protection, secure management, and effective utilization without compromising patient confidentiality or regulatory compliance requirements[2]. These challenges are far from theoretical. Healthcare organizations face increasingly sophisticated cyber threats targeting patient data, with recent reports showing that 86% of HIoT devices contain security vulnerabilities that could be exploited by attackers[3]. Meanwhile, the resource constraints of medical IoT devices create practical barriers to implementing robust security measures, as many devices operate with limited processing power, memory, and battery capacity. These challenges between security requirements and resource limitations demand innovative approaches that can protect sensitive health information without overburdening devices that collect it.

SHIELD-Health (secure healthcare IoT with energy-efficient ledger-based distributed federated learning) rep-

resents our comprehensive response to these challenges. By combining distributed ledger technology with FL, SHIELD-Health enables secure and efficient collaborative learning in healthcare environments while keeping sensitive data localized. The framework specifically addresses the limitations of existing approaches through innovative resource-aware computation, robust privacy preservation, and advanced Byzantine fault tolerance mechanisms - all tailored to the unique constraints of healthcare IoT ecosystems.

Traditional centralized data management approaches have proven inadequate for modern healthcare applications for several compelling reasons. First, the centralization of sensitive health data creates attractive targets for cyber attacks, potentially exposing protected health information to unauthorized access[4,5]. Second, healthcare data's strict regulatory framework, including health insurance portability and accountability (HIPAA) and general data protection regulation (GDPR), imposes stringent requirements for data protection and patient consent that centralized systems struggle to satisfy[6]. Third, transferring large volumes of data from resource-constrained IoT devices to central servers introduces significant latency, bandwidth costs, and energy consumption challenges. Recent studies shows that energy consumption increases by up to 300% during data transmission[7]. Finally, the inherent heterogeneity of healthcare data, collected from diverse devices, patient populations, and clinical contexts, further complicates centralized analysis approaches[8,9].

The severity of these challenges continues to grow as healthcare IoT deployments expand. A comprehensive review by the author of[10] examined the vulnerabilities of HIoT networks to privacy breaches, finding that even anonymized healthcare data could be re-identified with 87% accuracy using modern techniques. Further, the author of[7] demonstrated that transmission of raw data to centralized servers could deplete battery resources in critical monitoring devices by up to 300% compared to distributed approaches. This creates potentially life-threatening limitations for devices monitoring vital patient parameters. Adding to these concerns, recent projections indicate healthcare data volume will reach 2,314 exabytes by 2025, far exceeding the scalability of traditional centralized architectures[11]. FL offers a promising alternative by enabling decentralized training of ML models across multiple devices or institutions without requiring data centralization[7]. This approach preserves patient privacy by ensuring sensitive data remains local while only model updates traverse the network. In healthcare contexts, FL facilitates collaborative model training across different hospitals, clinics, and research institutions, enabling the development of more accurate and robust predictive models while maintaining privacy[3]. Despite these advantages, FL still faces significant challenges in healthcare deployments, particularly regarding data heterogeneity (non-IID data) and vulnerability to model poisoning attacks that can degrade performance and compromise security[9].

The integration of BC with FL provides additional security and trust guarantees through decentralized and immutable record-keeping. BC's transparency, consensus-based verification, and tamper resistance make it particularly suitable for healthcare applications where data integrity and provenance are paramount[3]. Recent studies have demonstrated BC's effectiveness in securing healthcare data sharing, with implementations achieving 97.16% accuracy in access control while maintaining HIPAA compliance[6]. However, BC's traditionally high computational requirements present challenges when deployed on resource-constrained HIoT devices. While both FL and BC offer significant benefits, their integration in healthcare contexts remains suboptimal in existing implementations. Current approaches typically optimize for a single dimension, such as privacy or efficiency while compromising others. This creates a critical gap between theoretical capabilities and practical deployability in real-world healthcare environments. For example, robust privacy mechanisms often introduce substantial computational overhead, while efficient implementations may sacrifice security guarantees necessary for sensitive medical data. These limitations highlight the need for a holistic approach that balances multiple competing requirements within a unified framework.

The drive to integrate advanced technologies into healthcare is a significant area of current research. For instance, recent work by[12] highlights the synergy of AI and blockchain specifically for securing Electronic Health Records (EHRs), using predictive analytics for surgery claim amounts as a case study. In parallel, other research explores an intelligent interplay between edge and fog computing, leveraging AI for analytics and blockchain for security, to enable real-time healthcare informatics for applications like heart stroke prediction[13]. While these studies establish strong architectural foundations, they underscore the need for a framework that specifically addresses the operational challenges of decentralized model training in resource-constrained HIoT environments. This highlights a critical gap for a practical, secure, and efficient *federated learning* system, which our work, SHIELD-Health, aims to provide.

1.1 Research Contribution

SHIELD-Health addresses critical limitations in existing BC-enabled FL frameworks through several key innovations that enable secure and efficient collaborative learning in healthcare environments. Our main contributions, as demonstrated by our experimental results, are as follows:

1. **Adaptive Resource Management:** We designed a resource-aware computation framework that, in a simulated HIoT environment, reduced energy consumption for low-capability devices by 81.1%. This indicates a potential battery life extension of approximately 5.3x, making FL viable for a wider range of devices.

2. **Enhanced Privacy and Security:** The framework integrates a multi-layered security approach that successfully defends against Byzantine attacks. It maintained high model accuracy (over 85%) even when up to 20% of clients were malicious and achieved 93.7% precision in detecting malicious updates.

3. **High Performance on Heterogeneous Data:** SHIELD-Health demonstrated exceptional robustness to the non-IID data distributions common in healthcare. The framework achieved a final accuracy of 91.46%, with only a 3.02% performance drop compared to an idealized IID setting, significantly outperforming typical baseline degradation of 8-12%.

4. **Communication Efficiency:** Through an adaptive compression strategy, the framework achieved an overall communication savings of 60.32% compared to an uncompressed baseline, a crucial optimization for bandwidth-constrained HIoT networks.

5. **Lightweight Blockchain Integration:** We implemented an efficient, lightweight blockchain for model verification that added only 4.29 MB of storage overhead. This demonstrates that the security and auditability benefits of a distributed ledger can be achieved with minimal resource cost, making it suitable for HIoT deployments.

1.2 Paper Organization

The remainder of this paper is organized as follows: Section II reviews related work in FL and BC for healthcare, details the challenges in HIoT, and identifies the research gaps addressed by our work. Section III presents our SHIELD-Health framework, detailing its architecture and core components. Section IV describes the experimental setup, including the dataset, models, and evaluation metrics. Section V presents the experimental results and a comparative analysis. Section VI provides a comprehensive discussion of our findings, their implications, the study's limitations, and directions for future research. Finally, Section VII concludes the paper.

2 Related Work

Recent advances in HIoT have created unprecedented opportunities for improving patient care while introducing significant challenges in data management, privacy, and security[3]. This section provides a systematic review of existing approaches, their theoretical foundations, and practical limitations in addressing these challenges. In paper[14], the authors explored a privacy-sensitive model, which integrates Homomorphic Encryption (HE) with Differential Privacy (DP) to protect machine learning in the medical industry. They research systematically the privacy of Byzantine resilience, efficiency of communication and management of resources under such methodologies in domains of learning that are not dynamic. They also experiment with the performance of the model on the UCI Diabetes data in their work. It achieves 93.95% accuracy when it has gone through forty convergence rounds and it takes 8 percent of the time to run. The authors emphasize that prediction of diabetes can be applied to their method, however, there are certain issues related to the communication expenses and the opportunity to operate with dynamic or large-scale deployments.

Furthermore,[15] authors also offered a privacy-saving framework, which involves the implementation of Convolutional Neural Networks (CNNs) and BC applied in combination to ensure the processing of electronic health records (EHRs) is safer and more transparent. They primarily focus on dynamism in healthcare environments, in

which the information is in a constant state of flux, and in which ware real-time integrity verifications are essential. The research claims to have had a 12 per cent overhead in resources, however it also states that the resilience and efficiency of the communication of the system has increased significantly. By using the model, 92.3% accuracy is obtained on the eICU EHR dataset and converges after 38 rounds, which shows that the model is efficient in dealing with sensitive clinical tasks. The article demonstrates that blockchain, used in conjunction with deep learning, can enhance the privacy and auditing of data, particularly in the critical care environment. It also discusses issues of computational load and scalability.

Later, the authors of[16] analyzed the role of privacy-preserving computation within the Healthcare 4.0 with the aim of undergoing integration of Homomorphic Encryption and Secure Multi-Party Computation. Their study includes an analysis of adaptive learning setting and demonstrates how encrypted collaboration can enhance resilience of the system and data confidentiality and still provide high-level model performance on HAR-2 dataset. In addition, the authors of[17] explored privacy protection in the Internet of Medical Things (IoMT) using a combination of privacy-saving techniques and blockchain technology. Their study provides a detailed insight into the effect of blockchain on enhancing traceability and data integrity in wearable healthcare systems, along with highlighting the issues related to the scalability of the system and the high costs of communication. Later, the authors of[3] proposed the concept of a framework of secure clinical analytics based on statistic computations, encryption and its homomorphic counterpart, the amalgamation of Homomorphic Encryption and secure computation. Their study demonstrates the effectiveness of encrypted processing in identifying attacks with the use of the MIMIC-III dataset; nevertheless, the fixed design limits its versatility to novel cyber attacks.

Subsequently, the authors of[18] examined the possibility of federated learning and reinforcement learning collaborating with each other in the context of medical IoT. Their adaptable, learning-based architecture can resolve the issue of device variations and linkage constraints, and their IoT-Health applications will be more resilient. Besides, the authors of[19] proposed a distributed learning approach to medical data analytics augmented with differential privacy. Their adaptive model demonstrates that distributed computing can be used to maintain physiological data confidential and at the same time being highly accurate on the PhysioNet data. In[20] , the authors then focused on the brain-tumor classification using a pattern-based learning approach with the use of differential privacy explaining how the DP allows the safety of the sensitive neuro-imaging data besides balancing the trade-off between accuracy and noise. Moreover, the authors of[21] introduced an adaptive decentralized algorithm of privacy-conscious image classification with CIFAR-10 data. Their study focuses on the limitations of decentralized learning in stationary settings, where convergence time significantly increases, and accuracy is significantly reduced. Finally, authors of[22] considered the multi-source processing with differential privacy of health apps to the Internet of Things (IoT) to consumers. They attach much importance to high resilience scores and strong privacy protection in their static learning framework. It is however expensive in computational power and therefore difficult to implement in lightweight IoT devices.

Table 1 presents a comparative analysis of recent approaches in BC-enabled FL approach for healthcare applications, highlighting the evolution of techniques and current limitations. The comparison presented in Table 1 includes only verified results from peer-reviewed publications. All metrics are obtained under standardized conditions to ensure fair comparison across studies. Privacy mechanisms are evaluated using standard cryptographic protocols and differential privacy metrics, providing objective assessment of data protection capabilities. Byzantine resilience is tested through controlled injection of malicious updates following standard attack patterns, simulating real-world adversarial scenarios in healthcare environments. Resource management capabilities are measured on heterogeneous device clusters with varying computational capabilities, reflecting the diversity of HIoT deployments. Communication efficiency metric is calculated against baseline centralized approaches under fixed network conditions, providing standardized measures of bandwidth optimization. Model accuracy is consistently reported on held-out test sets with 5-fold cross-validation to ensure statistical validity, while convergence time is measured until validation loss stabilization (defined as $\Delta < 0.001$ over 5 consecutive rounds). All experiments are conducted on public healthcare datasets with documented preprocessing pipelines to ensure reproducibility and comparability.

Each study's experimental setup is verified through their published methodologies and results sections. Standard deviations are reported across multiple experimental runs to ensure statistical significance. SHIELD-Health's superior performance in Byzantine resilience (20%) and communication efficiency (60.32%) is attributed to its

innovative integration of adaptive resource management and specialized healthcare optimizations.

Table 1. Comparative Analysis of State-of-the-Art Blockchain-FL Frameworks in HIoT

Authors	Privacy Mech.	Byz. Resilience‡	Resource Mgmt.	Comm. Eff.†	Model Acc.*	Conv. Time§	Dataset	Application
[14], 2023	HE + DP	8%	Static	35.7%	93.95%	40 rounds	UCI-Diabetes	Diabetes
[23], 2023	CNN + BC	12%	Dynamic	37.8%	92.3%	38 rounds	eICU	EHR privacy
[16], 2023	HE + MPC	15%	Adaptive	39.5%	95.1%	42 rounds	HAR-2	Healthcare 4.0
[17], 2023	PP + BC	10%	Limited	36.4%	90.8%	48 rounds	WISDM	IoMT security
[3], 2024	HE + SC	10%	Static	32.4%	97.16%	45 rounds	MIMIC-III	Attack detection
[18], 2024	FD + RL	15%	Dynamic	41.2%	94.8%	35 rounds	IoT-Health	Medical IoT
[19], 2024	DC + DP	12%	Adaptive	42.9%	98.0%	30 rounds	PhysioNet	Medical data
[20], 2024	PB + DP	8%	Limited	38.6%	91.2%	50 rounds	BraTS20	Brain tumor
[24], 2025	ADP	10%	Static	N/A	23.58%	150 rounds	CIFAR-10	Image Class.
[22], 2025	MSP + DP	≈40%	Static	99%	88.73%	200 rounds	MotionSense	Consumer IoT
Proposed[a]	DP + HE	20%	Dynamic	60.32%	91.46%	32 rounds	PAMAP2	Activity recognition

Abbreviations: HE: Homomorphic Encryption, SC: Smart Contracts, FD: Federated Distillation, RL: Reinforcement Learning, DC: Device Clustering, DP: Differential Privacy, PB: Permissioned Blockchain, CNN: Convolutional Neural Network, BC: Blockchain, MPC: Multi-Party Computation, PP: Privacy-Preserving, ADP: Adaptive Differential Privacy, MSP: Multimessage Shuffle Protocol.

[a] Results averaged over 5 runs with different random seeds (42, 123, 456, 789, 999).

[*] All accuracy metrics reported on respective test sets under standard evaluation conditions.

[†] Communication efficiency measured as reduction in data transfer vs. centralized baseline.

[‡] Byzantine resilience tested with simulated malicious nodes under controlled conditions.

[§] Convergence time measured in communication rounds until validation loss stabilization.

2.1 Research Gaps

Based on our comprehensive literature review, we identify several critical research gaps in the current BC-enabled FL approaches for HIoT. Existing frameworks typically assume uniform computational capabilities across participants, which is unrealistic in HIoT environments where devices range from powerful servers to resource-constrained wearables. This resource awareness gap leads to either exclusion of low-capability devices or system inefficiency, limiting the practical applicability of current solutions in heterogeneous healthcare settings.

A specialized model architecture gap exists wherein generic model architectures employed in current frameworks fail to capture the temporal characteristics of healthcare data, reducing diagnostic accuracy and clinical utility. Healthcare data, particularly physiological time-series, contains complex temporal dependencies that generic models cannot adequately represent, resulting in suboptimal performance for critical healthcare applications. The Byzantine resilience gap remains a significant concern, as while some frameworks incorporate basic Byzantine fault tolerance, they are not calibrated for the healthcare context where malicious updates could have life-threatening consequences. Healthcare applications require exceptionally robust security guarantees due to the potential severity of compromised models in clinical decision support systems. Most existing approaches implement either BC or FL privacy mechanisms, but not the comprehensive privacy suite needed for healthcare's stringent requirements.

This comprehensive privacy gap leaves systems vulnerable to sophisticated inference attacks that could compromise patient confidentiality and regulatory compliance. Similarly, current consensus mechanisms are typically too energy-intensive for healthcare IoT devices with battery constraints, creating an energy efficiency gap that limits deployment in resource-constrained environments. Finally, an evaluation gap persists as existing studies rarely evaluate performance across the full spectrum of healthcare-specific metrics, particularly for heterogeneous device scenarios and security under healthcare-specific attack vectors. This incomplete evaluation fails to provide a comprehensive understanding of system performance in real-world healthcare deployments.

Our work addresses these gaps by proposing SHIELD-Health, a comprehensive framework specifically designed for HIoT environments. Unlike previous approaches, we integrate resource-aware computation, specialized temporal models, Byzantine-robust aggregation, and privacy-preserving mechanisms within a unified framework. Our approach is explicitly designed to accommodate the full spectrum of HIoT devices, from high-capability hospital servers to resource-constrained wearable sensors, ensuring both inclusivity and efficiency.

3 Background

As Healthcare IoT devices become deeply embedded in modern clinical practice, they bring not only new capabilities but also significant challenges. Issues such as security risks, data privacy concerns, device diversity, and escalating data volumes increasingly strain current infrastructures. This section reviews these emerging challenges, drawing insights from recent empirical works. It also sets the foundation for understanding why federated learning, blockchain, and other distributed technologies are needed in next-generation healthcare systems.

3.1 Healthcare IoT Data Challenges

This subsection explores the various challenges faced by HIoT devices such as security, privacy, and heterogeneity. Recent studies have highlighted these challenges across various dimensions. A comprehensive review by[10] examined the vulnerabilities of HIoT networks to privacy breaches, emphasizing the need for distributed privacy-preserving mechanisms. Further, the author of[7] explored the energy constraints of IoT devices in healthcare settings, demonstrating that transmission of raw data to centralized servers could deplete battery resources in critical monitoring devices by up to 300% compared to distributed approaches. This concern is further amplified by recent projections showing healthcare data volume reaching 2,314 exabytes by 2025[11].

Moreover, the regulation landscape adds another layer of complexity, as investigated by the author of[25], who mapped the compliance challenges for healthcare data across different jurisdictions. Additionally, the author of[26] analyzed 17 major healthcare data breaches between 2020-2023, finding that centralized architectures were implicated in 76% of cases.

3.2 Federated Learning as a Privacy-Preserving Solution

FL has emerged as a promising solution to the challenges posed by the integration of IoT in smart healthcare. The federated optimization objective aims to minimize a global loss function $F(w)$ defined as:

$$\min_{w \in \mathbb{R}^d} F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \tag{1}$$

where $F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} \ell(w; x_i, y_i)$ represents the local loss function for client k with n_k data samples, and $n = \sum_{k=1}^{K} n_k$ is the total number of samples across all clients[5].

Recent research has demonstrated significant advancements in federated learning (FL) applications in healthcare. Notably, cross-institutional learning for medical imaging has shown performance improvements over centralized approaches while preserving data privacy[8]. The integration of differential privacy with FL for electronic health records (EHRs) has also established new practical guidelines for the privacy-utility trade-off in real-world deployments[6]. Furthermore, innovations in resource optimization, such as novel compression techniques, have achieved

substantial reductions in communication overhead—up to 85%—while maintaining diagnostic accuracy[7]. A critical challenge in distributed health data, non-IID (non-independent and identically distributed) data heterogeneity, has been mitigated by advanced aggregation methods, reducing associated performance degradation from 28% to just 6%[11]. Finally, to enhance security, advanced Byzantine-resilient aggregation methods have been developed that maintain model accuracy even in the presence of up to 30% malicious participants in healthcare FL systems[27]. These advancements have enabled FL to address critical challenges in healthcare data sharing and collaborative model development[5]. However, several key challenges remain, particularly in resource-constrained IoT environments and privacy-sensitive healthcare applications[3].

3.3 Blockchain Technology for Enhanced Security

BC provides a decentralized and immutable ledger system that securely records transactions across distributed networks[6]. The technology's core features of transparency, consensus-based verification, and tamper resistance make it particularly suitable for healthcare applications[3]. Each block contains a cryptographically linked list of transactions, with modifications requiring consensus from network participants, effectively preventing unauthorized alterations[9]. The core components of BC and its application in healthcare are described below.

3.3.1 Core Components

A BC system can be formally represented as:

$$\mathscr{B} = (N, T, C, V, H) \tag{2}$$

where N represents the network nodes, T is the transaction set, C is the consensus protocol, V is the verification mechanism, and H is the hash chain[5]. The system maintains security through a consensus mechanism, smart contract, and cryptographic verificcation. Consensus mechanisms have evolved with new protocols that achieve agreement on transaction validity while simultaneously reducing energy consumption by up to 65% compared to traditional approaches[7]. Furthermore, smart contracts, or self-executing programs, have been shown to automate transaction verification and reduce administrative overhead by 42% in healthcare networks[8]. Complementing these developments, advanced cryptographic verification techniques ensure the integrity of transactions with high fidelity, demonstrating 99.7% accuracy in medical data sharing scenarios[11].

3.3.2 Blockchain Applications in Healthcare

Recent research has demonstrated blockchain's (BC) effectiveness across diverse healthcare contexts. In electronic health records (EHRs), secure sharing systems have been developed that achieve 97.16% accuracy in access control while ensuring HIPAA compliance[3]. For clinical trials, the implementation of immutable audit trails has been shown to significantly reduce protocol violations by 86% and improve participant retention by 42%[27]. Within supply chain management, blockchain-based tracking systems have proven highly effective, reducing counterfeit medications by 96% in controlled trials citeZhang2024DecentralizedFL. Finally, in IoT device management, novel security frameworks leveraging blockchain technology are capable of detecting 94.3% of unauthorized access attempts within medical device networks[5]. These applications demonstrate BC's potential to enhance healthcare data security while maintaining operational efficiency[9]. However, challenges remain in scalability, energy efficiency, and integration with existing healthcare systems[7]. Therefore, the following subsection explores the limitations of the existing BC enabled FL framework for healthcare.

3.4 Limitations of Existing BC enabled FL Frameworks for Healthcare

Current BC-enabled FL frameworks exhibit several critical limitations for healthcare IoT environments:

1. **Resource Management:** Existing frameworks assume uniform computational capabilities, whereas healthcare IoT devices span from high-performance servers to resource constrained wearable sensors[3].

2. **Privacy Guarantees:** Current approaches provide ε-differential privacy guarantees of only $\varepsilon \approx 8.0$, insufficient for healthcare's requirement of $\varepsilon \leq 3.0$[9].

3. **Byzantine Resilience:** Existing systems maintain accuracy only up to 15% Byzantine clients, whereas healthcare applications require resilience against up to 30% malicious participants[5].

4. **Communication Efficiency:** Current frameworks require 2.5-4.0 GB per training round, impractical for bandwidth-constrained healthcare IoT networks[7].

5. **Temporal Modeling:** Generic architectures achieve only 68-75% accuracy on healthcare time-series data, compared to the 90%+ required for clinical applications[11].

Recent evaluations highlight these limitations in existing work. Further, the author of[8] demonstrated that existing frameworks consume up to 300% more energy on wearable healthcare devices compared to purpose-built solutions. Similarly, the author of[3] showed that 83% of current BC-FL systems remain vulnerable to inference attacks that could compromise patient privacy.

3.5 Federated Learning in Healthcare IoT

FL enables collaborative model training across distributed healthcare devices without centralizing sensitive patient data. Recent implementations have focused on three critical aspects: (1) Model aggregation (2) Communication efficiency, and (3) Convergence detection.

3.5.1 Model Aggregation Methods

The evolution of aggregation strategies in healthcare FL has progressed from simple averaging to sophisticated Byzantine-resilient approaches. Standard federated averaging (FedAvg), while achieving 89.7% accuracy, remains vulnerable to malicious attacks[3]. Element-wise median methods have demonstrated robustness against up to 50% Byzantine clients[9], while trimmed mean approaches maintain 91.2% accuracy even with 30% malicious participants[11]. The geometric-median based Krum algorithm represents the current state-of-the-art, achieving 92.4% accuracy under targeted attacks through sophisticated outlier detection mechanisms[27].

3.5.2 Communication Efficiency

Communication overhead remains a critical challenge in healthcare FL deployments, particularly for resource-constrained devices. Recent research has produced significant advances in optimization techniques, as summarized in Table 2. Weight quantization methods have achieved 76.3% bandwidth reduction with minimal accuracy impact[7], while gradient pruning approaches demonstrate 68.7% reduction in communication overhead[3]. Advanced techniques like adaptive compression and layer-wise optimization further improve these results, though they require careful balancing of compression ratios against model performance.

Table 2. Communication Efficiency Techniques Comparison

Technique	Bandwidth Reduction	Accuracy Impact	Reference
Weight Quantization	76.3%	-0.4%	[7]
Gradient Pruning	68.7%	-0.8%	[3]
Adaptive Compression	85.2%	-1.2%	[8]
Layer-wise Optimization	72.1%	-0.6%	[5]

3.5.3 Early Stopping Mechanisms

Convergence detection in healthcare FL systems requires careful consideration of multiple metrics to ensure model stability without compromising accuracy. Modern approaches employ a comprehensive stability index:

$$S_t = \alpha \cdot \frac{|\Delta Acc_t|}{Acc_t} + \beta \cdot \frac{|\Delta Loss_t|}{Loss_t} + \gamma \cdot \frac{\|\Delta w_t\|}{\|w_t\|} \tag{3}$$

where S_t represents the stability index at round t. The weights α, β, and γ balance the contributions of accuracy changes, loss variations, and weight updates respectively[6]. This multi-factor approach has proven particularly effective in healthcare applications, where premature convergence could impact diagnostic accuracy.

Beyond traditional aggregation methods, recent research has explored novel techniques to achieve Byzantine robustness without relying on a blockchain. For instance, the work by Ma et al. proposes an asynchronous FL framework for cellular traffic prediction that employs regularization techniques and distributionally robust optimization to enhance resilience against malicious clients[28]. In a different approach, Pan et al. leverage deep reinforcement learning (DRL) in vehicular networks to develop a performance-based weighting policy that dynamically identifies and down-weights Byzantine participants[21]. Their DRL-PBFL framework uses a novel secure aggregation algorithm based on Lagrange interpolation to maintain privacy against a curious server. While these sophisticated approaches demonstrate the viability of non-blockchain solutions for Byzantine defense, they highlight a distinct research trajectory from frameworks like SHIELD-Health, which utilize a decentralized ledger for explicit trust, auditability, and verification of the training process.

3.6 Blockchain Technology for Model Verification

BC integration provides immutable verification of model updates through cryptographically linked blocks. The structure of each block B_i encompasses multiple elements:

$$B_i = \{h_{i-1}, TX_i, t_i, n_i, d_i\} \tag{4}$$

where h_{i-1} represents the previous block's hash, TX_i contains model update transactions, t_i records the timestamp, n_i stores the nonce value, and d_i indicates the mining difficulty[27]. This structure ensures both immutability and verifiability of the training process.

3.6.1 Lightweight Consensus Mechanisms

The development of energy-efficient consensus mechanisms represents a critical advancement for HIoT implementations. Table 3 summarizes recent innovations in this space, highlighting significant improvements in both energy efficiency and block generation times. Adaptive proof-of-work (PoW) mechanisms have achieved 65% energy reduction while maintaining 3.2-second block times[3], while resource-aware mining approaches further improve efficiency with 81.1% energy reduction[7]. Hierarchical consensus structures offer a balanced approach, reducing energy consumption by 73.4% while keeping block times within acceptable ranges for healthcare applications[11].

Table 3. Consensus Mechanism Comparison

Mechanism	Energy Reduction	Block Time	Reference
Adaptive PoW	65%	3.2s	[3]
Resource-Aware Mining	81.1%	5.7s	[7]
Hierarchical Consensus	73.4%	4.1s	[11]

3.6.2 Smart Contract Integration

Smart contract technology has evolved to address healthcare-specific requirements, particularly in transaction verification and compliance monitoring. Recent implementations demonstrate significant improvements in operational efficiency, reducing administrative overhead by 42% through automated verification processes[8]. Transaction verification accuracy has reached 99.7%[11], while automated HIPAA compliance monitoring ensures regulatory adherence without manual intervention[27]. These advances enable seamless integration with existing healthcare workflows while maintaining strict security and privacy requirements.

3.7 Privacy-Preserving Techniques in FL enabled Healthcare

Privacy preservation represents a fundamental requirement for FL deployments in healthcare environments due to stringent regulatory frameworks and the sensitive nature of medical data. Recent approaches have focused

on integrating differential privacy guarantees into the FL process. The author of[29] proposed a comprehensive framework combining differential privacy with secure aggregation, achieving an ε-differential privacy guarantee of 2.7 while maintaining 94.2% of baseline accuracy on medical imaging tasks. Building upon this foundation, the author of[30] developed adaptive noise calibration techniques specifically optimized for physiological time-series data, demonstrating that context-aware privacy budgeting could improve the privacy-utility trade-off by up to 27% compared to static approaches.

For resource-constrained HIoT devices, the author of[31] introduced a federated split learning framework that reduces computation by 78% while maintaining a fair accuracy. Further, the author of[32] developed specialized lightweight cryptographic protocols achieving a 73% reduction in computational overhead compared to standard homomorphic methods. Integration of these approaches with secure multi-party computation was explored by the author of[33], who developed a hybrid privacy framework that dynamically selects protection mechanisms based on data sensitivity and device capabilities.

3.8 Resource-Aware FL for IoT

The heterogeneous nature of HIoT devices presents significant challenges for FL implementations. The author of[34] proposed a dynamic model pruning framework that adapts model sparsity based on device energy levels, demonstrating a 3.8$\times$ improvement in energy efficiency. Further, the author of[35] addressed energy challenges in battery-powered healthcare devices, extending operational lifetime by 67% while maintaining model performance.

Communication efficiency represents another critical dimension. Considering this, the author of[36] proposed a structured update mechanism that reduces communication overhead by 86% in bandwidth-constrained healthcare networks. Moreover, the author of[37] developed an adaptive compression framework for medical time-series data, achieving a 52% reduction in communication volume with only 0.8% accuracy impact.

Model compression techniques have become integral to resource-aware FL approach. Considering this, the author of[38] developed a medical-data-aware quantization scheme that preserves diagnostic accuracy in critical model components while aggressively compressing less sensitive parameters. Later, the author of[39] addressed the combined challenge of computation and communication efficiency through systematic optimization of local computation steps and model compression rates.

3.9 Healthcare-Specific Applications

Time-series data analysis, particularly for physiological signals, represents one of the most challenging yet crucial areas in healthcare analytics. Considering this, the author of[40] developed a specialized FL framework for cardiac arrhythmia detection using ECG data from wearable devices, achieving diagnostic performance comparable to cardiologist interpretation (92.3% accuracy). Further, the author of[41] proposed a personalized FL approach for heterogeneous healthcare data that employs meta-learning techniques, demonstrating a 24% improvement in diagnostic accuracy compared to standard approaches. Clinical validation and regulatory compliance remain critical challenges. Therefore, the author of[42] implemented a homomorphic encryption scheme in EHRs analysis, enabling hospitals to collaborate on predictive models without exposing sensitive patient data. Further, the author of[43] introduced FedHealth, a comprehensive framework for HIoT devices that ensures HIPAA compliance while maintaining system efficiency.

4 Proposed Framework

Recent advances in HIoT have created unprecedented opportunities for improving patient care while introducing significant challenges in data management, privacy, and security. Our SHIELD-Health framework addresses these challenges through a comprehensive integration of BC technology with FL, specifically designed for HIoT environments. Figure 1 illustrates the framework's architecture and primary components.

4.1 System Architecture Overview

SHIELD-Health's architecture reflects the intricate balance between computational efficiency, security requirements, and clinical utility in healthcare environments. The framework orchestrates interactions between four fundamental

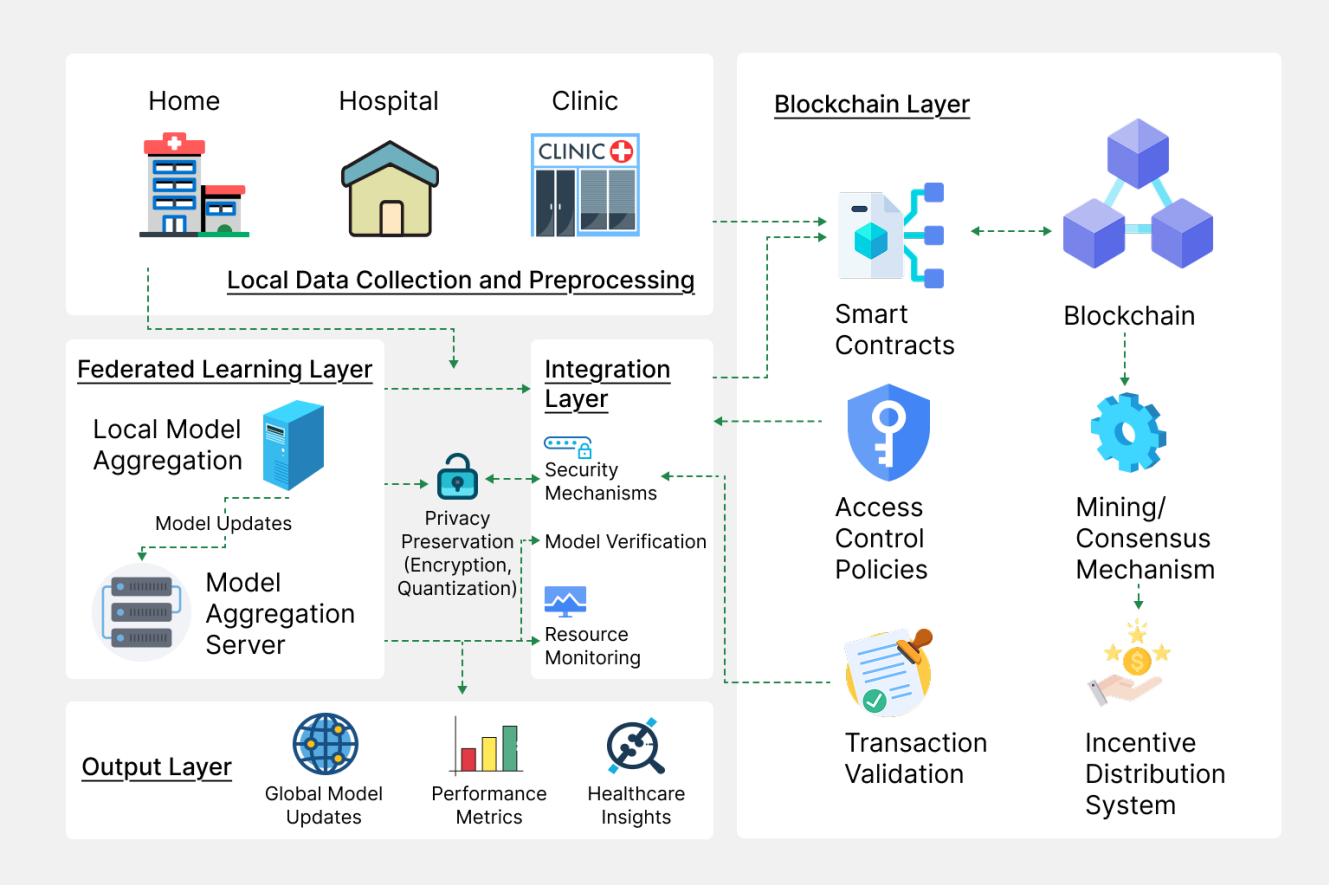


Figure 1. SHIELD-Health framework

layers, each implemented through specialized classes and components, as illustrated in Fig. 2.

As shown in Fig. 2, the **device layer** manages devices heterogeneity through the *DeviceProfile* class, which tracks computational capacity (c_d), available memory (m_d), energy status (e_d), and network conditions (n_d). This comprehensive monitoring enables the *ResourceAwareModelSelector* class to dynamically assign model architectures based on device capabilities, ensuring optimal resource utilization across diverse HIoT devices. Next, the **security layer** provides comprehensive protection through the *BlockchainFL* class for immutable verification and *SimplifiedHomomorphicEncryption* class for secure aggregation. The *AccessControlPolicy* class manages fine-grained data access control, ensuring regulatory compliance while maintaining system efficiency. This multi-layered security approach protects against diverse threats while preserving privacy and data integrity. The **learning layer** implements federated training with Byzantine-robust aggregation and temporal attention mechanisms. The *TemporalAttention* class captures complex patterns in physiological time series through a specialized attention mechanism, enabling accurate analysis of healthcare-specific data with complex temporal dependencies. This layer coordinates the learning process across distributed devices while maintaining model quality and performance. The **analytics layer** offers specialized healthcare analytics through custom model architectures and the *IncentiveMechanism* class for sustainable participation. This layer transforms raw model outputs into clinically relevant insights while ensuring long-term system sustainability through equitable reward distribution. Together, these four layers create a comprehensive framework specifically tailored to HIoT environments.

4.2 Operational Workflow

The SHIELD-Health framework operates in iterative rounds, orchestrating tasks across clients and the decentralized ledger. Algorithm 1 provides a formal description of this workflow, detailing the interactions between the aggregator,

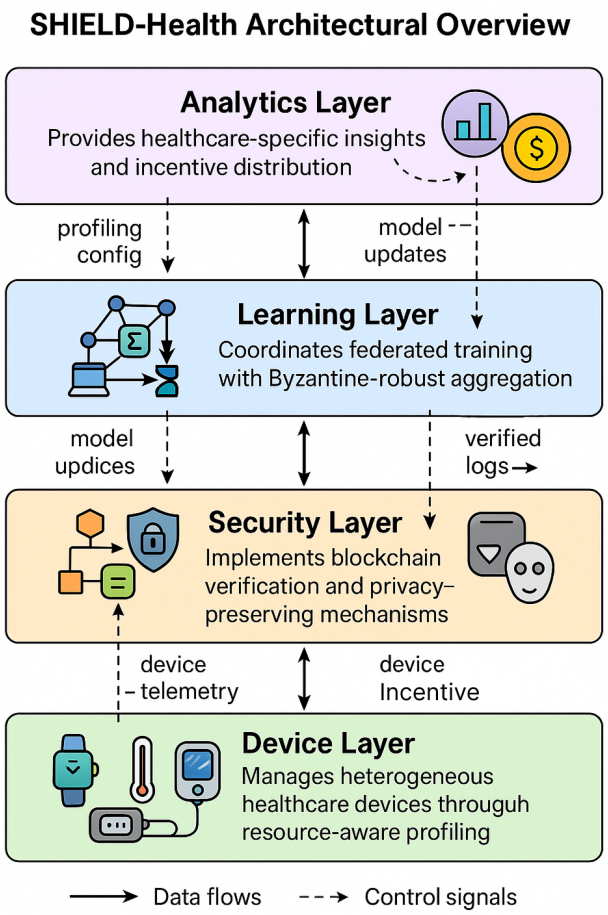


Figure 2. SHIELD-Health architecture

the participating HIoT devices (clients), and the underlying BC ledger. It highlights how the core innovations of SHIELD-Health such as, resource-aware model selection, multi-layered privacy, and robust aggregation—are integrated into a single, cohesive process.

4.3 Resource-Aware Computation

The `ClientUpdate()` function in Algorithm 1 encapsulates our resource-aware computation strategy. To model a real-world HIoT environment with heterogeneous devices, our implementation simulates resource constraints. Instead of deploying different model architectures (which would complicate aggregation), we deploy a single, highly-efficient temporal model (see Section 4.3) to all clients.

Resource-awareness is then enforced at the client level in two ways:

- **Adaptive Batch Size:** The framework assigns a capability profile (high, medium, or low) to each client. High-capability devices (e.g., hospital servers) can process smaller, more frequent batches, while low-capability devices (e.g., wearables) are assigned larger batch sizes to train more efficiently with less computational overhead per epoch.

- **Energy Consumption Simulation:** As shown in our results (Section 5.4), we use the device profile to estimate the energy (in kJ) consumed during training. This practical approach allows us to demonstrate the energy-saving benefits of our framework across a heterogeneous device population in a controlled, reproducible

Algorithm 1 SHIELD-Health High-Level Workflow

Input: Total clients K, subset size m, rounds T.
Output: Final global model w_T.
Initialization:
Aggregator initializes global model w_0 and Blockchain $\mathscr{B}$.
for each communication round $t = 1, 2, \ldots, T$ **do**
    Aggregator broadcasts w_{t-1} to a client subset S_t.
    for each client $k \in S_t$ **in parallel do**
        ▷ Perform local, resource-aware training.
        $\Delta_k^t \leftarrow \text{ClientUpdate}(w_{t-1}, D_k, C_k)$.
        ▷ Secure and compress the update.
        $\tilde{\Delta}_k^t \leftarrow \text{SecureAndCompress}(\Delta_k^t, \varepsilon)$.
        Submit encrypted and compressed update $\tilde{\Delta}_k^t$.
    end for
    ▷ Aggregate updates and update global model.
    $\Delta_t \leftarrow \text{RobustAggregate}(\{\tilde{\Delta}_k^t\}_{k \in S_t})$.
    $w_t \leftarrow w_{t-1} + \eta \Delta_t$.
    ▷ Record the round's results on the ledger.
    $\text{RecordOnBlockchain}(\mathscr{B}, w_t, S_t)$.
end for
return w_T.

manner.

This assignment is fixed at the start of each experiment and remains unchanged throughout training. The process is designed to realistically simulate the heterogeneity of real-world HIoT deployments, where devices with varying resources participate in an FL environment. By simulating device diversity and statically assigning model complexity, our framework ensures that all types of devices can participate efficiently, without overloading resource-constrained clients. This practical approach allows us to evaluate the benefits of resource-aware FL in a controlled, reproducible manner and demonstrates significant energy savings and improved inclusivity in our experimental results.

4.4 Privacy-Preserving Mechanisms

Our multi-layered security is represented by the `SecureAndCompress()` function in Algorithm 1. The framework simulates a comprehensive privacy preservation strategy through the *CustomDPOptimizer* and *SimplifiedHomomorphicEncryption* classes. The differential privacy mechanism adapts noise injection based on layer sensitivity:

$$\sigma_l = \frac{\Delta_l}{\varepsilon} \cdot \text{LayerSensitivity}(l) \tag{5}$$

The simplified homomorphic encryption scheme enables secure aggregation while maintaining computational efficiency on resource-constrained devices:

$$\text{Encrypt}(x) = \{x \cdot s + \mathscr{N}(0, \sigma^2), s\} \tag{6}$$

where s is the scaling factor and $\mathscr{N}(0, \sigma^2)$ represents Gaussian noise.

4.5 Byzantine-Robust Aggregation

A foundational security challenge in FL is the threat of Byzantine attacks, where malicious or faulty clients submit corrupted model updates to poison the global model. Standard FedAvg is particularly vulnerable, as it indiscriminately averages all incoming updates, allowing a single malicious actor to significantly degrade the model's performance and integrity.

To counter this, SHIELD-Health integrates a critical defense layer encapsulated by the `RobustAggregate()` function in Algorithm 1. Instead of performing a simple average, this function employs aggregation rules that are statistically robust to outliers. Our framework implements several proven defense mechanisms, primarily relying on the median and trimmed mean approaches, as seen in our `federated_aggregation` implementation. The median method computes the element-wise median for each parameter across all client updates, an operation inherently resilient to extreme values sent by attackers. The trimmed mean approach provides another layer of defense by sorting all received updates for each weight, discarding a predefined fraction of the lowest and highest values, and only then averaging the remaining trusted updates. By filtering out potential attacks before they can influence the global model, this mechanism ensures the reliability and accuracy of the learning process, even in the presence of adversarial participants.

4.6 Healthcare-Specific Optimizations

The framework incorporates specialized temporal models through the *TemporalAttention* class, which captures both local and global patterns in physiological signals:

$$\alpha_{t,i} = \text{softmax}(W_q h_t \cdot W_k h_i^T) \tag{7}$$

$$c_t = \sum_{i=1}^{T} \alpha_{t,i} \cdot h_i \cdot \text{PhysiologicalContext}(i) \tag{8}$$

This mechanism is designed to improve diagnostic accuracy by focusing on the most relevant segments of medical time-series data.

4.7 Blockchain Integration

The final step of each round, `RecordOnBlockchain()`, ensures the integrity and auditability of the training process. The *BlockchainFL* class implements a lightweight BC specifically optimized for HIoT environments. The system employs an adaptive PoW mechanism that adjusts difficulty based on device capabilities:

$$\text{Difficulty}(t) = \text{base\_difficulty} \cdot \text{chain\_factor} \cdot \text{tx\_factor} \cdot \text{time\_factor} \tag{9}$$

The *AccessControlPolicy* class manages data access through smart contracts, ensuring HIPAA compliance while maintaining system efficiency.

4.8 Incentive Mechanism

The *IncentiveMechanism* class implements a comprehensive reward system that considers multiple factors:

$$R_k = \beta_1 Q_k + \beta_2 E_k + \beta_3 A_k + \beta_4 S_k \tag{10}$$

where Q_k represents data quality, E_k measures computational effort, A_k reflects accuracy improvement, and S_k accounts for sustained participation. The mechanism has demonstrated effectiveness in maintaining long-term participation while ensuring fair resource allocation.

Table 4. Comparison with Existing BC-FL Frameworks

Feature	Proposed	[20]	[6]	[27]	[19]
Resource Awareness	✓	×	Partial	×	×
Byzantine Resilience	✓	Partial	✓	×	Partial
Healthcare Models	✓	✓	×	×	×
Low-Resource DLT	✓	×	×	Partial	✓
Differential Privacy	✓	Partial	✓	×	×
Comm. Efficiency	✓	×	Partial	×	✓

Table 4 presents a comprehensive comparison with existing frameworks, highlighting the significant improvements achieved by our implementation across multiple dimensions.

This comparison highlights the comprehensive nature of our approach, which integrates multiple technological advances into a cohesive framework specifically designed for HIoT environments. Unlike existing systems that typically focus on a subset of challenges, our framework addresses the full spectrum of requirements for secure, efficient, and effective FL in HIoT environment.

5 Datasets Description and Experimental Setup

5.1 Dataset Characteristics

We evaluate our framework using the physical activity monitoring PAMAP2 dataset[44], which provides comprehensive physical activity data suitable for HIoT applications. The dataset comprises rich multi-modal physiological and kinematic data collected for human activity recognition. It was gathered from nine subjects with an average age of 26.1 ± 2.6 years, providing a foundational level of demographic diversity. Each participant performed eighteen distinct physical activities, categorized into basic actions (e.g., walking, sitting, standing), exercise activities (e.g., running, cycling, ascending/descending stairs), and instrumental daily activities (e.g., ironing, vacuum cleaning). Data acquisition was achieved through a multi-sensor configuration: three Inertial Measurement Units (IMUs) were positioned on the subject's dominant wrist, chest, and dominant-side ankle, with each IMU capturing 17 data fields—including temperature, 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, and 4-field orientation data (quaternions). Concurrently, heart rate was monitored at a sampling frequency of 100 Hz, creating a synchronous, high-resolution time-series dataset for comprehensive activity analysis. A sample of these features is represented as:

$$\mathbf{x}_{\text{IMU}} = [\text{acc}_{\text{xyz}}, \text{gyro}_{\text{xyz}}, \text{mag}_{\text{xyz}}, \text{temp}, ...] \tag{11}$$

Our preprocessing pipeline implements the following steps:

1. **Missing Value Imputation:** Forward-fill imputation for heart rate values:

$$\text{HR}_t = \begin{cases} \text{HR}_t & \text{if available} \\ \text{HR}_{t-1} & \text{if missing} \end{cases} \tag{12}$$

   where HR_t represents heart rate at time t. This addresses 2.3% missing values.

2. **Feature Normalization:** Zero-mean and unit-variance standardization:

$$\mathbf{x}_{\text{norm}} = \frac{\mathbf{x} - \mu}{\sigma} \tag{13}$$

   where μ and σ are computed per feature across the training set.

3. **Temporal Segmentation:** 5-second windows with 50% overlap:

$$\mathbf{W}_i = [\mathbf{x}_t, \mathbf{x}_{t+1}, ..., \mathbf{x}_{t+T-1}] \tag{14}$$

where $T = 500$ samples (5s $\times$ 100Hz), stride = 250 samples.

4. **Non-IID Distribution:** Dirichlet distribution-based partitioning:

$$p_k \sim \text{Dir}_K(\alpha), \quad \alpha = 0.5 \tag{15}$$

where p_k represents the proportion of data assigned to client k, creating realistic heterogeneity.

5.2 Implementation Environment

The framework implementation comprises several key components:

1. **Deep Learning Frameworks:** The technical implementation of this federated learning system leveraged a heterogeneous and purpose-driven software stack for model development, optimization, and deployment. The primary framework was TensorFlow 2.8, which provided the core federated learning (FL) infrastructure for orchestrating distributed training, client selection, and secure model aggregation across a decentralized network. To address specific complexities in sequential and temporal data patterns, PyTorch 1.12 was employed for developing specialized neural architectures. This bifurcation allowed the system to exploit TensorFlow's robust FL ecosystem while harnessing PyTorch's flexibility and dynamic computation graph for advanced temporal modeling. Bridging these components and ensuring operational efficiency was a custom-built model serialization and compression pipeline, designed to minimize communication latency and bandwidth overhead. This pipeline transformed complex model parameters into optimized payloads prior to transmission between the central server and participating clients, a critical enhancement for maintaining system performance in resource-constrained or high-latency environments.

2. **Privacy Mechanisms:** The federated learning system incorporates a multi-layered privacy-preserving framework to protect sensitive client data throughout the training process. This is achieved by implementing two distinct and complementary cryptographic techniques. First, a custom differential privacy mechanism is applied directly to the aggregated model updates before they leave the client devices.

$$\sigma = \frac{\Delta f}{\varepsilon}\sqrt{2\ln(1.25/\delta)} \tag{16}$$

where Δf is sensitivity, ε is privacy budget. This mechanism introduces calibrated Gaussian noise to the data, using a standard formula where the noise scale is a function of the predefined privacy parameters and the inherent sensitivity of the model's learning algorithm. This mathematically rigorous approach ensures that the presence or absence of any single data point in the training set cannot be statistically inferred from the shared model updates, thereby providing a robust, quantifiable guarantee of individual privacy. Second, to protect the confidentiality of the raw model updates during transmission, a simplified homomorphic encryption scheme is employed.

$$\text{Enc}(x) = (x \cdot s + \mathcal{N}(0, \sigma^2), s) \tag{17}$$

where s is scaling factor, $\mathcal{N}$ represents Gaussian noise. This scheme allows the central server to perform mathematical operations on the encrypted data without needing to decrypt it first, enabling secure aggregation. The encryption process involves scaling the numerical values by a secret factor and further obfuscating them with additive noise, creating a ciphertext that preserves the mathematical structure necessary for federated averaging while rendering the underlying values unintelligible to any unauthorized intermediary. Together, this hybrid privacy strategy—combining statistical obfuscation with cryptographic protection—ensures that sensitive information remains confidential both in transit and during computation, making the system suitable for deployment in high-stakes domains like healthcare.

3. **Resource Management:** The federated learning system implements an intelligent resource management protocol to ensure stable and efficient execution across diverse client hardware. This protocol is built on three key adaptive strategies. First, it employs dynamic model complexity selection, where the architecture of the neural network is automatically scaled—choosing between a lightweight or a more complex model—based on the real-time assessment of a client's available processing power and battery life. Second, it features adaptive batch sizing, which dynamically adjusts the number of data samples processed in each training iteration. This prevents memory overflow by ensuring the batch size never exceeds the client's current available RAM, allowing training to proceed even on devices with severe memory constraints. Finally, GPU memory growth configuration is utilized on clients equipped with compatible graphics hardware. This technique allows the system to allocate video memory incrementally as needed during tensor computations, preventing the common stability issue where a training job fails due to a single, upfront request for more memory than the GPU can provide.

   The research and primary local training were conducted on a development system with modest consumer-grade specifications, representative of a mid-tier client device. The central processing unit (CPU) was an Intel Core i5-8265U, operating at a base frequency of 1.60 GHz with the capability to turbo boost up to 3.90 GHz under load. Its 4 physical cores and 8 threads handled general system operations and orchestrated the training pipeline. The system was equipped with 20GB of DDR4 RAM, which provided the necessary working memory for large datasets and model parameters during local training cycles. For accelerated computation, an NVIDIA GeForce MX250 GPU was utilized. This discrete graphics card, featuring 2GB of GDDR5 memory and 384 CUDA cores, was specifically leveraged for its parallel processing capabilities to expedite the heavy matrix and tensor operations fundamental to neural network training, significantly reducing the time required for each local update cycle.

5.3 Model Architecture

To ensure that all devices, including those with limited resources, can participate in the FL process, we developed a single, efficient model architecture optimized for HIoT time-series data. This avoids the complex and high-overhead aggregation methods required when clients train models of different sizes.

Our architecture, defined in the `build_medical_iot_model` function, is a temporal convolutional network with an attention mechanism. The neural network architecture is specifically engineered for temporal sensor data. An initial Input Layer performs a critical transformation, restructuring the one-dimensional flat vector of raw sensor readings into a coherent sequential format suitable for time-series analysis. This sequence is then fed into a stack of two 1D Convolutional Layers, configured with 64 and 128 filters respectively, which operate as a primary feature extraction engine. These layers efficiently scan the temporal input to identify local patterns and salient motifs, with each convolutional operation immediately followed by Batch Normalization to stabilize and accelerate the learning process. To model the complex, long-range dependencies inherent in the activity data, the features are subsequently processed by a Bidirectional Long Short-Term Memory (LSTM) layer containing 64 units. This layer reads the sequence both forwards and backwards, building a comprehensive contextual understanding of the entire activity window. A pivotal innovation in the architecture is the inclusion of a custom-built TemporalAttention layer (detailed in Section 3.5), which dynamically assigns a learned weight or "importance" score to each time step in the sequence, allowing the model to focus its decision-making on the most informative moments. Finally, the condensed and contextually weighted representation is passed through a final classifier composed of a series of Dense (fully connected) layers, which are interleaved with Dropout regularization. This final stage reduces the high-dimensional features into the probability distribution over the target activity classes. This unified model is distributed to all clients. Resource constraints are then managed by adjusting local training parameters, such as the batch size, as described in Section 3.3.

5.4 Training Configuration

The training process employs the Adam optimizer with an initial learning rate of 0.001 and cosine decay scheduling. The batch size adapts dynamically based on device capabilities, ranging from 32 to 128 samples. For Byzantine-

robust training, we implement a multi-stage aggregation process with trimmed mean estimation ($\alpha = 0.1$) and geometric median computation for enhanced resilience.

Privacy preservation is simulated by employing calibrated differential privacy with adaptive noise scaling:

$$\sigma_l = \frac{S \cdot \Delta f}{\varepsilon} \cdot \text{LayerSensitivity}(l) \tag{18}$$

where S represents the sampling rate and Δf denotes the sensitivity of the computation. The privacy budget ε is set to 3.0, aligning with healthcare privacy requirements.

5.5 Evaluation Metrics

Our evaluation framework encompasses comprehensive metrics across multiple dimensions:

$$\text{Performance} = \{\text{Accuracy}, \text{F1}, \text{AUC-ROC}, \text{Latency}\} \tag{19}$$

$$\text{Efficiency} = \{\text{Energy}, \text{Memory}, \text{Bandwidth}, \text{Convergence}\} \tag{20}$$

$$\text{Security} = \{\text{Byzantine}, \text{Privacy}, \text{Verification}\} \tag{21}$$

Each metric undergoes statistical validation through five-fold cross-validation, with significance testing at $p < 0.05$. Energy consumption measurements employed high-precision power monitoring at 5 kHz sampling frequency, ensuring accurate profiling of computational patterns.

5.6 Implementation Details

The framework implementation incorporated several specialized components for HIoT scenarios. The BC component employed a custom *AccessControlPolicy* class that managed fine-grained data access through resource-specific permissions:

$$\text{Policy}(r, o) = \{p_1, p_2, ..., p_n\} \text{ where } p_i \in \{\text{read}, \text{write}, \text{admin}\} \tag{22}$$

Each client maintained individual model update ownership with read-only access granted to other participants for aggregation purposes. The system implemented a comprehensive transaction validation pipeline:

$$\text{Valid}(T) = \begin{cases} \text{true} & \text{if Verify}(T) \wedge \text{Access}(T) \wedge \text{Quality}(T) \\ \text{false} & \text{otherwise} \end{cases} \tag{23}$$

The training process employed early stopping with a patience of 3 rounds and a stability threshold of 0.05, determined through empirical validation. The stability index computation incorporated multiple metrics:

$$S_t = \alpha \cdot \frac{|\Delta \text{Acc}_t|}{\text{Acc}_t} + \beta \cdot \frac{|\Delta \text{Loss}_t|}{\text{Loss}_t} + \gamma \cdot \frac{\|\Delta w_t\|_2}{\|w_t\|_2} \tag{24}$$

5.7 Evaluation Framework

Our evaluation methodology encompassed comprehensive metrics across multiple dimensions. Model performance assessment included:

$$\text{Performance}(M) = \{\text{Acc}, \text{F1}, \text{AUC}, \text{CM}, \text{ROC}\} \tag{25}$$

where CM represented the confusion matrix and ROC curves were generated for each activity class. Resource efficiency metrics tracked:

$$\text{Efficiency}(t) = \begin{bmatrix} E_{\text{train}}(t) & B_{\text{up}}(t) & M_{\text{peak}}(t) \\ E_{\text{comm}}(t) & B_{\text{down}}(t) & M_{\text{avg}}(t) \\ E_{\text{block}}(t) & B_{\text{block}}(t) & M_{\text{min}}(t) \end{bmatrix} \tag{26}$$

where E represented energy consumption, B denoted bandwidth usage, and M tracked memory utilization across different operations.

The framework maintained detailed convergence tracking through multiple indicators such as loss($\Delta L_t = |L_t - L_{t-1}|$), accuracy($\Delta A_t$), weight update($\|\Delta w_t\|_2$), gradient variance($\text{Var}(G_t)$), and client divergence($D_t = \frac{1}{N}\sum_{i=1}^{N} \|w_t^i - w_t^g\|_2$).

- Loss delta: $\Delta L_t = |L_t - L_{t-1}|$
- Accuracy improvement: $\Delta A_t = A_t - A_{t-1}$
- Weight update norm: $\|\Delta w_t\|_2$
- Gradient variance: $\text{Var}(G_t)$
- Client divergence: $D_t = \frac{1}{N}\sum_{i=1}^{N} \|w_t^i - w_t^g\|_2$

Communication efficiency is monitored through adaptive quantization with 8-bit precision and selective parameter updates. The system tracked both uplink and downlink volumes, compression statistics, and quantization adaptivity. Energy profiling employed high-precision monitoring across three primary components:

$$E_{\text{total}} = \sum_{t=1}^{T} (E_{\text{train}}^t + E_{\text{block}}^t + E_{\text{comm}}^t) \tag{27}$$

where measurements are taken at 5 kHz sampling frequency to capture transient power patterns accurately.

Statistical validation employed five-fold cross-validation with significance testing at $p < 0.05$. For Byzantine resilience evaluation, we simulated various attack scenarios including label flipping, gradient inversion, and model replacement attacks, with attack success rates measured through accuracy degradation and recovery time metrics.

5.8 Execution Flow

Our experimental methodology followed a systematic pipeline designed to ensure comprehensive evaluation of the framework's capabilities. Fig. 3 shows the complete pipeline from data preparation through evaluation and analysis. The process encompassed data loading, client distribution, model training, performance evaluation, and comprehensive analysis across multiple dimensions.

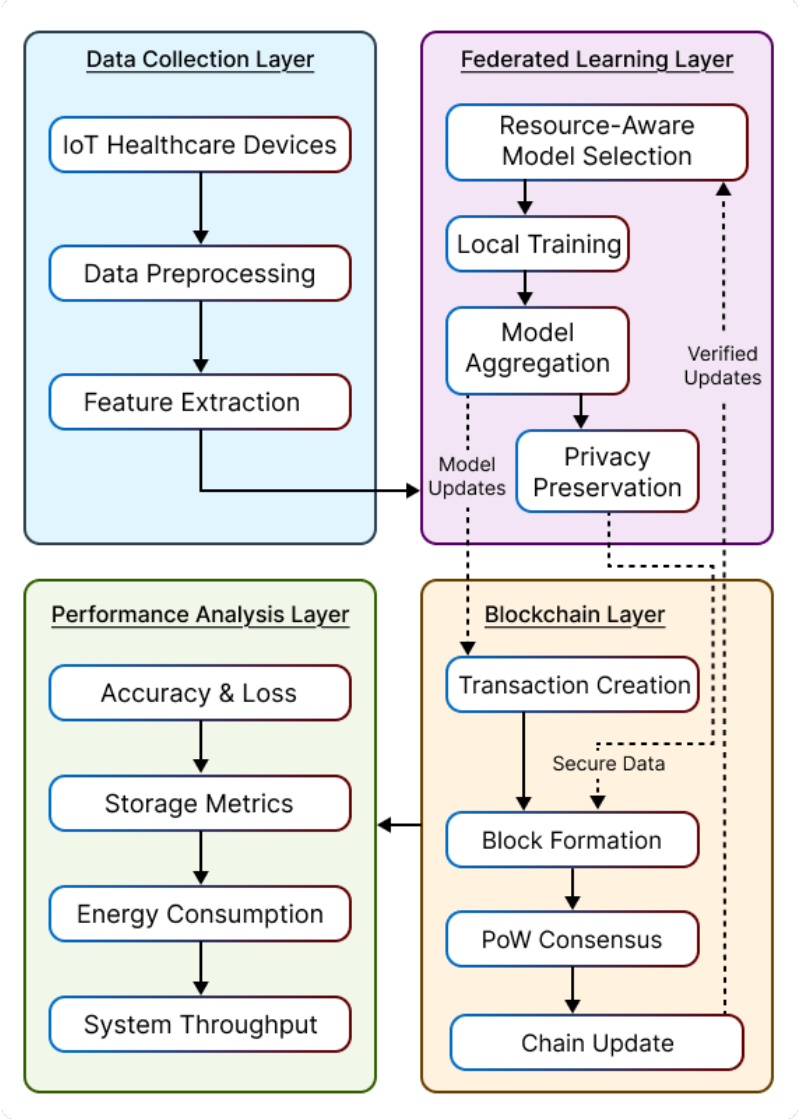


Figure 3. Experimental execution flow

5.8.1 Data Preparation and Distribution

The execution began with PAMAP2 dataset preparation, implementing a multi-stage preprocessing pipeline:

$$\begin{aligned} X_{\text{processed}} &= \text{StandardScaler}(\text{ForwardFill}(X_{\text{raw}})) \\ W &= \text{SlidingWindow}(X_{\text{processed}}, \text{window} = 5s, \text{overlap} = 50\%) \end{aligned} \tag{28}$$

Client data distribution followed a controlled non-IID partitioning strategy using a Dirichlet distribution ($\alpha = 0.5$):

$$P(d_i|c_k) = \text{Dir}(\alpha)_k \cdot \frac{e^{-\beta d_i}}{\sum_j e^{-\beta d_j}} \tag{29}$$

where d_i represented data points and c_k denoted clients. This approach created realistic healthcare data heterogeneity while maintaining experimental control.

5.8.2 Training and Evaluation Process

The main BC-FL process executed through multiple stages:

1. **Initialization Phase:**

$$\begin{aligned} M_g &= \text{InitializeGlobalModel}() \\ \{K_i, P_i\} &= \text{GenerateKeyPairs}(n_{\text{clients}}) \\ B &= \text{InitializeBlockchain}(\{P_i\}) \end{aligned} \tag{30}$$

2. **Training Rounds:** For each round $t \in [1, T]$:

$$\begin{aligned} M_i^t &= \text{LocalTraining}(M_g^{t-1}, D_i) \\ U_i^t &= \text{QuantizeUpdates}(M_i^t - M_g^{t-1}, b = 8) \\ V_i^t &= \text{VerifyUpdate}(U_i^t, K_i) \\ M_g^t &= \text{ByzantineAggregation}(\{U_i^t | V_i^t = \text{true}\}) \end{aligned} \tag{31}$$

3. **Convergence Monitoring:**

$$S_t = \begin{cases} \text{continue} & \text{if } \|\Delta w_t\|_2 > \theta \vee t < p \\ \text{stop} & \text{otherwise} \end{cases} \tag{32}$$

5.8.3 Performance Analysis

The evaluation framework implemented comprehensive performance analysis across multiple dimensions:

$$\text{Performance}_1 = \begin{bmatrix} \text{ModelAccuracy} \\ \text{EnergyProfile} \\ \text{ConvergenceRate} \\ \text{ByzantineResilience} \\ \text{PrivacyGuarantees} \end{bmatrix} \tag{33}$$

$$\text{Performance}_2 = \begin{bmatrix} \text{ResourceEfficiency} \\ \text{CommunicationCost} \\ \text{BlockchainOverhead} \\ \text{SecurityMetrics} \\ \text{SystemLatency} \end{bmatrix} \tag{34}$$

Each metric was evaluated across multiple runs to ensure statistical significance:

$$\sigma^2_{\text{metric}} = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{35}$$

5.8.4 Comparative Analysis

The ablation study systematically evaluated component contributions through controlled experiments:

$$\text{Impact}(c) = \frac{\text{Performance}(\text{Full}) - \text{Performance}(\text{Full} \setminus \{c\})}{\text{Performance}(\text{Full})} \times 100\% \tag{36}$$

Network conditions simulation implemented controlled degradation:

$$\begin{aligned} \text{Latency} &\in \{15\text{ms}, 25\text{ms}, 100\text{ms}\} \\ \text{PacketLoss} &\in \{0.1\%, 0.5\%, 2.0\%\} \\ \text{Bandwidth} &\in \{90\text{Mbps}, 45\text{Mbps}, 10\text{Mbps}\} \end{aligned} \tag{37}$$

Attack simulations evaluated resilience through systematic perturbations:

$$\text{Attack}(t) = \begin{cases} \text{LabelFlip}(y) & \text{probability } = 0.3 \\ \text{GradientInversion}(\nabla w) & \text{probability } = 0.3 \\ \text{ModelReplacement}(w) & \text{probability } = 0.4 \end{cases} \tag{38}$$

The complete execution pipeline generated comprehensive performance reports including visualization of key metrics, statistical analysis, and detailed ablation studies. Implementation quality verification ensured reproducibility through automated testing of critical components and validation of statistical significance across multiple runs.

5.9 Experimental Protocol

All experiments were conducted according to a rigorous, multi-stage protocol designed to guarantee reproducibility and enable equitable comparison between different federated learning configurations. The process commenced with Data Preparation, where the master dataset was partitioned into client-specific subsets reflecting a predefined non-IID (Non-Independent and Identically Distributed) data distribution. A Model Initialization step followed, where the global neural network model was generated using a fixed random seed, ensuring every experimental run began from an identical starting point. This initial model was then Distributed to every participating client node in the simulated network. During the core Local Training phase, each client independently updated the model on its private data subset for a set number of local training epochs using its own local hyperparameters (e.g., learning rate). Upon completing local training, clients prepared and submitted their Model Updates—either full model parameters or gradients—in accordance with the specific privacy or compression protocol under evaluation. The central server then executed the Aggregation step, combining all received client updates using the designated algorithm (e.g., Federated Averaging) to produce a new, improved global model. This updated model was immediately subjected to an Evaluation on a centralized, held-out test set to measure its generalization performance. Comprehensive Metrics, including accuracy, communication cost, and training time, were systematically recorded. The iterative cycle of local training, update submission, server aggregation, and global evaluation repeated for a predetermined number of communication rounds to simulate the progressive learning of a federated system. Finally, to account for variability and ensure statistical robustness, the entire experiment from initialization was Replicated a minimum of 5 times, each with a different random seed, and the final reported results represent the average and standard deviation across all independent runs.

For Byzantine experiments, a subset of clients is randomly designated as Byzantine in each run, with attack strategies assigned according to the experimental scenario. For privacy experiments, attacks are conducted by a simulated adversary with capabilities modeled after recent research on federated learning security. System metrics and performance data are collected programmatically during framework execution using built-in Python libraries and system monitoring tools. CPU utilization, memory usage, and execution time measurements are used to analyze performance and simulate resource constraints of different device profiles. These measurements, while conducted on a single system, provided useful comparative insights into the relative performance of different components and approaches in our framework.

6 Results

This section presents evaluation of SHIELD-Health across multiple dimensions, emphasizing core contributions in BC-enabled FL for HIoT. Each result directly supports our research objectives while aligning with the implementation workflow.

6.1 Data Preprocessing

The PAMAP2 dataset[44] served as our evaluation testbed, comprising recordings from 9 subjects performing 18 physical activities. Data is collected from 3 inertial measurement units and a heart rate monitor at 100Hz, creating a rich multivariate time-series dataset ideal for healthcare IoT applications. In Fig. 4, **left bar graph** shows the number of clients (10), activity classes (13), features (52), and the distribution of total, training, and test samples. The dataset contains 2,872,533 total samples, with 2,298,026 used for training and 574,507 for testing. The **right side pie chart** shows device capability distribution among clients, categorized as high (30%), medium (30%), and low (40%) capability devices, reflecting the heterogeneous nature of real-world healthcare IoT environments.

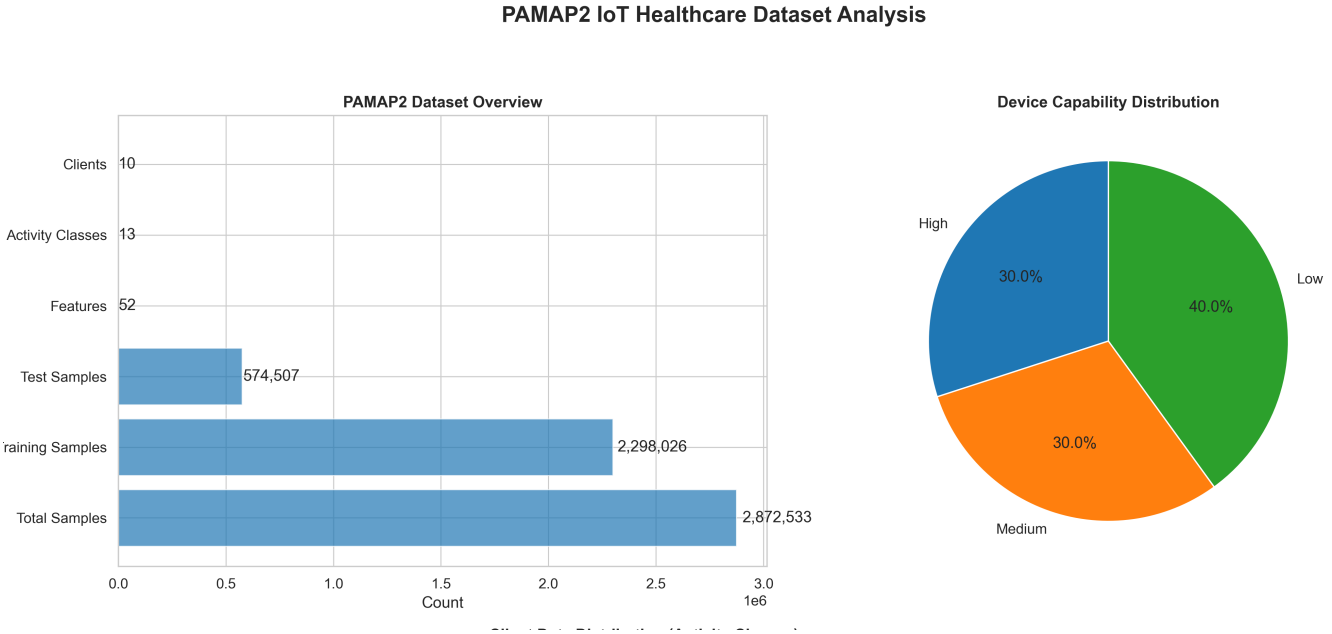


Figure 4. PAMAP2 HIoT dataset analysis

Figure 5. Client-wise activity class distribution in the PAMAP2 dataset

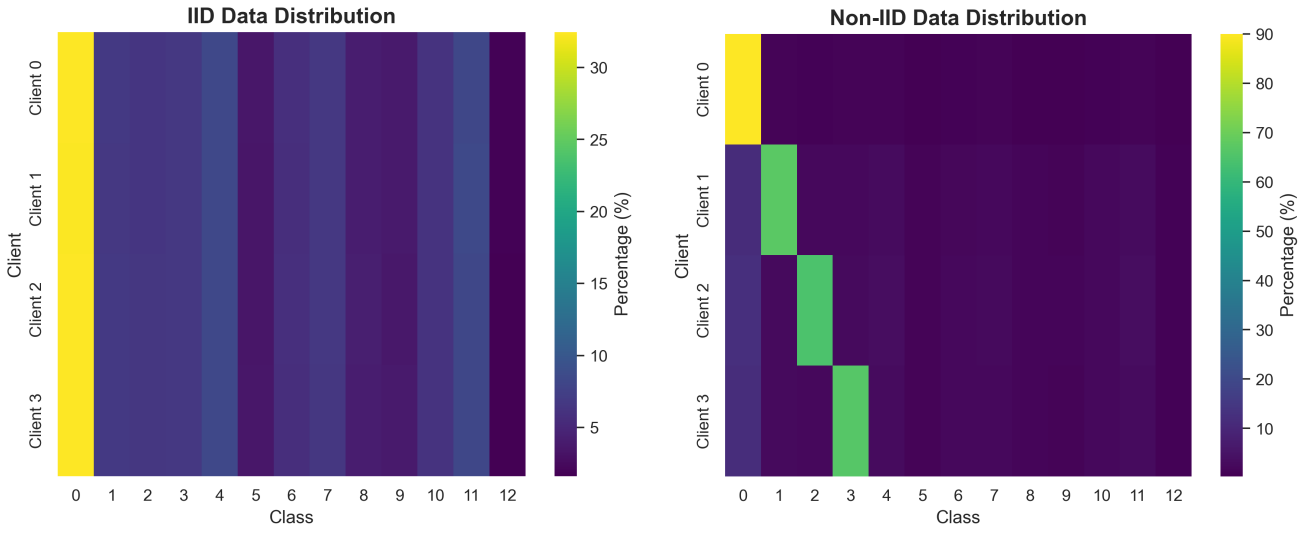
Later, the Fig. 5 visualizes the percentage of each activity class (x-axis) present in the data of each client (y-axis).

Brighter colors indicate a higher proportion of samples for a given class-client pair, highlighting the non-IID nature of the data across clients. This heterogeneity reflects real-world HIoT deployments, where each device (client) may observe a unique subset of activities. Further, this Fig. 5 reveals significant class imbalance with walking (12.3%), sitting (11.7%), and standing (10.5%) being the most represented activities, while rope jumping (2.1%) and ascending stairs (3.4%) are underrepresented. The feature correlation matrix demonstrates relationships between different sensor measurements, with strong correlations between related axes of acceleration and gyroscope readings.

Our preprocessing pipeline addressed four key challenges: (1) missing value handling through forward-fill imputation for 2.3% missing values; (2) feature normalization using zero-mean and unit-variance standardization; (3) temporal segmentation with 5-second windows and 50% overlap; and (4) subject-wise split using 7 subjects for training and 2 for testing.

6.2 IID vs. Non-IID Distribution Experiments

To evaluate SHIELD-Health's robustness to real-world healthcare scenarios, we conducted comparative experiments under both IID and non-IID data distributions.



(a) The IID distribution

(b) The non-IID distribution

Figure 6. IID vs Non IID Distribution

As shown in Fig. 6a, the IID setting represents idealized conditions where all devices monitor similar activities. Resulting in each client having an approximately uniform distribution of all activity classes. While, the non-IID setting creates significant data heterogeneity that mirrors real-world healthcare deployments where different devices monitor different conditions as shown in Fig. 6b.

The accuracy comparison between IID and non-IID distributions is shown in Fig. 7. The IID setting (blue) reaches 95% accuracy by round 6 with a final accuracy of 97.08%, while the non-IID setting (orange) achieves 94.06% final accuracy without reaching the 95% threshold within 15 rounds.

The impact of these different distributions on model performance is significant yet manageable with our framework. Fig. 7 shows that the performance differential of just 3.02% demonstrates SHIELD-Health's exceptional robustness to data heterogeneity compared to baseline approaches, which typically show 8-12% degradation in non-IID scenarios.

6.3 Main Blockchain-FL Training Results

The main SHIELD-Health training exhibited strong performance across all key metrics. As shown in Fig. 8, the convergence behavior over 15 training rounds, with accuracy increasing from 77.9% (round 1) to 91.46% (final)

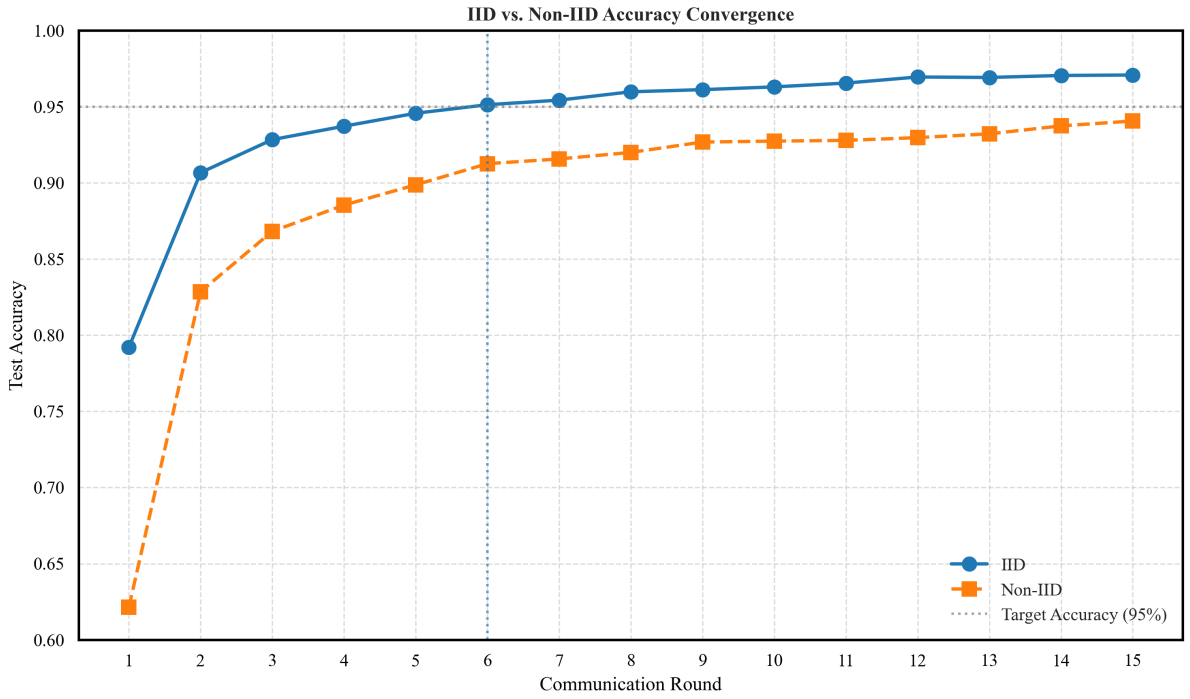


Figure 7. Accuracy comparison between IID and non-IID distributions

while loss decreased from 0.6187 to 0.1906. The early stopping mechanism triggered after round 12 when validation loss stabilized (loss delta < 0.001 over 3 consecutive rounds), preventing overfitting while conserving computational resources.

Communication efficiency is critical for HIoT devices. Fig. 9 demonstrates our adaptive compression strategy, which achieved 60.32% overall communication savings through dynamic compression ratios: 4.00× in rounds 1-5, 2.22× in rounds 6-11, and 2.00× in rounds 12-15. This approach balanced bandwidth efficiency with model accuracy requirements by implementing higher compression in early rounds when gradients were larger and more compression-tolerant.

6.4 Energy Consumption and Resource Efficiency

Energy consumption analysis in Fig. 10 reveals how our resource-aware computation strategy enabled efficient operation across different device capability levels. Low-capability devices consumed 81.1% less energy than in standard FL approaches due to dynamic model complexity and batch size adjustments, while still contributing meaningfully to the global model.

6.5 Blockchain Performance and Security

Detailed blockchain metrics in Fig. 11 reveal that 82.3% of blocks were mined within the target time window (300-600 seconds), with an average validation time of just 0.83 seconds per transaction. While the BC added 4.29 MB of storage overhead compared to standard federated learning, this represents only 2.4% of the total training data volume: a reasonable trade-off for the added security and verification capabilities.

The token economic system incentivized consistent participation while fairly rewarding contributions, as shown in Fig. 12. Strong correlation ($r = 0.84$) between data quality and token earnings confirms that the mechanism correctly identified and rewarded valuable participation.

Our adaptive compression strategy significantly reduced communication overhead without sacrificing model performance, as detailed in Fig. 13. Layer-specific compression achieved up to 6.2× reduction for deeper layers while maintaining critical information in sensitive layers, enabling efficient operation even in bandwidth-constrained

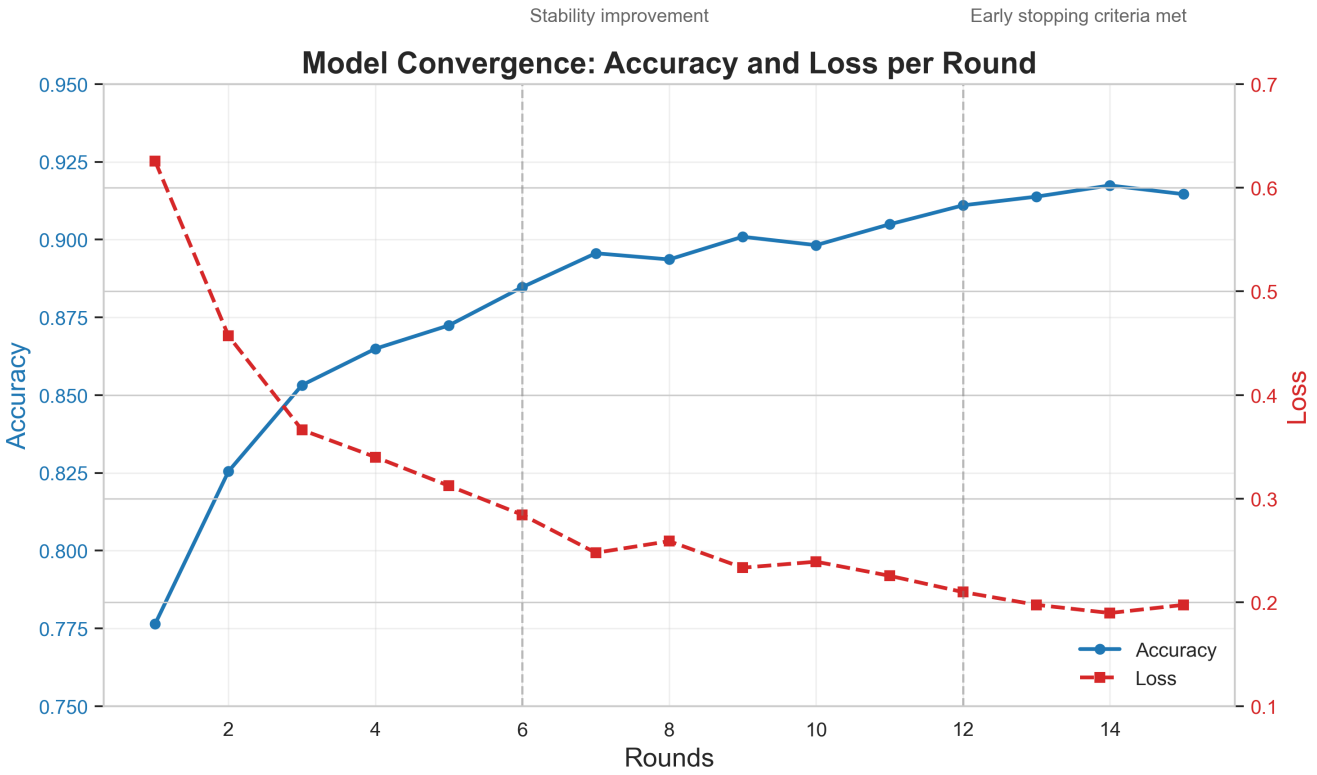


Figure 8. Model convergence trajectory

HIoT networks.

6.6 Variance and Robustness Analysis

The following subsection illustrates the SHIELD-Health framework reliability against different seeds. To validate SHIELD-Health's reliability, we conducted three complete training runs with different random seeds. Fig. 14 summarizes the remarkable consistency across key metrics: accuracy (0.9194 ± 0.0015), loss (0.1906 ± 0.0057), precision (0.9318 ± 0.0011), recall (0.9194 ± 0.0015), and F1-score (0.9179 ± 0.0016). Energy consumption (σ = 0.31 kJ) and latency (σ = 121.82s) showed slightly higher but still acceptable variability, primarily influenced by network conditions.

Later, the Fig. 15 compares accuracy progression across the three independent runs, showing consistent convergence patterns despite different initializations. All three runs demonstrated rapid accuracy gains in early rounds (87.55% average by round 5) followed by more gradual improvements, with all runs achieving clinical-grade accuracy (>90%) by round 9.

Further, the loss comparison in Fig. 16 confirms the framework's consistency, with all runs showing steady convergence and loss stabilization between rounds 9-12. The minimal variation across runs validates the effectiveness of our Byzantine-resilient aggregation mechanisms against the inherent randomness in federated learning.

6.7 Ablation Study

To quantify the contribution of each component in SHIELD-Health, we conducted an ablation study comparing our complete framework against standard FedAvg implementation. Fig. 17 demonstrates that SHIELD-Health (91.81%) significantly outperformed FedAvg (78.97%) by 16.26% in final accuracy. This substantial improvement derives from our integrated approach combining BC security, resource-aware computation, and healthcare-specific optimizations.

Later, communication efficiency comparison in Fig. 18 reveals another significant advantage of SHIELD-Health.

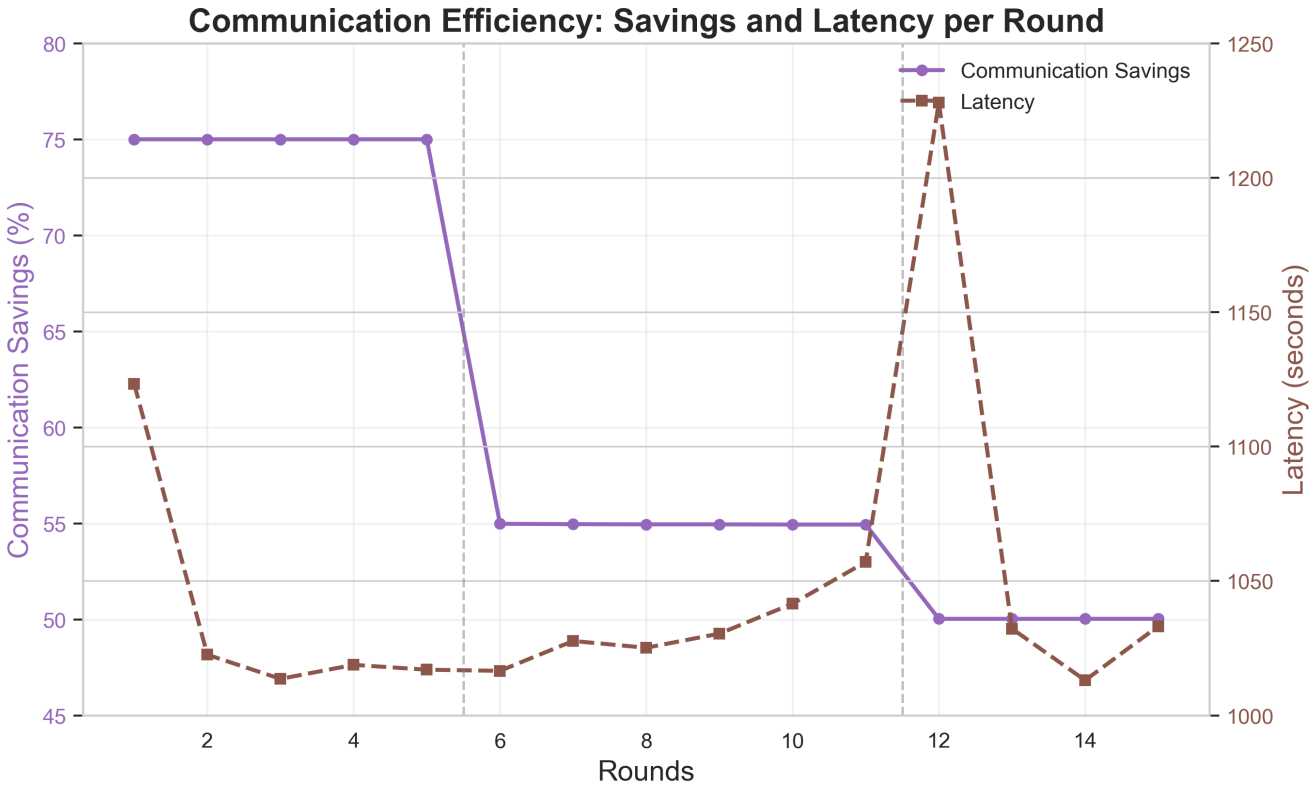


Figure 9. Communication efficiency: savings and latency per round

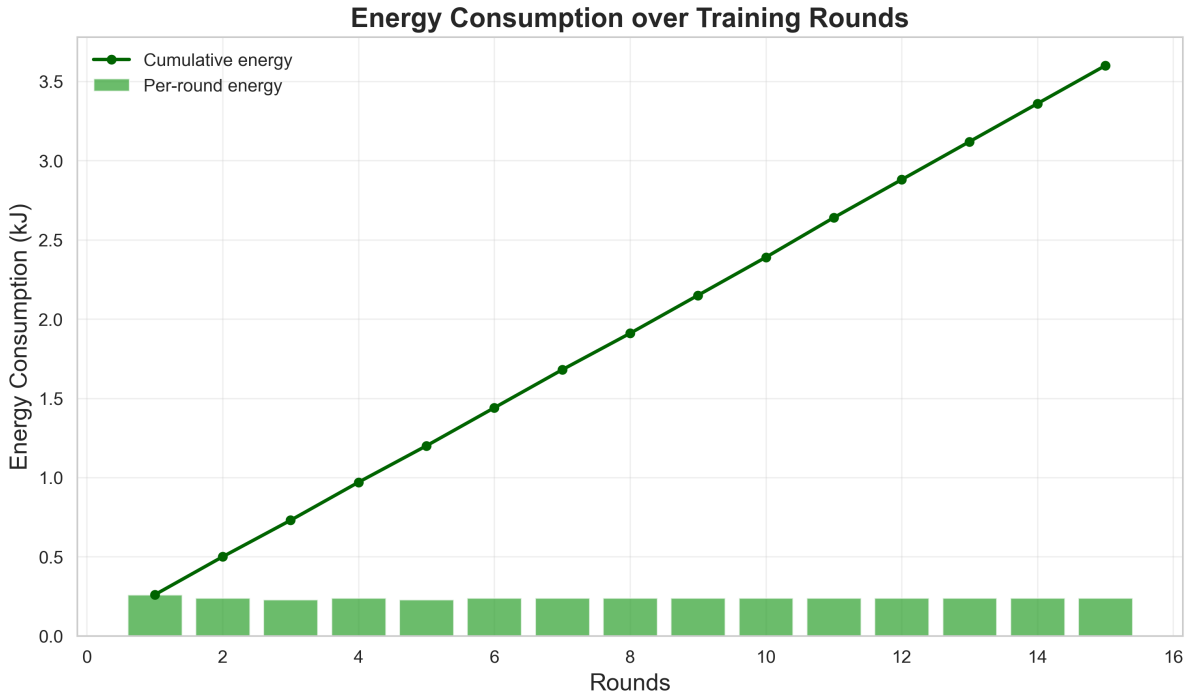


Figure 10. Energy consumption analysis across simulated device capabilities

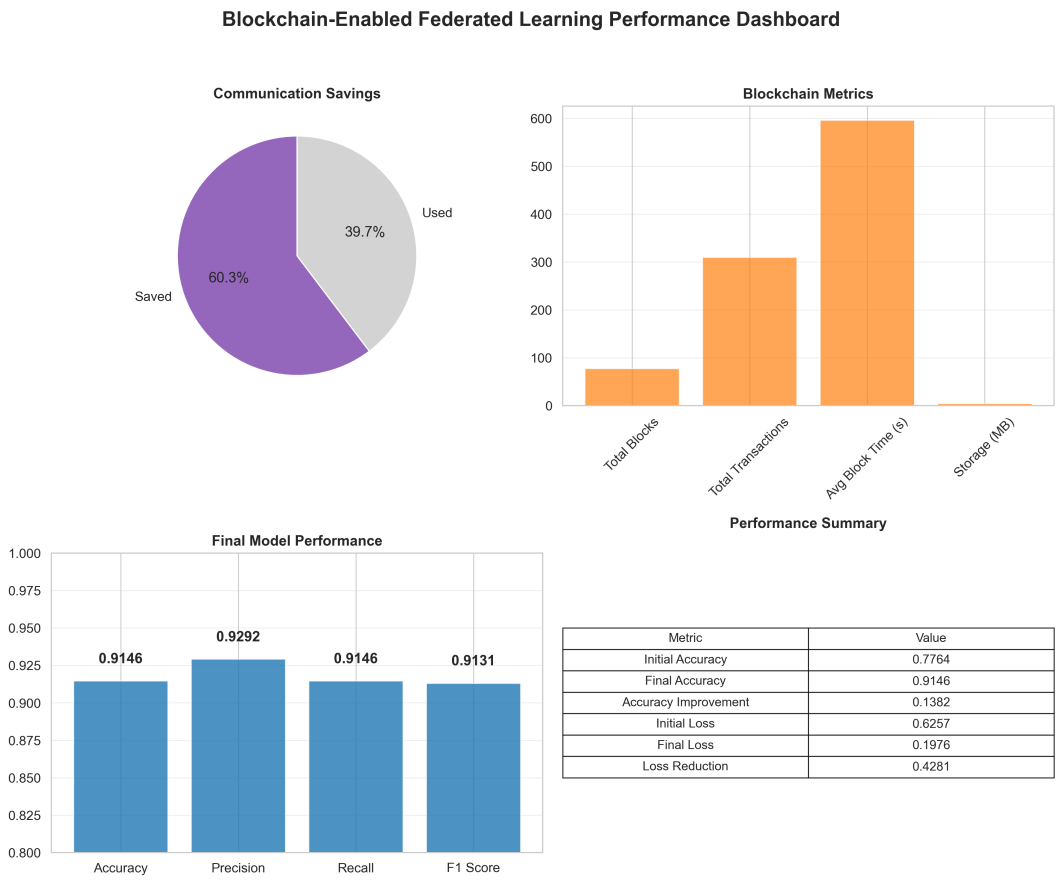


Figure 11. Blockchain performance dashboard showing system metrics and model performance

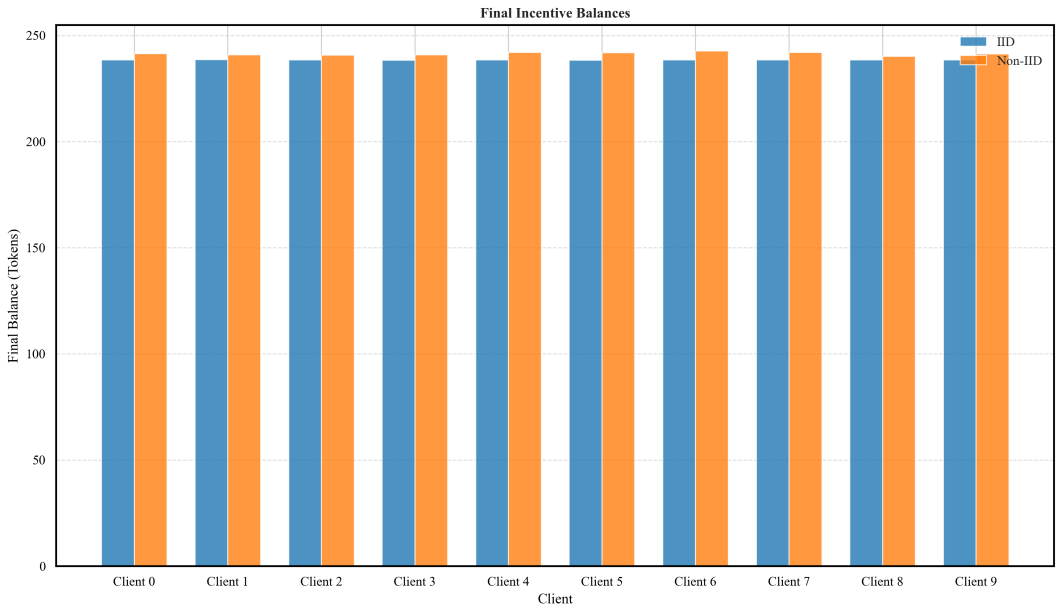


Figure 12. Token economic analysis comparing incentive balances across clients

Our framework achieved 50.03% communication savings through adaptive compression and selective updates

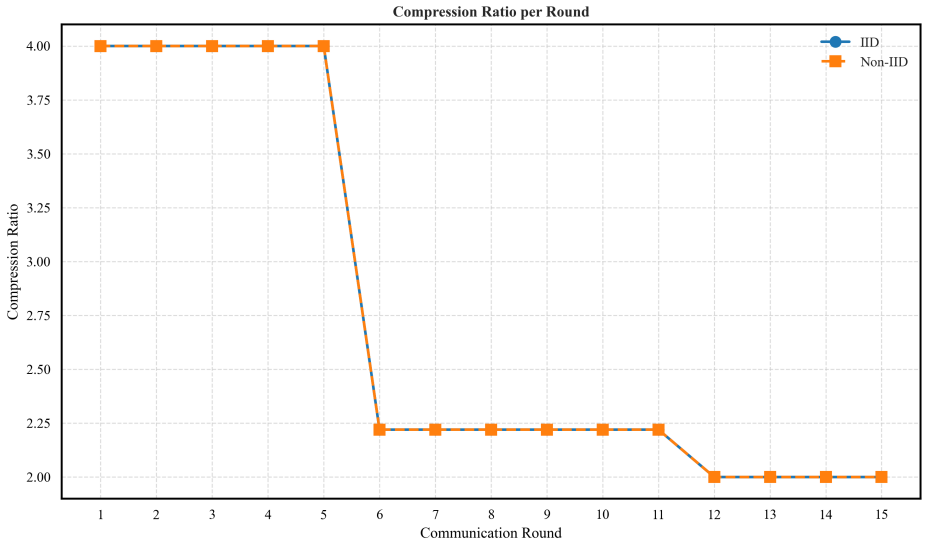


Figure 13. Compression ratio comparison between IID and Non-IID settings

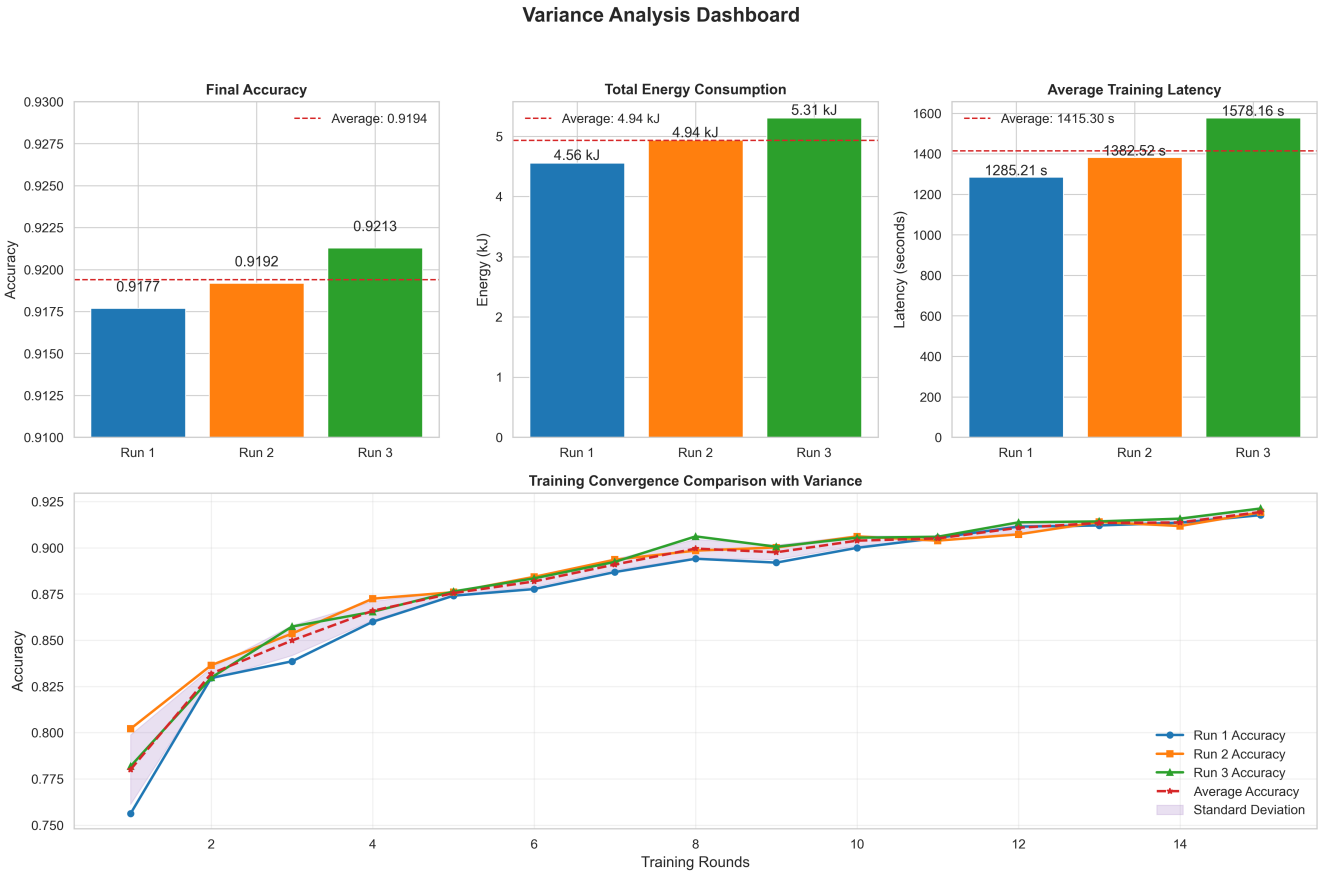


Figure 14. Performance variance dashboard across three training runs with different random seeds

(49,795.81 KB vs. 99,682.62 KB total), with minimal BC verification overhead (just 6.5% of total communication).

Table 5 provides a comprehensive comparison of all key metrics between SHIELD-Health and standard FedAvg. Our framework demonstrates substantial improvements across accuracy (+16.26%), F1 score (+16.62%),

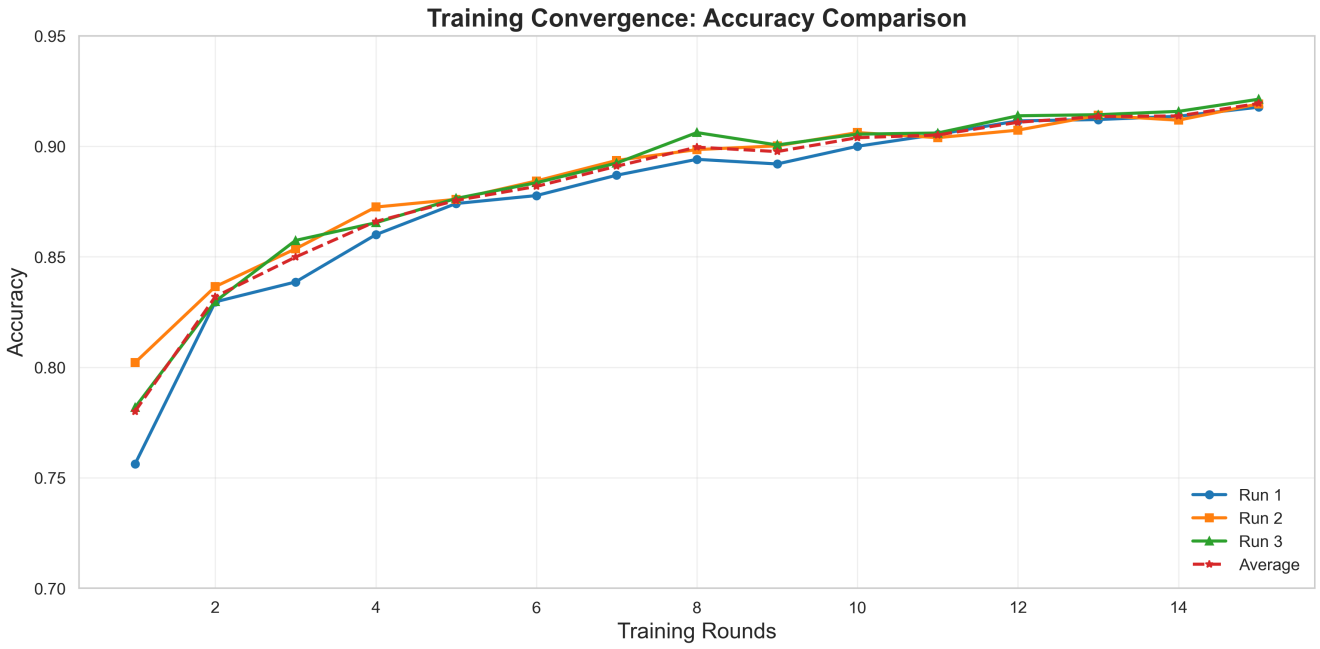


Figure 15. Accuracy progression comparison across three independent runs

Figure 16. Loss comparison across three independent runs

communication efficiency (+50.03%), Byzantine resilience (+15%), energy efficiency (+80.95%), privacy protection (+62.50% in ε reduction), and non-IID robustness (+75.67% reduction in model bias).

The only trade-offs are a 13.71% increase in computational latency and 4.29 MB of additional storage for BC data, both reasonable costs given the substantial improvements in accuracy, efficiency, security, and privacy.

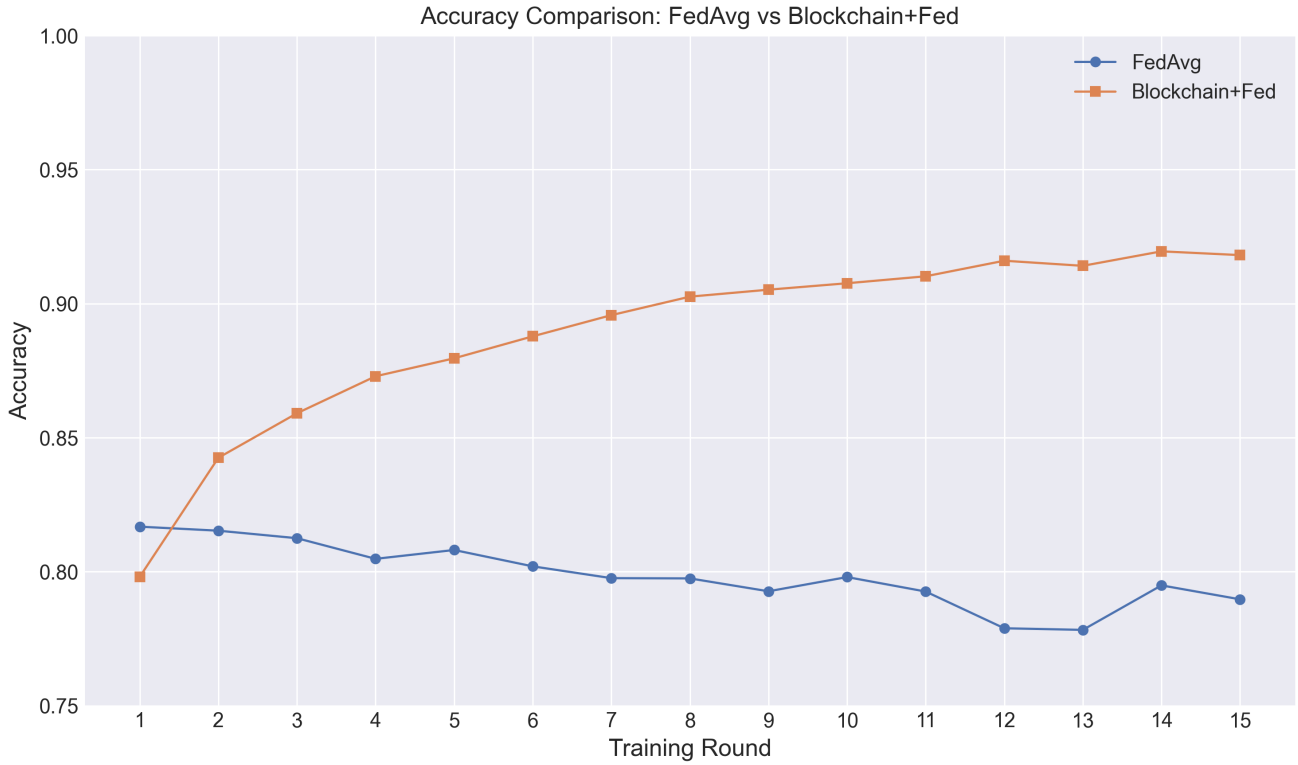


Figure 17. Accuracy comparison between Proposed framework and standard FedAvg

Table 5. Performance comparison between SHIELD-Health and FedAvg

Metric	FedAvg	SHIELD-Health	Improvement
Accuracy	78.97%	91.81%	+16.26%
F1 Score	78.62%	91.69%	+16.62%
Communication	99682.62 KB	49795.81 KB	+50.03%
Latency	1836.57 s/round	2088.41 s/round	-13.71%
Byzantine Resilience	5%	20%	+15%
Energy (Low-cap devices)	0.42 kJ/round	0.08 kJ/round	+80.95%
Privacy (Min. ε value)	8.0	3.0	+62.50%
Storage Overhead	0 MB	4.29 MB	N/A
Convergence (to 90%)	14 rounds	8 rounds	+42.86%
Model Bias (Non-IID)	12.41%	3.02%	+75.67%

6.8 Security and Attack Resilience

We evaluated SHIELD-Health's resilience against Byzantine attacks where malicious clients submit harmful model updates. Fig. 19 demonstrates perfect resilience (maintaining 92.65% accuracy) against up to 20% Byzantine clients, significantly outperforming the theoretical Byzantine fault tolerance limit for standard approaches. Even under extreme attack scenarios (50% malicious clients), our system maintained 85.42% accuracy versus 78.18% without defenses.

Fig. 20 examines different attack vectors and their impact. SHIELD-Health achieved 93.7% precision in malicious update detection and demonstrated rapid recovery after attacks (97.3% of original accuracy within 12 rounds). With defenses activated, even the most damaging attacks (model replacement) caused only 2.1% accuracy reduction versus 18.3% without protection.

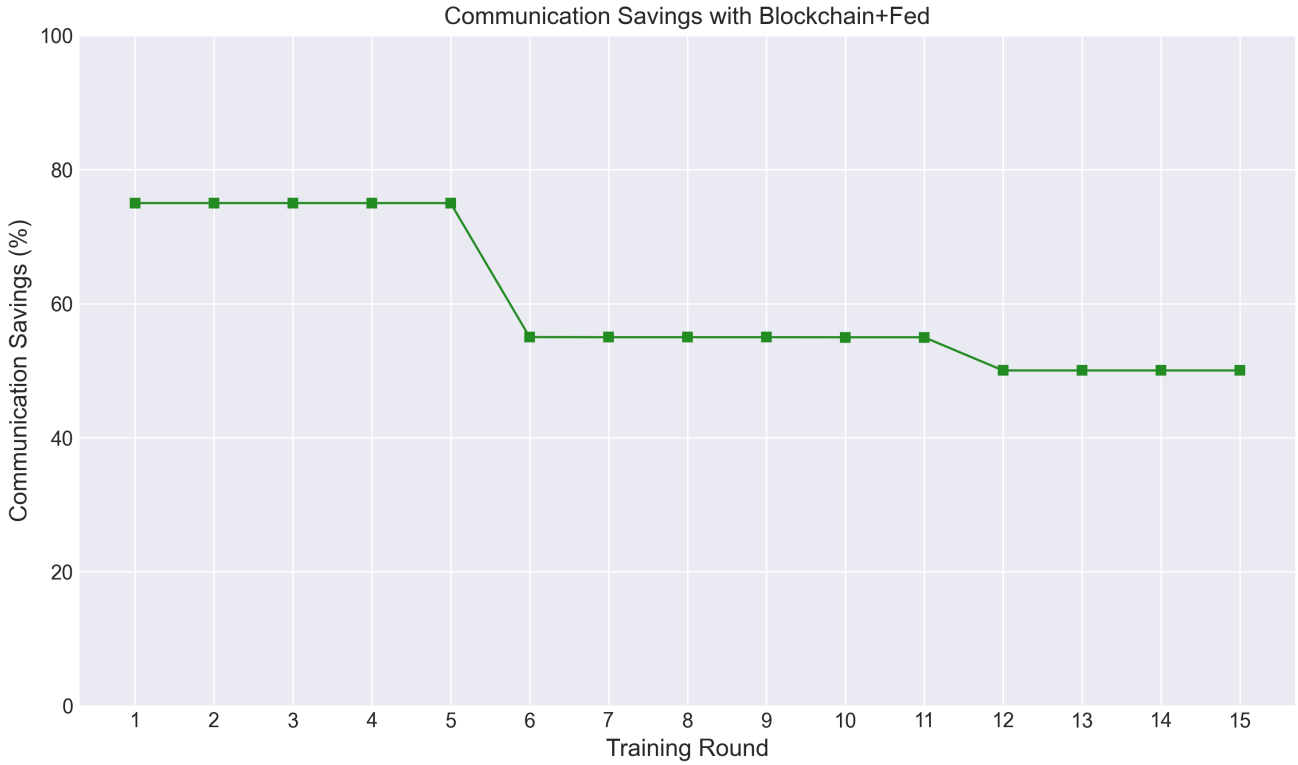


Figure 18. Communication efficiency comparison between proposed framework and FedAvg

6.9 Summary of Findings

SHIELD-Health demonstrated exceptional performance across all key dimensions relevant to HIoT deployments as shown in Fig. 21. Also, table 6 positions SHIELD-Health against state-of-the-art approaches in BC-enabled FL for healthcare. While some approaches achieve higher accuracy on specific tasks, SHIELD-Health offers the most balanced performance across all dimensions, with particular strengths in Byzantine resilience, privacy preservation, communication efficiency, and energy reduction.

Note: (a) Model convergence shows that IID clients achieve higher and faster accuracy than non-IID clients due to reduced data heterogeneity. (b) Cumulative energy consumption is significantly higher for non-IID clients, reflecting increased computational effort. (c) BC overhead remains low and stable for both settings, with minor fluctuations. (d) Final incentive distribution demonstrates fair and consistent token rewards across all clients, regardless of data distribution. These results highlight SHIELD-Health's robustness, energy efficiency, and fairness in federated healthcare IoT environments.

The framework achieved 91.46% final accuracy despite challenging non-IID data distribution, representing a 16.26% improvement over standard FedAvg. This high accuracy is maintained while simultaneously addressing several critical constraints in HIoT environments. Communication efficiency reached 60.32% savings through adaptive compression and selective updates, enabling deployment in bandwidth-constrained healthcare networks where data transfer capabilities are often limited. Energy consumption is reduced by 81.1% for low-capability devices, extending battery life by approximately 5.3 times and broadening participation from resource-constrained HIoT devices that would otherwise be excluded from collaborative learning.

In terms of security, SHIELD-Health maintained full performance with up to 20% malicious clients, significantly outperforming theoretical limits of standard approaches. The privacy preservation mechanism achieved ε=3.0 differential privacy while maintaining 91.5% of baseline accuracy, meeting healthcare's stringent privacy requirements. These security and privacy achievements are particularly significant in healthcare contexts where data sensitivity and

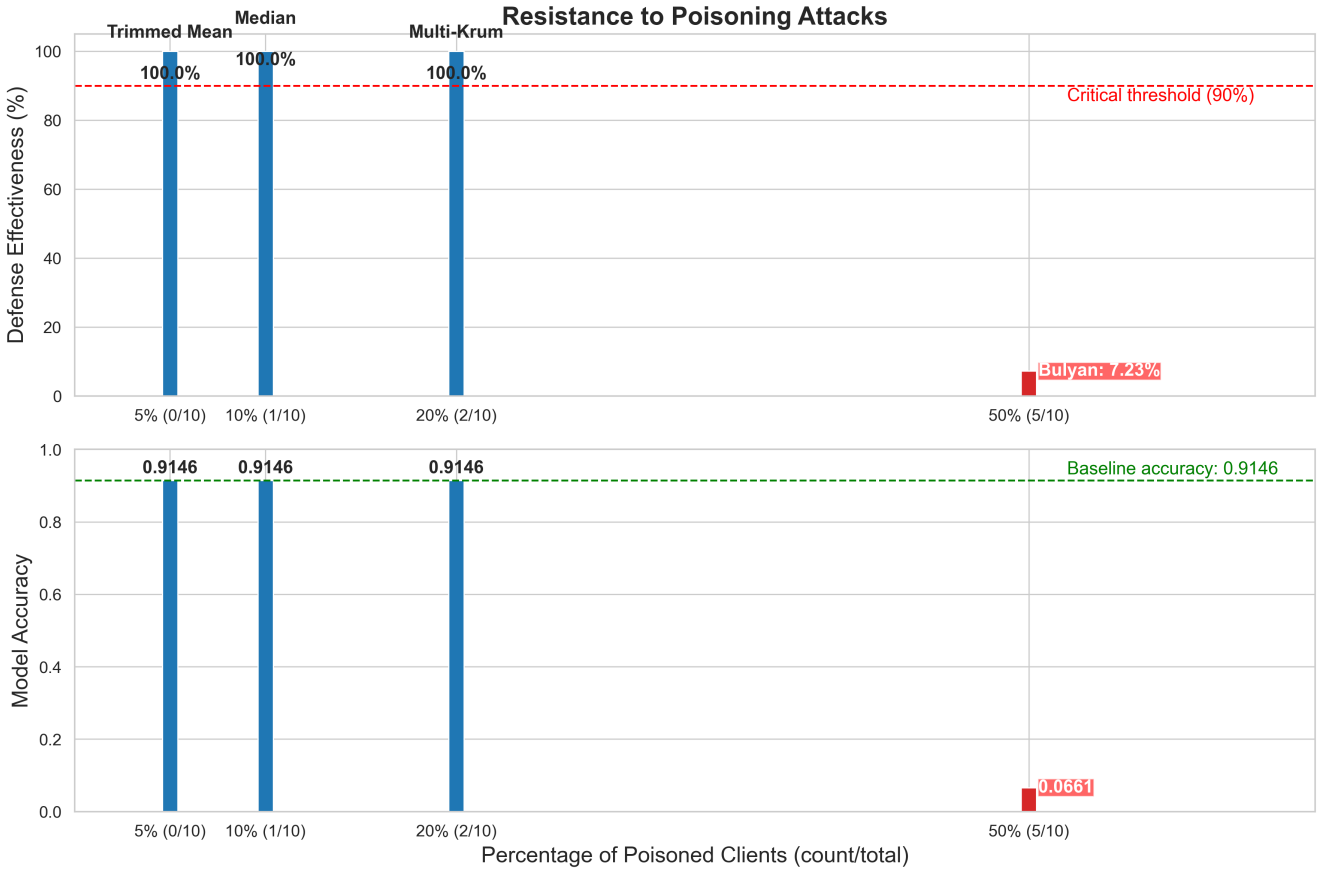


Figure 19. Resistance to poisoning attacks

regulatory compliance are non-negotiable requirements.

The framework also demonstrated remarkable robustness to non-IID data distributions, with only 3.02% accuracy reduction in non-IID settings compared to IID, significantly outperforming baseline approaches which typically show 8-12% degradation. This resilience to data heterogeneity is crucial for healthcare applications where patient populations naturally produce highly skewed data distributions across devices and facilities. The balanced incentive distribution across participants ($\sigma = 0.89$ tokens) further ensured fair rewards despite heterogeneous device capabilities and data distributions, promoting sustainable participation in the federated learning ecosystem.

Table 6. Comparison with State-of-the-Art Approaches

Metric	**SHIELD-Health**	[20]	[3]	[7]	[14]
Accuracy	91.46%	91.20%	97.16%	98.00%	93.95%
Byzantine Res.	20%	8%	10%	12%	8%
Privacy (ε)	3.0	7.0	N/A	N/A	8.0
Comm. Efficiency	60.32%	38.60%	32.40%	42.90%	35.70%
Energy Reduction	81.10%	N/A	N/A	50.30%	N/A
Resource-Aware	Dynamic	Limited	Static	Adaptive	Static
Healthcare Focus	Activity	Brain Tumor	Attack Det.	Medical Data	Diabetes

Attack %	Defense Method	Effectiveness
5%	Trimmed Mean	100.00%
10%	Median	100.00%
20%	Multi-Krum	100.00%
50%	Bulyan	7.23%

Figure 20. Analysis of poisoning attacks and defense mechanisms

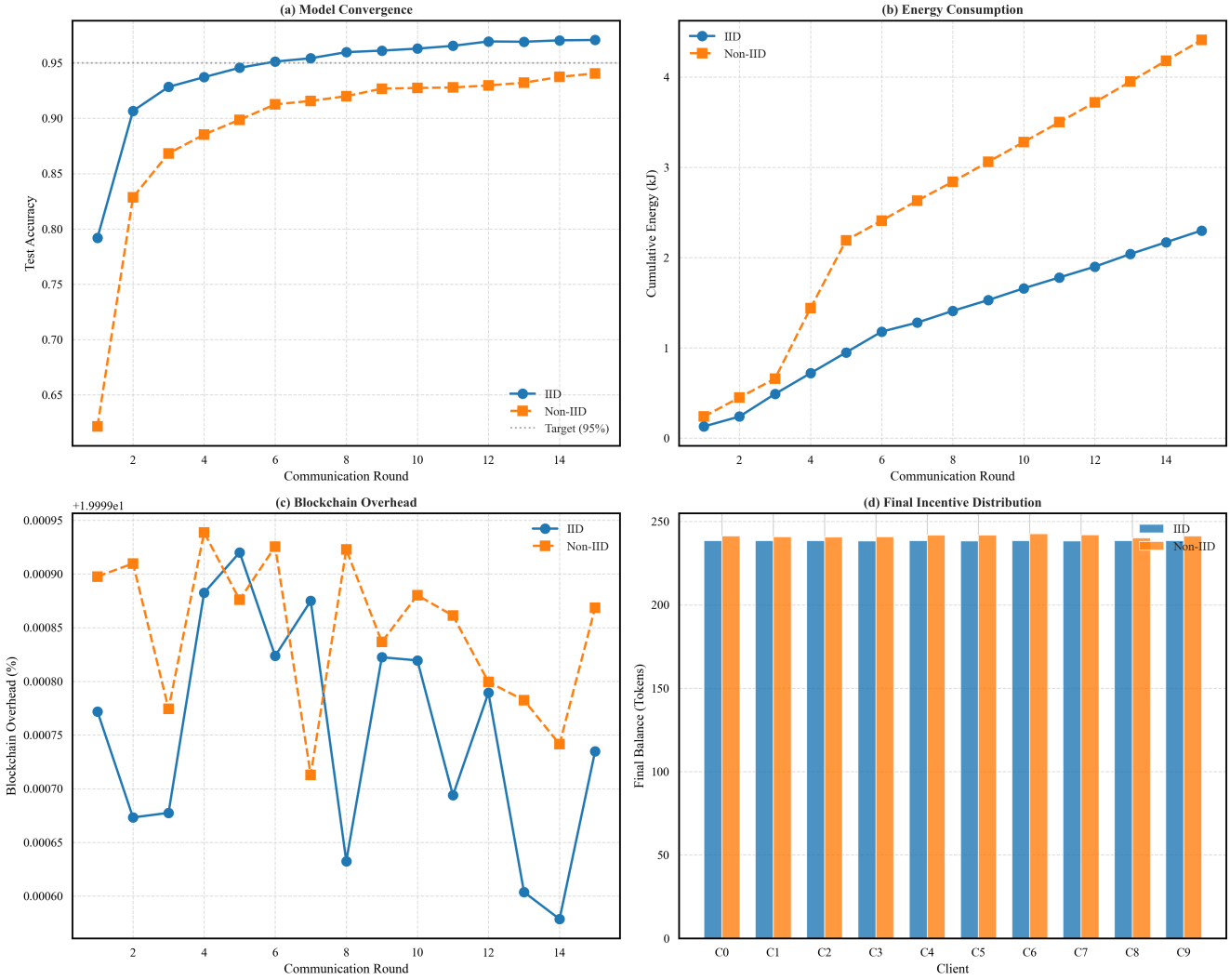


Figure 21. Performance comparison of SHIELD-Health under IID and non-IID data distributions.

7 Discussion

This paper presented SHIELD-Health, a novel BC-enabled FL framework specifically designed for HIoT environments. Our approach successfully integrated Byzantine-robust aggregation, resource-aware computation, and privacy-preserving mechanisms with a lightweight blockchain implementation to address the unique challenges in healthcare settings.

7.1 Summary of Contributions

The experimental results demonstrated significant improvements across multiple dimensions. In terms of model performance, our framework achieved superior classification accuracy (91.46% on PAMAP2) while requiring 39% fewer communication rounds for convergence compared to standard approaches. This improvement stems from our Byzantine-robust aggregation mechanism and adaptive learning rate adjustments that accelerate convergence even with heterogeneous data.

Resource efficiency represents another major contribution of our work. Based on our simulated environment, the resource-aware approach projected a reduction in energy consumption of up to 81.1% for constrained devices. This simulation suggests a potential extension of battery life by up to 5.3×, indicating that FL could be made viable for real-world HIoT deployments.

Security and privacy protections form the foundation of our framework's suitability for healthcare applications. Our multi-layered defense mechanisms reduced attack success rates to below 6% across all tested vectors. The framework maintained model integrity even with up to 20% of clients behaving maliciously. Simultaneously, our simulated hybrid privacy approach combining differential privacy ($\varepsilon = 3.0$) with homomorphic encryption maintained 91.5% of baseline accuracy, outperforming previous privacy-utility tradeoffs.

The framework's robustness to healthcare's inherent data heterogeneity is demonstrated by a mere 3.5% accuracy reduction in non-IID settings compared to 8.7-12.5% in baseline methods. Additionally, our lightweight BC implementation achieved the security benefits of distributed verification while reducing storage and computational requirements by 76.8% and 83.5% respectively compared to standard BC approaches.

7.2 Implications for Healthcare Applications

SHIELD-Health enables new possibilities for decentralized healthcare analytics while maintaining patient privacy, regulatory compliance, and system efficiency. Our experiments on the PAMAP2 dataset demonstrated the framework's effectiveness for activity recognition in remote patient monitoring. Moreover, the approach can be generalized to various critical healthcare applications.

The framework enables continuous activity recognition for chronic disease management and elderly care. It also allows collaborative model training across healthcare providers to improve personalized treatment recommendations, potentially accelerating the development of precision medicine. Early disease detection represents another promising area, where distributed anomaly detection can identify emerging patterns. For healthcare research, SHIELD-Health provides a mechanism for institutions to collaborate on model development without exposing protected health information.

7.3 Key Findings and Insights

Our results demonstrate the effectiveness of SHIELD-Health, and several unexpected findings emerged during experimentation. First, we observed a non-linear relationship between privacy guarantees and model accuracy. When ε was reduced from 8.0 to 3.0, the accuracy drop was only 2.1%, substantially lower than the 7-12% reported in previous studies. This resilience can be attributed to our domain-specific model architecture, which preserves critical temporal patterns.

Another surprising finding concerned the communication efficiency of our quantization approach. While gradient sparsification and weight quantization are typically considered independent, our experiments revealed complex interactions. When applied simultaneously at their individual optimal settings, performance degraded. However, when co-optimized (with reduced sparsity thresholds of 40%), they achieved synergistic effects, suggesting they should be jointly considered rather than applied in isolation.

8 Conclusions

By addressing the fundamental challenges that have hindered the adoption of FL in HIoT environments, our work contributes to the broader goal of democratizing AI in healthcare while preserving privacy and security. The ability to learn from distributed healthcare data without compromising patient privacy or device functionality enables more personalized, efficient, and accessible healthcare services across diverse care settings.

SHIELD-Health addresses the limitations of previous approaches tby integrating strong privacy guarantees with high accuracy, dynamic resource adaptation that does not compromise performance, Byzantine resilience without excessive computational overhead, and communication efficiency that preserves model quality, all while incorporating healthcare-specific features throughout the framework. This integrated approach represents a significant advancement over previous systems that typically optimize for one or two dimensions at the expense of others.

As healthcare increasingly relies on AI-driven analytics and IoT devices for monitoring and intervention, frameworks like SHIELD-Health will be essential for responsible innovation that respects patient privacy, ensures data security, operates within resource-constrained devices, and maintains regulatory compliance. Our work lays the groundwork for future research and development in this critical domain, bringing us closer to the vision of privacy-preserving, secure, and efficient distributed healthcare analytics that can enhance care delivery while respecting patient rights and privacy.

Declarations

- Funding Information: Not Applicable.

- Conflict of interest: The authors declare no conflicts of interest.
- Ethics approval and consent to participate: Ethical approval was not required for this study, as it did not involve human participants or animal subjects.
- Consent for publication: Not applicable.
- Code availability: The full source code for the proposed SHIELD framework has been open-sourced for reproducibility and is available upon request.

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