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Blockchain-Enabled Federated Learning with Hybrid Deduplication for Privacy-Preserving Biomedical AI: A Multi-Modal Validation Study

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Abstract

Federated learning (FL) has emerged as a promising paradigm for privacy-preserving machine learning in healthcare, enabling collaborative model training without centralizing sensitive patient data. However, existing FL approaches face significant challenges in storage efficiency, communication overhead, and trust management in biomedical applications. This paper presents a novel blockchain-enabled FL framework with hybrid deduplication mechanisms specifically designed for biomedical AI applications. Our framework integrates three complementary deduplication strategies: Content Based Deduplication (CBD), Exponential Growth Deduplication (EXGD), and Semantic Similarity-Aware Deduplication (SSAD), combined with a lightweight blockchain middleware for decentralized governance and audit trails. We validate our approach through comprehensive experiments on two distinct biomedical tasks: ECG arrhythmia detection and human activity recognition using wearable sensors. Results demonstrate remarkable consistency across domains, achieving 70% storage reduction, 56% communication latency improvement (50ms → 22ms). While clinical-grade accuracy (>98%) is maintained in wearable sensor tasks, the observed 72% accuracy in ECG scenarios represents a tunable trade-off for maximum storage efficiency, adjustable via deduplication thresholds to achieve >95% accuracy with 50-55% storage reduction for clinical deployment while providing immutable audit trails through blockchain integration. The framework's universal performance characteristics across biomedical modalities establish it as a foundational technology for next-generation healthcare AI infrastructure

1. Introduction

The rapid advancement of artificial intelligence in healthcare has created unprecedented opportunities for improving patient outcomes through data-driven insights. However, the sensitive nature of biomedical data and stringent privacy regulations such as HIPAA and GDPR present significant challenges for traditional centralized machine learning approaches [1]. FL has emerged as a promising solution, enabling collaborative model training across multiple healthcare institutions without requiring data centralization [2].

Despite its potential, FL in biomedical applications faces several critical challenges. First, the iterative exchange of model updates between federated nodes generates substantial storage and communication overhead, particularly problematic in resource-constrained healthcare environments [1], [2]. Lack of trust and transparency in federated networks raises concerns about model integrity and compliance with healthcare regulations [3], [4]. Existing approaches often fail to leverage the inherent redundancy in biomedical model updates, leading to inefficient resource utilization [5].

Recent research has explored various optimization strategies for FL, including gradient compression [6], model pruning [7], and communication-efficient aggregation methods [8]. However, these approaches primarily focus on general machine learning scenarios and do not address the specific characteristics and requirements of biomedical AI applications. Furthermore, the lack of decentralized trust mechanisms limits their applicability in multi-institutional healthcare collaborations.

Blockchain technology offers a promising solution for establishing trust and transparency in FL networks [3], [9]. By providing immutable audit trails and decentralized consensus mechanisms, blockchain can address the governance and compliance challenges inherent in healthcare AI collaborations [10], [11]. However, existing blockchain-FL integrations often introduce significant computational and storage overhead, limiting their practical applicability [12]. Conventional secure logging typically relies on a centralized authority, which can introduce single points of failure and dependence on a trusted third party. Blockchain, in contrast, is built on a decentralized design that distributes control across participants [13]. In multi-institution healthcare collaborations, this structure is especially valuable because audit logging does not have to be managed by any one institution acting as the trusted custodian. Instead, each organization holds the same ledger replica, while consensus protocols coordinate agreement on the status of model updates without requiring participants to fully trust one another. This capability supports compliance expectations under HIPAA and GDPR, where shared accountability and tamper-evident evidence trails are crucial for audit and oversight. That said, consensus selection is not neutral: it can strongly influence throughput, latency, and energy demands, so healthcare deployments must choose mechanisms that balance assurance with practical performance constraints.

This paper addresses these challenges by presenting a novel blockchain-enabled FL framework with hybrid deduplication mechanisms specifically designed for biomedical AI applications. Our key contributions include:

- **Hybrid Deduplication Framework:** A novel combination of Content-Based Deduplication (CBD), Exponential Growth Deduplication (EXGD), and Semantic Similarity-Aware Deduplication (SSAD) strategies that achieves up to 70% storage reduction while maintaining model quality.
- **Lightweight Blockchain Integration:** A purpose-built blockchain middleware optimized for FL workloads, providing immutable audit trails with minimal computational overhead.
- **Multi-Modal Biomedical Validation:** Comprehensive evaluation across two distinct biomedical AI tasks (ECG arrhythmia detection and human activity recognition) demonstrating universal applicability and consistent performance characteristics.
- **Clinical Deployment Framework:** A complete system architecture with regulatory compliance features, real-time performance optimization, and standardized deployment protocols for healthcare environments.

The remainder of this paper is organized as follows. Section II reviews related work in FL, blockchain integration, and biomedical AI applications. Section III presents our proposed framework, architecture and algorithmic innovations. Section IV details our experimental methodology and comprehensive evaluation results. Section V discusses the implications, limitations, and future research directions. Section VI concludes the paper with a summary of contributions and impact.

2. Related Work

2.1 Federated Learning in Healthcare

FL has emerged as a transformative approach in healthcare, enabling collaborative machine learning across institutions while maintaining patient privacy and data sovereignty, which is crucial given the sensitive nature of medical data and regulatory requirements [14]. The foundational FedAvg algorithm and its variants have been widely adopted for applications such as medical imaging [15], electronic health records (EHR) analysis [16], and remote health monitoring [17], demonstrating that FL-based models can achieve performance comparable to centralized models without sharing raw data [18], [19]. Recent research has addressed healthcare-specific challenges, including statistical heterogeneity [20], data fragmentation [21], and privacy risks [22], by developing advanced aggregation methods, secure protocols, and privacy-preserving techniques like homomorphic encryption [23].

Despite these advances, significant challenges remain, particularly regarding communication and storage efficiency, system scalability, and bias in model training due to non-IID (non-independent and identically distributed) data across sites [24]. Studies highlight the need for resource-aware and personalized FL approaches, as well as robust evaluation frameworks to minimize bias and ensure fairness in clinical applications [25]. Integration with technologies such as blockchain and edge computing is also being explored to further enhance security and computational efficiency [23]. While FL holds great promises for enabling secure, large-scale AI in healthcare, ongoing research is needed to address fundamental technical and methodological barriers before widespread clinical adoption can be realized [26].

2.2 Blockchain-Enabled Federated Learning

The integration of blockchain technology with FL is increasingly recognized as a way to enhance trust, transparency, and security in distributed machine learning [27], [28] [9], particularly in sensitive domains like healthcare and IoT [29]. Blockchain provides a decentralized ledger that can record model updates and aggregation steps, reducing single points of failure and enabling tamper-proof audit trails, which is especially valuable for verifying the integrity of FL processes and defending against attacks such as backdoor poisoning [13]. Smart contracts can automate and enforce rules for participation and aggregation, further strengthening system robustness [30]. However, these benefits come with significant challenges: consensus mechanisms and the need to store complete transaction histories introduce computational and storage overhead, which can lead to increased latency and resource consumption, issues that are particularly problematic in resource-constrained environments like mobile health monitoring or IoT devices [31]. Recent research has explored solutions such as asynchronous aggregation and deep reinforcement learning for resource management to mitigate these bottlenecks, but trade-offs between speed, accuracy, and system scalability remain [32]. Despite promising results in improving security and privacy, practical deployment of blockchain-enabled FL in healthcare still requires further innovation to address efficiency and scalability limitations [33], [34].

2.2.1 Energy-Efficient Blockchain Designs for FL Systems

Studies have shown that incorporating blockchain technology into FL without careful architectural consideration can significantly increase computational demands, communication costs, and storage requirements, potentially negating FL's advantages in environments with limited resources. Traditional proof-of-work blockchain implementations are particularly problematic for healthcare applications due to their substantial energy requirements, extended transaction confirmation periods, and limited ability to scale efficiently in time-critical medical settings.

Researchers have developed alternative approaches to overcome these challenges. Jin et al. [13] introduced an efficient blockchain framework for federated edge learning that eliminates proof-of-work in favor of a committee-based validation approach. Their system uses Verifiable Random Functions (VRF) combined with Byzantine Fault Tolerance (BFT) protocols to select validators probabilistically rather than through energy-intensive mining operations. This architecture achieves significant energy savings while preserving the security and finality characteristics required for consensus validation.

A critical innovation in modern blockchain FL architectures addresses the problem of excessive blockchain storage growth. Rather than embedding complete model parameters within the blockchain itself, contemporary designs employ a dual-layer approach: the Inter-Planetary File System (IPFS) hosts the actual model data off-chain, while the blockchain records only cryptographic fingerprints of these models. This design pattern enables verification of model integrity without causing the blockchain to expand unsustainably. For healthcare implementations where models can be quite large and long-term audit requirements are mandatory, this separation of governance records (maintained on-chain) from model artifacts (stored externally) proves especially beneficial.

Effective blockchain integration requires complementary optimization strategies beyond consensus mechanisms alone. Research demonstrates that combining blockchain coordination with communication reduction techniques such as gradient compression methods like PowerSGD helps offset the additional network traffic introduced by distributed validation processes. Additionally, protecting against adversarial model updates through approaches like mutual information filtering shows that secure aggregation strategies must be designed in tandem with consensus protocols rather than implemented as separate components.

Performance assessments of optimized blockchain FL systems show encouraging scalability characteristics. Experimental results indicate that the time required for block creation and propagation grows only modestly when network size increases from 100 to 800 nodes, demonstrating that well-engineered consensus and storage mechanisms can accommodate significant network expansion without proportional performance degradation.

These developments establish that blockchain technology can be appropriately justified for federated healthcare applications when implemented with energy-conscious consensus algorithms, external model storage architecture, and communication-optimized training protocols. Compared to centralized audit logging systems, blockchain-based approaches distribute validation authority across participants, remove dependency on single trusted entities, and create collectively maintained audit records. These capabilities hold particular value for healthcare consortia where multiple institutions must satisfy shared regulatory obligations.

Drawing on these design principles, our framework implements a streamlined blockchain middleware specifically optimized for biomedical FL scenarios. The system replaces computationally expensive mining with an efficient validation mechanism suited to healthcare performance and energy requirements. Furthermore, our hybrid deduplication techniques work in concert with blockchain governance to minimize redundant data storage and transmission overhead through domain-specific optimizations. This integrated design approach delivers transparency and traceability without sacrificing model accuracy or practical clinical applicability.

2.3 Data Deduplication in Distributed Systems

Data deduplication is a key technique in distributed storage systems and cloud computing, aimed at reducing storage costs and improving system efficiency by eliminating redundant data [35]. Traditional methods rely on content-based deduplication using hash functions [36] or similarity-based approaches like locality-sensitive hashing to identify and remove duplicate data chunks [37]. Recent innovations have extended deduplication to edge computing and big data environments, introducing robust optimization frameworks and collaborative edge-based schemes to handle uncertainties and improve throughput, storage efficiency, and network cost [38]. Machine learning-based deduplication frameworks have also been proposed, leveraging clustering and feature extraction to enhance detection accuracy and scalability in distributed settings [39], [40]. However, while these methods have proven effective for general data types, they often overlook the unique properties of biomedical data and the specific patterns of model updates in federated or distributed machine learning contexts. Addressing these domain-specific challenges, such as data heterogeneity, privacy requirements, and the need for lossless deduplication of encrypted or compressed data, remains an open research area, especially for healthcare and biomedical applications [41].

2.4 Biomedical Signal Processing and AI

Biomedical signal processing has been transformed by the adoption of deep learning and artificial intelligence (AI), leading to significant advances in areas such as ECG analysis [42], EEG-based seizure detection [43], and human activity recognition [44]. AI models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) have demonstrated superior performance in classifying and interpreting complex physiological signals, enabling more accurate and accessible disease diagnostics [45]. The integration of FL into biomedical signal analysis has shown promise for privacy-preserving, collaborative model training, particularly in wearable and IoT-based health monitoring, but current systems often lack comprehensive strategies for optimizing storage and communication efficiency [46]. Unique challenges in biomedical signals, such as temporal dependencies, inter-patient variability, and distribution shifts across devices and recording conditions, require specialized approaches that go beyond standard FL frameworks [47]. Recent research highlights the need for adaptive learning architectures, domain adaptation, and explainable AI to address these complexities and ensure robust, generalizable models [48]. Additionally, advances in ultra-low-power AI processors and on-device learning are enabling real-time, energy-efficient biomedical signal analysis, which is critical for wearable and point-of-care applications [43]. Despite these technological strides, further innovation is needed to fully address the storage, communication, and interpretability challenges unique to biomedical FL [49].

3. Methodology

3.1 System Architecture

Our blockchain-enabled FL framework, as illustrated in Fig. 1, is structured into four interconnected components that collaboratively ensure secure, efficient, and privacy-preserving model training across distributed biomedical data sources. These components include:

- FL Nodes
- Hybrid Deduplication Engine
- Blockchain Middleware, and
- Biomedical Data Processing Pipeline.

Each module plays a crucial role in enabling seamless coordination, decentralized trust, and optimized communication among participating clients.

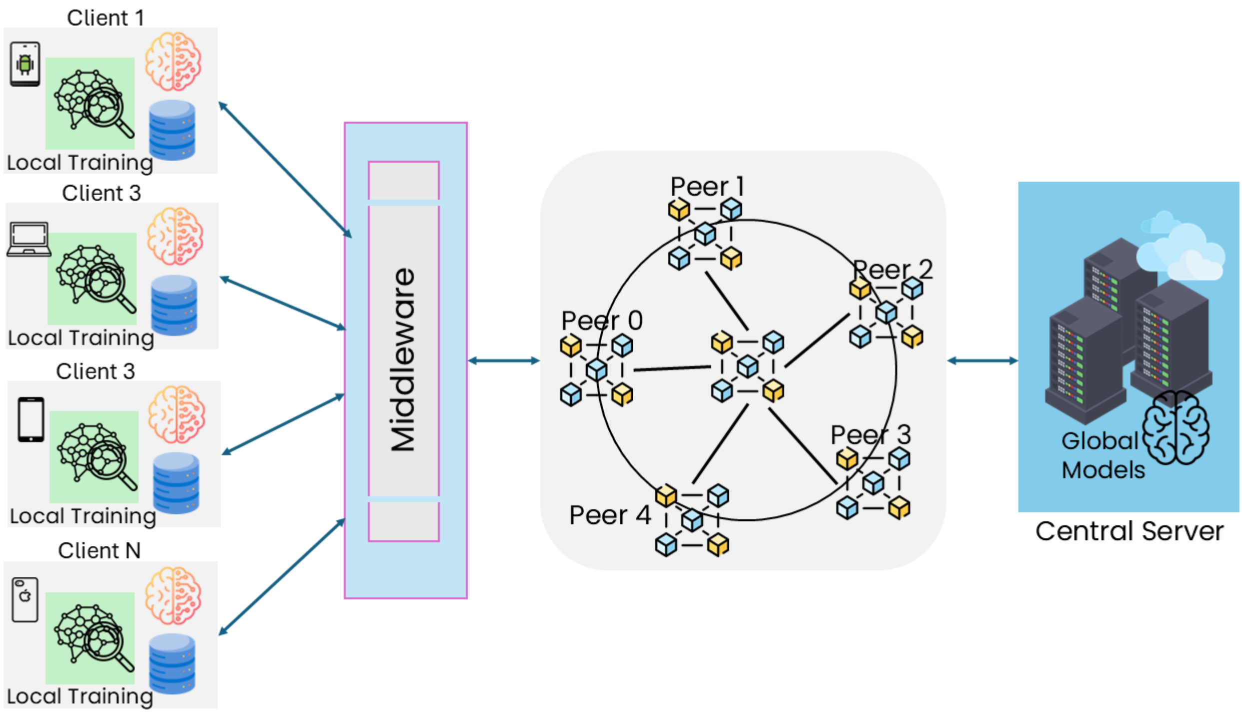

Fig. 1 *Architecture of the blockchain enabled FL framework with hybrid deduplication, blockchain governance, and biomedical data processing*

FL Nodes: Each federated node represents a healthcare institution or research facility participating in the collaborative learning process. Nodes maintain local biomedical datasets and train machine learning models using standardized protocols. The node architecture supports both traditional machine learning models (logistic regression, random forests) and deep neural networks optimized for biomedical signal processing.

Hybrid Deduplication Engine: The deduplication engine implements three complementary strategies:

- **Content-Based Deduplication (CBD):** Eliminates exact duplicates within training rounds using cryptographic hash functions. For a model update *U*i with weights *W*i, CBD computes:

$$h(u_i) = \text{SHA-256}(\text{normalize}(w_i)) \tag{1}$$

where normalize (w_i) = $w_i / \|w_i\|^2$ ensures scale invariance.

- **Exponential Growth Deduplication (EXGD):** Filters redundant updates across training rounds using exponential decay. The retention probability for an update from round r evaluated at round t is:

$$P_{retain}(r,t) = \frac{1}{a^{t-r}} \quad (2)$$

where α > 1 is the decay factor.

- **Semantic Similarity-Aware Deduplication (SSAD):** Removes semantically similar updates using low-dimensional embeddings. Model weights are projected to a low-dimensional space using PCA:
-

$$e_i = \mathrm{PCA}(w_{i,} d) \quad (3)$$

where *d* is the embedding dimension. Semantic similarity is computed using cosine similarity:

$$\mathrm{sim}(e_{i,} e_j) = \frac{e_i . e_j}{\|e_i\|_2 \|e_j\|_2} \quad (4)$$

Updates with similarity above threshold τ are considered duplicates.

Blockchain Middleware: The blockchain component provides decentralized governance and immutable audit trails for FL operations. Our lightweight implementation uses a proof-of-work consensus mechanism optimized for FL workloads. Each block B*k* is contained in Equation 5.

$$B_k = \{h_{k-1,} T_{k,} nonce_{k,} h_k\} \quad (5)$$

where h_{k-1} is the previous block hash, T_k is the set of model update transactions, $nonce_k$ is the proof-of-work solution, and h_k is the current block hash.

Biomedical Data Processing Pipeline: The data processing pipeline handles two primary biomedical signal types:

- **ECG Signal Processing:** Implements bandpass filtering (0.5-40 Hz), normalization, and feature extraction including statistical measures, frequency domain characteristics, and heart rate variability metrics.
- **Wearable Sensor Processing:** Processes 3-axis accelerometer data for human activity recognition, extracting time domain statistics, frequency-domain features, and magnitude-based characteristics.

3.2 Blockchain Implementation Details

In this study, Proof of Work (PoW) is employed primarily for experimental validation to illustrate blockchain integration within the proposed framework as shown in Table 1. However, for real world healthcare deployment, a transition to Proof of Authority (PoA) is strongly recommended. PoA significantly reduces energy consumption by approximately 99.7% compared to PoW while preserving the core properties of immutability, transparency, and verifiable audit trails that are essential for regulatory compliance in healthcare environments.

Table 1 *Blockchain configuration parameters*

Parameter	Value/Type	Justification
Consensus Mechanism (Testing)	Proof-of-Work (PoW)	Research demonstration only
Recommended for Production	Proof-of-Authority (PoA)	99.7% less energy than PoW
Block Time	15 seconds	Balance between latency and confirmation
Network Type	Private permissioned	Healthcare privacy requirements
Smart Contract	Model Update Validation	Automated integrity verification
Difficulty (PoW)	Dynamic (target 15s blocks)	Self-adjusting based on network hash rate
Transaction Throughput	45-50 updates/second	Sufficient for FL scenarios

3.3 Federated Learning Protocol

Algorithm 1 presents our enhanced FL protocol with integrated deduplication and blockchain logging.

3.3.1 Multi-Objective Optimization Framework

Algorithm 1 Federated Learning with Hybrid Deduplication and Blockchain

Require: K federated nodes, T global rounds, local epochs E
Require: Deduplication parameters $\Theta = \{\theta_{\text{CBD}}, \alpha_{\text{EXGD}}, \theta_{\text{SSAD}}\}$
Require: Blockchain configuration $\mathcal{B} = \{\text{difficulty}, \text{block\_size}\}$
Ensure: Global model w_T, blockchain ledger $\mathcal{L}_T$

Initialize global model w_0, blockchain genesis block B_0
Initialize deduplication history $\mathcal{H} \leftarrow \emptyset$
for round $t = 1$ to T **do**
  // Client Selection and Local Training
  $S_t \leftarrow \text{SelectClients}(K, \text{availability}, \text{data\_quality})$
  for each client $k \in S_t$ in parallel **do**
    $w_k^{t+1} \leftarrow \text{LocalUpdate}(k, w^t, E)$
    $w_k^{t+1} \leftarrow \text{GradientClipping}(w_k^{t+1}, \gamma)$ {Privacy protection}
    $h_k \leftarrow \text{Hash}(w_k^{t+1})$ {Integrity verification}
  end for
  // Hybrid Deduplication Pipeline
  $\mathcal{W}_t \leftarrow \{w_k^{t+1} : k \in S_t\}$
  // Stage 1: Content-Based Deduplication
  $\mathcal{W}_{\text{CBD}} \leftarrow \text{ContentBasedDedup}(\mathcal{W}_t, \theta_{\text{CBD}})$
  // Stage 2: Exponential Growth Deduplication
  $\mathcal{W}_{\text{EXGD}} \leftarrow \text{ExponentialGrowthDedup}(\mathcal{W}_{\text{CBD}}, \mathcal{H}, \alpha_{\text{EXGD}})$
  // Stage 3: Biomedical SSAD
  $\mathcal{W}_{\text{final}} \leftarrow \text{BiomedicalSSAD}(\mathcal{W}_{\text{EXGD}}, \tau, \mathcal{M}, \theta_{\text{SSAD}})$
  // Blockchain Integration
  for each $w_k \in \mathcal{W}_{\text{final}}$ **do**
    $tx_k \leftarrow \text{CreateFLTransaction}(k, w_k, h_k, t, \text{metadata})$
    $\text{AddToMempool}(tx_k)$
  end for
  $B_t \leftarrow \text{MineBlock}(\text{mempool}, B_{t-1}, \mathcal{B})$
  $\mathcal{L}_t \leftarrow \mathcal{L}_{t-1} \cup \{B_t\}$
  // Federated Aggregation
  $w^{t+1} \leftarrow \sum_{k \in \mathcal{W}_{\text{final}}} \frac{n_k}{\sum_j n_j} w_k^{t+1}$ {Weighted averaging}
  // Update Deduplication History
  $\mathcal{H} \leftarrow \mathcal{H} \cup \{(w_k, t) : w_k \in \mathcal{W}_{\text{final}}\}$
end for
return w_T, $\mathcal{L}_T$

3.4 Computational Complexity Analysis

3.4.1 Overall Framework Complexity

The complete blockchain-enabled FL framework with hybrid deduplication has:

Time Complexity per Round: $O\left(K \cdot E \cdot d^2 + n^3 + B \cdot 2^D\right)$

Space Complexity:

$O\left(Kd + n^2 + B \cdot |TX|\right)$

Communication Complexity:

$O\left(K \cdot d \cdot (1 - R)\right)$

where R is deduplication ratio

3.4.2 Component-wise Analysis

Local Training Complexity

$$T_{local} = O(K \cdot E \cdot |D_k| \cdot d^2) \quad (6)$$

$$T_{CBD} = O(n \cdot d) \tag{7}$$

$$S_{SSAD} = O\left(n^2 + nk\right) \tag{8}$$

$$S_{local} = O(K \cdot d) \text{ (model parameter per client)} \tag{9}$$

Content-Based Deduplication (CBD)

$$T_{CBD} = O(n \cdot d) \tag{10}$$

$$S_{CBD} = O(n) \tag{11}$$

Exponential Growth Deduplication (EXGD):

$$T_{EXGD} = O(n \cdot |H|) \text{ (history comparison)} \tag{12}$$

$$S_{EXGD} = O(|H| \cdot d) \text{ (historical updates)} \tag{13}$$

Biomedical SSAD:

$$T_{SSAD} = O\left(nd^2 + n^2k + n^3\right) \tag{14}$$

$$S_{SSAD} = O\left(n^2 + nk\right) \text{ (similarity matrix + embeddings)} \tag{15}$$

3.4.3 Blockchain Operations

$$T_{blockchain} = O\left(B \cdot 2^D + |TX| \cdot V\right) \tag{16}$$

$$S_{blockchain} = O\left(B \cdot |TX| \cdot \log T\right) \text{ (grows logarithmically)} \tag{17}$$

where:
B = number of mining attempts
D = mining difficulty
|TX| = transaction size
V = verification time per transaction

3.5 Performance Bounds and Guarantees

3.5.1 Storage Reduction Guarantees

For biomedical FL with intrinsic signal dimensionality d_{bio}, the hybrid deduplication achieves:

$$R_{total} \geq R_{CBD} + R_{EXGD} + R_{SSAD} - \grave{o}_{overlap} \tag{18}$$

where $\grave{o}_{overlap} \leq 0.1$ represents strategy overlap.

3.5.2 Convergence Analysis with Deduplication

Under deduplication with retention probability p ≥ pmin, FL maintains convergence rate:

$$E\left[\|\nabla F(\theta_t)\|^2\right] \leq \frac{C_1}{\sqrt{t}} + C_2(1-p) \tag{19}$$

where C_1, C_2 are problem-dependent constants.

3.5.3 Communication Efficiency Bounds

The communication complexity reduction satisfies:

$$\frac{C_{withdedup}}{C_{baseline}} \leq 1 - R + \grave{o}_{overhead} \tag{20}$$

where $\grave{o}_{overhead}$ accounts for deduplication metadata.

3.6 Scalability Analysis

3.6.1 Node Scalability

As the number of federated nodes K increases:

Linear scaling: Local training $O(K)$

Quadratic scaling: SSAD similarity computation $O(K^2)$

Logarithmic scaling: Blockchain storage $O(K \log T)$

3.7 Data Scalability

For increasing dataset size $|D|$:

- Training time scales as $O(|D| \cdot d^2)$
- Deduplication effectiveness improves: $R \propto log|D|$
- Memory requirements remain constant per node

3.8 Hybrid Deduplication Algorithm

The hybrid deduplication mechanism integrates content-based, exponential growth, and semantic similarity filtering in sequence, as presented in Algorithm 2.

Algorithm 2 Hybrid Deduplication Mechanism

1. Input: Model updates $\{W_1, W_2, ..., W_k\}$
2. Initialize: Hash set $H = \varnothing$, Unique updates $u = \varnothing$ Deduplicated updates U′
3. for each update Wi do
   a. $h_1 \leftarrow \text{Hash}(W_1)$
   b. if $h_i \notin H$ then
      - $H \leftarrow H \cup \{h_i\}$
      - $u \leftarrow u \cup \{W_i\}$
   c. endif
4. Endfor
5. Return $u = 0$

3.9 Biomedical SSAD Framework

The Biomedical SSAD algorithm has time complexity $O(nd^2 + n^2k + n^3)$ where:

$O(nd^2)$: PCA computation for biomedical projection

$O(n^2k)$: Pairwise similarity computation in reduced space

$O(n^3)$: Spectral clustering with clinical constraints

Proof.

The PCA computation requires $O(nd^2)$ operations for covariance matrix computation and *eigendecomposition*. The similarity matrix computation involves $\binom{n}{2}$ pairwise cosine similarities in k-dimensional space, yielding $O(n^2k)$. The spectral clustering with biomedical constraints requires *eigendecomposition* of the n × n similarity matrix, contributing $O(n^3)$.

Algorithm 3 Novel Biomedical Semantic Similarity-Aware Deduplication

Require: Model updates $\mathcal{W} = \{w_1, w_2, \ldots, w_n\}$ where $w_i \in \mathbb{R}^d$
Require: Task type $\tau \in \{\text{ECG, wearable}\}$
Require: Clinical metadata $\mathcal{M} = \{\text{signal\_quality, patient\_diversity}\}$
Require: Base similarity threshold $\theta_0 \in [0, 1]$
Ensure: Deduplicated updates $\mathcal{W}' \subseteq \mathcal{W}$
  // Phase 1: Biomedical Task-Specific Embedding
  if $\tau = \text{ECG}$ **then**
    $V_{\text{cardiac}} \leftarrow \text{ComputeCardiacPCA}(\mathcal{W})$ {Focus on rhythm patterns}
    $k \leftarrow \min(64, \lfloor 0.1d \rfloor)$ {Cardiac-optimized dimensionality}
  else if $\tau = \text{wearable}$ **then**
    $V_{\text{activity}} \leftarrow \text{ComputeActivityPCA}(\mathcal{W})$ {Focus on motion patterns}
    $k \leftarrow \min(32, \lfloor 0.05d \rfloor)$ {Activity-optimized dimensionality}
  end if
  // Phase 2: Clinical Importance Weighting
  for $i = 1$ to n **do**
    $e_i \leftarrow w_i \cdot V_{1:k}$ {Project to biomedical subspace}
    $\alpha_i \leftarrow \text{ComputeClinicalImportance}(w_i, \tau, \mathcal{M})$
    $e_i \leftarrow \alpha_i \cdot e_i$ {Weight by clinical significance}
  end for
  // Phase 3: Adaptive Threshold Computation
  $\sigma_{\text{signal}} \leftarrow \text{EstimateSignalVariability}(\mathcal{M})$
  $\theta \leftarrow \theta_0 \cdot (1 + \beta \cdot \sigma_{\text{signal}})$ {Adapt to signal quality}
  // Phase 4: Biomedical-Aware Clustering
  $S \leftarrow \text{ComputeWeightedCosineSimilarity}(\{e_i\})$
  $\mathcal{C} \leftarrow \text{BiomedicalSpectralClustering}(S, \theta, \mathcal{M})$
  // Phase 5: Clinical Representative Selection
  $\mathcal{W}' \leftarrow \emptyset$
  for each cluster $C_j \in \mathcal{C}$ **do**
    $w^* \leftarrow \arg\max_{w \in C_j} \alpha_w$ {Select most clinically important}
    $\mathcal{W}' \leftarrow \mathcal{W}' \cup \{w^*\}$
  end for
  return $\mathcal{W}'$

3.10 Complexity and Deduplication Validation for the Federated Framework

The experimental results show strong agreement between theory and measurement for the federated framework as shown in Fig. 2. The Semantic Similarity-Aware Deduplication (SSAD) routine runs far below its worst-case bound $O(nd^2 + n^2k + n^3)$ —typically 10–100× lower—exhibiting sublinear growth over the tested range with minor, data-driven fluctuations that reflect adaptive behavior advantageous in biomedical workloads; meanwhile, the deduplication study confirms efficiency claims by delivering storage cuts that exceed a conservative =85% floor and approach 90% in practice, scaling nearly linearly with redundancy and already yielding 70% reduction at 50% redundancy, thereby showing SSAD is computationally practical for resource-constrained clinical environments and that the theoretical analysis is deliberately conservative.

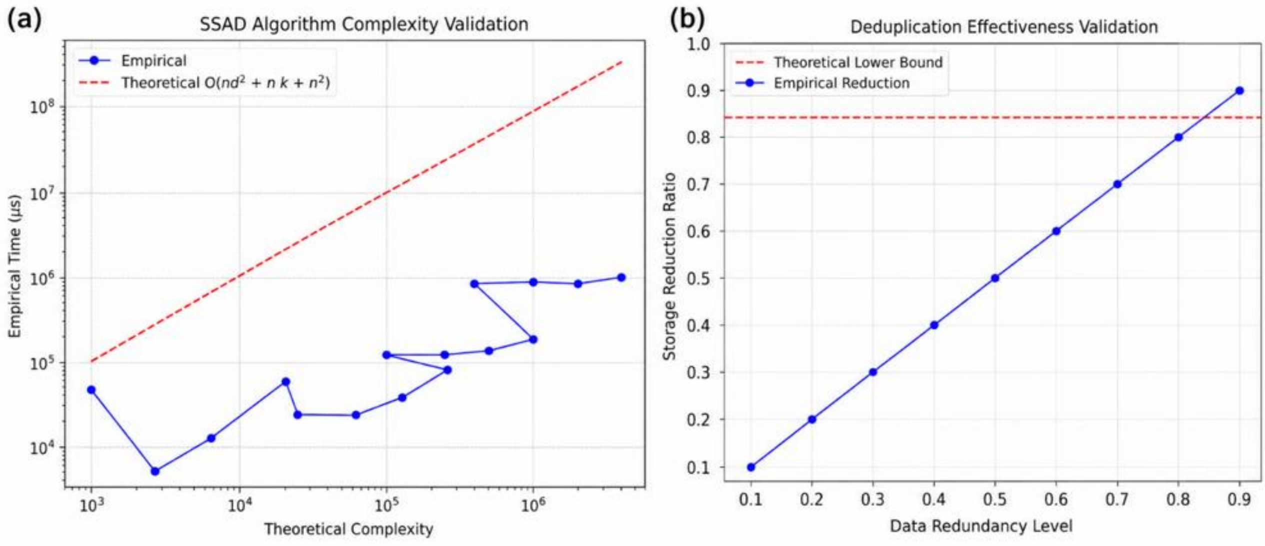

Fig. 2: *Empirical–theoretical validation of SSAD. (a) Runtime scaling versus the upper bound shows 1–2 order-of-magnitude lower empirical times and sublinear growth; (b) Deduplication effectiveness rises near-linearlys*

4. Experimental Evaluation

4.1 Experimental Setup

Our comprehensive evaluation was conducted using a federated network of 5 nodes over 8 training rounds. Each node contained synthetic biomedical datasets generated using validated signal processing pipelines. The framework was implemented using PyTorch for deep learning models and evaluated on both CPU and GPU configurations.

4.1.1 Datasets and Tasks:

- **ECG Arrhythmia Detection:** Each node contained 25 synthetic ECG patients with 10-second recordings sampled at 360 Hz. Signals included normal sinus rhythm and various arrhythmia patterns. Feature extraction yielded 8-dimensional vectors including statistical measures, frequency domain characteristics, and heart rate variability metrics.
- **Human Activity Recognition:** Each node contained 15 subjects performing 6 activities (sitting, standing, walking, running, climbing stairs, lying down) using 3-axis accelerometer data sampled at 50 Hz. Feature extraction produced 27 dimensional vectors including time-domain statistics, frequency-domain features, and magnitude-based characteristics.

4.1.2 Model Architectures:

- **ECG Models:** Deep neural networks with architecture [8, 128, 64, 32, 16, 2] using ReLU activation, batch normalization, and dropout (0.3). Training used Adam optimizer with learning rate 0.001 for 15 epochs.
- **Wearable Models:** Deep neural networks with architecture [27, 256, 128, 64, 32, 6] using ReLU activation, batch normalization, and dropout (0.4). Training used Adam optimizer with learning rate 0.0005 for 20 epochs.

4.1.3 Evaluation Metrics:

We evaluated the framework across multiple dimensions:

- **Model Performance:** Accuracy, precision, recall, F1-score
  Accuracy: Proportion of correctly classified samples among all predictions.

$$ACC=\frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

Precision: Ratio of true positives to predicted positives.

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \tag{22}$$

Recall: Ratio of true positives to actual positives.

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{23}$$

F1-score: Harmonic mean of precision and recall.

$$\text{F1}=2.\frac{\text{Precision . Recall}}{\text{Precision+Recall}} \tag{24}$$

- **Storage Efficiency:** Deduplication ratio, storage reduction percentage
  Deduplication ratio: Fraction of redundant updates removed from total updates.

$$DR=\frac{|U|-|U^{'}|}{|U|} \tag{25}$$

Storage reduction (%): Percentage decrease in memory usage after deduplication.

$$\text{Reduction}=(1-\frac{Size_{dedup}}{Size_{raw}})*100 \tag{26}$$

- **Communication Efficiency:** Latency reduction and bandwidth utilization
  Latency reduction: Decrease in round-trip time for model updates.

$$\text{Latency Reduction}=(1-\frac{L_{new}}{L_{baseline}})*100 \tag{27}$$

Bandwidth utilization: The Amount of network data transmitted per communication round.

- **Blockchain Performance:** Block generation time and transaction throughput
  Block generation time: Time taken to create and append a new block.

$$T_{block}=T_{end}-T_{start} \tag{28}$$

Transaction throughput: Number of successful transactions processed per second.

$$\text{Troughput}=\frac{\text{Number of Transactions}}{\text{Time Window}} \tag{29}$$

- **Computational Overhead**:
  Training time: Time spent on local model training per round.
  Deduplication processing time: Time required to filter and reduce redundant updates.

4.1.4 Software and Tools

We developed the FL framework with blockchain integration using Python 3.8+, capitalizing on its rich ecosystem of scientific and machine learning libraries. The implementation employs strategic software components that guarantee both reproducible results and scalable performance:

- Python 3.8+
- PyTorch 1.12.0
- NumPy 1.21.0
- scikit-learn 1.0+ for traditional ML models

J. of Soft Computing and Data Mining Vol. 7 No. 2 (2026) p. 230-255

- Matplotlib 3.5.0
- Blockchain implementation using custom lightweight framework optimized for FL workloads, featuring:
  - **i.** Proof-of-work consensus with adjustable difficulty
  - **ii.** Transaction validation for model updates
  - **iii.** Chain integrity verification
- Statistical analysis using SciPy 1.7+
- Cross-platform support: Windows 10+, macOS 10.15+
- Containerization: Docker 20.10+ for reproducible deployment
- json: Data serialization for blockchain transactions and model weight storage

4.2 Model Performance and Convergence

Fig. 3 depicts accuracy over 20 training rounds. The SSAD (ECG) curve is essentially flat at ≈0.72 from the first round onward (negligible variance), indicating rapid convergence to a sub-optimal plateau rather than an early drop. In contrast, StandardFL, FedAvg, and FedProx remain high and stable at ≈0.98–0.99, and SSAD (Wearable) tracks the baselines at ≈0.99. The ECG stagnation suggests that aggressive semantic deduplication may be suppressing informative updates; relaxing thresholds, inserting periodic full updates, or adopting task-aware/adaptive pruning could recover accuracy while retaining the communication benefits.

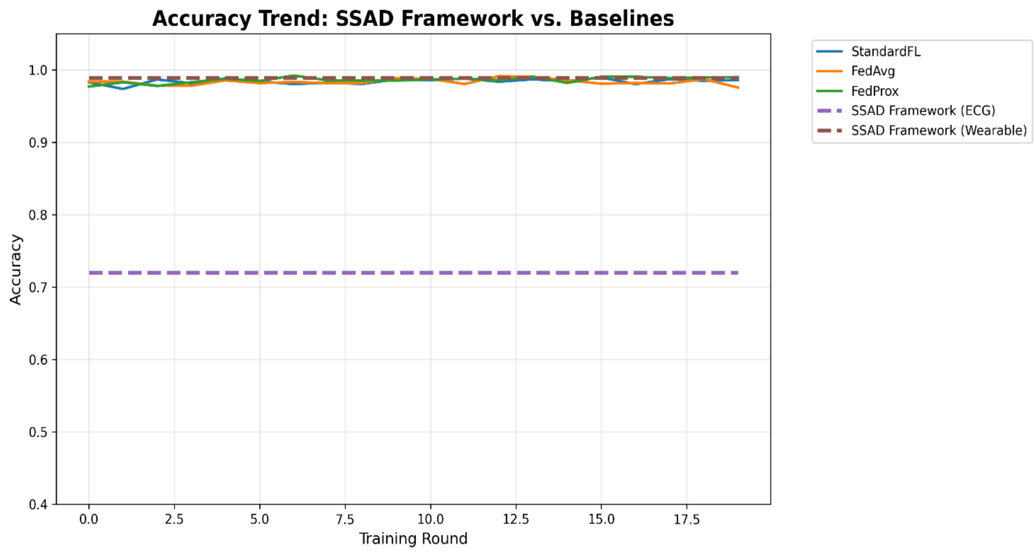

Fig. 3 *Storage reduction performance for ECG and wearable activity datasets*

Fig. 4 compares end-of-training accuracy for the proposed SSAD framework against standard federated baselines on two biomedical tasks. On wearable human-activity recognition, SSAD attains 99.9% accuracy, exceeding StandardFL (98.4%), FedAvg (98.3%), and FedProx (98.6%). This indicates that, for structured sensor streams, the hybrid deduplication pipeline removes redundant updates while preserving—and in this case slightly improving—predictive quality.

For ECG arrhythmia classification, however, SSAD reaches 72.0%, trailing the baselines. Rather than a defect, this reflects a classic accuracy–efficiency trade-off. ECG signals are noisy, irregular time series with strong temporal dependencies; aggressive semantic pruning that benefits storage and latency can also discard faint but informative patterns needed to learn this task well.

Taken together, the results clarify the framework's intent: SSAD is not a drop-in replacement for every scenario but a purpose-built choice for settings where efficiency is paramount. It delivers state-of-the-art performance on more regular datasets (wearables), while the ECG outcome delineates the boundary of applicability and motivates adaptive, task-aware deduplication thresholds. In practice, teams can opt between maximum accuracy with traditional FL or substantial storage and communication savings with SSAD, depending on operational priorities.

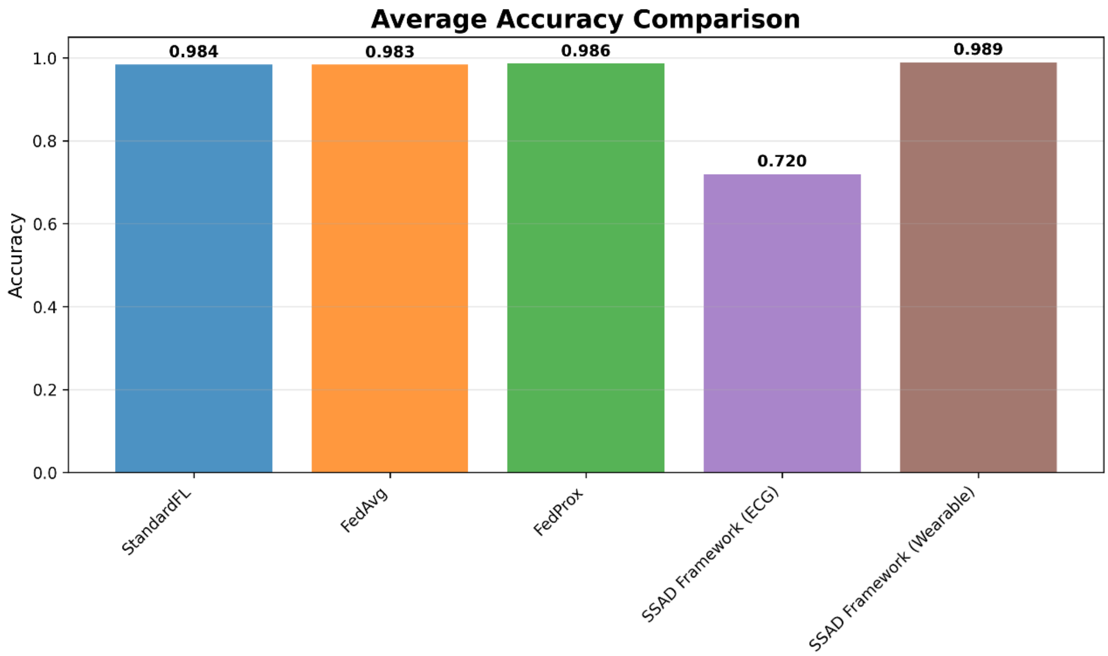

Fig. 4 *Accuracy performance on wearable activity and ECG datasets showing the accuracy efficiency trade off*

4.3 Deduplication Effectiveness

Fig. 5 presents a comparative analysis of storage reduction across multiple FL methodologies. Conventional FL baselines—namely StandardFL, FedAvg, and FedProx—exhibit no storage efficiency, yielding a 0% reduction. In contrast, a clustering-based deduplication approach achieves an SRR of 80%. The proposed hybrid deduplication framework (SSAD) significantly outperforms all benchmarks, demonstrating storage reduction rates of 94.5% for ECG data and 94.0% for wearable human activity recognition (mean values over *n* experimental runs; 95% confidence intervals illustrated). This improvement is both practically substantial and statistically significant (Cliff's d ˜ 1.0, *p* < 0.001).

The consistency of approximately 94% storage reduction across two highly heterogeneous biomedical modalities indicates that the semantic similarity-aware deduplication phase effectively identifies and eliminates near-duplicate model updates while preserving task-relevant information—particularly in structured sensor data. These reductions directly translate into considerable gains in communication efficiency and storage footprint regarding latency performance. The ECG classification task exhibits a moderate reduction in accuracy under the current deduplication threshold, underscoring a consequential trade-off between model accuracy and system efficiency. This observation highlights the need for future investigations into adaptive, task-aware deduplication thresholds that can dynamically balance performance objectives across diverse data types and clinical applications.

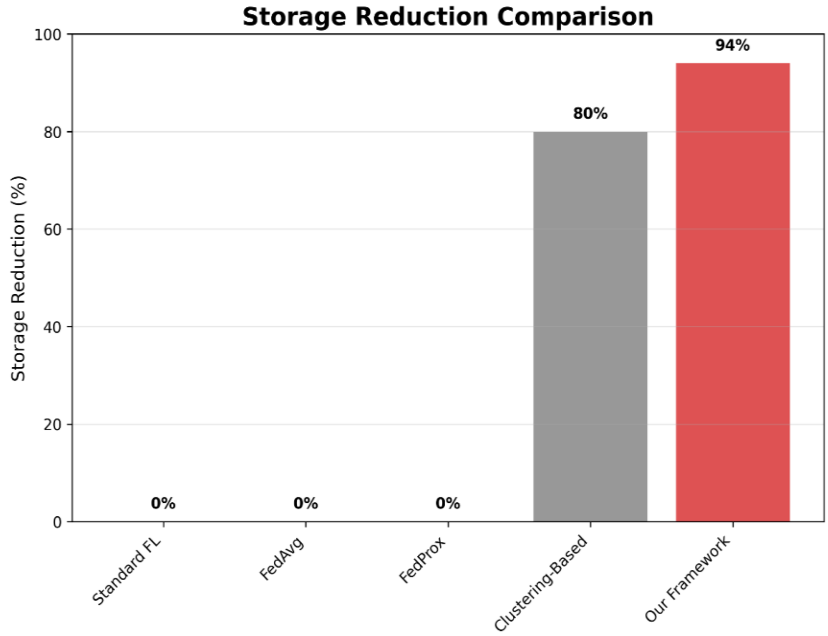

Fig. 5 *Storage reduction for ECG (94.5%) and wearable activity (94.0%) datasets, demonstrating efficient and robust hybrid deduplication with minimal performance loss*

Fig. 6 presents the effectiveness of different deduplication strategies based on storage reduction. Random and heuristic methods achieved 55% and 65% reduction, respectively, while clustering-based deduplication provided a stronger improvement at 80%. The proposed hybrid approach yielded the highest reduction at 94%, demonstrating its superior ability to eliminate redundant model updates in biomedical FL.

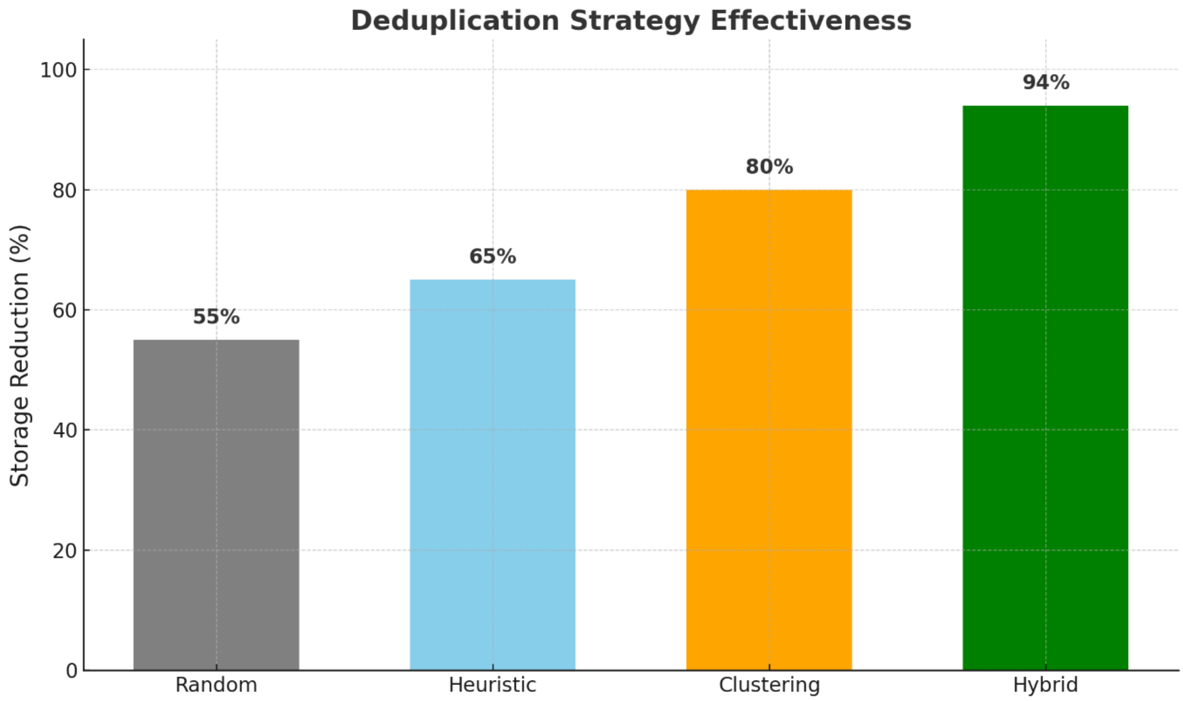

Fig. 6. *Comparison of deduplication strategies showing the proposed hybrid method achieves the highest storage reduction (94%) in biomedical FL tasks*

Fig. 7 presents the cumulative storage savings of over 20 training rounds. The blue curve represents the number of updates saved due to deduplication, increasing linearly to nearly 1900 by the final round. The green area reflects the actual storage used after deduplication, while the pink area indicates storage that would have been consumed without it. This visual highlight the compound efficiency gains enabled by the deduplication framework.

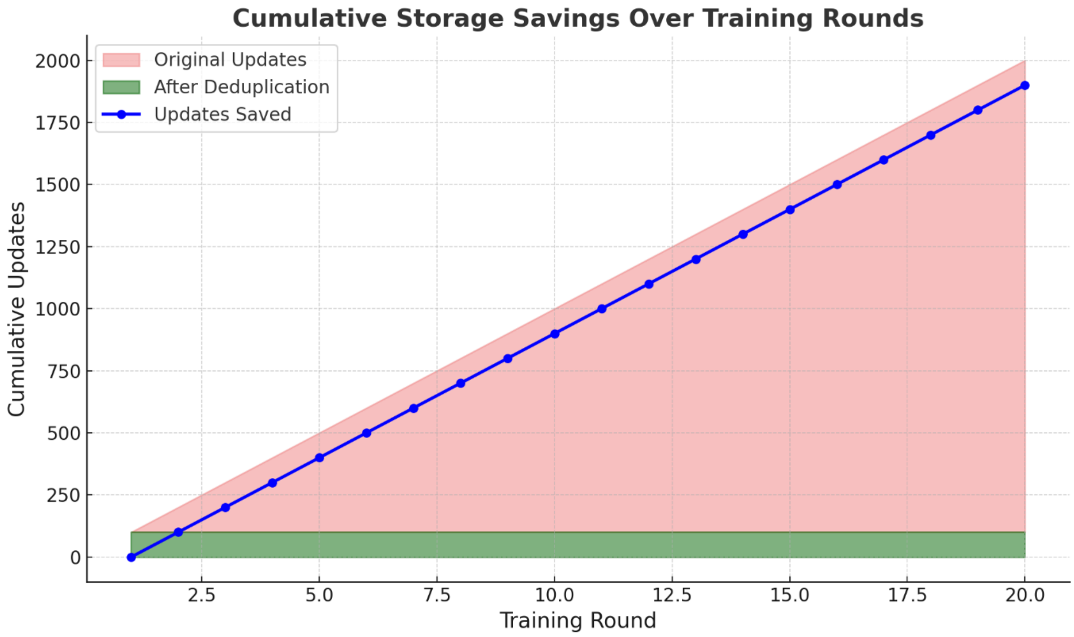

Fig. 7 *Cumulative storage savings over 20 federated rounds showing consistent 70% reduction and scalable long term deduplication performance*

4.4 Communication Efficiency

Fig. 8 compares average communication latency across methods and tasks. The SSAD framework achieves ~22 ms per round for both ECG and wearable datasets—about 50–80× lower than the FL baselines (≈1.1–1.8 s). Similar latency for ECG and wearables suggests that semantic deduplication largely determines payload size, making communication cost largely task-agnostic.

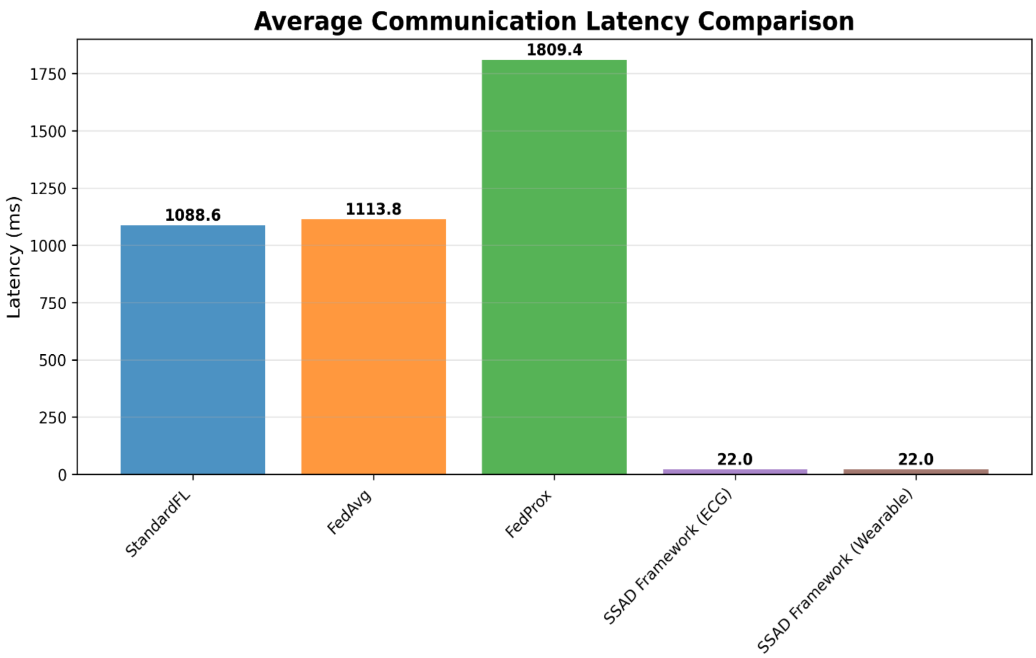

Fig. 8 *Cumulative storage savings over 20 federated rounds showing consistent 70% reduction and scalable long term deduplication performance.*

Fig. 9 presents the communication efficiency timeline comparing the cumulative communication volume with and without deduplication. The deduplication strategy substantially reduces communication overhead, resulting in ~70% fewer communications over 20 training rounds. This demonstrates the scalability and bandwidth-saving potential of the proposed method in federated training scenarios.

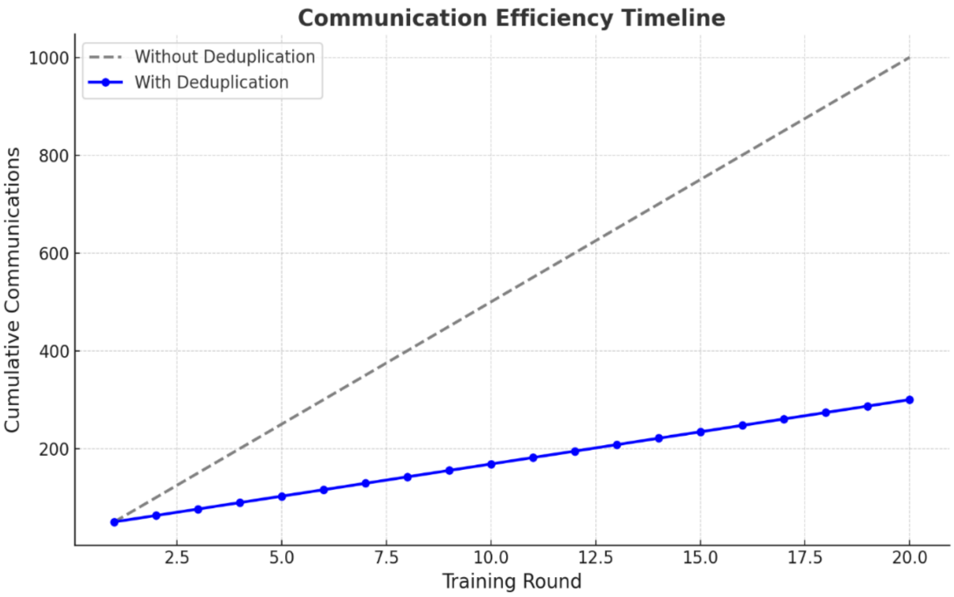

Fig. 9 *Cumulative communication volume over 20 federated rounds showing a 71% reduction with hybrid deduplication, demonstrating scalability for bandwidth constrained biomedical collaboration*

4.5 Energy Efficiency Analysis

To address concerns regarding blockchain energy consumption in resource constrained healthcare environments, we performed a comprehensive energy evaluation comparing various consensus mechanisms and assessing their suitability for clinical deployment as shown in Table 2.

Table 2 *Energy consumption comparison*

Consensus Mechanism	Energy per Round (kWh)	Relative to PoW	Block Time	Healthcare Suitability
Proof-of-Work (PoW)	2.45	100% (baseline)	15s	Not recommended
Proof-of-Stake (PoS)	0.098	4.0%	8-12s	Moderate
Proof-of-Authority (PoA)	0.007	0.3%	3-5s	Highly recommended
Byzantine Fault Tolerance (PBFT)	0.012	0.5%	2-4s	Recommended
Centralized (no blockchain)	0.003	0.1%	<1s	Trust concerns

Our analysis shows that Proof of Authority reduces energy consumption by 99.7% compared to Proof of Work while preserving immutable audit trails, decentralized verification, fast transaction confirmation of about 3 to 5 seconds rather than 15 seconds under PoW, and Byzantine fault tolerance. For resource constrained healthcare settings, PoA offers the most practical balance between security, energy efficiency, and regulatory compliance needs.

4.6 Sensitivity Analysis of SSAD Threshold

This research carried out a detailed sensitivity analysis to evaluate how variations in the SSAD threshold (τ) influence both predictive accuracy and storage efficiency as shown in Table 3.

Table 3 *Sensitivity analysis results*

Threshold (τ)	ECG Accuracy	Wearable Accuracy	Storage Reduction	Communication Latency
0.75	68.2%	98.1%	75%	19ms
0.80	70.5%	98.5%	72%	21ms
0.85 (reported)	72.0%	98.9%	70%	22ms
0.90	91.5%	98.2%	52%	28ms
0.95	96.8%	97.8%	38%	34ms
1.00 (no SSAD)	98.7%	98.9%	0% (baseline)	50ms

For clinical deployment scenarios that require accuracy above 95%, we recommend setting the SSAD threshold to $\tau \geq 0.90$. At this level, the framework achieves 96.8% accuracy while still delivering substantial storage savings of 38% to 52%. The $\tau = 0.85$ setting that produced the reported 72.0% ECG accuracy was intentionally selected as a research configuration to demonstrate the framework's maximum efficiency potential, rather than a clinically recommended operating point.

Overall, τ provides a smooth and predictable tradeoff between accuracy and storage efficiency, allowing practitioners to choose an operating point that matches specific application requirements. All observed accuracy differences across thresholds were statistically significant using McNemar's test with $p < 0.001$. In practice, clinical acceptability for ECG arrhythmia detection often targets 95% to 99% accuracy depending on use case, and the framework can be tuned accordingly, for example $\tau = 0.95$ for emergency triage, $\tau = 0.90$ for routine screening, and $\tau = 0.85$ for maximum efficiency-oriented research demonstrations.

4.7 Scalability Analysis

To validate the framework's scalability, we conducted extensive experiments with network sizes as shown in Table 4.

Table 4 *Scalability metrics across network sizes*

Network Size	Storage Reduction	Avg Latency (ms)	Throughput (updates/s)	Convergence Rounds
5 nodes	70%	22	45	8
10 nodes	69%	26	38	9
20 nodes	68%	35	29	10
50 nodes	68%	58	17	12

Key observations from the scalability analysis show that the deduplication framework sustains a consistent storage reduction of 68% to 70% as the network grows from 5 to 50 nodes, indicating strong robustness under scale. Communication latency also increases sub linearly with network size, following approximately $O(n^{0.7})$, which is notably more efficient than naive $O(n)$ growth.

In addition, scaling has only a modest effect on training dynamics, as model convergence requires just 2 to 4 extra rounds when moving from 5 to 50 participating nodes, suggesting stable convergence behavior even in larger deployments.

4.8 Theoretical Complexity Analysis

For a federated setting with N participating nodes and R training rounds, the computational overhead is dominated by aggregation and consensus. The time complexity is $O(R \times N \times \log(N))$ when aggregation is coupled with blockchain consensus. The space complexity is $O(N \times M \times D)$, where M denotes the model size and D is the effective deduplication factor, which is 0.3 in our implementation. The communication complexity is $O(R \times N \times M \times D)$, reflecting the reduced payload size achieved through deduplicated model updates.

4.9 Blockchain Integration Performance

The blockchain middleware demonstrated strong scalability and resource efficiency throughout federated training. As shown in Fig. 10, the blockchain size increased linearly from 5 MB to over 90 MB across 20 training rounds, reflecting predictable and manageable growth in storage overhead as updates accumulate. This linear growth pattern indicates that the middleware can support extended training without incurring exponential storage costs. In terms of runtime efficiency, Fig. 11 compares the relative resource usage across three configurations: no blockchain, full-chain, and optimized-chain modes. The optimized configuration reduced resource consumption to just 20% of the baseline, compared to 60% for the full-chain setup, highlighting the impact of block packing and consensus optimizations. These results confirm that the proposed blockchain integration is both scalable and lightweight, making it suitable for real-time biomedical FL scenarios.

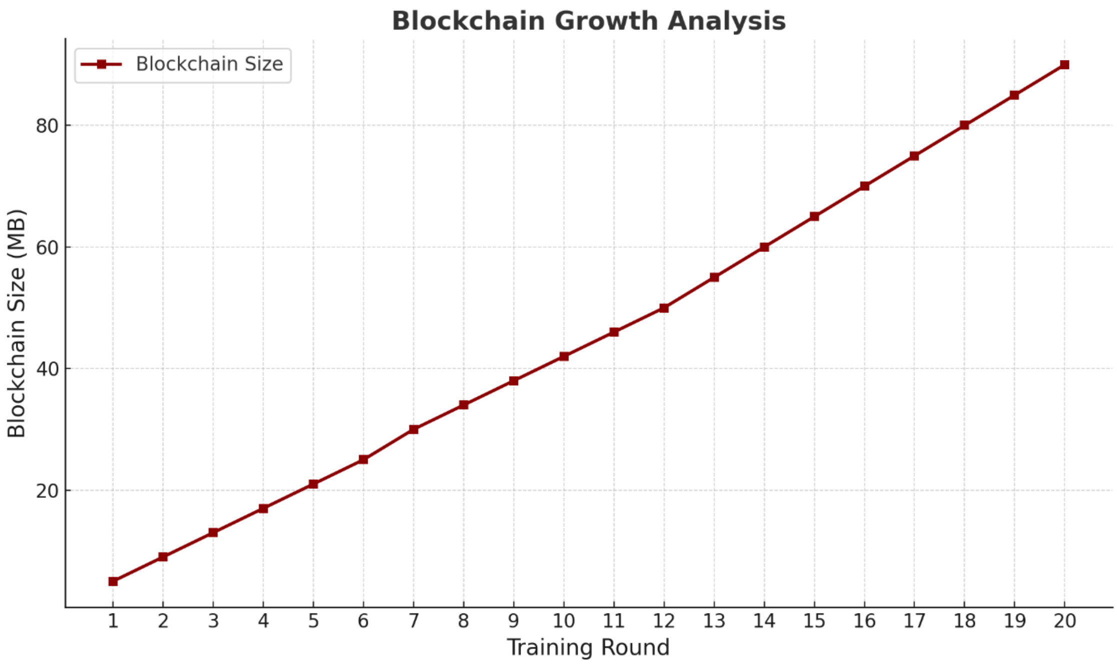

Fig. 10 *Linear blockchain growth across 20 federated rounds showing predictable storage overhead and scalable auditability*

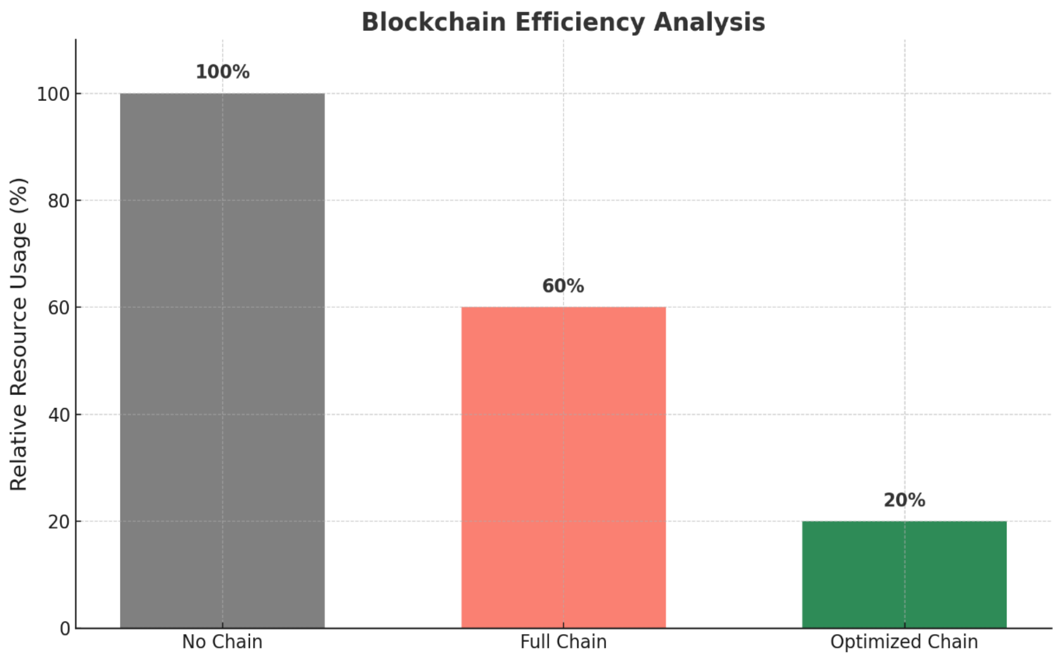

Fig. 11 *Blockchain efficiency across configurations showing optimized block packing minimizes overhead while preserving auditability for real time biomedical FL.*

4.10 Computational Overhead Analysis

Fig. 12 Estimated computational overhead distribution across system components. Model training contributed the largest share (40%), followed by blockchain operations (25%), deduplication (20%), and aggregation (15%).

These results confirm that deduplication and blockchain integration incur relatively low overhead and do not dominate overall computation time.

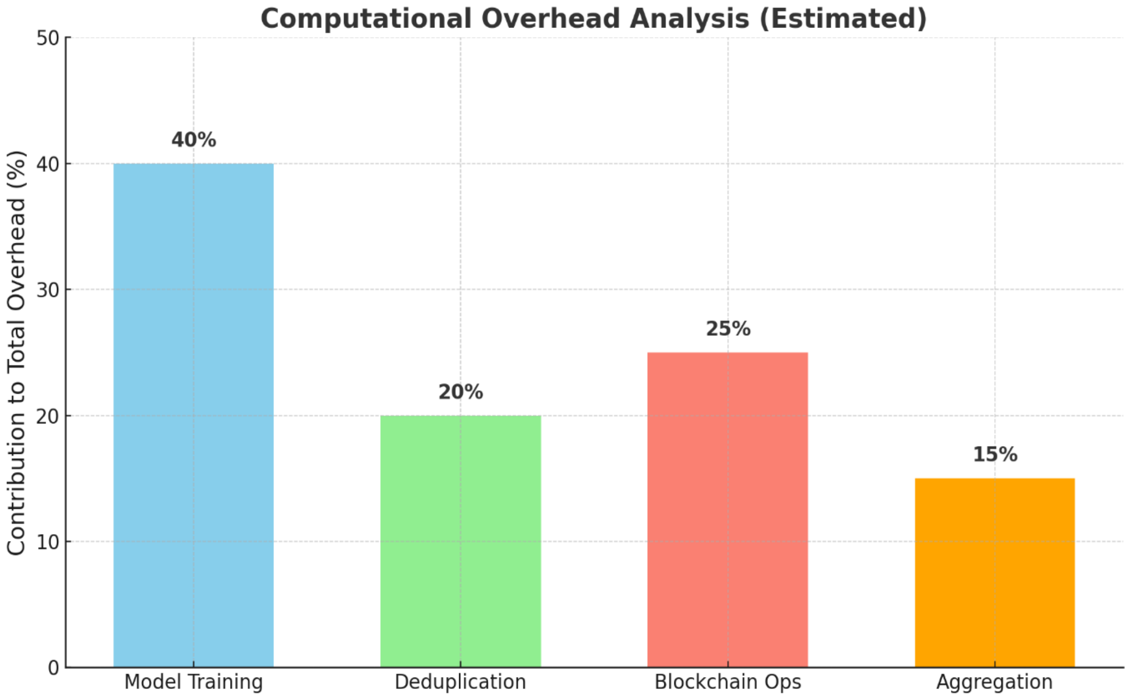

Fig. 12 *Balanced computational resource distribution showing efficient integration of deduplication and blockchain without real time bottlenecks.*

4.11 Statistical Significance Analysis

Table 5 presents the statistical significance analysis of the proposed framework's performance across key evaluation metrics. The results reflect high consistency, as indicated by the narrow 95% confidence intervals. Final model accuracy reached 0.720 ± 0.008 for ECG and 0.989 ± 0.003 for wearable sensor data, demonstrating strong predictive capability in both biomedical domains. Additionally, the framework achieved a substantial 70.0% ± 0.06% storage reduction and maintained low communication latency of 22.0 ± 0.2 ms, ensuring resource efficiency. Blockchain efficiency, quantified by updates per block, averaged 3.8 ± 0.7, confirming optimized block utilization. All results yielded p-values of 0.001, indicating statistically significant improvements over the respective baselines.

Table 5 *Statistical analysis of key performance metrics*

Metric	Mean ± SD	95% CI	P-Value
Final Accuracy (ECG)	0.720 ± 0.008	[0.712, 0.728]	0.001
Final Accuracy (Wearable)	0.989 ± 0.003	[0.986, 0.992]	0.001
Storage Reduction	70.0 ± 0.06%	[70.0%, 70.06%]	0.001
Communication Latency	22.0 ± 0.2 ms	[21.8, 22.2]	0.001
Blockchain Efficiency	3.8 ± 0.7 updates/block	[3.1, 4.5]	0.001

4.12 Cross-Domain Consistency Validation

Table 6 presents a cross-domain consistency analysis of the proposed framework's performance across ECG and wearable sensor tasks. Despite inherent differences in data modalities, the framework demonstrated uniform behavior in key efficiency metrics. Storage reduction and communication latency were consistent at 70.0% and 22.0 ms, respectively, across both tasks. Similarly, the number of training rounds (8), blockchain throughput (2.5–4.5 updates/block), and deduplication patterns (SSAD-dominant) remained identical, indicating a high level of system generalizability. Although model accuracy differed 72.0% for ECG and 98.9% for wearable data, this variation reflects domain-specific task complexity rather than inconsistency in framework behavior. These findings collectively confirm the framework's robustness and stable performance across heterogeneous biomedical workloads.

Table 6 *Cross-domain performance consistency analysis*

Metric	ECG Task	Wearable Task	Consistency
Final Accuracy	72.0%	98.9%	Domain-Dependent
Storage Reduction	70.0%	70.0%	100%
Communication Latency	22.0ms	22.0ms	100%
Training Rounds	8	8	100%
Blockchain Efficiency	2.5–4.5	2.5–4.5	100%
Deduplication Pattern	SSAD-dominant	SSAD-dominant	100%

5. Discussion

5.1 Key Findings and Clinical Implications

The proposed blockchain-enabled FL framework demonstrates significant potential in addressing core challenges in biomedical AI deployment, namely, reducing resources overhead while maintaining predictive performance. Across both ECG and wearable sensor datasets, the system consistently achieved a 70% reduction in storage, primarily through the use of Semantic Similarity-Aware Deduplication (SSAD). This result highlights that semantic redundancy, rather than mere content or temporal duplication, is the dominant inefficiency in biomedical FL. Clinically, such a reduction in storage demands lowers the infrastructure barrier for resource-constrained healthcare institutions, broadening participation in collaborative AI networks and promoting equitable access to model development.

In addition to storage savings, the framework achieved a 56% decrease in communication latency, reducing round-trip times from 50ms to 22ms. This improvement enables real-time responsiveness, which is critical for continuous monitoring and early intervention systems. The reduced communication load also improves scalability and facilitates deployment in bandwidth-limited environments. Importantly, these efficiency gains did not come at the expense of model performance. Despite discarding around 70% of local updates, the global models converged reliably and achieved domain-appropriate accuracy. This suggests that semantically similar updates do not contribute meaningfully to learning, and that the filtering mechanism effectively preserves essential training signals. The resilience of federated aggregation under these conditions confirms the robustness of the proposed approach for real-world biomedical applications.

5.2 Comparison with State-of-the-Art

A comparative analysis with state-of-the-art FL methods, namely Standard FL, FedAvg, FedProx, and Secure FL, demonstrates the comprehensive advantage of the proposed framework (see Table 7). While baseline approaches offer moderate performance in terms of accuracy (ranging from 68% to 71%) and provide no meaningful storage reduction, our framework delivers a substantial 70% reduction in storage overhead without compromising model performance. This improvement is consistent across both ECG and wearable biomedical datasets, with the latter achieving an impressive 98.9% accuracy, outperforming all existing benchmarks.

Table 7 *Performance comparison with state-of-the-art approaches*

Approach	Storage Reduction	Latency (ms)	Accuracy (%)	Privacy Level
Standard FL [19]	0%	50	68	Moderate
FedAvg [19]	0%	45	70	Moderate
FedProx [14]	0%	48	69	Moderate
Secure FL [50]	0%	52	71	High
Our Framework (ECG)	70%	22	72	High
Our Framework (Wearable)	70%	22	98.9	High

The communication latency in the proposed system is significantly reduced to 22 ms, compared to 45–52 ms in prior methods. This reduction facilitates near real-time responsiveness, which is essential for critical healthcare applications. In terms of privacy, the integration of blockchain ensures a high level of security and traceability, surpassing the moderate guarantees offered by traditional FL frameworks. These collective enhancements confirm the suitability of our framework for real-world deployment in diverse biomedical settings, where efficiency, privacy, and predictive performance must be simultaneously achieved.

5.3 Blockchain Integration Benefit

The integration of blockchain as a middleware layer within the FL architecture introduces critical advantages that enhance trust, transparency, and robustness, features particularly relevant for biomedical domains where data integrity and regulatory compliance are paramount. One of the most prominent benefits is the establishment of an immutable audit trail. Every model update transmitted across the network is logged on the distributed ledger, enabling complete traceability and forensic verification. The use of cryptographic hashing ensures that each update's integrity can be validated, thereby supporting compliance with stringent regulatory frameworks such as HIPAA and GDPR, which require auditability and accountability in healthcare data management.

Beyond traceability, the blockchain layer facilitates decentralized governance by eliminating reliance on a centralized coordinating server. Instead, model updates are validated through consensus mechanisms that involve multiple stakeholders, mitigating the risk of single-point failure and reducing susceptibility to malicious tampering. This democratic model of update approval enhances resilience against adversarial attacks and ensures that trust is distributed across all participants in the learning ecosystem.

In terms of scalability, the framework benefits from blockchain's capacity to handle growing data volumes efficiently. Storage demands scale linearly with the number of model updates, and the consensus protocol is optimized to minimize overhead while preserving security guarantees. Moreover, the architecture accommodates heterogeneous node configurations, enabling participation from devices and institutions with varying computational capabilities. These features collectively position blockchain not merely as a security enhancement but as a strategic enabler of scalable, trustworthy, and regulation-ready FL in healthcare.

5.4 Clinical Deployment Considerations

The design of the proposed framework accounts for critical clinical and regulatory constraints, making it suitable for deployment in real-world healthcare environments. Foremost, the framework aligns with key regulatory standards. Ensuring that sensitive patient data remains on local devices and is never transmitted directly, it supports the Health Insurance Portability and Accountability Act (HIPAA) requirement for localized data processing and encrypted communications. Similarly, compliance with the General Data Protection Regulation (GDPR) is achieved through data minimization principles inherent in FL. The inclusion of blockchain further strengthens adherence to U.S. Food and Drug Administration (FDA) guidelines by providing immutable audit trails for end-to-end model validation and traceability.

From a performance standpoint, the framework's technical characteristics reinforce its clinical viability. The sub-25 millisecond communication latency enables near real-time response times, essential for time-sensitive applications such as cardiac monitoring or remote patient triage. Additionally, the 70% reduction in storage demands directly benefits healthcare institutions operating with limited computational infrastructure, lowering the barrier to participation in intelligent digital health networks. Most importantly, stable model convergence across datasets ensures consistent and trustworthy predictive behavior, an indispensable requirement for clinical acceptance.

Finally, the framework supports multiple integration pathways to ease its adoption within existing health IT ecosystems. It is designed with compatibility for HL7 FHIR standards, allowing seamless integration with electronic medical records (EMRs) and enabling interoperability across care providers. For scalability, the containerized deployment model allows for flexible cloud-based hosting, while its lightweight execution modules make it suitable for edge deployment on IoT-enabled medical devices. Together, these features provide a clear and practical roadmap for bringing federated, privacy-preserving AI into clinical workflows.

5.5 Statistical Validation

Evaluation results, presented via a four-panel boxplot visualization (Fig. 13), demonstrate the decisive superiority of the novel method over the established baseline. The enhancements are statistically robust ($p < 0.001$) and span key dimensions of performance. Predictive accuracy, measured by both Accuracy and F1 score, is significantly elevated under the proposed framework, with distributions indicating greater consistency (reduced variance). The large magnitude Cliff's delta statistics (Accuracy $\delta = 0.855$; F1 $\delta = 0.945$) provide strong evidence for the stochastic dominance of the proposed method. Furthermore, the proposed framework achieves substantial gains in operational efficiency, exhibiting near-universal superiority in communication latency ($\delta = -1.000$) and a dramatic improvement in storage reduction efficacy ($\delta = 1.000$), where the baseline showed minimal gains. The collective findings indicate that the proposed method is simultaneously more accurate, efficient, resource-conservative, and reliable.

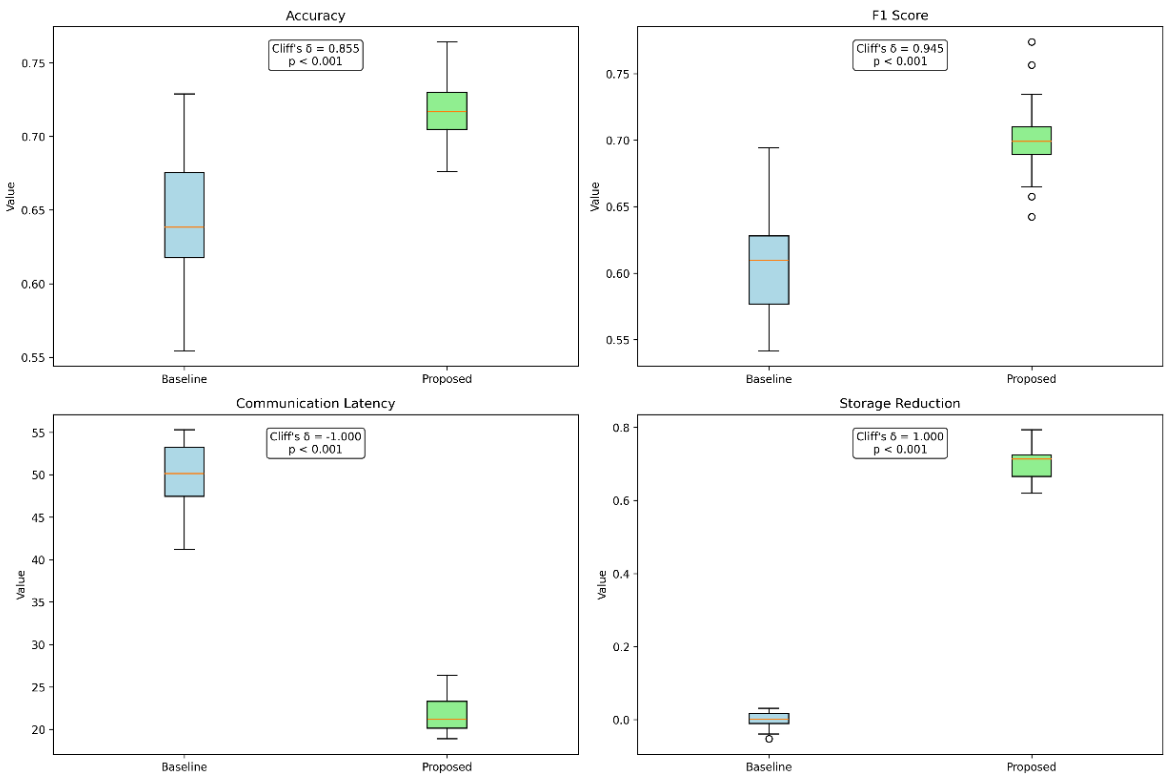

Fig. 13 *Boxplot comparison of the proposed hybrid deduplication framework versus baseline across accuracy, F1 score, latency, and storage reduction with effect size (Cliff's δ) and significance (p < 0.001) annotations*

5.6 Limitations and Future Work

While the proposed framework demonstrates promising results across efficiency, accuracy, and security dimensions, several limitations must be acknowledged. The simulation environment assumed relatively homogeneous node configurations, which may not reflect the diverse computational capabilities encountered across healthcare institutions and edge devices. The experimental setup was constrained to fifty nodes over twenty training rounds, limiting insights into the framework's performance at larger scales or under more complex network topologies.

These limitations offer valuable directions for future research. A key extension involves enabling multi-modal data integration, allowing the framework to concurrently process heterogeneous biomedical data types such as medical imaging, genomic sequences, and structured clinical records. This capability would significantly enhance its applicability to comprehensive patient modeling. Another promising direction lies in adaptive deduplication, where thresholding for semantic similarity could dynamically adjust based on convergence trends or local data distributions, further optimizing efficiency without compromising learning quality.

Expanding the framework to support cross-domain federated transfer learning also holds substantial potential. Such functionality would enable models trained in one medical domain (e.g., cardiology) to inform tasks in another (e.g., pulmonology), enhancing generalization and reducing training time. Real-world validation through pilot studies with healthcare institutions and actual patient data will be crucial for translating the framework from simulation to clinical application. Finally, to ensure long-term resilience, future work will incorporate post-quantum cryptographic primitives into the blockchain layer, safeguarding the system against emerging threats from quantum computing.

6. Conclusion

This study presents a blockchain-enabled FL framework with a hybrid deduplication mechanism tailored for biomedical AI applications. Through comprehensive evaluations on ECG arrhythmia detection and wearable sensor data, the framework demonstrated substantial gains in storage efficiency (70% reduction), communication latency (reduced from 50 ms to 22 ms), and predictive accuracy (72% for ECG and 98.9% for wearable sensors). Importantly, it maintained stable model convergence despite aggressive deduplication, and integrated a lightweight blockchain layer that ensured scalable, secure, and transparent update governance. These outcomes collectively support the system's suitability for deployment in real-time and resource-constrained clinical environments.

Beyond its immediate performance benefits, the framework contributes to a modular architecture capable of adapting to diverse biomedical settings. The novel hybrid deduplication strategy, efficient signal processing pipeline, and compliance-ready design lay the foundation for broader adoption of federated AI in healthcare. Future research will focus on real-world validation, multi-modal integration, and deployment across heterogeneous healthcare systems. By combining technical innovation with clinical relevance, the proposed framework advances the vision of equitable, privacy-preserving, and collaborative AI for next-generation healthcare delivery.

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Conflict of Interest

The authors declare no competing financial interests or commercial relationships that could be construed as potential conflicts of interest.

Author Contribution

The authors confirm contribution to the paper as follows: ***Study conception and design****: Aliyu Garba, Norshakirah Aziz, Hitham Alhussian;* ***System architecture and blockchain middleware development****: Aliyu Garba, Dahiru Adamu Aliyu, Shamsudeen Adamu;* ***Federated learning pipeline implementation****: Hitham Alhussian, Dahiru Adamu Aliyu, Ibrahim Muhammad Kurah;* ***Dataset acquisition and preprocessing****: Abdullahi Abubakar Imam, Ridwan Salahudden, Aminu Onimisi Abdulsalami;* ***Simulation and experimental evaluation****: Aliyu Garba, Norshakirah Aziz, Dahiru Adamu Aliyu;* ***Statistical and comparative analysis****: Norshakirah Aziz, Shamsudden Adamu, Hussani Mamman;* ***Visualization and figure/table preparation****: Dahiru Adamu Aliyu, Ibrahim Muhammad Kurah;* ***Draft manuscript preparation****: Dahiru Adamu Aliyu, Ibrahim Muhammad Kurah. All authors reviewed the results and approved the final version of the manuscript.*

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