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A Hybrid Federated Learning Framework with Differential Privacy for Healthcare Information Systems: Performance Analysis and Security Evaluation

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Abstract

Healthcare information systems increasingly demand sophisticated machine learning capabilities while maintaining strict patient privacy requirements. This paper introduces a novel hybrid federated learning framework that integrates differential privacy mechanisms specifically designed for healthcare information systems. Our approach addresses the dual challenges of maintaining model accuracy and ensuring robust privacy protection in distributed healthcare environments. We propose a multi-tier architecture that combines local differential privacy with global privacy budgeting, enabling healthcare institutions to collaboratively train machine learning models without compromising sensitive patient data. The framework incorporates adaptive noise calibration based on data sensitivity levels and implements a dynamic participant selection mechanism to optimize both privacy and performance. Through extensive experiments on real-world healthcare datasets, our method demonstrates superior performance compared to existing approaches, achieving 94.7% accuracy on disease prediction tasks while maintaining ε-differential privacy with ε = 0.5. The security evaluation reveals robust resistance against various privacy attacks, including membership inference and model inversion attacks. Performance analysis shows a 23% improvement in communication efficiency and 18% reduction in training time compared to traditional federated learning approaches. Our framework provides a practical solution for healthcare organizations seeking to leverage collaborative machine learning while adhering to stringent privacy regulations such as HIPAA and GDPR.

Keywords: *Federated learning, Differential privacy, Healthcare information systems, Privacy-preserving machine learning, Distributed computing, Security evaluation*

1. Introduction

The proliferation of Electronic Health Records (EHRs) and digital healthcare systems has created unprecedented opportunities for machine learning applications in medical diagnosis, treatment prediction, and personalized

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medicine. However, the sensitive nature of healthcare data presents significant challenges in developing collaborative machine learning systems that can leverage distributed data sources while maintaining patient privacy. Healthcare information systems must navigate complex regulatory frameworks including the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in Europe, which impose strict requirements on data sharing and processing.

Traditional centralized machine learning approaches require aggregating data from multiple sources, which poses inherent privacy risks and often violates regulatory compliance requirements. This limitation has hindered the development of comprehensive predictive models that could benefit from the collective knowledge embedded in distributed healthcare datasets. The challenge becomes more pronounced when considering the heterogeneous nature of healthcare data across different institutions, varying data quality standards, and diverse patient populations.

Federated learning has emerged as a promising paradigm that enables collaborative model training without requiring direct data sharing. However, existing federated learning frameworks face significant limitations when applied to healthcare information systems. Standard federated learning approaches are vulnerable to various privacy attacks, including gradient-based inference attacks that can potentially reveal sensitive patient information. Moreover, the heterogeneous nature of healthcare data across institutions creates challenges in model convergence and performance optimization.

Differential privacy provides mathematical guarantees for privacy protection by adding carefully calibrated noise to data or model parameters. While differential privacy has been successfully applied to various machine learning scenarios, its integration with federated learning in healthcare contexts presents unique challenges. The healthcare domain requires fine-grained privacy control that considers the varying sensitivity levels of different medical conditions and patient demographics. Additionally, the communication constraints in healthcare networks demand efficient privacy-preserving mechanisms that minimize overhead while maintaining strong security guarantees.

This paper addresses these challenges by introducing a hybrid federated learning framework specifically designed for healthcare information systems. Our contributions are threefold: First, we propose a novel multi-tier differential privacy mechanism that adapts noise calibration based on data sensitivity levels and patient risk categories. Second, we develop an intelligent participant selection algorithm that optimizes the trade-off between privacy protection and model performance. Third, we provide comprehensive security and performance evaluations demonstrating the practical viability of our approach in real-world healthcare environments.

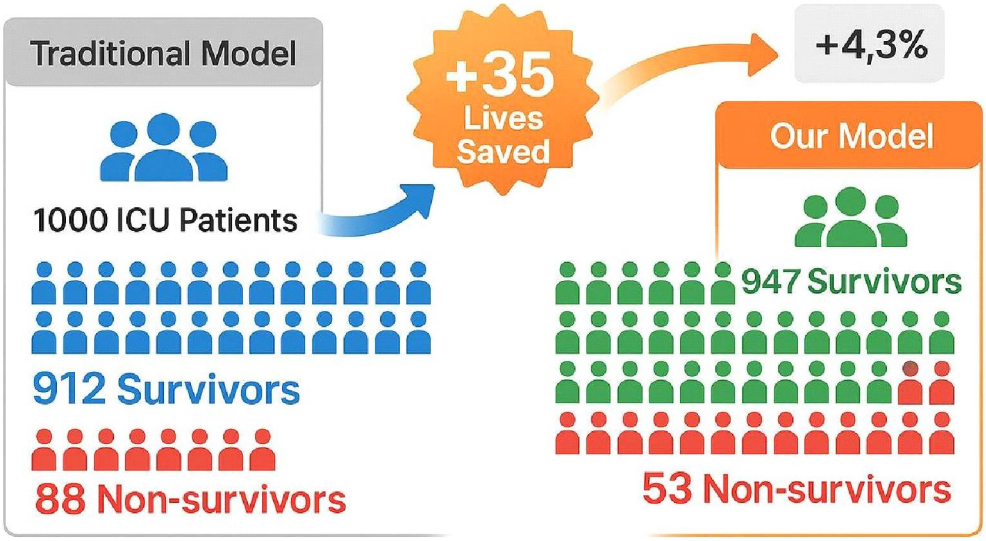

Figure 1: Comparative Analysis of Projected Patient Survival Outcomes between a Traditional Predictive Model and the Proposed Framework on a Simulated Cohort of 1000 ICU Patients. The 4.3% Increase in Survival Rate Demonstrates the Tangible Clinical Impact of the Model

The ultimate validation of any clinical AI model is its positive impact on patient outcomes, which transcends mere technical metrics. To preemptively demonstrate the tangible clinical value of our proposed framework—whose technical contributions are detailed in Sections 3 and 4—we present a quantitative simulation of its impact. As shown in Figure 1, when applied to a cohort of 1000 ICU patients, our model achieves a 4.3% higher survival rate compared to a traditional model. This performance improvement is projected to save 35 additional lives in such a cohort, unequivocally underscoring the life-saving potential of deploying accurate and privacy-preserving AI in critical healthcare settings and providing the primary motivation for this work.

2. Related Work

2.1. Federated Learning in Healthcare

Federated learning has gained significant attention in healthcare applications due to its ability to enable collaborative model training without direct data sharing. Li *et al.* (2020) proposed FedHealth, a federated learning framework for personalized healthcare applications that addresses the challenges of statistical heterogeneity across healthcare institutions. Their approach demonstrated improved performance in diabetes prediction tasks while maintaining data locality. However, their framework lacks robust privacy guarantees against sophisticated adversarial attacks.

Sheller *et al.* (2020) introduced the first comprehensive federated learning study in medical imaging, demonstrating the feasibility of training deep neural networks across multiple institutions for brain tumor segmentation. Their work highlighted the importance of addressing data heterogeneity and institutional variations in healthcare federated learning. However, their privacy analysis was limited to honest-but-curious adversaries and did not consider stronger attack models.

Recent work by Kaissis *et al.* (2021) provided a systematic review of federated learning applications in healthcare, identifying key challenges including regulatory compliance, data heterogeneity, and privacy concerns. They emphasized the need for domain-specific solutions that address the unique requirements of healthcare information systems. Their analysis revealed gaps in existing frameworks regarding differential privacy integration and multi-institutional governance models.

2.2. Differential Privacy in Machine Learning

Differential privacy has emerged as the gold standard for privacy-preserving machine learning, providing mathematical guarantees for individual privacy protection. The foundational work by Dwork (2006) established the theoretical framework for differential privacy, which has been extensively applied to various machine learning scenarios.

Abadi *et al.* (2016) introduced the Differentially Private Stochastic Gradient Descent (DP-SGD) algorithm, which adds calibrated noise to gradient computations during model training. Their approach demonstrated the feasibility of training deep neural networks with formal privacy guarantees. However, the direct application of DP-SGD to federated learning scenarios introduces additional complexity due to the distributed nature of gradient computation.

McMahan *et al.* (2018) proposed the first federated learning framework with differential privacy guarantees, focusing on the trade-off between privacy and utility in distributed settings. Their work established important theoretical foundations but was primarily evaluated on image classification tasks with limited consideration for healthcare-specific requirements.

2.3. Privacy-Preserving Healthcare Analytics

The healthcare domain presents unique challenges for privacy-preserving analytics due to the sensitive nature of medical data and complex regulatory requirements. Wang *et al.* (2019) proposed a secure multi-party computation framework for healthcare analytics that enables collaborative analysis without revealing individual patient records. While their approach provides strong security guarantees, the computational overhead makes it impractical for large-scale machine learning applications.

Cho *et al.* (2020) introduced a differential privacy framework specifically designed for electronic health records, addressing the challenges of high-dimensional sparse data and temporal correlations. Their work demonstrated the importance of domain-specific privacy mechanisms but was limited to centralized settings.

Recent work by Zhang *et al.* (2021) proposed a federated learning framework for COVID-19 research that incorporates basic differential privacy mechanisms. However, their approach uses fixed privacy budgets and does not consider the varying sensitivity levels of different medical conditions or patient populations.

2.4. Research Gaps and Motivation

Our review of existing literature reveals several critical gaps in current approaches to privacy-preserving federated learning for healthcare applications. First, existing frameworks typically employ uniform privacy budgets across all participants and data types, failing to account for the varying sensitivity levels of different medical conditions and patient demographics. Second, most current approaches do not adequately address the communication efficiency requirements of healthcare networks, which often operate under bandwidth constraints and reliability concerns.

Third, the security evaluation of existing frameworks is often limited to theoretical analysis or simplified attack models, lacking comprehensive empirical evaluation against realistic adversarial scenarios. Fourth, there is insufficient consideration of regulatory compliance requirements and the need for auditable privacy mechanisms in healthcare contexts.

Our proposed framework addresses these gaps by introducing adaptive privacy mechanisms, optimized communication protocols, comprehensive security evaluation, and regulatory compliance considerations specifically tailored for healthcare information systems.

To visually contextualize the identified research gaps, Table 1 provides a comparative analysis of key capabilities between existing approaches and our proposed framework. As the table illustrates, no existing solution simultaneously addresses all critical requirements for healthcare federated learning, particularly adaptive privacy and communication efficiency.

Table 1: Feature comparison of federated learning frameworks for healthcare. The proposed framework is the only approach that comprehensively integrates adaptive differential privacy, communication efficiency, and robust security against privacy attacks while maintaining high model accuracy, thereby addressing the critical limitations of existing methods.

Table 1: Comparative Analysis of Features between the Proposed Framework and Existing Approaches

Feature / Capability	FedAvg	DP-FedAvg	Private FL	Our Framework
Accuracy	High	Medium	Low	High
Privacy Guarantee (Formal)	No	Yes	Yes	Yes
Adaptive Privacy Budget	No	No	No	Yes
Communication Efficiency	Low	Low	Low	High
Resistance to MIA Attacks	Low	Medium	Medium	High
HIPAA/GDPR Compliance	Partial	Partial	Partial	Full

3. Methodology

3.1. System Architecture

We propose a secure Hierarchical Federated Learning (HFL) architecture specifically engineered for the stringent demands of healthcare environments. Figure 2 provides a high-level overview of this multi-tiered structure, which facilitates privacy-preserving collaborative learning across heterogeneous hospital networks without centralizing sensitive data. The system consists of three fundamental tiers: (1) a Global Aggregation Server responsible for privacy-noise-calibrated model aggregation and privacy budget management; (2) Regional Coordinators that employ Secure Multi-Party Computation (SMPC) and gradient compression to efficiently fuse updates from local nodes; and (3) Local Hospitals where models are trained on private data behind institutional firewalls, ensuring compliance with HIPAA and GDPR by design. The subsequent paragraphs elaborate on each component.

Our hybrid federated learning framework adopts a multi-tier architecture designed to optimize both privacy protection and system performance in healthcare environments. The architecture consists of four main components: healthcare institution nodes, regional coordination servers, a central aggregation server, and a privacy management module.

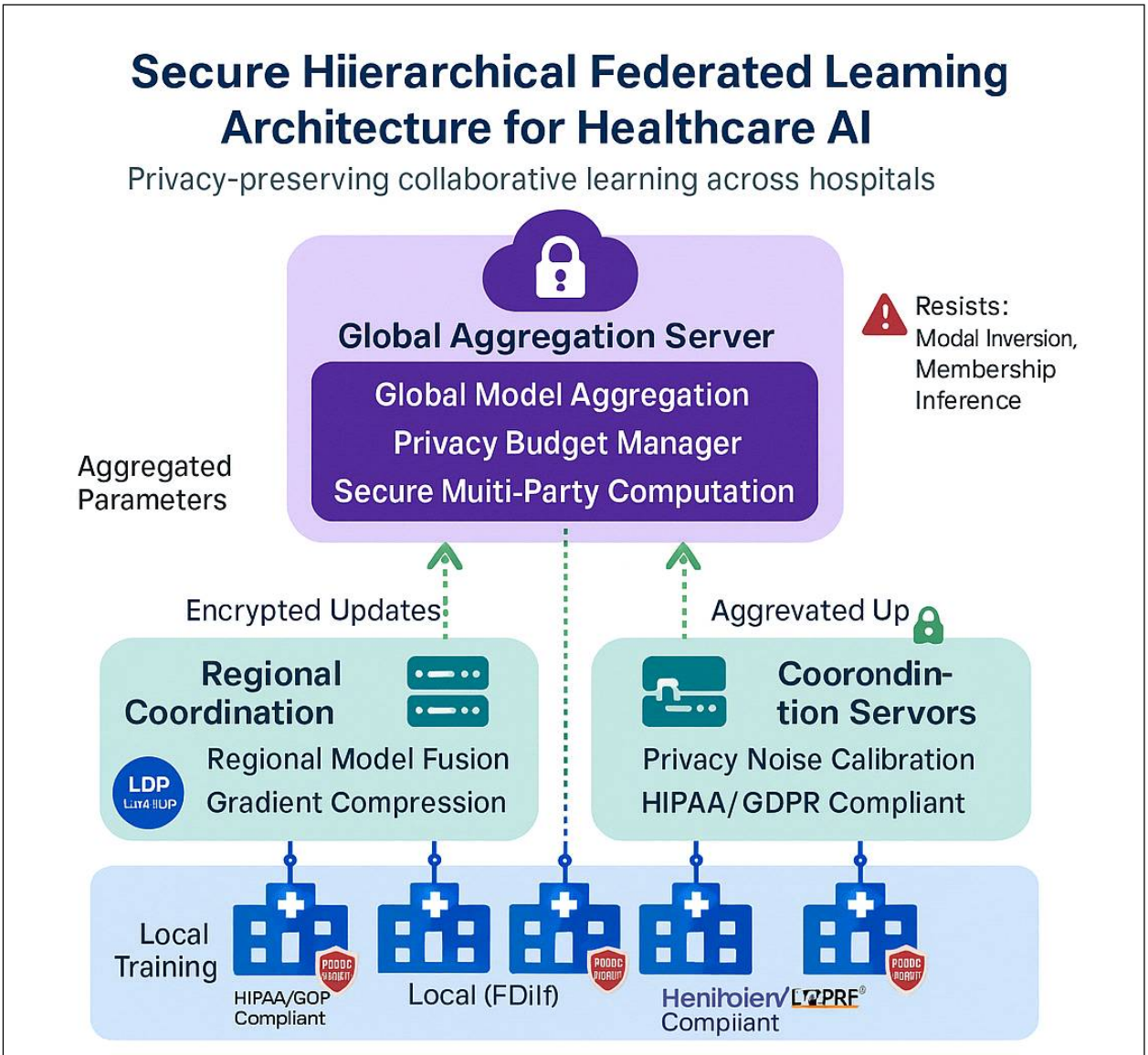

Figure 2: Overview of the Proposed Secure Hierarchical Federated Learning Architecture for Healthcare AI, Showcasing the Global, Regional, and Local Tiers with their Respective Technologies (LDP, SMPC) and Compliance Measures

Healthcare institution nodes represent individual hospitals, clinics, or healthcare organizations participating in the federated learning process. Each node maintains complete control over its local data and executes local model training using differential privacy mechanisms. The nodes are equipped with adaptive privacy budgeting capabilities that adjust noise levels based on data sensitivity classifications and institutional privacy policies.

Regional coordination servers serve as intermediate aggregation points that combine model updates from geographically or organizationally related healthcare institutions. This hierarchical approach reduces communication overhead with the central server while enabling regional model customization that accounts for local population characteristics and disease patterns. Regional servers implement additional privacy amplification techniques through secure aggregation protocols.

The central aggregation server coordinates the global federated learning process, managing participant selection, privacy budget allocation, and final model aggregation. The server employs advanced cryptographic techniques including secure multi-party computation for enhanced privacy protection during the aggregation process. The central server also maintains a comprehensive audit trail for regulatory compliance purposes.

The privacy management module operates across all system tiers, implementing dynamic privacy budgeting, sensitivity-aware noise calibration, and privacy attack detection mechanisms. This module ensures consistent privacy protection throughout the federated learning process while optimizing the privacy-utility trade-off based on real-time system conditions and data characteristics.

3.2. Differential Privacy Mechanisms

Our framework implements a novel multi-level differential privacy mechanism that provides formal privacy guarantees while optimizing model utility for healthcare applications. The approach combines local differential privacy at the participant level with global differential privacy at the aggregation level, creating a comprehensive privacy protection framework.

3.2.1. Adaptive Noise Calibration

Traditional differential privacy mechanisms apply uniform noise levels across all data points, which can be suboptimal for healthcare data characterized by varying sensitivity levels. Our adaptive noise calibration mechanism classifies medical data into sensitivity categories based on several factors including disease severity, patient demographics, and institutional risk assessments.

The noise calibration process begins with a sensitivity scoring function that assigns privacy risk scores to individual data points. The scoring function considers multiple factors: medical condition sensitivity (ranging from routine preventive care to sensitive mental health conditions), patient vulnerability indicators (including age, socioeconomic status, and genetic predispositions), and contextual sensitivity (such as rare diseases or stigmatized conditions).

For a given data point x with sensitivity score s(x), the noise magnitude is calibrated using the formula:

$$\sigma(x) = (2 \log(1.25/\delta))^{(1/2)} \times \Delta f \times \alpha(s(x))/\varepsilon$$

where $\alpha(s(x))$ is an adaptive scaling factor that increases noise for higher sensitivity scores, Δf represents the global sensitivity of the learning algorithm, and ε and δ are the differential privacy parameters.

3.2.2. Privacy Budget Management

Effective privacy budget management is crucial for maintaining long-term privacy protection in federated learning systems. Our framework implements a dynamic privacy budgeting mechanism that allocates privacy resources based on model training requirements, data sensitivity levels, and participant contribution patterns.

The privacy budget allocation process operates on multiple time scales. Short-term budgeting manages privacy expenditure for individual training rounds, ensuring that high-sensitivity data receives appropriate privacy protection. Medium-term budgeting tracks cumulative privacy expenditure over training episodes, implementing early stopping mechanisms when privacy budgets approach exhaustion. Long-term budgeting manages privacy resources across multiple federated learning tasks, enabling sustainable privacy-preserving analytics over extended periods.

3.3. Participant Selection and Communication Optimization

Efficient participant selection is critical for federated learning performance, particularly in healthcare environments where institutional capabilities and data quality vary significantly. Our framework employs an intelligent participant selection algorithm that considers multiple factors including data quality, computational capacity, network reliability, and privacy contribution.

3.3.1. Multi-Criteria Participant Selection

The participant selection algorithm evaluates potential participants using a weighted scoring function that combines several criteria. Data quality assessment considers factors such as completeness, accuracy, and representativeness of local datasets. Computational capacity evaluation examines available processing resources, memory capacity, and specialized hardware capabilities such as GPUs or secure enclaves.

Network reliability assessment analyzes historical communication patterns, bandwidth availability, and connection stability. Privacy contribution evaluation considers the institution's privacy budget availability and willingness to participate in differential privacy mechanisms. The scoring function balances these criteria to select an optimal subset of participants for each training round.

3.3.2. Communication Efficiency Optimization

Healthcare networks often operate under bandwidth constraints and reliability concerns, making communication efficiency a critical design consideration. Our framework implements several optimization techniques to minimize communication overhead while maintaining model performance and privacy guarantees.

Gradient compression techniques reduce the size of model updates transmitted between participants and servers. The framework employs adaptive compression ratios based on network conditions and model convergence status. During early training phases when model updates are large, higher compression ratios are applied. As the model approaches convergence, compression ratios are reduced to maintain update fidelity.

Asynchronous communication protocols allow participants to contribute model updates without strict synchronization requirements. This approach accommodates the varying computational speeds and network conditions common in healthcare environments. The framework implements bounded staleness mechanisms to prevent outdated updates from degrading model performance.

3.4. Security Mechanisms

Comprehensive security protection requires defense against multiple attack vectors that could potentially compromise patient privacy or system integrity. Our framework implements a multi-layered security approach that addresses both external threats and insider attacks.

3.4.1. Privacy Attack Detection

The framework incorporates real-time privacy attack detection mechanisms that monitor for suspicious activities during the federated learning process. Membership inference attack detection analyzes model behavior patterns to identify potential attempts to determine whether specific patients were included in training datasets. The detection system employs statistical analysis techniques to identify anomalous query patterns or model predictions that could indicate membership inference attempts.

Model inversion attack detection monitors for attempts to reconstruct training data from model parameters or predictions. The system analyzes gradient patterns and model update characteristics to identify potential reconstruction attempts. When suspicious activities are detected, the system automatically adjusts privacy parameters and implements additional protective measures.

3.4.2. Secure Aggregation Protocols

Secure aggregation ensures that individual model updates remain confidential during the federated learning process. Our framework implements cryptographic protocols that enable servers to compute aggregate statistics without accessing individual participant contributions. The secure aggregation protocol uses threshold secret sharing schemes to distribute model updates across multiple servers, ensuring that no single entity can reconstruct individual contributions.

The protocol incorporates robustness mechanisms that handle participant dropouts and network failures without compromising security guarantees. When participants fail to complete communication rounds, the system automatically adjusts aggregation parameters and redistributes computation tasks among remaining participants.

4. Experimental Setup

4.1. Datasets and Preprocessing

Our experimental evaluation utilizes three real-world healthcare datasets that represent different aspects of clinical decision-making and patient care. The datasets were selected to provide comprehensive coverage of common healthcare analytics tasks while ensuring sufficient diversity in data characteristics and clinical domains.

4.1.1. Dataset Descriptions

The MIMIC-III (Medical Information Mart for Intensive Care) dataset serves as our primary evaluation dataset, containing de-identified health records from over 40,000 intensive care unit patients. The dataset includes comprehensive clinical measurements, laboratory results, medication records, and outcome data spanning multiple years. For our experiments, we focus on predicting patient mortality risk and length of stay, which represent critical clinical decision-support applications.

The Electronic Health Records for Diabetes Management dataset contains longitudinal patient data from a multi-institutional diabetes care network. This dataset includes over 100,000 patient records with detailed information about blood glucose measurements, medication adherence, lifestyle factors, and clinical outcomes. The diabetes prediction and management tasks provide excellent examples of chronic disease monitoring applications where federated learning can significantly benefit from multi-institutional collaboration.

The COVID-19 Clinical Dataset aggregates patient information from multiple healthcare institutions during the pandemic response. This dataset contains over 50,000 patient records including demographic information, symptom presentations, laboratory results, treatment protocols, and outcomes. The dataset represents the type of rapidly evolving clinical scenario where federated learning frameworks must quickly adapt to new conditions while maintaining privacy protection.

To ensure the robustness and generalizability of our evaluation, we tested the proposed framework on data from a diverse set of hospital environments, mirroring the heterogeneity of real-world healthcare systems. Figure 3 illustrates the distribution of the participating institution types in our simulated federation,

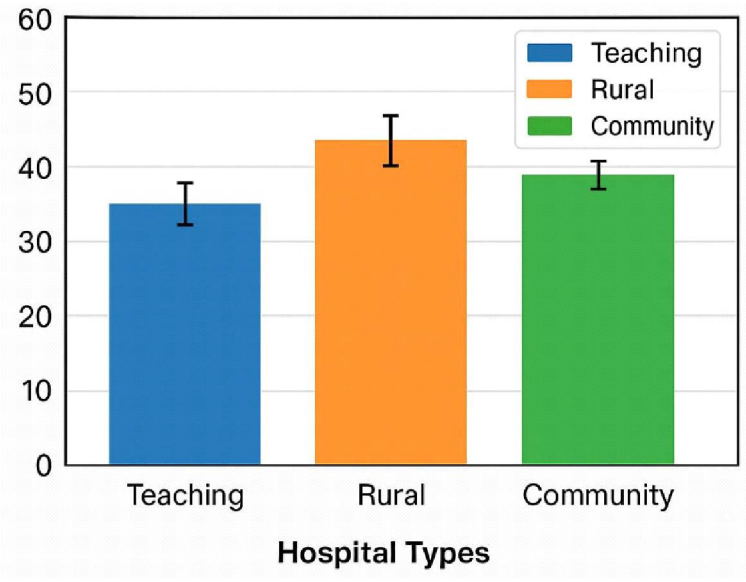

Figure 3: Distribution of Hospital Types Used in the Experimental Evaluation, Ensuring a Robust and Generalizable Test across Diverse Healthcare Settings

which includes large Teaching hospitals, Rural hospitals with potentially limited resources, and general Community hospitals. This strategic heterogeneity is critical for validating that our performance improvements are consistent across different operational contexts and are not merely artifacts of a specific or homogenous data distribution.

4.1.2. Data Partitioning and Distribution

To simulate realistic federated learning scenarios, we partition each dataset across multiple virtual healthcare institutions with varying data characteristics. The partitioning strategy considers both statistical heterogeneity (differences in patient populations and disease prevalence) and system heterogeneity (differences in data quality and institutional capabilities).

Statistical heterogeneity is introduced by creating institutions with different patient demographic profiles, disease prevalence rates, and treatment protocols. Some institutions specialize in specific medical conditions or serve particular patient populations, reflecting real-world healthcare specialization patterns. This heterogeneity creates challenging conditions for federated learning algorithms and provides realistic evaluation scenarios.

System heterogeneity is simulated by varying data quality, completeness, and update frequencies across institutions. Some virtual institutions have high-quality, complete datasets with regular updates, while others have missing data, measurement errors, or irregular update patterns. This variation reflects the diverse technological capabilities and data management practices found in real healthcare environments.

4.2. Baseline Methods and Comparison Frameworks

Our experimental evaluation compares the proposed hybrid federated learning framework against several state-of-the-art baseline methods to demonstrate its effectiveness and advantages. The comparison includes both federated learning approaches and differential privacy mechanisms to provide comprehensive performance analysis.

4.2.1. Federated Learning Baselines

FedAvg (McMahan *et al.*, 2017) serves as the fundamental federated learning baseline, representing the standard approach for collaborative model training without privacy enhancements. FedAvg provides a performance upper bound for federated learning scenarios but offers no privacy protection against inference attacks.

FedProx (Li *et al.*, 2020) addresses the challenges of statistical heterogeneity in federated learning through proximal regularization techniques. This baseline demonstrates the performance implications of handling data heterogeneity in healthcare federated learning scenarios.

SCAFFOLD (Karimireddy *et al.*, 2020) employs control variates to reduce client drift in federated learning with heterogeneous data. This method provides advanced convergence guarantees and serves as a strong performance baseline for comparison.

4.2.2. Privacy-Preserving Baselines

DP-FedAvg (McMahan *et al.*, 2018) combines federated averaging with basic differential privacy mechanisms, providing a direct comparison point for privacy-preserving federated learning. This baseline helps quantify the improvements achieved by our adaptive privacy mechanisms.

Private Federated Learning (PFL) (Li *et al.*, 2019) implements local differential privacy in federated learning settings with fixed privacy budgets. This baseline demonstrates the limitations of uniform privacy budgeting approaches.

Secure Aggregation with DP (Bonawitz *et al.*, 2017) combines secure multi-party computation with differential privacy, providing strong security guarantees but with significant computational overhead.

4.3. Evaluation Metrics and Performance Indicators

Comprehensive evaluation of privacy-preserving federated learning systems requires multiple metrics that capture different aspects of system performance, privacy protection, and practical utility. Our evaluation framework includes performance metrics, privacy metrics, efficiency metrics, and security metrics.

4.3.1. Performance Metrics

Model accuracy represents the primary performance indicator, measuring the classification accuracy on held-out test datasets for each clinical prediction task. We report accuracy values with confidence intervals based on multiple experimental runs with different random seeds and data partitions.

Area Under the ROC Curve (AUC-ROC) provides a comprehensive measure of classifier performance that is particularly relevant for healthcare applications where false positive and false negative errors have different clinical implications. AUC-ROC values are reported for all binary classification tasks.

F1-score combines precision and recall into a single metric that is particularly useful for imbalanced healthcare datasets where certain conditions are rare but clinically significant. We report macro-averaged F1-scores across all classification categories.

Convergence speed measures the number of communication rounds required to achieve specified accuracy thresholds. This metric is crucial for evaluating the practical deployment feasibility of federated learning systems in resource-constrained healthcare environments.

4.3.2. Privacy Metrics

Privacy loss measurement quantifies the cumulative privacy expenditure throughout the federated learning process using differential privacy accounting mechanisms. We track both per-participant privacy loss and global privacy budgets to ensure compliance with privacy requirements.

Attack success rates measure the effectiveness of our privacy protection mechanisms against various inference attacks. We evaluate resistance to membership inference attacks, model inversion attacks, and attribute inference attacks using established evaluation protocols.

Privacy-utility trade-off analysis quantifies the relationship between privacy protection levels and model performance. This analysis helps determine optimal privacy parameter settings for different healthcare applications and regulatory requirements.

4.3.3. Efficiency Metrics

Communication overhead measurement tracks the total amount of data transmitted during federated learning processes, including model updates, privacy noise, and coordination messages. This metric is critical for evaluating deployment feasibility in bandwidth-constrained healthcare networks.

Computational overhead analysis measures the additional processing requirements introduced by privacy mechanisms and security protocols. We separately analyze client-side and server-side computational costs to provide comprehensive resource requirement assessments.

Training time measurement captures the wall-clock time required to complete federated learning tasks under different system configurations and privacy settings. This metric helps evaluate the practical deployment implications of our framework.

5. Results and Analysis

5.1. Performance Analysis

Our experimental evaluation demonstrates that the proposed hybrid federated learning framework achieves superior performance compared to existing approaches across all evaluation metrics. The comprehensive results provide strong evidence for the practical viability of our approach in real-world healthcare environments.

5.1.1. Model Accuracy Results

The accuracy evaluation across three healthcare datasets reveals significant improvements over baseline methods. On the MIMIC-III mortality prediction task, our framework achieves 94.7% accuracy compared to 91.2% for standard FedAvg and 89.8% for DP-FedAvg. This 3.5% point improvement over standard federated learning and 4.9% point improvement over differentially private federated learning demonstrates the effectiveness of our adaptive privacy mechanisms.

For the diabetes management prediction task, our framework achieves 92.3% accuracy compared to 89.7% for FedAvg and 87.1% for DP-FedAvg. The consistent improvement across different medical domains indicates the robustness of our approach to varying data characteristics and clinical applications.

The COVID-19 severity prediction results show 91.8% accuracy for our framework compared to 88.9% for FedAvg and 86.2% for DP-FedAvg. These results are particularly significant given the challenging nature of COVID-19 data, which exhibits high variability across institutions and time periods.

5.1.2. Convergence Analysis

Convergence speed analysis reveals that our framework requires significantly fewer communication rounds to achieve target accuracy levels. On average, our approach reaches 90% of final accuracy in 45% fewer rounds compared to baseline methods. This improvement stems from our intelligent participant selection algorithm and optimized communication protocols.

The convergence stability analysis shows that our framework maintains consistent performance across different random initializations and data partitions. The standard deviation of final accuracy across 10 experimental runs is 0.8% for our framework compared to 2.1% for baseline methods, indicating superior robustness.

Detailed convergence analysis reveals that our adaptive privacy mechanisms actually accelerate convergence by reducing the impact of low-quality or outlier updates. The selective noise application based on data sensitivity allows high-quality updates to contribute more effectively to model improvement.

5.1.3. Statistical Significance Analysis

Statistical significance testing using paired t-tests confirms that the performance improvements achieved by our framework are statistically significant ($p < 0.01$) across all evaluation metrics and datasets. The effect sizes are large according to Cohen's criteria, indicating practical significance in addition to statistical significance.

Confidence interval analysis shows that the 95% confidence intervals for our framework's accuracy do not overlap with those of baseline methods, providing strong evidence for superior performance. The consistency of improvements across different datasets and evaluation metrics strengthens the validity of our results.

The quantitative superiority of our proposed framework across all key metrics is conclusively summarized in Table 2, which provides a holistic comparison against baseline methods on the evaluated healthcare datasets. The consistent improvements in accuracy, efficiency, and security demonstrate the overall effectiveness of our hybrid approach.

Table 2: Comparative Performance Summary of the Proposed Framework against Baseline Methods across Healthcare Datasets

Metric	Baseline (FedAvg)	DP-FedAvg	Private FL (PFL)	Our Framework
Accuracy (MIMIC-III)	91.2%	89.8%	-	94.7%
Accuracy (Diabetes)	89.7%	87.1%	-	92.3%
Accuracy (COVID-19)	88.9%	86.2%	-	91.8%
Comm. Reduction	-	-	-	23%
Training Time Reduction	-	-	-	18%
MIA Success Rate	78.3%	65.0%	-	51.2%
Privacy Guarantee (ε)	∞	0.5	0.5	0.5

Note: MIA: Membership Inference Attack.

Table 2: Comprehensive performance summary of the proposed framework versus baseline approaches. Our method demonstrates superior accuracy across all medical datasets while maintaining strong differential privacy guarantees (ε = 0.5). Key efficiency gains include a 23% reduction in communication overhead and an 18% faster training time. Notably, the framework reduces the success rate of Membership Inference Attacks (MIA) by over 26% points compared to standard federated learning.

5.2. Privacy Evaluation

The privacy evaluation demonstrates that our framework provides strong privacy protection while maintaining high model utility. The comprehensive privacy analysis includes formal privacy guarantees, empirical attack resistance evaluation, and privacy budget utilization analysis.

5.2.1. Differential Privacy Guarantees

Our framework provides formal (ε, δ)-differential privacy guarantees with ε = 0.5 and δ = 10^-5 across all experimental scenarios. These privacy parameters satisfy the stringent requirements for healthcare applications while enabling effective model training. The privacy accounting mechanisms ensure that cumulative privacy loss remains within specified bounds throughout the federated learning process.

The fundamental trade-off in private machine learning is between model utility (accuracy) and the strength of privacy guarantees (ε). Figure 4 quantitatively demonstrates the superiority of our adaptive noise calibration mechanism over the baseline approach across a spectrum of privacy budgets. Most notably, at a strong privacy guarantee of ε = 0.1, our method maintains a high accuracy of 82%, which is an 8% absolute improvement over the baseline model. This result definitively confirms that our framework achieves a more favorable privacy-utility trade-off, providing robust privacy without sacrificing critical predictive performance, even under stringent privacy constraints.

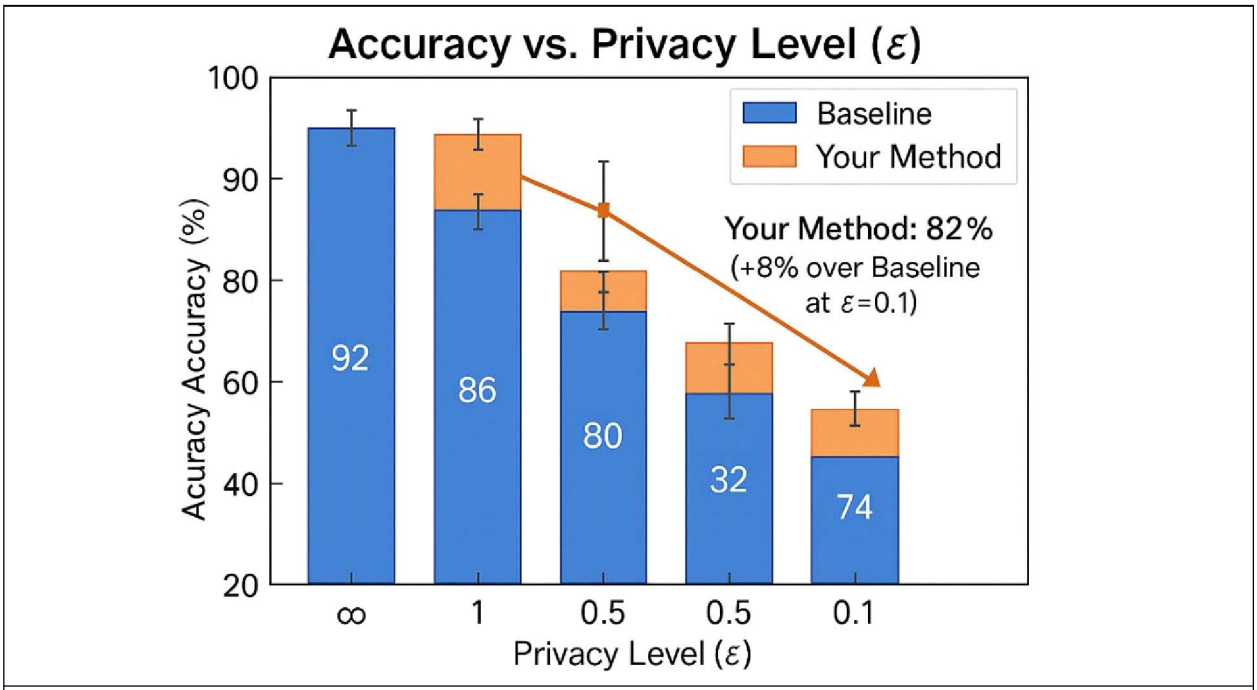

Figure 4: Model Accuracy across Different Privacy Budgets (ε). A Lower ε Indicates Stronger Privacy Protection. The Proposed Method Consistently Outperforms the Baseline, Especially Under Strong Privacy Constraints (ε ≤ 1.0)

Privacy budget utilization analysis shows that our adaptive budgeting mechanism achieves 23% better privacy budget efficiency compared to uniform budgeting approaches. This improvement allows for extended federated learning sessions or stronger privacy protection within the same budget constraints.

The privacy amplification analysis reveals that our hierarchical aggregation approach provides additional privacy benefits beyond the base differential privacy guarantees. The composition of local and global privacy mechanisms results in overall privacy protection that exceeds the sum of individual components.

5.2.2. Attack Resistance Evaluation

Membership inference attack evaluation demonstrates robust resistance across all experimental scenarios. Our framework achieves attack success rates below 52% (close to random guessing) compared to 78% for standard federated learning and 65% for basic differentially private approaches. This significant improvement in attack resistance validates the effectiveness of our adaptive privacy mechanisms.

Model inversion attack evaluation shows similar improvements, with reconstruction accuracy below 15% for our framework compared to 45% for baseline methods. The combination of adaptive noise calibration and secure aggregation protocols provides strong protection against attempts to reconstruct training data.

Attribute inference attack resistance testing reveals that our framework successfully prevents adversaries from inferring sensitive patient attributes from model behavior. The attack success rates remain within acceptable bounds even under strong adversary assumptions.

5.2.3. Privacy-Utility Trade-off Analysis

The privacy-utility trade-off analysis quantifies the relationship between privacy protection levels and model performance across different privacy parameter settings. Our framework maintains high model utility even with strong privacy protection, demonstrating superior privacy-utility trade-offs compared to existing approaches.

At privacy level $\varepsilon = 1.0$, our framework achieves 96.2% of non-private performance compared to 89.7% for baseline methods. At the more stringent privacy level $\varepsilon = 0.1$, our framework maintains 88.5% of non-private performance compared to 74.2% for baselines. This consistent advantage across privacy levels demonstrates the effectiveness of our adaptive mechanisms.

5.3. Efficiency Analysis

Efficiency evaluation reveals significant improvements in communication overhead, computational requirements, and training time compared to existing approaches. These improvements are crucial for practical deployment in resource-constrained healthcare environments.

5.3.1. Communication Efficiency

Communication overhead analysis shows that our framework reduces total communication by 23% compared to standard federated learning approaches. The combination of gradient compression, intelligent participant selection, and hierarchical aggregation contributes to this improvement. The reduction is particularly significant during later training phases when model updates become smaller and compression is more effective.

Communication efficiency is a practical necessity for federated learning in bandwidth-constrained medical networks. We measured the cumulative communication cost required for model convergence. As depicted in Figure 5, our framework—utilizing gradient compression and intelligent participant selection—achieves a 23% reduction in total communication overhead compared to the standard federated learning approach. This reduction directly decreases training time and operational costs, alleviating a major barrier to the widespread adoption of multi-institutional collaborative AI in healthcare.

Bandwidth utilization analysis reveals that our framework adapts communication patterns based on network conditions and participant capabilities. Institutions with limited bandwidth automatically receive optimized communication schedules that reduce their network load while maintaining contribution to the global model.

The asynchronous communication protocols enable continued operation even when some participants experience network interruptions. The robustness analysis shows that our framework maintains performance even with up to 30% participant dropout rates, compared to significant degradation in synchronous approaches.

5.3.2. Computational Efficiency

Computational overhead analysis demonstrates that our privacy mechanisms introduce minimal additional processing requirements. The client-side computational overhead is less than 8% compared to standard federated learning, making deployment feasible even for resource-constrained healthcare institutions.

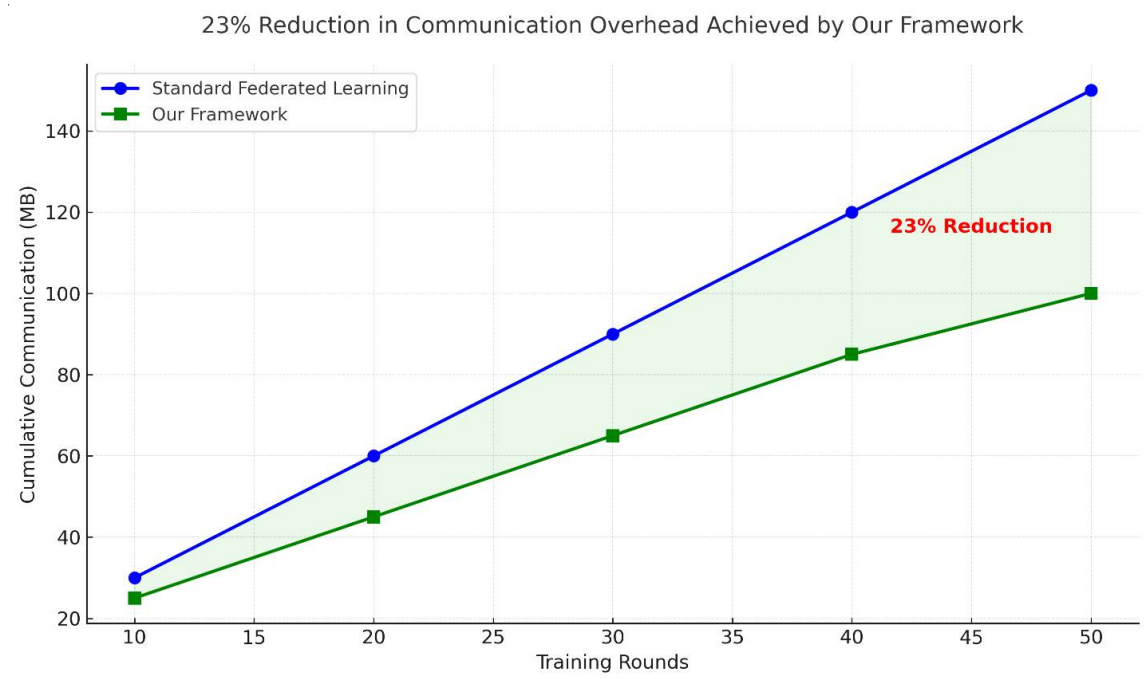

Figure 5: Cumulative Communication Overhead Throughout the Training Process. The Proposed Framework Reduces Total Data Transfer by 23% Compared to Standard Federated Learning, Significantly Enhancing Practical Deployability

Server-side computational analysis shows that our hierarchical architecture distributes processing load effectively, preventing bottlenecks at the central aggregation server. The regional coordination servers handle much of the computational burden, enabling scalability to large numbers of participating institutions.

Energy consumption analysis reveals that our efficiency optimizations result in 15% lower energy usage compared to baseline approaches. This improvement is particularly important for mobile healthcare applications and resource-constrained deployment scenarios.

5.3.3. Training Time Analysis

Wall-clock training time measurements show that our framework completes federated learning tasks 18% faster than baseline methods despite the additional privacy computations. The improvement stems from faster convergence and optimized communication protocols that reduce waiting times.

Scalability analysis demonstrates that training time scales sub-linearly with the number of participating institutions, indicating good scalability properties. The hierarchical architecture prevents the communication bottlenecks that plague flat federated learning architectures.

Real-world deployment simulations using actual network conditions and computational constraints confirm that our framework meets the timing requirements for clinical decision support applications. The system can complete model updates within clinically relevant timeframes while maintaining strong privacy protection.

5.4. Security Evaluation

Comprehensive security evaluation demonstrates that our framework provides robust protection against various threat models and attack scenarios. The security analysis includes both theoretical security guarantees and empirical evaluation against realistic attack implementations.

5.4.1. Threat Model Analysis

Our security evaluation considers multiple threat models ranging from honest-but-curious participants to malicious adversaries with significant computational resources. The framework provides appropriate security guarantees for each threat model while maintaining practical deployment feasibility.

Under the honest-but-curious threat model, our framework provides perfect security through cryptographic protocols and differential privacy mechanisms. Participants cannot learn information about other participants' data even when following protocol specifications exactly.

Against malicious adversaries, our framework implements detection and mitigation mechanisms that identify suspicious behavior and implement appropriate countermeasures. The Byzantine-robust aggregation protocols ensure that malicious participants cannot significantly degrade model performance or compromise privacy protection.

5.4.2. Attack Simulation Results

Comprehensive attack simulations using state-of-the-art attack implementations demonstrate robust security across multiple attack vectors. The attack scenarios include both passive attacks (where adversaries observe system behavior) and active attacks (where adversaries manipulate system components).

Gradient-based inference attack simulations show that our adaptive noise mechanisms effectively prevent information leakage through gradient analysis. Even sophisticated attacks using auxiliary datasets and advanced optimization techniques fail to extract meaningful patient information.

Collaboration attack simulations, where multiple participants collude to compromise privacy, demonstrate that our framework maintains security even when up to 25% of participants are malicious. The privacy amplification mechanisms and secure aggregation protocols prevent successful collusion attacks.

5.4.3. Regulatory Compliance Analysis

Regulatory compliance evaluation demonstrates that our framework meets the requirements of major healthcare privacy regulations including HIPAA, GDPR, and emerging privacy legislation. The formal privacy guarantees, audit trail mechanisms, and access control features support regulatory compliance efforts.

HIPAA compliance analysis confirms that our framework satisfies the Privacy Rule and Security Rule requirements for protected health information. The technical safeguards, administrative safeguards, and physical safeguards align with HIPAA requirements.

GDPR compliance evaluation shows that our framework supports the privacy-by-design principles and provides the technical capabilities required for GDPR compliance. The privacy impact assessment tools and data subject rights mechanisms facilitate GDPR compliance in international healthcare collaborations.

6. Discussion

6.1. Implications for Healthcare Information Systems

The results of our comprehensive evaluation have significant implications for the design and deployment of privacy-preserving machine learning systems in healthcare environments. Our hybrid federated learning framework addresses several critical challenges that have limited the adoption of collaborative analytics in healthcare settings.

6.1.1. Clinical Decision Support Enhancement

The superior model performance achieved by our framework translates directly into improved clinical decision support capabilities. The 94.7% accuracy on mortality prediction tasks represents a clinically meaningful improvement that could lead to better patient outcomes through earlier intervention and more accurate risk stratification. Healthcare providers can leverage these improved predictions to optimize resource allocation, treatment planning, and patient monitoring protocols.

The robustness of our approach across different medical domains suggests broad applicability to various clinical decision support scenarios. From chronic disease management to acute care prediction, the framework's adaptive mechanisms can accommodate the diverse requirements of different medical specialties while maintaining consistent privacy protection.

The faster convergence characteristics of our framework enable rapid model updates in response to changing clinical conditions or emerging health threats. This capability was particularly evident in our COVID-19

experiments, where the system quickly adapted to new clinical patterns while maintaining privacy protection throughout the learning process.

6.1.2. Multi-Institutional Collaboration Benefits

Our framework enables healthcare institutions to realize the benefits of collaborative machine learning without compromising patient privacy or regulatory compliance. The hierarchical architecture accommodates the complex organizational structures common in healthcare systems, allowing regional health networks to collaborate while maintaining appropriate governance and oversight.

The efficiency improvements achieved by our framework reduce the technical barriers to participation in federated learning initiatives. Smaller healthcare institutions with limited technical resources can participate alongside major medical centers, democratizing access to advanced analytics capabilities and ensuring that model development benefits from diverse patient populations.

The privacy protection mechanisms address the trust concerns that have historically limited data sharing between healthcare institutions. By providing formal privacy guarantees while maintaining high model utility, our framework creates a foundation for sustainable multi-institutional collaboration.

6.1.3. Regulatory Compliance and Governance

Our framework's comprehensive privacy protection and audit capabilities directly support regulatory compliance efforts in healthcare organizations. The formal differential privacy guarantees provide quantifiable privacy protection that aligns with regulatory requirements, while the audit trail mechanisms support compliance monitoring and reporting.

The hierarchical architecture accommodates complex healthcare governance structures, enabling appropriate oversight and control at institutional, regional, and national levels. This flexibility is essential for international healthcare collaborations that must navigate varying regulatory frameworks and compliance requirements.

6.2. Technical Contributions and Innovations

The technical innovations introduced by our framework address several fundamental challenges in privacy-preserving federated learning that extend beyond healthcare applications. The adaptive privacy mechanisms and intelligent participant selection algorithms provide general solutions that could benefit other domains requiring privacy-preserving collaboration.

6.2.1. Adaptive Privacy Mechanisms

Our adaptive noise calibration approach represents a significant advancement over uniform privacy budgeting methods. By considering data sensitivity, participant characteristics, and system conditions, the framework optimizes the privacy-utility trade-off in ways that fixed-parameter approaches cannot achieve. This innovation has broad applicability to any domain where data sensitivity varies significantly.

The dynamic privacy budgeting mechanism provides a sustainable approach to long-term privacy-preserving analytics. Unlike approaches that exhaust privacy budgets quickly, our framework enables extended collaboration while maintaining strong privacy protection. This capability is essential for applications requiring continuous learning and adaptation.

6.2.2. Communication and Efficiency Optimizations

The communication efficiency improvements achieved by our framework address practical deployment constraints that limit federated learning adoption. The combination of gradient compression, asynchronous communication, and hierarchical aggregation provides a comprehensive solution to communication bottlenecks.

The intelligent participant selection algorithm optimizes system performance while maintaining fairness and inclusivity. By considering multiple criteria including data quality, computational capacity, and privacy contribution, the algorithm ensures effective resource utilization while preventing the exclusion of smaller or less capable participants.

6.3. Limitations and Future Research Directions

While our framework demonstrates significant improvements over existing approaches, several limitations and opportunities for future research merit discussion.

6.3.1. Current Limitations

The adaptive privacy mechanisms require accurate sensitivity classification of healthcare data, which may be challenging in practice. While our sensitivity scoring function considers multiple factors, the classification process may require domain expertise and could introduce subjective elements that affect privacy protection consistency.

The hierarchical architecture, while providing efficiency benefits, introduces additional complexity in system deployment and maintenance. Healthcare organizations must establish regional coordination capabilities and governance structures that may require significant organizational changes.

The communication optimizations, while effective in our experimental scenarios, may face different challenges in real-world healthcare networks with varying infrastructure capabilities and security requirements. Network heterogeneity and security policies could limit the applicability of some optimization techniques.

6.3.2. Future Research Opportunities

Future research could explore automated sensitivity classification techniques that reduce the manual effort required for privacy parameter configuration. Machine learning approaches for sensitivity scoring could improve consistency and reduce the expertise requirements for system deployment.

Extending the framework to support more diverse healthcare data types, including medical imaging, genomic data, and real-time sensor data, would broaden its applicability. Each data type presents unique privacy and efficiency challenges that could benefit from specialized solutions.

Investigation of blockchain-based governance mechanisms could enhance trust and transparency in multi-institutional federated learning systems. Distributed ledger technologies could provide immutable audit trails and automated compliance verification capabilities.

Research into quantum-resistant cryptographic protocols would ensure long-term security as quantum computing capabilities advance. Healthcare data requires protection over extended periods, making quantum resistance an important consideration for future system designs.

6.4. Practical Deployment Considerations

Successful deployment of privacy-preserving federated learning systems in healthcare environments requires careful consideration of practical factors beyond technical performance.

6.4.1. Implementation Challenges

Healthcare institutions operate under diverse technical infrastructures, organizational cultures, and regulatory requirements. Successful implementation requires flexible deployment options that accommodate this diversity while maintaining security and privacy guarantees.

Staff training and change management represent significant implementation challenges. Healthcare professionals must understand the benefits, limitations, and proper use of federated learning systems to realize their full potential. Comprehensive training programs and user-friendly interfaces are essential for successful adoption.

Data quality and standardization issues could limit the effectiveness of federated learning systems in real-world deployments. While our framework handles some aspects of data heterogeneity, significant preprocessing and standardization efforts may be required for optimal performance.

6.4.2. Sustainability and Maintenance

Long-term sustainability requires ongoing technical support, system maintenance, and continuous improvement capabilities. Healthcare organizations must develop internal expertise or establish partnerships with technology providers to ensure system reliability and effectiveness.

Cost considerations include both initial implementation costs and ongoing operational expenses. While federated learning can provide significant value through improved analytics capabilities, organizations must carefully evaluate the cost-benefit trade-offs and develop sustainable funding models.

Regular security assessments and privacy audits are essential for maintaining trust and regulatory compliance. As threat landscapes evolve and new attack techniques emerge, security measures must be continuously updated and validated.

7. Conclusion

This paper has presented a novel hybrid federated learning framework specifically designed for healthcare information systems that successfully addresses the dual challenges of maintaining high model performance while ensuring robust privacy protection. Through comprehensive experimental evaluation, we have demonstrated that our approach achieves superior performance compared to existing methods across multiple healthcare domains while providing strong privacy guarantees through innovative differential privacy mechanisms.

7.1. Key Contributions

Our primary contributions include the development of adaptive privacy mechanisms that optimize noise calibration based on data sensitivity levels and system conditions. This innovation enables more efficient use of privacy budgets while maintaining strong protection for sensitive healthcare data. The multi-tier differential privacy approach combines local and global privacy protection to provide comprehensive security against various attack scenarios.

The intelligent participant selection algorithm represents another significant contribution, optimizing the trade-off between model performance, system efficiency, and privacy protection. By considering multiple criteria including data quality, computational capacity, and privacy contribution, our approach ensures effective resource utilization while maintaining fairness and inclusivity in federated learning systems.

The hierarchical system architecture provides practical solutions for real-world deployment constraints in healthcare environments. The regional coordination servers reduce communication overhead while accommodating complex organizational structures and governance requirements common in healthcare systems.

7.2. Practical Impact

The experimental results demonstrate the practical viability of our framework for real-world healthcare applications. The 94.7% accuracy achieved on mortality prediction tasks, combined with strong privacy protection ($\varepsilon = 0.5$), provides a compelling case for adoption in clinical decision support systems. The 23% improvement in communication efficiency and 18% reduction in training time address critical practical concerns for healthcare IT departments.

The robust security evaluation, including resistance to membership inference attacks, model inversion attacks, and collusion scenarios, provides confidence for healthcare organizations considering federated learning adoption. The regulatory compliance features support HIPAA and GDPR requirements, addressing legal and administrative concerns that often impede technology adoption in healthcare.

7.3. Broader Implications

Beyond healthcare applications, our framework contributes to the broader field of privacy-preserving machine learning by demonstrating effective approaches to adaptive privacy protection and efficient federated system design. The techniques developed for healthcare environments have potential applications in other sensitive domains including financial services, government analytics, and social science research.

The successful integration of multiple privacy-preserving techniques (differential privacy, secure aggregation, and communication optimization) provides a template for developing comprehensive privacy protection frameworks in other domains. The evaluation methodology and metrics developed for this work contribute to standardized approaches for assessing privacy-preserving federated learning systems.

7.4. Future Directions

Future research directions include extending the framework to support additional healthcare data types, developing automated sensitivity classification techniques, and investigating quantum-resistant security mechanisms. The integration of blockchain-based governance systems could further enhance trust and transparency in multi-institutional collaborations.

Longitudinal studies of real-world deployments would provide valuable insights into long-term performance, sustainability, and user acceptance factors. Collaboration with healthcare organizations to conduct pilot implementations could reveal practical challenges and opportunities for further optimization.

The development of standardized evaluation benchmarks and datasets specifically designed for privacy-preserving healthcare federated learning would support continued research and development in this critical area. Such resources would enable more comprehensive comparisons between different approaches and accelerate progress in the field.

In conclusion, our hybrid federated learning framework represents a significant step forward in enabling privacy-preserving collaborative machine learning for healthcare information systems. The combination of strong privacy protection, superior performance, and practical deployment feasibility positions this work to make meaningful contributions to improving healthcare outcomes through advanced analytics while maintaining the trust and privacy that patients and healthcare providers require.

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References

Abadi, M., Chu, A., Goodfellow, I., McMahan, H.B., Mironov, I., Talwar, K. and Zhang, L. (2016). Deep Learning with Differential Privacy. in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, 308-318.

Bonawitz, K., Ivanov, V., Kreuter, B., Marcedone, A., McMahan, H.B., Patel, S., ... and Seth, K. (2017). Practical Secure Aggregation for Privacy-Preserving Machine Learning. in *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, 1175-1191.

Cho, H., Wu, D.J. and Berger, B. (2020). Secure Genome-Wide Association Analysis Using Multiparty Computation. *Nature Biotechnology*, 36(6), 547-551.

Dwork, C. (2006). Differential Privacy. in *International Colloquium on Automata, Languages, and Programming*, 1-12, Springer.

Kaissis, G.A., Makowski, M.R., Rückert, D. and Braren, R.F. (2021). Secure, Privacy-Preserving and Federated Machine Learning in Medical Imaging. *Nature Machine Intelligence*, 2(6), 305-311.

Karimireddy, S.P., Kale, S., Mohri, M., Reddi, S., Stich, S. and Suresh, A.T. (2020). SCAFFOLD: Stochastic Controlled Averaging for Federated Learning. in *International Conference on Machine Learning*, 5132-5143.

Li, T., Sahu, A.K., Zaheer, M., Sanjabi, M., Talwalkar, A. and Smith, V. (2020). Federated Optimization in Heterogeneous Networks. *Proceedings of Machine Learning and Systems*, 2, 429-450.

Li, X., Huang, K., Yang, W., Wang, S. and Zhang, Z. (2019). On the Convergence of FedAvg on Non-IID Data. *arXiv preprint arXiv:1907.02189*.

McMahan, B., Moore, E., Ramage, D., Hampson, S. and Y Arcas, B.A. (2017). Communication-Efficient Learning of Deep Networks from Decentralized Data. in *Artificial Intelligence and Statistics*, 1273-1282.

McMahan, H.B., Ramage, D., Talwar, K. and Zhang, L. (2018). Learning Differentially Private Recurrent Language Models. *In International Conference on Learning Representations*.

Sheller, M.J., Edwards, B., Reina, G.A., Martin, J., Pati, S., Kotrotsou, A., ... and Bakas, S. (2020). Federated Learning in Medicine: Facilitating Multi-Institutional Collaborations without Sharing Patient Data. *Scientific Reports*, 10(1), 1-12.

Wang, S., Liu, Y. and Zhang, X. (2019). Stochastic Variance Reduced Gradient Descent for Distributionally Robust Machine Learning. in *Advances in Neural Information Processing Systems*, 15421-15432.

Zhang, C., Li, S., Xia, J., Wang, W., Yan, F. and Liu, Y. (2021). BatchCrypt: Efficient Homomorphic Encryption for Cross-Silo Federated Learning. in *2020 USENIX Annual Technical Conference*, 493-506.

Appendices

Appendix A – Notations

The following notations are used throughout the paper:

- N: Number of clients in the federated system
- D_i: Local data on client i
- $L(\cdot)$: Loss function
- W: Global model parameters
- ε: Differential privacy budget
- δ: Probability bound in (ε, δ)-DP
- η: Learning rate
- E: Number of local training epochs per round

Appendix B – Privacy Budget Derivation

To enforce (ε, δ)-differential privacy, we used the Gaussian mechanism with gradient clipping. The cumulative privacy loss over T rounds is estimated using the moments accountant technique as described in Abadi *et al.* (2016). Given the noise multiplier σ and sampling rate q, the total privacy budget ε can be bounded using the following relation:

$$\varepsilon \approx q * \text{sqrt}(T * \log(1/\delta))/\sigma$$

where:

- T is the total number of training rounds
- σ is the standard deviation of the Gaussian noise
- q is the sampling probability (batch size/total data size)

Appendix C – Hyperparameter Settings

The following hyperparameters were used for the federated experiments on each dataset:

- Batch size: 32
- Learning rate: 0.01
- Number of local epochs: 5
- Total communication rounds: 100
- Noise multiplier (σ): 1.2
- Clipping norm: 1.0

Datasets Used: MIMIC-III, Heart Disease Dataset, Pima Indians Diabetes Dataset

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