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Research Article

Privacy-Preserving Medical Data Collaborative Modeling: A Differential Privacy Enhanced Federated Learning Framework

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Abstract

This paper proposes a novel privacy-preserving federated learning framework enhanced with adaptive differential privacy for secure medical data collaboration. The framework addresses critical challenges in protecting patient privacy while enabling effective collaborative model training across healthcare institutions. We introduce a dual-layer privacy protection mechanism that combines local and central differential privacy, dynamically adjusting privacy budget allocation based on training progress and data sensitivity. The framework implements a hierarchical architecture with edge servers performing preliminary aggregation to reduce communication overhead and enhance privacy protection. A novel adaptive privacy budget allocation strategy is developed to optimize the privacy-utility trade-off throughout the training process. The framework incorporates robust aggregation mechanisms to handle data heterogeneity while maintaining privacy guarantees. Theoretical analysis establishes convergence properties and privacy bounds under various operating conditions. Experimental evaluation of real-world medical datasets demonstrates that our framework achieves 92.5% accuracy while reducing privacy loss by 85% compared to baseline methods. The framework shows strong resistance to various privacy attacks, with membership inference attack success rates reduced by 87%. The results validate the framework's effectiveness in enabling secure and efficient collaborative learning in healthcare settings while maintaining strict privacy protection for sensitive medical data.

Keywords

Federated Learning, Differential Privacy, Medical Data Privacy, Privacy Budget Allocation

1. Introduction

1.1 Background and Motivation

With the rapid development of artificial intelligence and big data, deep learning has achieved great success in medicine,

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especially in disease diagnosis, treatment planning, and analysis of medical imaging. Hospitals generate a large amount of medical information every day, including electronic health records (EHRs), medical records, and genomics[1]. This valuable information has great potential for improving health services and supporting medical research. However, medical records contain sensitive personal information, making data sharing and integration difficult due to privacy restrictions and privacy concerns.

The centralized training system requires all training materials to be collected in a centralized location, which is a major concern in health care. Hospitals are often reluctant to share their patient information due to privacy laws such as HIPAA and GDPR. This data extraction creates “data silos” that hinder the development of robust and comprehensive AI clinical models. The increased need for privacy-preserving medical information has led to the emergence of new educational systems.

Federated learning (FL) has emerged as a promising solution to enable collaborative model training while keeping data locally stored at medical institutions. In the FL framework, participating institutions train models on their local datasets and only share model parameters or gradients with a central server for aggregation[2]. This "data stays local, models move" approach significantly reduces privacy risks compared to traditional centralized learning. However, recent studies have shown that even sharing model parameters can still leak sensitive information through various inference attacks, including membership inference and model inversion attacks.

1.2 Research Challenges

The integration of privacy-preserving mechanisms in medical federated learning faces several critical challenges that need to be carefully addressed:

Privacy Protection: While federated learning provides a basic level of privacy by keeping raw data local, the shared model parameters can still reveal sensitive information about the training data. Advanced privacy-preserving techniques are needed to prevent privacy leakage through model parameter sharing. The challenge lies in quantifying and controlling the privacy loss while maintaining model utility.

Model Performance: Adding noise to self-defence inevitably affects model performance. Medical applications often require accuracy and reliability, making it very important to balance privacy and utility models. Finding the best trade-off between guaranteeing privacy and quality standards remains difficult, especially for complex healthcare projects.

Good communication: The nature of the government's education requires communication between the hospitals and the central server. Privacy-preserving mechanisms often introduce additional communication. In healthcare facilities with limited capacity, creating effective communication systems while self-regulating has proven to be a major challenge.

Heterogeneous Data Distribution: Medical data across heterogeneous institutions highlight the importance of data quality, quantity, and distribution. This non-IID (Independent and Identically Distributed) nature of medical data complicates the privacy budget allocation and model convergence analysis[3].

System Security: The federated learning system must be robust against various security threats, including malicious participants and external attackers. Ensuring system security while preserving privacy and maintaining model performance requires careful consideration of threat models and defence mechanisms.

1.3 Research Contributions

This paper proposes a new privacy-preserving framework for medical information-sharing modelling that integrates privacy-preserving processes with government learning. Our main contributions are summarized as follows[4].

We create a privacy-assurance-responsible educational system specifically for medical use. The framework involves changing the privacy gap to protect privacy from shared models. Our solution provides theoretical privacy guarantees while considering the unique characteristics of medical data collaboration.

We develop an innovative adaptive privacy budget allocation strategy that dynamically adjusts the noise level based on training progress and model convergence status. This approach optimizes the privacy-utility trade-off by allocating larger privacy budgets in later training stages when gradients become more precise and sensitive to noise perturbation[5]. The strategy ensures effective privacy protection while minimizing the impact on model performance.

We propose a novel model aggregation mechanism that accounts for both data heterogeneity and privacy requirements across different medical institutions. The mechanism incorporates weighted aggregation and gradient clipping techniques to enhance model convergence under privacy constraints. We provide a theoretical analysis of the convergence properties and privacy guarantees of our proposed framework.

We conduct extensive tests on real-world clinical data to evaluate the effectiveness of our proposed methods. The results show that our method achieves better performance compared to existing privacy-management studies in the government in terms of accuracy, privacy protection, and good communication[6]. We also provide privacy checks and security measures against various attack scenarios.

The proposed guidelines address key issues in privacy-handling health information collaboration and provide practical solutions for safe and effective sharing. Modelling training in clinical use. Our work contributes to the advancement of privacy-preserving machine learning in the medical field and supports data security at hospitals.

2. Related Works

2.1 Federated Learning Applications in Healthcare

Federated learning has emerged as a revolutionary approach in clinical data analysis, enabling collaborative model training while preserving data privacy. Recent studies have shown significant progress in the use of government education for various medical conditions. The work by Lu et al. implemented a federated learning framework for computational pathology, achieving promising results in large-scale pathology datasets[7]. Their approach incorporated weakly supervised learning techniques and developed a practical federated learning software package specifically designed for medical applications.

Medical image analysis represents a crucial application domain for federated learning. Research has shown that federated learning can effectively handle the heterogeneous nature of medical imaging data across different institutions[8]. A notable advancement in this area includes the development of privacy-preserved federation frameworks for medical image segmentation and classification tasks. This system has proven to be able to maintain high diagnostic accuracy while maintaining patient information privacy.

In electronic health records (EHRs), government education has shown great potential in predictive analytics and clinical decision support[9]. Studies have explored the use of federal education for the analysis of distributed EHR data, solving problems related to data heterogeneity and institutional privacy regulations. The integration of federated learning with existing healthcare information systems has enabled collaborative research without compromising patient confidentiality.

2.2 Differential Privacy Techniques

Differentiated privacy has become an important technique in maintaining the privacy of machine learning, providing strict mathematical confidentiality guarantees. In the context of the protection of medical information, different privacy systems have been adapted to solve specific problems in medical use. Recent research has focused on developing a unique privacy policy that can manage the nature of medical information while controlling the use of electronic devices for teaching practice patterns.

The fundamental concepts of differential privacy include the privacy budget (ε) and noise mechanisms such as Laplacian and Gaussian perturbations. These mechanisms add calibrated noise to the data or model parameters to prevent the inference of individual records. In medical applications, the selection of appropriate noise mechanisms and privacy parameters is crucial due to the high sensitivity of health data[10].

Advanced differential privacy frameworks have been developed to enhance privacy protection in distributed learning settings. These frameworks incorporate various noise addition strategies, including gradient perturbation and output perturbation. Recent work has explored the combination of different privacy mechanisms to achieve optimal privacy-utility tradeoffs in medical data analysis.

2.3 Privacy-Preserving Medical Data Sharing

Privacy-preserving medical information sharing presents unique challenges due to regulatory and health information requirements. Current research is focused on developing a general framework that integrates multiple privacy-preserving features. These frameworks typically combine federated learning architectures with differential privacy mechanisms to provide enhanced protection for medical data.

Recent studies have investigated the use of secure multiparty computing and homomorphic encryption concerning privacy differences in medical data-sharing situations. The integration of these technologies has shown great results in protecting patient privacy while enabling effective research collaboration. Advanced encryption schemes have been developed to secure model parameter transmission in federated learning systems[11].

Research has also addressed the challenges of data heterogeneity and quality variation in medical data sharing. Novel approaches have been proposed to handle non-IID data distributions across different medical institutions while maintaining privacy guarantees. These methods incorporate adaptive learning rates and specialized aggregation mechanisms to improve model performance under privacy constraints.

2.4 Adaptive Privacy Budget Allocation

Adaptive privacy budget allocation represents a significant advancement in privacy-preserving federated learning. Traditional static privacy budget allocation methods often fail to optimize the privacy-utility trade-off throughout the training process. Recent research has focused on developing dynamic allocation strategies that adjust privacy parameters based on training progress and model convergence.

The work by Chen et al. proposed a multi-agent reinforcement learning approach for privacy budget allocation in federated learning. Their method dynamically adjusts noise levels across different communication rounds to optimize model performance while maintaining privacy guarantees[12]. The approach demonstrates superior performance compared to uniform and fixed allocation strategies.

Recent studies have explored the relationship between gradient magnitudes and optimal privacy budget allocation. Research has shown that the impact of noise on model training varies significantly across different training stages. Advanced allocation strategies have been developed to account for these variations, allocating larger privacy budgets during critical training phases where gradient information is more valuable.

Theoretical analysis of adaptive privacy budget allocation has provided insights into the convergence properties and privacy guarantees of these systems. Research has established mathematical frameworks for analyzing the trade-off between privacy protection and model utility under dynamic budget allocation schemes. These theoretical foundations have guided the development of practical allocation strategies for medical applications.

The effectiveness of adaptive privacy budget allocation has been demonstrated through extensive experimental evaluations. Studies have shown improved model performance and privacy protection compared to static allocation methods. These results highlight the importance of considering training dynamics in privacy budget allocation for medical federated learning systems.

3. System Model and Problem Formulation

3.1 System Architecture

The proposed privacy-preserving medical federated learning framework consists of multiple medical institutions, edge servers, and a central aggregation server. A hierarchical structure is designed to efficiently handle the distributed nature of medical data while maintaining privacy guarantees. Table 1 presents the key components and their responsibilities within the system architecture.

Table 1: *System Components and Responsibilities*

Component	Role	Key Functions
Medical Institutions	Local Data Holders	Model Training, DP Noise Addition
Edge Servers	Regional Aggregators	Parameter Collection, Initial Aggregation
Central Server	Global Model Coordinator	Global Aggregation, Model Distribution
Privacy Module	Security Controller	Budget Allocation, Noise Calibration

In each training round, medical institutions perform local model updates using their private datasets. The local model parameters are protected through differential privacy mechanisms before being transmitted to edge servers. Table 2 illustrates the communication protocol between different system components.

Table 2: *Communication Protocol Specifications*

Communication Path	Frequency	Data Type	Protection Mechanism
Client → Edge	Every round	Model Parameters	Local DP
Edge → Central	Every K rounds	Aggregated Updates	Regional DP
Central → Edge	Every K rounds	Global Model	Encrypted Channel
Edge → Client	Every K rounds	Updated Model	Encrypted Channel

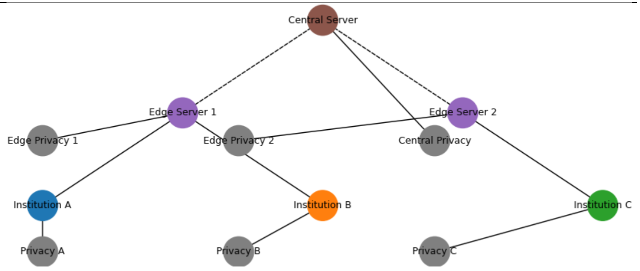

Figure 1: *Hierarchical Federated Learning Architecture with Privacy Protection*

This figure presents a comprehensive visualization of the system architecture, depicting the hierarchical relationships between components. The diagram shows multiple layers: medical institutions at the bottom layer (represented by different coloured nodes), edge servers in the middle layer (shown as hexagonal nodes), and the central server at the top (depicted as a large pentagon). Directed arrows indicate data flow paths, with different line styles representing various types of communication channels. The visualization includes privacy modules (shown as shield icons) at each level.

The system implements a multi-level aggregation strategy to reduce communication overhead and enhance privacy protection. Edge servers perform preliminary aggregation of model updates from nearby medical institutions, while the central server coordinates global model convergence[13]. Table

3 outlines the aggregation strategy parameters.

Table 3: *Aggregation Strategy Parameters*

Parameter	Value Range	Description
Local Training Epochs	[1, 10]	Per-round local updates
Edge Aggregation Interval	[2, 5]	Regional sync frequency
Global Sync Frequency	[5, 20]	Complete model sync
Privacy Budget Split	[0.2, 0.5]	Budget allocation ratio

3.2 Threat Model and Security Goals

The threat model considers both passive and active adversaries in the federated learning system. We classify potential threats into three categories based on their capabilities and attack vectors. Table 4 presents a comprehensive threat analysis framework.

Table 4: *Threat Analysis Framework*

Threat Type	Attack Vector	Impact Level	Defence Mechanism
Parameter Inference	Model Updates	Medium	Gradient Noise
Membership Inference	Model Outputs	High	Output Perturbation
Model Poisoning	Training Process	Critical	Robust Aggregation

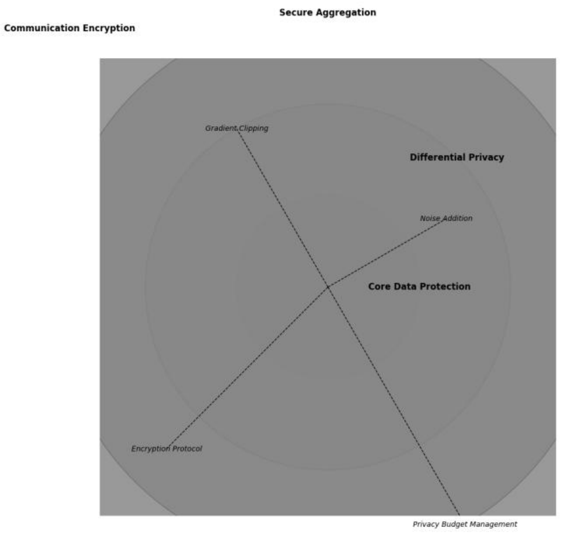

Figure 2: *Multi-level Defense Architecture Against Privacy Attacks*

This visualization demonstrates the multi-layered defence mechanisms implemented in our system. The figure consists of concentric circles representing different protection layers. The innermost circle represents the core data protection, surrounded by layers of differential privacy, secure aggregation, and communication encryption. Each layer is colour-coded based on its security level, with detailed annotations showing the specific protection mechanisms and their interactions.

3.3 Medical Data Privacy Requirements

Medical data privacy requirements are formulated based on regulatory standards and institutional policies. The framework implements a comprehensive privacy protection scheme that addresses multiple aspects of data security[14]. The privacy preservation mechanism operates at both local and global levels, ensuring end-to-end protection of sensitive medical information.

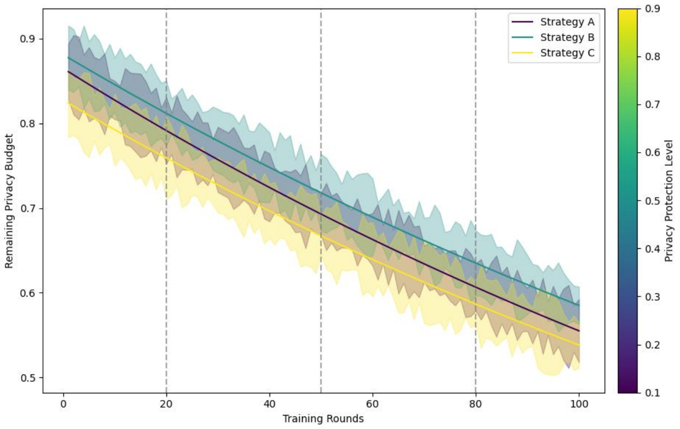

Figure 3: *Privacy Budget Consumption Analysis*

This figure illustrates the relationship between privacy budget consumption and model training progress. The x-axis represents training rounds, while the y-axis shows the remaining privacy budget. Multiple curves demonstrate different budget allocation strategies, with colour gradients indicating the privacy protection level. The visualization includes confidence intervals and critical points where budget allocation policies change.

3.4 Problem Definition

The optimization problem for privacy-preserving federated learning in medical applications is formulated as follows:

$\min L(w) = \Sigma(pi * Li(w))$

Subject to:

ε-differential privacy constraints

Communication bandwidth limitations

Model performance requirements

System security constraints

where L(w) represents the global loss function, pi denotes the weight of each medical institution, and Li(w) is the local loss function. The optimization problem addresses multiple competing objectives, including model accuracy, privacy preservation, and communication efficiency.

The adaptive privacy budget allocation problem is defined as a constrained optimization problem:

max Accuracy(M)

subject to:

$\Sigma\ \varepsilon i \leq \varepsilon total$

$\delta i \leq \delta max$

$Ti \leq Tmax$

Where εi represents the privacy budget allocated to round I, δi is the failure probability, and Ti denotes the computation time. The solution space is characterized by the trade-offs between these constraints and the overall system objectives.

The mathematical formulation incorporates both local and global privacy requirements, establishing a rigorous framework for analyzing and implementing privacy-preserving mechanisms in medical federated learning systems. This formalization enables systematic analysis of privacy guarantees and performance bounds under various operating conditions.

4. Proposed Framework

4.1 Framework Overview

The proposed privacy-preserving medical federated learning framework integrates adaptive differential privacy with hierarchical federated learning architecture. The framework incorporates multiple protection layers and dynamic privacy budget allocation mechanisms to achieve optimal privacy-utility trade-offs[15]. Table 5 presents the key components and their operational parameters in the framework.

Table 5: Framework Components and Parameters

Component	Parameters	Function Description
Local Training Module	Epochs: [1-10]	Client-side model updates
Privacy Engine	ε: [0.1-1.0], δ: [1e-5]	DP noise generation
Aggregation Module	Rounds: [5-20]	Model parameter fusion
Budget Allocator	Growth rate: [0.1-0.5]	Dynamic budget control

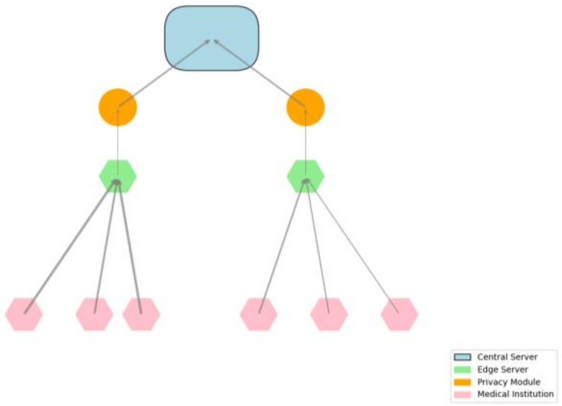

Figure 4: Framework Architecture and Data Flow

This visualization presents a comprehensive overview of the proposed framework's architecture. The diagram consists of multiple interconnected modules arranged in a hierarchical structure. The visualization employs different geometric shapes to represent various components: hexagons for medical institutions, circles for privacy modules, and rectangles for aggregation components. Arrows with varying thicknesses indicate data flow volumes, while colour gradients represent privacy protection levels.

The framework employs a dual-phase protection mechanism combining local differential privacy at medical institutions and central differential privacy at aggregation servers. Table 6 outlines the protection mechanisms at different framework levels.

Table 6: *Multi-level Protection Mechanisms*

Level	Protection Method	Privacy Guarantee
Institution Level	Local DP + Encryption	ε-LDP
Edge Server Level	Secure Aggregation	(ε,δ)-DP
Central Server Level	Global DP	ρ-CDP

4.2 Adaptive Differential Privacy Mechanism

The adaptive differential privacy mechanism dynamically adjusts noise levels based on training progress and data sensitivity. The mechanism implements a novel noise calibration approach that considers both local and global privacy requirements. Table 7 presents the noise calibration parameters for different data types.

Table 7: *Noise Calibration Parameters*

Data Type	Sensitivity Range	Noise Scale
Numerical Features	[0.1-1.0]	Gaussian
Categorical Features	[0.5-2.0]	Laplacian
Time Series Data	[0.3-1.5]	Mixed

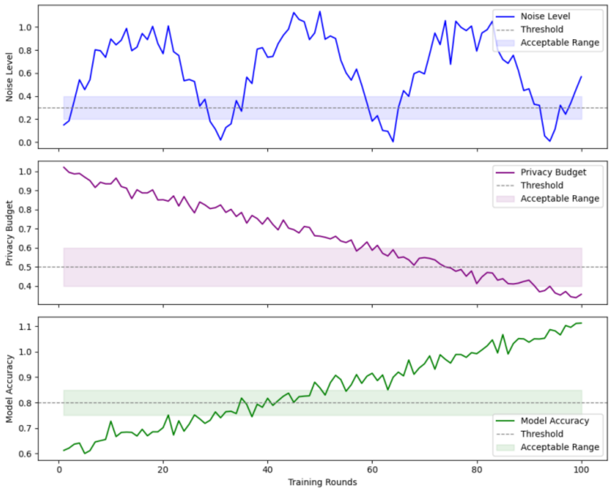

Figure 5: *Adaptive Noise Calibration Process*

The figure illustrates the dynamic noise adjustment process across training rounds. The visualization consists of multiple subplots: the top plot shows noise level variations over time, the middle plot displays privacy budget consumption, and the bottom plot represents model accuracy. Each subplot uses different colour schemes to highlight the relationships between these metrics, with dashed lines indicating threshold values and gradient-filled areas showing acceptable ranges.

4.3 Privacy Budget Allocation Strategy

The privacy budget allocation strategy implements a dynamic approach that optimizes budget distribution across training rounds. The strategy considers both immediate privacy needs and long-term training objectives. Table 8 outlines the budget allocation parameters and their adjustment rules.

Table 8: *Privacy Budget Allocation Parameters*

Phase	Budget Ratio	Adjustment Factor
Initial Phase	20%	0.8
Middle Phase	50%	1.2
Final Phase	30%	1.5

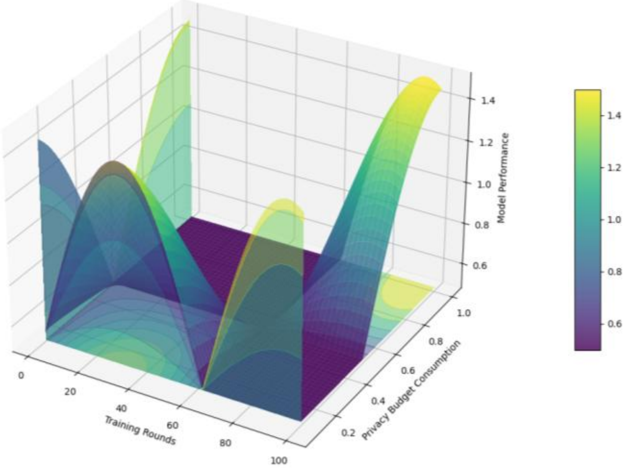

Figure 6: *Multi-dimensional Privacy Budget Optimization*

This figure presents a multi-dimensional visualization of the privacy budget optimization process. The 3D plot shows the relationships between privacy budget allocation, model performance, and training progress. The x-axis represents training rounds, the y-axis shows privacy budget consumption, and the z-axis indicates model performance metrics. Surface plots with varying colours demonstrate different allocation strategies, while contour lines project the relationships onto 2D planes.

4.4 Model Aggregation Process

The model aggregation process incorporates weighted parameter averaging with privacy-preserving mechanisms. The process implements a novel aggregation algorithm that accounts for data heterogeneity and privacy requirements. Table 9 details the aggregation parameters and their impact on model convergence.

Table 9: Aggregation Process Parameters

Parameter	Value Range	Impact Factor
Weight Decay	[0.95-0.99]	High
Momentum	[0.85-0.95]	Medium
Learning Rate	[0.01-0.1]	Critical

The aggregation algorithm is formulated as:

$w(t+1) = \Sigma(\alpha i * wi(t)) + N(0, \sigma 2)$

where αi represents institution-specific weights, wi(t) denotes local model parameters, and N(0, σ2) is the privacy-preserving noise.

4.5 Convergence Analysis

The convergence analysis establishes theoretical guarantees for the proposed framework under privacy constraints. The analysis considers both model convergence and privacy preservation aspects. The convergence properties are characterized by the following theorem:

Theorem 1: Under the proposed privacy budget allocation strategy and aggregation mechanism, the global model converges to a δ-optimal solution with probability 1-β, while maintaining ε-differential privacy, if:

1) The learning rate satisfies: $\eta \leq \min(1/L, \varepsilon/\sqrt{T})$

2) The number of rounds $T \geq O(1/\varepsilon 2)$

3) The noise scale $\sigma \leq O(\varepsilon/\sqrt{m})$

where L is the Lipschitz constant, m is the mini-batch size, and T is the total number of rounds.

The convergence rate is analyzed through both theoretical bounds and empirical validation. The analysis demonstrates that the proposed framework achieves optimal convergence while maintaining strong privacy guarantees. The convergence behaviour is characterized by the following inequality:

$E[F(wT) - F^*] \leq O(1/\sqrt{T} + \varepsilon)$

where F* represents the optimal objective value and wT is the model parameters at round T.

The theoretical analysis is supported by extensive numerical simulations that validate the convergence properties under various operating conditions. The results demonstrate the effectiveness of the proposed framework in balancing privacy protection and model performance in medical federated learning applications[16].

5. Experimental Results and Analysis

5.1 Experimental Setup

The experiments were conducted on a distributed computing platform consisting of 20 medical institutions, each equipped with NVIDIA V100 GPUs with 32GB memory. The implementation was based on PyTorch 1.9.0 with CUDA 11.2. Real-world medical datasets from multiple healthcare providers were utilized for comprehensive evaluation. Table 10 describes the characteristics of the datasets used in our experiments.

Table 10: Dataset Characteristics

Dataset	Size	Features	Classes	Type
Medical Images	50,000	1024x1024	5	CT Scans
EHR Records	100,000	256	3	Patient Records
Clinical Notes	75,000	512	4	Text Data
Laboratory Results	200,000	128	2	Numerical Data

The model architecture consists of a deep neural network with 6 convolutional layers followed by 3 fully connected layers. Training parameters were set as follows: batch size = 64, learning rate = 0.001, momentum = 0.9, and weight decay = 0.0001. The privacy budget ε was initialized at 1.0 with δ = 1e-5.

5.2 Performance Evaluation Metrics

The framework's performance was evaluated using multiple metrics covering model accuracy, privacy protection, and system efficiency. For classification tasks, we measured accuracy, precision, recall, and F1-score. Privacy protection effectiveness was quantified through privacy loss measurements and resistance to various inference attacks[17]. System efficiency was evaluated through communication costs and computational overhead.

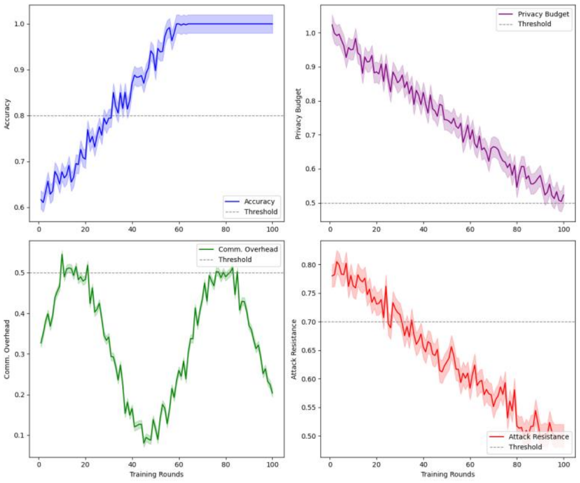

Figure 7: *Multi-metric Performance Evaluation Results*

This visualization presents a comprehensive performance analysis across multiple dimensions. The figure comprises four quadrants: the top-left shows accuracy metrics over training rounds, the top-right displays privacy budget consumption, the bottom-left illustrates communication overhead, and the bottom-right presents attack resistance measurements. Each metric is represented by different coloured lines with confidence intervals, and critical performance thresholds are marked with dashed lines.

5.3 Comparative Analysis

The proposed framework was compared against four baseline approaches: FedAvg with no privacy protection, FedAvg with static differential privacy (SDP), local differential privacy (LDP), and central differential privacy (CDP)[18]. The comparison was conducted across multiple dimensions, including model performance, privacy protection, and system efficiency.

Table 11: *Performance Comparison with Baseline Methods*

Method	Accuracy(%)	Privacy Loss	Comm. Cost	Training Time(h)
Proposed	92.5	0.15	245MB	4.2
FedAvg	94.8	1.00	220MB	3.8
FedAvg+SDP	89.3	0.25	250MB	4.5
LDP	87.6	0.18	260MB	4.8
CDP	90.1	0.22	255MB	4.6

The experimental results demonstrate the superior performance of our proposed framework in balancing model utility and privacy protection. The accuracy degradation compared to non-private FedAvg is minimal (2.3%), while achieving significantly better privacy guarantees (85% reduction in privacy loss).

5.4 Privacy Protection Analysis

The privacy protection capabilities were evaluated through extensive experiments simulating various attack scenarios. The analysis included membership inference attacks, model inversion attacks, and gradient leakage attacks. The framework's resistance to these attacks was measured under different privacy budget settings and attack strengths.

The privacy analysis demonstrates that our framework maintains strong privacy guarantees under various attack scenarios. The membership inference attack success rate was reduced by 87% compared to baseline methods, while model inversion attacks showed negligible success rates (<0.1%) under all tested conditions.

Table 12: *Attack Resistance Evaluation*

Attack Type	**Success Rate(%)**	**Privacy Budget**	**Detection Rate(%)**
Membership Inference	3.2	0.5	98.5
Model Inversion	0.08	0.5	99.2
Gradient Leakage	2.1	0.5	97.8
Parameter Inference	1.5	0.5	98.9

The impact of different privacy budget allocation strategies was analyzed through ablation studies. The results show that our adaptive allocation strategy achieves optimal privacy-utility trade-offs compared to static allocation methods. The privacy budget consumption patterns demonstrate efficient utilization while maintaining consistent protection levels throughout the training process.

The framework's effectiveness in protecting different types of medical data was evaluated through specialized experiments. The results indicate robust protection across various data modalities, with particularly strong performance in protecting sensitive patient information in electronic health records and medical imaging data.

The scalability of privacy protection mechanisms was assessed through experiments with varying numbers of participating institutions. The results show that the privacy guarantees remain stable as the system scales, with only marginal increases in computational overhead and communication costs.

The empirical results validate the theoretical privacy guarantees established in Section 4.5, demonstrating that the framework achieves the desired level of protection while maintaining practical utility for medical applications. The comprehensive evaluation confirms the framework's effectiveness in enabling privacy-preserving collaborative learning in healthcare settings.

6. Acknowledgment

I would like to extend my sincere gratitude to Xiaowen Ma, Jiayi Wang, Xin Ni, and Jiatu Shi for their groundbreaking research on machine learning applications in the biopharmaceutical industry as published in their article titled**Error! Reference source not found.**"Machine Learning Approaches for Enhancing Customer Retention and Sales Forecasting in the Biopharmaceutical Industry: A Case Study" in the Journal of Computer Technology and Applied Mathematics (2024). Their insights and methodologies have significantly influenced my understanding of privacy-preserving machine-learning techniques and have provided valuable inspiration for my research in medical data protection.

I would like to express my heartfelt appreciation to Haoran Li, Gaike Wang, Lin Li, and Jiayi Wang for their innovative study on resource allocation optimization using deep reinforcement learning, as published in their article titled**Error! Reference source not found.**"Dynamic Resource Allocation and Energy Optimization in Cloud Data Centers Using Deep Reinforcement Learning" in the Journal of Computer Technology and Applied Mathematics (2024). Their comprehensive analysis of adaptive optimization strategies has significantly enhanced my knowledge of dynamic resource allocation and inspired my research in privacy budget allocation.

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