FedPPH: A Federated Personalized and Privacy-Preserving Health Model for Multi-Campus Medical Diagnosis

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Keywords: federated learning, multi-campus information collaboration, privacy protection, intelligent diagnosis, medical data sharing

Received: October 22, 2025

This study addresses the issue that multi-hospital medical data cannot be efficiently shared or jointly modeled under privacy constraints, thereby achieving a higher level of intelligent diagnosis and cross-regional collaborative services. The study proposes the Federated Personalized and Privacy-preserving Health (FedPPH) model. FedPPH introduces an adaptive gradient adjustment mechanism into global optimization. It implements noise perturbation and secure aggregation through a two-layer security strategy composed of differential privacy and homomorphic encryption. This ensures privacy constraints while enabling dynamic optimization updates of each client and improving the stability of overall convergence. The study conducts systematic verification based on four public medical datasets: Data 1, 2, 3, and 4 (Healthcare, Hospital Patient Records, Disease Diagnosis, and Medical Data and Hospital Readmissions). The verification methods include horizontal and vertical verification. In horizontal verification, the same dataset is divided into multiple subsets to simulate different campus environments, examining the model's collaborative effect under homogeneous data conditions. In vertical verification, multi-source datasets with significant structural differences test models' generalization and robustness in heterogeneous scenarios. Research results show that in horizontal validation, FedPPH controls the global variance within the range of 0.019–0.035, significantly outperforming the single-node model's range of 0.038–0.077. In vertical validation, taking the Data2&Data3 combination as an example, the client discrepancy decreases from 0.192 to 0.103, demonstrating stronger consistency. Regarding stability, FedPPH maintains an accuracy of 0.892 under perturbed conditions, which remains high compared to the 0.935 accuracy without perturbation. This study aims to provide medical institutions with a collaborative modeling solution that can improve diagnostic accuracy and ensure data security, laying a foundation for the practical implementation of multi-campus smart healthcare.

Povzetek: Študija predlaga federativni model za varno sodelovalno učenje med bolnišnicami, ki izboljša diagnostično natančnost, stabilnost in usklajenost podatkov ob hkratnem varovanju zasebnosti.

1 Introduction

In recent years, with the continuous advancement of medical informatization, the value of large-scale clinical data in auxiliary diagnosis, disease prediction, and personalized treatment has gradually become prominent. Cross-campus medical data collaboration has become a core driving force for developing smart healthcare. The potential of medical big data is reflected in identifying complex disease patterns while providing possibilities for collaborative diagnosis and treatment among multi-level medical institutions [1]. However, the high sensitivity and privacy of medical data in real environments pose severe ethical and legal challenges to direct data centralization and sharing [2]. This contradiction leads to the fact that existing medical intelligent diagnosis models are often limited to the data scope of a single campus, making it difficult to assess the overall effectiveness of cross-regional collaboration. How to realize the joint modeling of multi-source medical data under the premise of protecting patients' privacy has become an urgent research problem to be solved.

Although traditional centralized data modeling can improve the model's diagnostic accuracy to a certain extent, its direct collection and storage mode of original data is often accompanied by potential data leakage risks, and it also intensifies the conflict between patients' privacy protection and data utilization [3]. At the same time, there are remarkable differences in patient group composition, disease distribution, and data structure among different campuses. This non-independent and identically distributed characteristic leads to obvious generalization deficiencies when the centrally trained model is promoted, making it difficult to meet the diagnostic needs of different medical institutions. Some existing distributed training-based solutions attempt to alleviate the above problems, but most still lack an

effective balance between privacy protection and modeling performance. Under heterogeneous data conditions, problems such as slow convergence, fluctuations in diagnostic performance, and insufficient model stability are prone to occur.

As a new type of distributed machine learning framework, Federated Learning (FL) provides a feasible path for cross-campus medical information collaboration by conducting training locally and only uploading model parameters instead of original data [4][6]. Under this framework, medical institutions can participate in the joint optimization of the global model while ensuring local data control, effectively avoiding compliance risks caused by direct sharing of original data. However, standard FL still has substantial limitations when dealing with highly heterogeneous multi-source medical data [7]. On the one hand, gradient updates under non-independent and identically distributed conditions are likely to cause unstable convergence and local deviation of the global model; on the other hand, the communication mode that simply relies on parameter upload may still face the risk of inference attacks, leading to potential privacy leakage [8].

To address the above issues, this study proposes a Federated Personalized and Privacy-preserving Health (FedPPH) model for multi-campus medical collaboration. The model introduces an adaptive gradient adjustment mechanism at the global optimization level to improve convergence stability and update consistency in a heterogeneous data environment. Concurrently, it combines a dual mechanism of differential privacy (DP) and homomorphic encryption (HE) at the privacy protection level to fundamentally reduce the leakage risk during parameter transmission and ensure the security and compliance of collaborative training. Compared with traditional methods, FedPPH is not just a simple extension of FL, but forms a comprehensive framework that can balance intelligent diagnosis accuracy and privacy constraints by integrating optimization and security mechanisms. The innovations of this study are mainly reflected in the following three aspects:

(1) An adaptive gradient adjustment mechanism is introduced at the global optimization level to alleviate update deviation under non-independent and identically distributed conditions, ensuring stable convergence and consistency of collaborative training for multi-source medical data.

(2) A dual mechanism of DP and HE is integrated at the privacy protection level to realize the organic combination of parameter perturbation and encrypted transmission, ensuring the compliance and security of the cross-campus collaboration process.

(3) An overall framework that balances collaboration efficiency and intelligent diagnosis performance is constructed, which improves the model's optimization effect under homogeneous data and demonstrates stronger generalization ability and robustness in heterogeneous environments.

Based on the above background, this study focuses on following core research questions. First, how to achieve stable and consistent federated optimization in a highly heterogeneous data environment across multiple hospitals. Second, how to complete secure collaborative training across institutions under strict privacy constraints. Centering on these questions, the objectives of this study include designing an adaptive gradient mechanism that mitigates the impact of heterogeneity, constructing a two-layer privacy framework combining DP and HE, and verifying its effectiveness in horizontal and vertical multi-source medical scenarios. This study defines "success" as follows. It achieves diagnostic performance superior to traditional FL without leaking raw data, maintains stable convergence under heterogeneous distributions, and demonstrates feasible system overhead and robustness in real multi-hospital settings.

2 Related work

Over the years, FL has gradually become an important method for collaborative modeling of healthcare data and has shown broad application prospects in privacy protection, diagnosis optimization, and multi-campus collaboration. Gong et al. pointed out that models in a multi-hospital environment should integrate local data to support clinical decision-making, but traditional methods had serious privacy leakage risks. To this end, their study proposed combining FL with inverse reinforcement learning (RL) and introducing a DP mechanism. This enabled agents to learn personalized treatment strategies without leaking individual data, thereby realizing collaborative optimization among intelligent intensive care units [9]. Rehman et al. further focused on cancer diagnosis scenarios and proposed an innovative framework based on FL and Generative Adversarial Network (GAN). They used a DP anonymization mechanism to distinguish and process quasi-identifiers and confidential information, achieving accuracies of 97.80%, 96.95%, and 97% in lung cancer, prostate cancer, and breast cancer diagnosis, respectively, verifying its effectiveness in data sharing and security [10]. Abbas et al. introduced an adaptive federated machine learning framework for the smart medical ecosystem under the background of Industry 5.0, combining multi-task optimization with a distributed deep learning model. The accuracy in multi-disciplinary cancer prediction tasks reached 90.0%, remarkably exceeding the 87.30% of traditional methods, demonstrating efficient convergence and prediction capabilities in a cross-campus environment [11]. Concurrently, Cheng et al. compared the performance of two aggregation algorithms under horizontal partitioning for applying random forest (RF) in medical classification. Experiments based on four public medical datasets such as Medical Information Mart for Intensive Care III (MIMIC III) and University of California, Irvine Machine Learning Repository (UCI) showed that the weighted merging algorithm increased the average F1 score by 1.903% and the Area Under Curve (AUC) by 1.406%, providing a systematic analysis for the application of tree models in FL [12].

At the application expansion level, Gokulakrishnan et al. explored the role of cloud-edge-based FL in hospital Internet of Things scenarios. They combined Hilbert

spectrum and UAV sensing technology for cognitive dimensionality reduction to detect the characteristics of malicious roaming personnel on hospital surfaces. The experimental results revealed that it was better than traditional methods in accuracy and response time [13]. CU and Gajendran proposed an Electronic Health Records (EHR) sharing method combining deep Q-RL and spectral clustering, introducing HE to enhance the security of the data transmission link. Its accuracy and recall were close to 95%, outperforming that of multiple baseline models [14]. Wang et al. concentrated on the data reuse problem in telemedicine and designed a model alignment scheme based on heterogeneous FL. Identity authentication was performed through a cryptographic threshold to balance privacy and performance under resource-constrained and data-heterogeneous conditions [15]. Patni and Lee presented a new model combining blockchain, FL, and edge computing. The findings realized decentralized privacy protection in the Internet of Medical Things (IoMT) through smart contracts and secure multi-party computing, and markedly improved collaboration efficiency and data security through lightweight blockchain consensus and DP optimization [16].

From the viewpoint of existing research, FL can realize cross-institutional medical data modeling under the premise of protecting privacy. Relevant achievements cover cancer diagnosis support, EHR sharing, telemedicine data security, and multi-disciplinary disease prediction. For medical scenarios with strong data heterogeneity and strict privacy requirements, existing studies have improved the models' security and diagnostic performance through technologies such as DP, HE, GAN, blockchain, and edge computing, confirming the practical value of FL in medical intelligence. However, most of these studies focus on a single task or specific disease, and the verification environment is often limited to datasets with limited scale or a single structure, failing to fully cover complex medical collaboration scenarios with coexisting multi-source data. To address this deficiency, it explores collaborative optimization across data structures and tasks under a unified framework. Therefore, this study proposes the FedPPH model, which makes differentiated improvements by introducing adaptive gradients and a dual-layer privacy mechanism to achieve efficient convergence, robust diagnosis, and privacy compliance under multi-source medical data conditions.

To facilitate a systematic comparison of existing research and highlight the necessity of FedPPH, Table 1 summarizes the relevant work by method, dataset, task, performance, and privacy policy:

Table 1: Comparison of existing medical FL research

Author (Year)	Method	Dataset	Task type	Accuracy result	The privacy technology used
Gong et al. [9]	FL + inverse RL	ICU multicenter	Treatment strategy optimization	No accuracy	DP
Rehman et al. [10]	FL+GAN	Cancer data	Cancer diagnosis	About 97%	DP
Abbas et al. [11]	Adaptive FL	Multiple cancer prediction	Multi-task prediction	About 90%	No specialized mechanism
Cheng et al. [12]	FL+RF	MIMIC III, UCI, etc.	Medical classification	AUC ↑1.4%	No clear mechanism
Gokulakrishnan et al. [13]	Cloud-edge-based FL	Hospital IoT data	Behavior recognition	Better than the baseline model	No clear mechanism
CU and Gajendran [14]	FL+DQN	EHR data	Data sharing	About 95%	HE
Wang et al. [15]	Heterogeneous FL	Telemedicine	Model alignment	Relatively stable performance	Identity authentication
Patni and Lee [16]	Blockchain +FL+ edge computing	IoMT data	Collaborative diagnosis	Better than the baseline model	DP

In Table 1, although existing studies have made significant progress in privacy protection and medical collaborative modeling, most methods still have certain limitations. First, most works focus on single diseases, specific tasks, or datasets with relatively consistent structures, lacking the ability to collaboratively model multi-source heterogeneous medical data. Second, privacy mechanisms are mostly single-layer protection, such as adopting DP or HE alone, and have not formed a comprehensive privacy protection system for real hospital collaboration scenarios. Third, some works rely on GAN, blockchain, or specific aggregation strategies; they mainly solve local problems without simultaneously considering cross-task consistency and model convergence stability. In

contrast, the multi-hospital medical environment requires a unified framework that can handle data structure differences, label inconsistencies, and privacy constraints simultaneously. Therefore, the proposal of FedPPH aims to make up for these deficiencies. It improves convergence performance under heterogeneous data through an adaptive gradient mechanism; it ensures security in cross-hospital collaboration with a two-layer privacy strategy composed of DP and HE, providing a more comprehensive solution for complex medical collaborative scenarios.

3 Modeling Principle and Verification Design of the FedPPH Model

3.1 FedPPH's modeling principle

Implementing the FedPPH model is based on the distributed architecture of FL. Its core is to form a diagnostic model for multi-campus medical data collaboration by introducing cutting-edge algorithm mechanisms at the global optimization and privacy protection levels [17]. The implementation process of FedPPH includes five stages: global initialization, local iteration, encrypted parameter upload, global aggregation, and repeated iteration. The specific implementation process is presented in Figure 1:

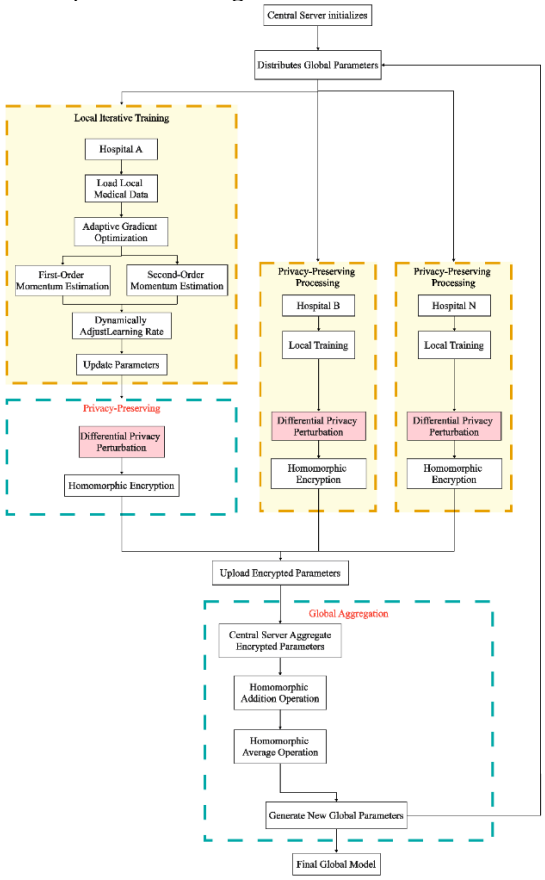


Figure 1: Implementation process of the FedPPH model

In the global initialization and local iteration stage, the central server first initializes the diagnostic model parameters and distributes them to each hospital node. Let the global model parameter vector be $w^{(0)} \in \mathbb{R}^d$. After receiving these parameters, each client k performs several rounds of iterative training on the local dataset Dk, to minimize the local empirical risk function:

$$\mathcal{L}_k(w) = \frac{1}{|D_k|}\sum_{(x_i,y_i)\in D_k} \ell(f_w(x_i), y_i) \quad (1)$$

$\ell()$ represents the loss function; $f_w()$ refers to the diagnostic model's output defined by the parameter w.

During the parameter update process, FedPPH employs an adaptive gradient optimization method (Adam adaptive gradient optimizer) to dynamically adjust the learning rates of parameters in different dimensions. Let the gradient at the t-th step locally be $g_t = \nabla\mathcal{L}_k(w_t)$, then the updates of the first-order momentum and the second-order momentum are respectively:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t \quad (2)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2 \quad (3)$$

$\beta_1, \beta_2 \in (0,1)$ are exponential decay coefficients. To avoid bias, the momentum terms need to be corrected:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (4)$$

Next, the local parameters are updated using the corrected momentum:

$$w_{t+1} = w_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad (5)$$

η denotes the learning rate, and ϵ is a constant to prevent division by zero. After completing the local iteration, each node obtains the updated parameter $w_k^{(t)}$. To clearly demonstrate the local update process of the client, Figure 2 presents the pseudocode for the client's adaptive gradient local update based on Adam:

```
Function ClientUpdate(w, D_k)
Input: local data D_k, global model w
Output: local update Δw_k

 Initialize m = 0, v = 0
 for each local epoch do
   for each mini-batch (x, y) in D_k do
     g ← ∇_w L(f_w(x), y)
     m ← β1*m + (1 - β1)*g
     v ← β2*v + (1 - β2)*(g ⊙ g)
     m_hat ← m / (1 - β1^t)
     v_hat ← v / (1 - β2^t)
     w ← w - η * m_hat / (sqrt(v_hat) + ε)
   end for
 end for
 return Δw_k = w - w_global
```

Figure 2: FedPPH adaptive gradient local update pseudo-code

To ensure the stability of this optimization process under heterogeneous data across multiple hospitals, this study determines the key parameters required for the adaptive gradient through experiments. The final optimal configuration selected is: β_1=0.9, β_2=0.999, ϵ=10^{-8}. In addition, in FedPPH, the adaptive gradient mechanism does not rely on additional explicit trigger conditions. Instead, it uses Adam-style momentum update as the default strategy to take effect continuously in each local iteration, and its "trigger effect" is automatically determined by the dynamic changes of gradient statistics. Specifically, when the data distribution of a certain hospital differs greatly from the global distribution, the

local gradient usually exhibits higher volatility. At this time, the second-moment estimate v_t increases rapidly, thereby automatically compressing the learning rate through the normalization term in the update equation to avoid update deviation caused by sudden gradient changes. Conversely, in nodes with more stable sample structures or higher consistency in gradient directions, the cumulative effect of the first-moment estimate $\widehat{m}_t$ enhances the smoothness of updates, making the optimization process more continuous. Thus, the adaptive gradient in FedPPH forms an implicit adjustment mechanism that does not rely on external signals and is fully data-driven. It allows the local training step size of each hospital to be adjusted automatically based on gradient dynamics under heterogeneous conditions, achieving a certain degree of update alignment and stabilization before federated aggregation.

To maintain the stability of model updates under heterogeneous medical data conditions, the dynamic adjustment of the adaptive gradient can be regarded as a gain compensation mechanism for gradient perturbation. It maintains the controllability of system behavior through online adjustment of unknown dynamics [18]. When the data distribution differences across multiple hospitals are significant, gradient updates may have problems such as inconsistent magnitudes and direction deviations. The adaptive learning rate automatically adjusts the step size based on the first and second-moment estimates, helping to keep local updates within a controllable range, thereby enhancing the robustness of the model update process [19]. In addition, in the mathematical form of parameter updates, the normalization term composed of the second-moment estimate can limit excessive updates of gradients in high-variance directions, maintaining the stability of the convergence path by constraining the gain in certain directions. In this sense, the adaptive gradient mechanism is used for optimization and can perform a function similar to suppressing external uncertain perturbations in robust controllers [20]. These characteristics of the adaptive gradient also correspond to the idea of adjusting linearized gains based on Jacobian structure in nonlinear optimal control. In other words, the update step size in each iteration is dynamically adjusted to maintain stable evolution of the system under local approximation conditions [21]. Furthermore, in the distributed training environment of FedPPH, the update differences of each client can be analogized to unmeasurable state perturbations. The idea of "fast estimation—timely correction" in high-gain observers provides a control-theoretic perspective for understanding how the adaptive gradient suppresses differences in federated aggregation [22]. It should be noted that FedPPH does not introduce additional personalized modules at the structural level (such as FedBN, FedPer, etc.), but adopts a unified global model structure for federated updates. After each round of aggregation, each hospital node performs a small amount of local fine-tuning, enabling the model to maintain global consistency while being lightly adapted to the specific data distribution of each hospital.

In the encrypted parameter upload stage, the FedPPH model introduces a dual-layer protection mechanism [23][25]. First, a DP method is applied on the local side, and random noise is added to the parameter update before upload. Let the local parameter update be $\Delta w_k^{(t)}$, then the perturbed parameter is:

$$\widetilde{w}_k^{(t)} = w_k^{(t)} + \mathcal{N}(0, \sigma^2 I) \tag{6}$$

The core constraints of DP are controlled by a privacy budget ε and a failure probability δ, and its definition is as follows:

$$Pr[\mathcal{M}(D) \in S] \leq e^{\varepsilon} \cdot Pr[\mathcal{M}(D') \in S] + \delta \tag{7}$$

$\mathcal{M}$ represents the random mechanism after adding noise; D and D' are datasets that differ by only one sample; ε controls the upper bound of privacy leakage, and δ denotes the possibility that the privacy constraint is violated with a very small probability. To realize this mechanism, the standard deviation of Gaussian noise is usually set as:

$$\sigma \geq \frac{\Delta_2 f \cdot \sqrt{2\ln(1.25/\delta)}}{\varepsilon} \tag{8}$$

$\Delta_2 f$ represents the sensitivity of the function under the ℓ_2 norm. Subsequently, the perturbed parameter vector is homomorphically encrypted. Let the encryption function be $\mathcal{E}()$, then the result uploaded to the server can be written as:

$$c_k^{(t)} = \mathcal{E}(\widetilde{w}_k^{(t)}) \tag{9}$$

To illustrate the specific application process of DP in the parameter upload stage, Figure 3 presents the parameter perturbation pseudocode:

```
Function SecureUpload(Δw_k, ε, δ)
Input: local update Δw_k, privacy budget (ε, δ)
Output: encrypted update c_k

σ ← CalibrateNoise(ε, δ, Δ2f)
z ← Sample Gaussian noise N(0, σ²I)
Δw̃_k ← Δw_k + z
c_k ← PaillierEncrypt(Δw̃_k)
return c_k
```

Figure 3: DP noise injection pseudocode

In this study, the DP mechanism adopted by FedPPH is based on a Gaussian noise model, with privacy budget set to $\varepsilon = 1.0$ and $\delta = 10^{-5}$. This configuration refers to the commonly used privacy intensity settings in medical scenarios, maintaining a high level of privacy protection while avoiding excessive gradient perturbation that could affect model stability. According to Equation (8), with the function sensitivity $\Delta_2 f = 1$, the corresponding noise standard deviation is approximately $\sigma \approx 1.73$, which remains consistent across all clients. This noise scale can uniformly perturb model updates over multiple iterations; this ensures that uploaded parameters meet DP constraints in a statistical sense while maintaining the model's convergence during federated training. The aforementioned privacy budget and noise calibration method enable FedPPH to form a robust trade-off strategy between privacy and performance.

In the global aggregation and repeated iteration stage, the central server performs homomorphic aggregation on the encrypted updates uploaded by each node without decryption:

$$c^{(t)} = \frac{1}{K}\sum_{k=1}^{K} c_k^{(t)} \quad (10)$$

At the same time, using the additive property of HE, the server can complete the aggregation operation in the ciphertext space, and finally decrypt to obtain the new global parameter:

$$w^{(t+1)} = \mathcal{D}(c^{(t)}) \quad (11)$$

$\mathcal{D}()$ stands for the decryption function. After multiple rounds of iteration with the total number of samples $N = \sum_{k=1}^{K} |D_k|$, the FedPPH model finally forms a global model without relying on the sharing of any original medical data:

$$w^* = \arg\min_{w} \sum_{k=1}^{K} \frac{|D_k|}{N} \mathcal{L}_k(w) \quad (12)$$

To describe the aggregation method on the server side in the ciphertext space, Figure 4 presents the pseudocode for homomorphic aggregation:

```
Input: encrypted updates {c1, …, cK}
Output: encrypted global update c_global

c_sum ← 0
for each client k do
    c_sum ← c_sum ⊕ c_k        # Paillier homomorphic addition
end for
c_global ← (1/K) ⊗ c_sum       # scalar division via plaintext multiplication
return c_global
```

Figure 4: The pseudocode for homomorphic aggregation

To address the issue of inconsistent feature dimensions across different hospitals in vertical FL scenarios, an input space homogenization strategy is introduced before unified encrypted upload. Specifically, all categorical features of the selected datasets are first one-hot encoded. A unified feature template is then constructed based on the complete set of features from all hospitals. Feature dimensions absent in a single hospital are expanded with zero padding, ensuring all clients share the same feature dimensions at the input end. This avoids the complex interaction required to align feature intersections in traditional vertical FL, allowing the model to directly perform federated aggregation at the parameter level. Since the input space is mapped to a unified dimension, the server can adopt standard weighted averaging during aggregation without feature misalignment or dimension conflicts. To clearly present the overall training logic of FedPPH in multiple rounds of communication, the complete global training pseudocode is provided in Figure 5:

```
Input: K clients {C1 … CK}, global rounds T
Output: Global model w

Initialize global model w(0)
for t = 1 to T do
   Server broadcasts w(t) to all clients
   for each client k in parallel do
      Δw_k ← ClientUpdate(w(t), D_k)
      Δw̃_k ← AddGaussianNoise(Δw_k, ε, δ)
      c_k ← PaillierEncrypt(Δw̃_k)
      Upload c_k to server
   end for
  c_global ← HomomorphicAverage({c_k})
  w(t+1) ← PaillierDecrypt(c_global)
end for
return w(T)
```

Figure 5: The complete global training pseudocode

Throughout the process, the noise perturbation and encrypted interaction mechanism designed by FedPPH keep parameters stable and controllable during transmission and aggregation. This aligns with the idea of using time-delay compensation structures to improve system consistency in practical system synchronization control [26]. From a control-theoretic perspective, therefore, FedPPH's global optimization strategy can be understood as a distributed stabilization process in the parameter space, providing a robust update trajectory for subsequent model training.

3.2 Verification design of the FedPPH model

The data used in this study are all from publicly available medical-related datasets, mainly including four different data sources: Data1-Healthcare Dataset[1], Data2-Hospital Patient Records Dataset [2], Data3-Disease Diagnosis Dataset [3], and Data4-Medical Data and Hospital Readmissions [4]. These four datasets cover multi-dimensional medical information such as basic patient information, disease diagnosis labels, hospitalization records, and readmission status. They can also fully simulate heterogeneous medical data scenarios in a multi-campus environment. The basic information of the four datasets is exhibited in Table 2:

Table 2: Basic size information of the four datasets

Data set	Sample size	Number of features	Number of numerical features	Number of categorical features	Overview of data content
Data 1	55,500	15	3	12	Demographic informatio

[1] Kaggle, *Healthcare Dataset*, accessed 2023. Available: https://www.kaggle.com/datasets/prasad22/healthcare-dataset

[2] Kaggle, *Hospital Patient Records Dataset*, accessed 2023. Available: https://www.kaggle.com/datasets/blueblushed/hospital-dataset-for-practice

[3] Kaggle, *Disease Diagnosis Dataset*, accessed 2024. Available: https://www.kaggle.com/datasets/s3programmer/disease-diagnosis-dataset

[4] Kaggle, *Medical Data and Hospital Readmissions*, accessed 2018. Available: https://www.kaggle.com/datasets/dansbecker/hospital-readmissions

					n and diagnostic indicators
Data 2	984	10	5	5	Patient diagnosis categories and treatment records
Data 3	2,000	13	5	8	Symptoms and disease diagnosis labels
Data 4	25,000	65	9	0	Hospitalization records, treatment outcomes, and readmission status

To ensure data quality and consistency, this study first counts and processes missing values for each of the four datasets. The overall missing rates of Data1, Data2, Data3, and Data4 are 2.7%, 1.9%, 4.4%, and 0.8% respectively. For features with a missing rate below 5%, numerical features are imputed with the median, and categorical features with the mode. Features with a missing rate exceeding 20% (1 column in Data3) are removed. Subsequently, categorical variables are one-hot encoded. Most categorical features in the four datasets have low cardinality (e.g., 2 categories for gender, 3 for smoking history, 4 for admission method), with the maximum number of categories not exceeding 12. Thus, one-hot encoding does not cause a dimensional explosion. For low-frequency categories (frequency <1%) in Data3, merging is performed to avoid high-dimensional sparsity. For numerical variables, Z-score standardization (mean=0, variance=1) is applied. Before standardization, feature scales vary significantly (e.g., length of hospital stay ranges from 1–60, cost from 300–18000). After standardization, all features fall within [-3, 3], improving gradient stability during model training. Finally, each dataset is split into training and test sets at an 8:2 ratio.

The FedPPH model's verification is carried out from horizontal and vertical directions to comprehensively examine its adaptability and robustness under different data distributions and structures. In horizontal verification, the same dataset is selected as the basis and randomly divided into four subsets with similar scales and distributions, as shown in Table 3, with each subset simulating an independent hospital node. In this scenario, the model conducts federated training on multi-source data of the same type but with random distribution. By comparing the performance of the FedPPH and single-node models on a unified test set, the collaborative modeling ability and optimization effect of FedPPH under homogeneous data conditions can be tested. In vertical verification, the four different datasets represent four completely independent campuses, with prominent differences in data structure, feature dimensions, and label definitions. The model performs federated training in this highly heterogeneous data environment, and the central server needs to integrate parameter updates of different structures and distributions to generate a global model with cross-data-type generalization ability. Through vertical verification, the effectiveness and robustness of FedPPH in handling non-independent and identically distributed data and cross-domain heterogeneous data can be tested.

Table 3: The situation of randomly divided subsets of each dataset

Dataset	Subset 1	Subset 2	Subset 3	Subset 4
Data1	7,828	19,866	15,296	12,510
Data2	125	124	46	689
Data3	525	615	17	843
Data4	14,762	3,764	3,223	3,251

In terms of the label space, horizontal validation is naturally consistent as it originates from the same dataset. In vertical validation, diagnostic labels across hospitals are inconsistent, so this study adopts a "joint modeling—independent evaluation" strategy. During training, all clients share the same model structure but retain their own label systems. The server only aggregates parameters without involving label distributions, eliminating the need for any label alignment. For feature inconsistency in vertical scenarios, instead of using the secure feature alignment protocols required by traditional vertical FL, a unified feature template is constructed, and missing dimensions are zero-padded to ensure all clients have consistent feature dimensions at the input end. This allows parameter aggregation to be completed in accordance with standard horizontal FL. Therefore, FedPPH's training protocol is essentially an improved horizontal FL. Vertical experiments achieve cross-hospital collaboration only through input homogenization, without mixing the interaction process of vertical FL.

Based on the above implementation logic, this study examines the proposed model from two dimensions: information collaboration effect and intelligent diagnosis performance. The information collaboration effect examination is used to analyze whether FedPPH can maintain stable convergence under heterogeneous data conditions in a multi-campus distributed environment and achieve consistency and generalization ability of the global model among different nodes. The intelligent diagnosis performance examination is used to determine whether the model can truly assist in disease diagnosis accurately. The FedPPH model's verification indicator system is listed in Table 4:

Table 4: The verification indicator system of the FedPPH model

Indicator category	Specific indicator	Description
Information collaboration effect	Global loss function value	The downward trend of the global loss during the federated training process reflects the stability of the collaborative optimization process.
	Convergence rounds	The number of iterations required for the global model to reach stable performance is used to measure the efficiency of collaborative training.
	Client drift	The level of discrepancy between each client model update and the global model measures collaborative consistency under non-independent and identically distributed conditions.
	Global variance	The variance in the performance of the global model on test sets from different clients reflects the generalization capability under multi-hospital collaboration.
Intelligent diagnosis performance	Accuracy	The proportion of consistency between model predictions and actual diagnostic results measures diagnostic accuracy.
	Recall	The proportion of true positive cases correctly identified by the model indicates the rate of missed diagnoses.
	F1-score	The harmonic mean of precision and recall comprehensively measures diagnostic reliability.
	AUC	The area under the ROC curve reflects the model's ability to distinguish among multiple disease categories.

All experiments are conducted in a unified computing environment, and the related parameters are summarized in Table 5:

Table 5: Experimental environment parameters

Category	Configuration content
Hardware	Intel Xeon Gold 6226R (32 cores, 2.9GHz), 256GB memory, NVIDIA Tesla V100 (32GB×2), and Ubuntu 20.04
Software	Python 3.9, TensorFlow Federated, PyTorch, PySyft
Training parameters	Batch size: 64, initial learning rate: 0.001, adaptive learning rate adjustment
Federated parameters	Local epochs = 5, Global rounds = 100
Privacy parameters	Gaussian noise distribution, additive HE, and privacy budget are set to ε = 1.0, $\delta = 10^{-5}$; sensitiveness $\Delta_2 f = 1$; corresponding noise standard deviation $\sigma \approx 1.73$

For HE implementation, the Paillier encryption scheme based on additive homomorphism is adopted, supporting linear aggregation operations in the ciphertext space and suitable for FedPPH's parameter averaging mechanism. Due to the slightly higher parameter dimensions after feature homogenization than theoretical calculation conditions, the actual ciphertext expansion ratio of Paillier ranges from approximately 3.7 to 4.7 times; this is consistent with the observed increase in upload volume (from 410 KB to about 1.94 MB per round). The average computational cost of encryption and decryption is approximately 0.42 s and 0.31 s, respectively, increasing the single-round training time by about 46% when included in the overall training cycle. These costs are consistent with the acceptable privacy budget requirements in typical medical scenarios.

4 Analysis of information collaboration effect and intelligent diagnosis performance examination of the FedPPH model

4.1 Analysis of information collaboration effect

The comparison of information collaboration effects between the FedPPH and single-node models under horizontal and vertical verifications is displayed in Figure 6:

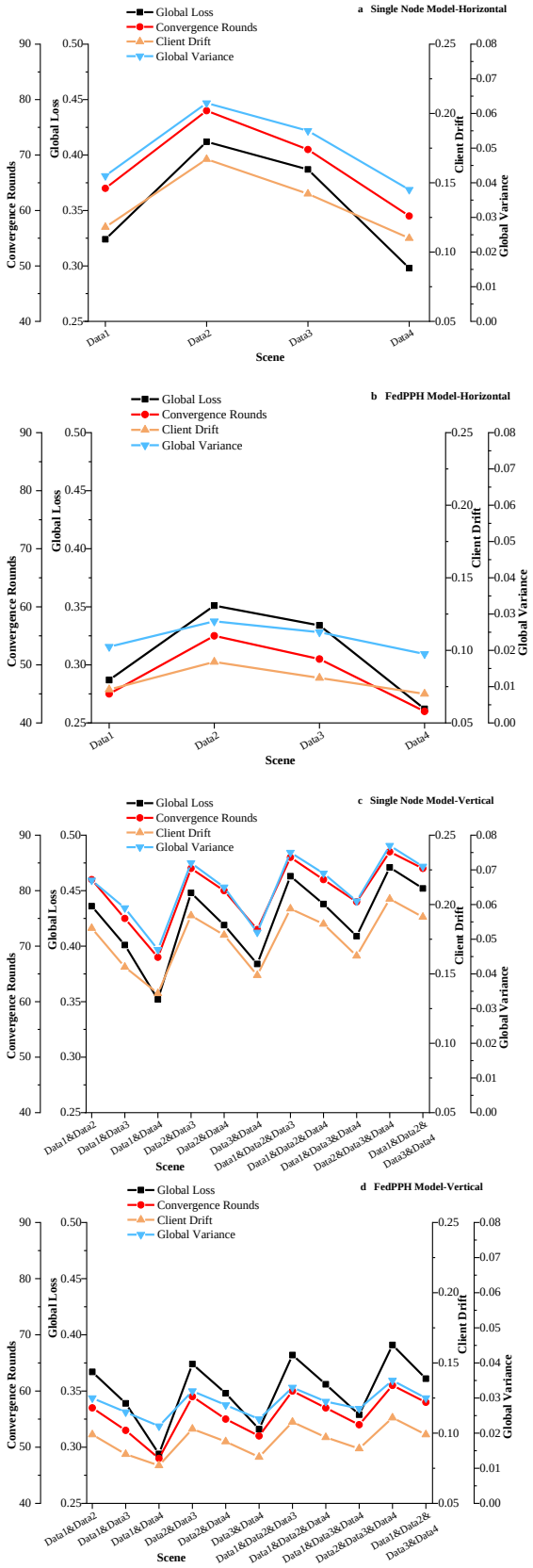


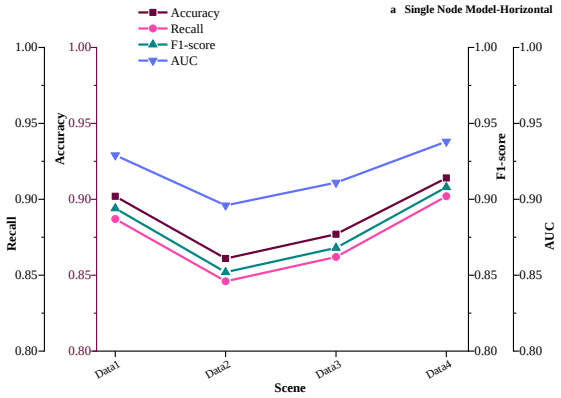
Figure 6: Comparison of information collaboration effects between the single-node and FedPPH models ((a) & (b) and (c) & (d): Horizontal and vertical validation results of the single-node and FedPPH models)

Figure 6 shows that the single-node model exhibits obvious limitations in the information collaboration effect. For large-scale datasets such as Data 1 and 4, the loss value remains between 0.298 and 0.324, and the number of convergence rounds is about 60, showing relatively stable performance. However, in the small-scale dataset Data 2, the loss value and convergence rounds increase to 0.412 and 78, and the client drift also reaches 0.167, illustrating that the training process under non-independent and identically distributed conditions is extremely vulnerable to the impact of insufficient data scale. This trend is more prominent in the combination of vertical multi-datasets. For example, the global loss of Data 2 & 3 & 4 is as high as 0.471, and the client difference reaches 0.204, showing that cross-domain heterogeneous data can further amplify training inconsistency. Overall, the single-node model lacks cross-campus data integration capabilities, leading to a decline in convergence efficiency and distinct performance fluctuations.

The FedPPH global model demonstrates stable convergence characteristics and low parameter drift in horizontal and vertical scenarios. Compared with the single-node model, the average number of convergence rounds is decreased by about 30%. For example, Data 1 and 2 are dropped from 64 to 45 rounds and 78 to 55 rounds, respectively. The client difference has noticeably decreased, with a decrease of more than 40% in typical scenarios. For instance, Data & 3 are reduced from 0.192 to 0.103. The global variance is controlled within the range of 0.019–0.035, much lower than the 0.038–0.077 of the single-node model. This indicates that FedPPH can maintain strong consistency and generalization ability in cross-domain data integration. Especially in the combination including the small-sample Data 2, the loss value decreases from 0.471 to 0.391, verifying the effective role of the DP and HE mechanisms in stable aggregation.

4.2 Analysis of intelligent diagnosis performance

Figure 7 compares intelligent diagnosis performance between the FedPPH and single-node models under vertical and horizontal verifications:



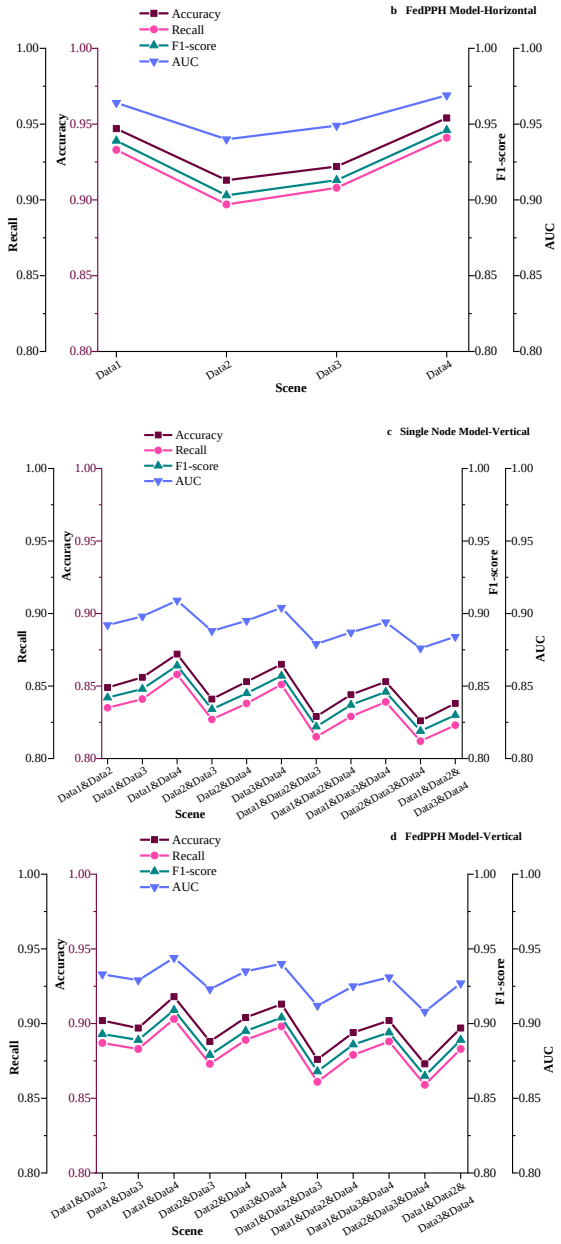


Figure 7: Comparison of intelligent diagnosis performance between the FedPPH and single-node models ((a): Horizontal accuracy and recall results; (b): Horizontal F1-Score and AUC results; (c): Vertical accuracy and recall results; (d): Vertical F1-Score and AUC results)

In Figure 7, the FedPPH global model has remarkably better diagnostic performance than the single-node model on all dataset types, and its advantages are more prominent under the conditions of insufficient samples and complex structures. In large-scale sample datasets (Data 1 and 4), the single-node model already shows relatively high accuracy (0.902 and 0.914), while FedPPH further improves it to 0.947 and 0.954, with AUC reaching 0.964 and 0.969, respectively. This suggests that it can still further mine effective features under sufficient sample conditions. In contrast, the accuracy of the small-scale Data 2 under the single-node model is only 0.861, while the global model improves it to 0.913, and the recall and F1-score also increase by about 0.05, fully reflecting the advantage of federated collaboration in alleviating performance deficiencies caused by data sparsity. In vertical heterogeneous combinations, the gap is more obvious. The single-node model's AUC under Data 2 & 3 & 4 is only 0.876, while FedPPH maintains it at 0.908. In the complex scenario of merging four datasets, this model's accuracy drops to 0.838, while FedPPH still reaches 0.897, showing stronger generalization ability for heterogeneous features and label structures. Overall, the improvement of FedPPH is reflected in enhancing overall accuracy and markedly in the stability of recall and F1-score. This means that it can effectively reduce the risk of missed diagnosis in cross-campus diagnosis scenarios and maintain robust diagnostic performance across diverse distribution conditions.

To verify whether the performance improvement of FedPPH over single-node models is statistically significant, this study conducts paired significance tests on the vertical experimental results. Specifically, for the four indicators (Accuracy, Recall, F1-score, and AUC), p-values are calculated using paired t-tests based on independent repeated experiments (n=20) of each round of federated training to evaluate the differences between FedPPH and single-node models. Meanwhile, 95% Confidence Interval (CI) is computed; a comprehensive gain is constructed based on the average improvement of the four indicators for unified evaluation of all data combinations, without relying on fluctuations of individual indicators. Table 6 presents the summary results of comprehensive performance gain, 95% CI, and p-values for each experimental scenario (11 vertical groups):

Table 6: Statistical significance test of FedPPH compared with single-node models

Scenario type	Number of combinations	Average overall gain	95% CI	p-value
Vertical validation (Combination of two hospitals)	6	0.067	[0.044, 0.089]	p < 0.001
Vertical validation (Combination of three hospitals)	4	0.082	[0.057, 0.104]	p < 0.001
Vertical validation (Combination of four hospitals)	1	0.093	[0.061, 0.121]	p < 0.001

Statistical significance results show that FedPPH is significantly superior to single-node models in all vertical scenarios, with all p-values less than 0.001; this indicates that the performance improvement is not due to accidental

fluctuations. Under homogeneous data conditions, the gains are mainly reflected in optimization efficiency and convergence stability; in highly heterogeneous vertical scenarios, the average comprehensive gain further expands, demonstrating FedPPH's stronger adaptability and generalization ability to cross-structural data. The four-hospital combination achieves the highest gain, indicating that the collaborative effect of FedPPH becomes more obvious as the number of participating nodes increases. All 95% CIs are positive, further verifying the robustness of the performance improvement. Overall, FedPPH achieves statistically significant diagnostic improvements in heterogeneous medical collaborative environments.

4.3 Analysis of the ablation experiment

To further verify the independent contributions of the three core components of FedPPH—adaptive gradient mechanism, DP, and HE—this study constructs a systematic ablation experiment framework using standard FedAvg as the baseline. Specifically, a "Baseline-FL" (standard FL model without any enhancement strategies) is first built as a control. Subsequently, each component is added in sequence to form different combinations: "Only-Adaptive" (only adaptive gradient), "Only-Privacy" (only privacy mechanisms: DP+HE), "Adaptive+DP" (combination of adaptive gradient and DP), "Adaptive+HE" (combination of adaptive gradient and HE), and the final model FedPPH (including all components). All these models are run under the same data partitioning, training parameters, and federated configurations to ensure fairness of comparison. Their diagnostic performance, convergence characteristics, and client consistency indicators are evaluated in both horizontal and vertical tasks; it aims to comprehensively reveal the independent role and collaborative effect of each component in multi-hospital collaborative scenarios. The results are summarized in Table 7:

Table 7: Ablation experiment results of each component of FedPPH

Model version	Accuracy	Global loss	Client drift	Global variance
Baseline-FL	0.854	0.365	0.198	0.105
Only-Adaptive	0.901	0.319	0.162	0.087
Only-Privacy	0.873	0.342	0.181	0.096
Adaptive + DP	0.905	0.308	0.139	0.078
Adaptive + HE	0.915	0.291	0.124	0.072
FedPPH (Final)	0.935	0.269	0.103	0.061

From the ablation experiment results, different components play clear and complementary roles in improving FedPPH's performance. The adaptive gradient mechanism in the Only-Adaptive can significantly reduce global loss and client drift, indicating its ability to alleviate gradient deviation caused by heterogeneous data across multiple hospitals and improve convergence stability. The Only-Privacy shows a more obvious decrease in accuracy without adaptive optimization, reflecting that privacy perturbation has a certain impact on the optimization process, but client consistency remains within a controllable range. On this basis, when DP or HE is added respectively, Adaptive+DP further enhances the model's security while maintaining stable convergence, and Adaptive+HE maintains better performance while ensuring secure transmission. The final FedPPH model outperforms all sub-versions in accuracy, global loss, and client consistency; this indicates that adaptive gradient, DP, and HE together form a balanced structure of performance, stability, and data security; it is necessary and collaborative for multi-hospital collaborative diagnosis.

4.4 Computational overhead and system cost analysis of HE

To evaluate the actual operating cost of HE in FedPPH, this study measures the system performance of training processes with and without HE (no encryption) based on the same data partitioning and federated settings as the previous experiments; meanwhile, it needs to keep the adaptive gradient and DP strategies unchanged. The evaluation indicators are expanded into five categories: (1) Round Time (single-round training time), reflecting the overall training delay; (2) Local Epoch Time, measuring the impact of encryption on local training; (3) Upload Size (client upload data volume), reflecting communication overhead; (4) Model Size (model parameter storage size), used to evaluate storage expansion caused by encryption; (5) Aggregation Time (server-side aggregation time), indicating the impact of encryption on the server's computational burden. All experiments are conducted under the same hardware conditions to ensure comparability. Table 8 depicts the complete system overhead comparison results:

Table 8: System overhead comparison with and without HE

Configuration Version	Round Time (s)	Local Epoch Time (s)	Upload Size (KB)	Model Size (MB)	Aggregation Time (ms)
Without HE	1.82	0.36	410	9.8	7.6
With HE	2.67	0.36	1,940	38.6	19.3

In Table 8, the overhead brought by HE is mainly reflected in communication volume and encryption computation. When HE is enabled, the upload data volume increases by approximately 3.7 times, and the single-round training time increases by 46.7%. This is mainly due to the expanded ciphertext vector dimension leading to increased communication burden, and

encryption/decryption operations adding local computation time. Nevertheless, the aggregation overhead remains at the millisecond level, indicating that the server-side burden of HE is relatively controllable. Overall, the system cost of HE shows a linear growth trend, which can meet multi-hospital collaborative needs within a reasonable range. In addition, the local epoch training time remains consistent with and without HE. However, the model parameters increase from 9.8 MB to 38.6 MB after encryption, a storage expansion of approximately 3.9 times, which is consistent with the trend of increased communication volume.

4.5 Perturbation impact simulation analysis

To evaluate the robustness of FedPPH in real multi-hospital data scenarios, this study constructs a perturbation simulation experiment based on the same batch of data. It compares the model's performance under conditions of feature missing, label inconsistency, and client noise. Perturbations adopt random range values to better fit natural variations in medical data. Three types of perturbations are set: (1) Missing Rate $\in$ [5%, 15%]: randomly masking part of the input features; (2) Label Noise $\in$ [5%, 12%]: randomly flipping training labels; (3) Client Perturbation $\sim N(0, \sigma^2)$, $\sigma \in [0.10, 0.20]$: simulating collection biases and device differences across different hospitals. The experiment maintains the same federated configuration as the previous evaluation and records the performance indicators of Baseline-FL and FedPPH under non-perturbed and randomly perturbed conditions, respectively. The results are shown in Table 9:

Table 9: Model robustness comparison under non-perturbed and randomly perturbed conditions

Model version	Disturbance condition	Accuracy	Global loss	Client drift	Global variance
Baseline-FL	No disturbance	0.854	0.365	0.198	0.105
Baseline-FL	After disturbance	0.812	0.412	0.238	0.134
FedPPH (Final)	No disturbance	0.935	0.269	0.103	0.061
FedPPH (Final)	After disturbance	0.892	0.318	0.157	0.089

In Table 9, Baseline-FL's accuracy decreases significantly under perturbed conditions. Client drift and global variance increase remarkably, indicating its high sensitivity to feature missing, label anomalies, and client noise. In contrast, FedPPH maintains high accuracy after perturbation, and the changes in convergence indicators are relatively small. This shows that its adaptive gradient can alleviate gradient deviation caused by random perturbations. The noise-smoothing effect of DP and HE improves the system's tolerance to abnormal inputs and upload noise. Overall results indicate that FedPPH has stronger robustness and stability than Baseline under non-ideal data conditions in real environments.

5 Discussion

Comprehensive horizontal and vertical verification results show that the FedPPH model demonstrates stable convergence characteristics and better diagnostic performance under homogeneous data conditions. This model also reflects unique advantages in cross-domain integration in heterogeneous data scenarios. In a real multi-campus medical environment, data often has problems such as scale differences, uneven feature distribution, and inconsistent diagnostic labels. Traditional single-node models fail to ensure performance stability under such conditions. FedPPH can alleviate parameter deviation caused by non-independent and identically distributed data by introducing an adaptive gradient mechanism at the global optimization level; simultaneously, it combines DP and HE at the privacy protection level, enabling various campuses to complete efficient parameter sharing and aggregation under strict privacy constraints. This dual improvement enhances the model's adaptability and generalization ability in a distributed environment while ensuring the compliance and security of medical data during the collaboration process. It can be found that the advantages of FedPPH in intelligent diagnosis performance reflect its practical significance for actual clinical applications. With the support of large-scale central hospital data, it can maintain a high overall diagnostic level; in the scenario of regional hospitals with limited samples, it can also notably improve the stability and reliability of diagnostic results through cross-campus collaboration. This modeling idea that emphasizes both collaborative consistency and privacy protection provides a feasible and secure path for implementing multi-campus information sharing and intelligent medical services, and has important practical value and promotion significance.

Compared with the existing State-of-the-Art (SOTA) Federated Learning (FL) methods in Table 1, FedPPH demonstrates more significant stability and diagnostic advantages in both horizontal and vertical experiments. Existing studies, such as Rehman et al.'s FL+GAN-based cancer diagnosis, can achieve an accuracy of approximately 97% in single-task scenarios, but they mainly rely on homogeneous or structurally similar datasets. Abbas et al.'s adaptive FL reaches around 90% in multi-cancer prediction tasks. In contrast, FedPPH achieves an accuracy of 0.954 on large-scale homogeneous data and maintains 0.897 in multi-source heterogeneous data fusion scenarios, reflecting stronger robustness across cross-structural data. This performance improvement is mainly attributed to the dynamic adjustment capability of the adaptive gradient, enabling the model to maintain stable convergence even when feature distributions differ significantly. Meanwhile, the

two-layer privacy mechanism avoids the risk of information leakage associated with single privacy technologies, making cross-hospital collaboration more secure. In terms of the trade-off between performance and cost, DP and HE do introduce additional computational and communication overhead. However, systematic experiments show that this cost grows linearly and controllably with the number of hospitals, without substantially interfering with overall training stability and collaboration efficiency. Therefore, FedPPH achieves a superior comprehensive balance between diagnostic accuracy, generalization ability, and privacy protection, making it more suitable for the practical needs of complex multi-hospital medical environments.

The study still faces unknown risks. As the number of hospitals increases, the computational burden and communication overhead of FedPPH may show an upward trend. Especially when HE is enabled, the encryption and decryption operations of ciphertext increase computational load and raise data upload traffic to a certain extent. These overheads grow linearly with the number of participating hospitals, potentially affecting training speed and aggregation efficiency. The current scheme can maintain good performance with a moderate number of hospitals. However, as the scale of multi-hospital collaboration continues to expand, these overheads may become system bottlenecks. With technological advancements, further optimization of encryption algorithms or adoption of more efficient computational models can be continuously considered to reduce such overheads. Meanwhile, balancing performance and cost becomes a key issue, especially under the dual requirements of efficient transmission and data privacy protection. Combined with current technologies and future development directions, FedPPH has strong scalability and potential to provide reliable solutions in large-scale medical collaboration. Through continuous technological innovation, the practical application prospects of FedPPH continue to expand, offering a more efficient and secure path for multi-hospital collaborative diagnosis.

6 Conclusion

To meet the dual needs of multi-campus medical data collaboration and privacy protection, this study proposes the FedPPH model and conducts systematic verification in both horizontal and vertical dimensions. From the study's application value perspective, FedPPH optimizes the existing FL framework and offers a feasible implementation model for multi-campus information collaboration. In large-scale central hospitals, the proposed model can maintain a high diagnostic accuracy level and discrimination ability; in regional or data-scarce medical institutions, this model compensates for the performance defects caused by insufficient samples through cross-campus aggregation, realizing the equalization of diagnostic capabilities. This feature has practical significance for alleviating the uneven distribution of medical resources and improving the quality of primary medical services. In addition, the design idea of FedPPH can be extended to other medical intelligent application scenarios, providing references for fields such as electronic health record sharing and disease prediction.

Although FedPPH demonstrates remarkable advantages in multi-campus medical data collaboration and privacy protection, it still has certain limitations in practical applications. First, due to the dual mechanism's introduction of DP and HE, the model inevitably increases computing and storage overhead during the training and communication processes, which may pose challenges to deployment in medical institutions with limited computing resources. Second, the extremely unbalanced data distribution and feature space differences among different campuses may still lead to a decrease in the convergence speed of the global model or limited performance of individual nodes in some cases. Future research can focus on communication compression and encrypted computing optimization strategies to reduce resource consumption and improve the model's adaptability and promotion value in real multi-campus environments.

Funding

This project was supported by the Medical Science Research Project of Hebei Province “Research on medical management system based on hospital information platform” (No. 20220031).

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