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Overcoming Data Scarcity in Pediatric Medicine: Federated Learning for Multi-institutional Diagnostic Models Without Data Migration

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Abstract

Pediatric disease diagnosis is often constrained by limited sample sizes, fragmented data distribution, and strict privacy requirements across medical institutions. To address these challenges, this study proposes a dynamic weighted federated learning framework (DW-FL) for multi-institutional pediatric disease diagnosis, enabling collaborative model training without sharing raw patient data. The proposed framework introduces a contribution-aware aggregation strategy that dynamically adjusts client weights based on model performance and data characteristics, and incorporates a weighted loss function to mitigate class imbalance commonly observed in pediatric datasets. Experiments conducted under both independent and non-independent data distribution settings demonstrate that the proposed approach achieves improved diagnostic performance and communication efficiency compared with conventional federated averaging methods. These results indicate that dynamic weighting mechanisms can enhance the robustness of federated learning in heterogeneous pediatric scenarios, providing a feasible solution for privacy-preserving multi-center clinical collaboration.

Keywords

Federated learning; Pediatric diagnosis; Data privacy; Multi-center collaboration; Dynamic aggregation

1. Introduction

Pediatric disease diagnosis increasingly relies on data-driven methods to support clinical decision-making. However, compared with adult medicine, pediatric clinical data are often limited in scale, highly fragmented across institutions, and subject to stricter privacy and ethical constraints. These challenges are particularly pronounced in rare and low-incidence diseases, where data scarcity and heterogeneity restrict the robustness and clinical impact of machine learning models (Amorim et al., 2025). In response, privacy-preserving paradigms such as federated learning have been increasingly explored to enable cross-institutional collaboration without centralized data sharing, especially in resource-constrained public health settings (Borges et al., 2026).

Multi-center collaboration is widely regarded as an effective approach to alleviating data scarcity by aggregating knowledge across institutions. However, traditional centralized learning frameworks require the transfer of patient-level data to a shared repository, which is often infeasible in healthcare due to regulatory constraints, data governance requirements, and the risk of privacy leakage (Rezaei et al., 2025). To address these limitations, privacy-preserving collaborative learning paradigms—particularly federated learning—have been proposed to enable distributed model training without sharing raw data, forming the basis for secure collaborative learning frameworks in sensitive domains such as healthcare (Tripathy et

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al., 2025). Nevertheless, even within federated settings, distributed learning environments remain exposed to security threats and potential privacy leakage, highlighting the need for robust protection mechanisms to ensure trustworthy collaboration (Ighofiomoni et al., 2025).

Federated learning (FL) has emerged as a promising paradigm for medical applications by enabling multiple institutions to collaboratively train models without sharing raw patient data. Recent surveys systematically categorize FL use cases in healthcare, highlighting its effectiveness in disease prediction and medical image analysis while also identifying persistent challenges such as data heterogeneity, non-IID distributions, and communication overhead (Rauniyar et al., 2023). In pediatric healthcare, machine learning adoption has grown rapidly, yet the application of FL remains comparatively limited, largely due to domain-specific constraints including small sample sizes, stricter privacy requirements, and the complexity of pediatric data governance (Ganatra, 2025). These factors suggest that, despite demonstrated success in general medical domains, federated learning in pediatric diagnosis remains underexplored and warrants targeted methodological and empirical investigation.

First, pediatric data distributed across institutions are often non-independent and non-identically distributed (Non-IID). Differences in patient demographics, disease prevalence, and clinical protocols introduce substantial statistical heterogeneity among local datasets, which degrades the convergence, performance, and stability of conventional federated learning algorithms (Lu et al., 2024; Karami & Karami, 2025). Second, pediatric datasets frequently suffer from severe class imbalance, particularly in rare diseases, leading global models to bias toward majority classes and increasing the risk of missed or delayed diagnoses (Borazjani et al., 2024). Third, communication efficiency represents a critical practical constraint in real-world medical deployments, as federated training must operate under limited network bandwidth and computational resources, further exacerbating the challenges posed by heterogeneity and non-IID data (Lu et al., 2024; Annappa et al., 2024).

Most existing federated learning (FL) approaches rely on static aggregation strategies, such as FedAvg or FedSGD, which weight client updates primarily by local data volume. While effective in relatively homogeneous settings, these methods often fail to account for variations in data quality, representativeness, and clinical relevance across institutions, limiting their suitability for complex healthcare and pediatric scenarios (Jayaram et al., 2022). Recent studies have demonstrated that adaptive aggregation mechanisms can better address these limitations by dynamically adjusting client contributions based on heterogeneity and learning behavior, thereby improving robustness and convergence in real-world medical applications (Haripriya et al., 2025; Song et al., 2025). In parallel, fairness- and stability-aware aggregation strategies have been proposed to mitigate bias and ensure balanced participation among clients, further highlighting the need for aggregation designs that jointly consider heterogeneity, contribution equity, and training stability in federated healthcare systems (Ray Chaudhury et al., 2022).

To address these challenges, this study proposes a dynamic weighted federated learning framework (DW-FL) tailored to pediatric disease diagnosis. The core idea is to dynamically adjust aggregation weights based on client contribution, rather than relying solely on dataset size. In addition, imbalance-aware optimization strategies are incorporated to improve sensitivity to underrepresented disease categories. The proposed framework is evaluated under controlled independent and non-independent data distribution settings to assess its effectiveness and robustness.

The main contributions of this work can be summarized as follows:

A contribution-aware dynamic aggregation strategy is introduced to improve model robustness under heterogeneous pediatric data distributions;

An imbalance-aware optimization design is employed to enhance diagnostic performance for rare pediatric conditions;

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A systematic experimental evaluation is conducted to analyze both diagnostic performance and communication efficiency in federated pediatric scenarios.

2. Related Work

2.1. Federated Learning in Healthcare

Federated learning has been increasingly explored as a privacy-preserving paradigm for collaborative model training in healthcare applications. By keeping patient data localized and exchanging only model parameters or gradients, FL provides a practical solution to data governance and privacy constraints commonly encountered in medical domains. Early studies demonstrated the feasibility of federated learning for distributed training of deep neural networks, highlighting its advantages in reducing communication overhead while preserving data confidentiality.

Subsequent research has extended federated learning to various medical tasks, including disease risk prediction, electronic health record analysis, and medical image classification. In these studies, federated learning was shown to achieve performance comparable to centralized training under certain conditions. However, most healthcare-oriented FL frameworks implicitly assume relatively balanced data distributions or focus on adult patient populations, where sample sizes are typically larger and more homogeneous.

In real-world clinical settings, especially in pediatric care, these assumptions often do not hold. Differences in institutional specialization, patient demographics, and diagnostic practices introduce substantial heterogeneity across participating sites, posing challenges to standard federated optimization algorithms.

2.2. Aggregation Strategies for Heterogeneous Data

Aggregation is a central component of federated learning, as it determines how local model updates are combined to form a global model. The classical federated averaging (FedAvg) algorithm aggregates client updates in proportion to local dataset size, which is effective under independent and identically distributed (IID) data conditions. However, under Non-IID settings, FedAvg may suffer from slow convergence, instability, or degraded model performance.

To address data heterogeneity, several variants have been proposed. Regularization-based methods introduce additional constraints to limit divergence between local and global models, while variance-reduction approaches aim to correct client drift during local training. Other studies explore personalized federated learning, allowing local models to adapt to institution-specific data distributions.

More recently, dynamic or adaptive aggregation strategies have been investigated, where client contributions are weighted according to model performance, gradient similarity, or distributional characteristics. While these approaches demonstrate improved robustness under heterogeneous conditions, most are designed for general machine learning benchmarks and do not explicitly consider the characteristics of pediatric clinical data, such as extreme class imbalance and small sample sizes.

2.3. Pediatric AI Diagnosis and Data Imbalance

Artificial intelligence applications in pediatric diagnosis have largely focused on imaging-based tasks for disease screening and diagnostic support. However, most existing studies rely on single-center datasets with limited sample sizes, restricting model robustness and cross-institutional generalizability (Wang et al., 2025). Similar limitations are reported in pediatric subspecialties such as urology, where promising deep learning tools remain constrained by institution-specific validation and ongoing ethical and privacy concerns (Chowdhury et al., 2024).

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Class imbalance is a persistent issue in pediatric datasets, particularly for rare diseases where positive samples are scarce. Conventional machine learning models trained on imbalanced data tend to favor majority classes, leading to reduced sensitivity for clinically critical conditions. Various imbalance-aware techniques, including re-sampling strategies and weighted loss functions, have been proposed to mitigate this problem. However, these methods are typically developed for centralized learning scenarios and have not been systematically integrated into federated learning frameworks for pediatric diagnosis.

2.4. Research Gap and Motivation

Although federated learning (FL) offers a promising foundation for privacy-preserving multi-center collaboration, existing approaches remain limited when applied to pediatric diagnostic scenarios. Prior studies on cross-institutional medical data collaboration indicate that static aggregation strategies struggle to accommodate inter-institutional data heterogeneity, leading to statistical bias and reduced model reliability across clients (Zhang, 2025). Moreover, secure FL frameworks that integrate advanced cryptographic protocols primarily focus on safeguarding data exchange, while challenges related to heterogeneity-aware optimization and imbalance handling are often addressed separately rather than jointly within the federated training process (Idowu & Idowu, 2025).

There remains a lack of federated learning frameworks that jointly consider adaptive aggregation, class imbalance, and communication efficiency in pediatric settings. This gap motivates the development of a dynamic weighted federated learning approach that can more effectively leverage heterogeneous pediatric data while maintaining privacy and practical feasibility.

3. Method

3.1. System Architecture

The proposed Dynamic Weighted Federated Learning (DW-FL) framework consists of a central coordination server and multiple hospital clients, as illustrated in Figure 1. The system is designed to enable collaborative pediatric disease diagnosis without sharing raw clinical data across institutions.

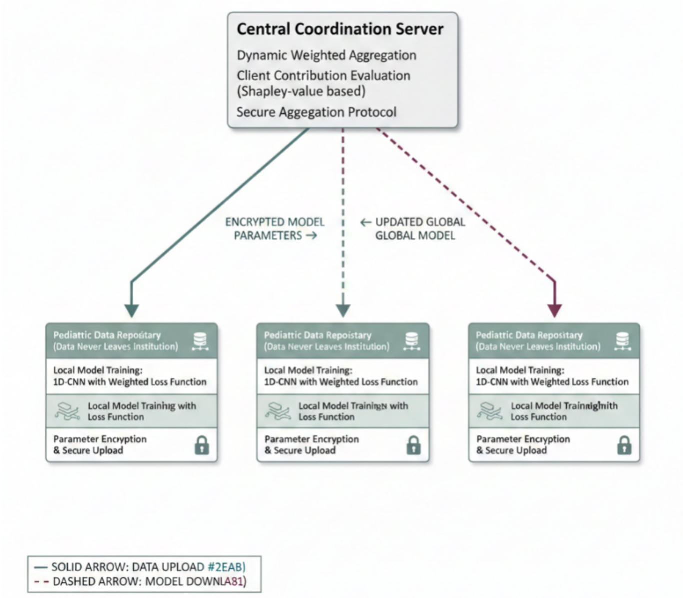

Figure 1: System architecture of the dynamic weighted federated learning (DW-FL) framework for multi-institutional pediatric diagnosis

ISSN: 3079-6601

The overall training workflow proceeds as follows. First, during the initialization phase, the central server distributes an initial global model to all participating hospitals.Second, in the local training phase, each hospital trains the model using its own pediatric clinical data, which remain stored within the local data repository.
Third, after local training, hospitals upload encrypted model parameters to the server, where a contribution evaluation process is performed to assess the relative usefulness of each local update.Fourth, based on the evaluated contributions, the server conducts dynamic weighted aggregation to update the global model.Finally, the updated global model is redistributed to all hospitals, and the above steps are iteratively repeated until model convergence.

This architecture ensures that raw pediatric data never leave the local institutions while allowing effective multi-center collaboration through model parameter exchange.

3.2. Dynamic Weighted Aggregation Algorithm

In conventional federated learning, the global model is updated using the Federated Averaging (FedAvg) algorithm, where client updates are weighted according to local dataset size:

$$\theta_{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} \theta_t^k,$$

where θ_t^kdenotes the local model parameters of client $k$at round t, $n_k$is the number of samples held by client k, and $N = \sum_{k=1}^{K} n_k$.

To better handle heterogeneous pediatric data distributions, this study introduces a dynamic weighted aggregation strategy. The global model is updated as:

$$\theta_{t+1} = \sum_{k=1}^{K} w_k \cdot \frac{n_k}{N} \theta_t^k,$$

where $w_k$is a dynamically assigned weight reflecting the contribution of client k.

The aggregation weight $w_k$is computed based on the client contribution score C_k:

$$w_k = \frac{\exp(\alpha \cdot C_k)}{\sum_{j=1}^{K} \exp(\alpha \cdot C_j)},$$

where $\alpha$is a scaling factor controlling the sensitivity of weight assignment.

The contribution score $C_k$is determined by jointly considering the following factors:

the classification accuracy of the local model evaluated on a server-side validation set;

the Kullback–Leibler (KL) divergence between the local class distribution and the global class distribution;

a historical contribution stability coefficient that reflects the consistency of the client's past updates.

As illustrated in Figure 1, this contribution-aware aggregation process is performed at the server side after receiving encrypted model parameters from all participating hospitals.

3.3. Pediatric Data Optimization Strategies

3.3.1. Weighted Cross-Entropy Loss

Pediatric datasets often exhibit severe class imbalance, particularly for rare diseases. To mitigate this issue during local training, a weighted cross-entropy loss function is employed:

$$\mathcal{L}_{WCE} = -\sum_{c=1}^{C} \beta_c \cdot y_c \log(\hat{y}_c),$$

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where Cdenotes the number of disease classes, $y_c$and $\hat{y}_c$represent the ground-truth label and predicted probability for class c, respectively, and $\beta_c$is the class-specific weight.

Higher weights are assigned to rare disease categories to enhance their influence on gradient updates. In this study, the weight for rare diseases is set to a higher value (e.g., $\beta_{rare} = 5.0$), which improves model sensitivity to underrepresented pediatric conditions.

3.3.2 One-Dimensional CNN Architecture

To model structured pediatric clinical data, such as laboratory indicators and vital signs, a one-dimensional convolutional neural network (1D-CNN) is adopted, as shown in Figure 2.

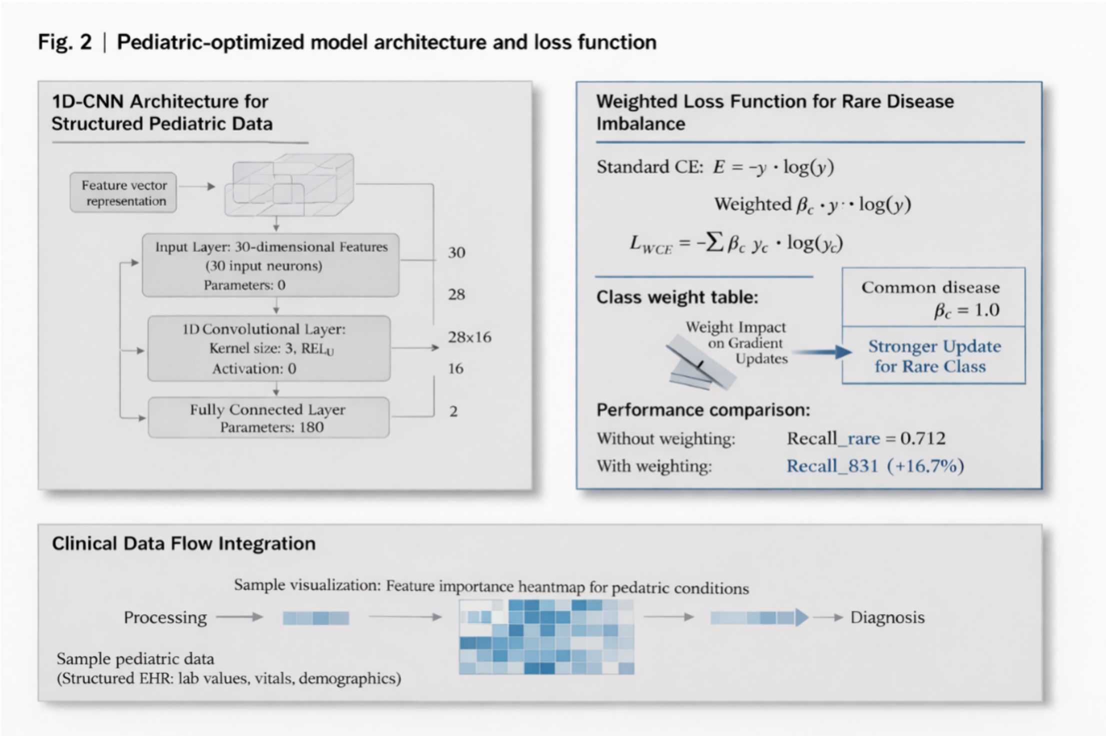

Figure 2: One-dimensional convolutional neural network (1D-CNN) architecture for pediatric clinical data modeling

The network architecture consists of an input layer with a feature dimension of 30, followed by a one-dimensional convolutional layer with a kernel size of 3 and 16 output channels. A pooling layer is applied to reduce feature dimensionality and improve robustness. Finally, a fully connected layer outputs the diagnostic predictions with an output dimension of 2. This lightweight architecture is designed to balance representational capacity and computational efficiency, making it suitable for federated learning environments with limited local training resources.

3.4. Privacy Preservation Mechanisms

To ensure data security and patient privacy, multiple privacy-preserving measures are integrated into the DW-FL framework.

First, gradient clipping and noise injection are applied during local training to satisfy (ϵ_m, δ)-differential privacy requirements. Second, a secure aggregation protocol based on Paillier homomorphic encryption is used to protect uploaded model parameters during communication. Third, raw pediatric data never leave the local hospital network, ensuring compliance with medical data governance and privacy regulations.Together, these mechanisms enable secure and privacy-preserving multi-center pediatric model training.

ISSN: 3079-6601

4. Results

4.1. Experimental Setup

Experiments were conducted using a pediatric-related subset derived from the publicly available MIMIC-III database, consisting of approximately 12,000 records with 30 structured clinical features. To simulate a multi-center pediatric setting, the dataset was partitioned into three virtual hospitals under both independent and identically distributed (IID) and non-independent and non-identically distributed (Non-IID) conditions.

Four methods were compared: centralized training (Centralized), conventional federated averaging (FedAvg), static weighted federated learning (Static-FL), and the proposed dynamic weighted federated learning framework (DW-FL). Model performance was evaluated using accuracy, recall, and F1-score. In addition, convergence efficiency was assessed in terms of the number of communication rounds and total communication volume.

4.2. Diagnostic Performance under Non-IID Distribution

Table 1 presents the diagnostic performance of different methods under the Non-IID data distribution scenario. Centralized training achieved the highest overall performance, serving as an upper performance bound.

Among federated learning approaches, DW-FL achieved the best diagnostic performance, with an accuracy of 0.932, a recall of 0.878, and an F1-score of 0.904. In comparison, FedAvg achieved an accuracy of 0.918 and a recall of 0.845, while Static-FL showed intermediate performance across all metrics.

Compared with FedAvg, DW-FL improved accuracy by 1.4% and recall by 3.3%, indicating that dynamic weighted aggregation is more effective than static aggregation strategies when handling heterogeneous pediatric data distributions.

Table 1: Diagnostic performance comparison under Non-IID distribution

Method	Accuracy	Recall	F1-score
Centralized	0.941	0.892	0.916
FedAvg	0.918	0.845	0.880
Static-FL	0.925	0.861	0.892
DW-FL	0.932	0.878	0.904

4.3. Convergence Efficiency and Communication Overhead

The convergence efficiency of different federated learning methods is summarized in Table 2. FedAvg required 320 communication rounds to converge, with a total communication volume of 45.2 MB. Static-FL reduced the number of rounds to 290 and the communication overhead to 41.8 MB.

DW-FL demonstrated the highest training efficiency, converging within 265 communication rounds and reducing total communication volume to 38.7 MB. Compared with FedAvg, DW-FL reduced the number of communication rounds by 17.2% and decreased communication overhead by 14.4%.

These results indicate that contribution-aware dynamic aggregation can effectively improve convergence speed and reduce communication cost in federated pediatric learning scenarios.

ISSN: 3079-6601

Table 2: Convergence efficiency and communication overhead

Method	Convergence rounds	Communication volume (MB)
FedAvg	320	45.2
Static-FL	290	41.8
DW-FL	265	38.7

4.4. Performance on Rare Disease Diagnosis

To further evaluate model robustness under class imbalance, a rare disease scenario was simulated, in which positive samples accounted for approximately 5% of the dataset. Recall for rare disease classes was used as the primary evaluation metric.

As shown in Table 3, DW-FL achieved a recall of 0.831 for rare disease diagnosis, compared with 0.712 achieved by FedAvg. This corresponds to a relative improvement of 16.7%. In addition, the missed diagnosis rate was reduced from 28.8% to 16.9%, indicating improved sensitivity to underrepresented pediatric disease categories.

Table 3: Rare disease diagnosis performance

Method	Recall (rare disease)	Missed diagnosis rate
FedAvg	0.712	28.8%
DW-FL	0.831	16.9%

4.5. Ablation Study

An ablation study was conducted to assess the individual contributions of the key components in the proposed framework. When only the weighted cross-entropy loss was applied, recall improved by 8.2% compared with FedAvg. When only the dynamic weighted aggregation mechanism was employed, convergence speed improved by 12.1%.

The combination of both components achieved the best overall performance, confirming that dynamic aggregation and imbalance-aware optimization are complementary in improving both diagnostic accuracy and training efficiency.

5. Discussion

5.1. Balancing Privacy and Model Performance

In healthcare applications, particularly in pediatric settings, data privacy remains a fundamental constraint for large-scale collaborative model training. Federated learning (FL) has therefore emerged as a practical paradigm by enabling institutions to jointly train models without sharing raw patient data. However, prior studies indicate that privacy-preserving mechanisms may introduce performance degradation, communication overhead, or optimization instability, limiting real-world deployment (Hall et al., 2025).

The proposed dynamic weighted federated learning (DW-FL) framework demonstrates that model performance can be substantially improved without increasing privacy risks. By avoiding data migration and relying solely on parameter-level exchanges, DW-FL preserves institutional data sovereignty while achieving performance comparable to centralized training under non-IID conditions. This finding aligns with recent evidence suggesting that carefully

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designed aggregation strategies can mitigate the traditional trade-off between privacy protection and predictive accuracy in medical federated learning systems (Zhang, 2025).

5.2. Pediatric Applicability Analysis

Pediatric datasets are inherently heterogeneous across institutions due to variations in patient demographics, disease prevalence, and clinical protocols. Such heterogeneity poses significant challenges for conventional FL methods that adopt static aggregation strategies. The dynamic weighting mechanism in DW-FL allows adaptive adjustment of client contributions based on data characteristics and model behavior, making it particularly suitable for multi-center pediatric collaboration.

In addition, pediatric diagnosis often involves severe class imbalance, especially for rare diseases, which increases the risk of biased global models and missed diagnoses. By incorporating a weighted loss function into the federated optimization process, DW-FL effectively alleviates class imbalance at both local and global levels. This integrated treatment of heterogeneity and imbalance addresses limitations commonly observed in existing FL studies, where imbalance-aware optimization is often considered independently of the federated aggregation process (Lu et al., 2024; Ganatra, 2025).

5.3. Limitations

Despite its advantages, this study has several limitations. First, the experimental evaluation is conducted on simulated datasets, and further validation using real-world multi-center pediatric data is required to confirm clinical robustness and generalizability. Second, the current framework focuses on unimodal data and does not consider multimodal fusion scenarios, such as the joint use of medical imaging and clinical text, which are increasingly common in pediatric diagnosis (Borazjani et al., 2024; MedLeak, 2024). Third, extreme heterogeneity scenarios—such as cross-national deployments with substantially different diagnostic standards and healthcare infrastructures—are not explicitly investigated and remain an open challenge for future research.

6. Conclusion and Future Directions

This paper proposes a dynamic weighted federated learning framework tailored for pediatric disease diagnosis. By jointly addressing data heterogeneity, class imbalance, and communication efficiency, the proposed approach enables privacy-preserving multi-institutional collaboration while maintaining high diagnostic performance. Experimental results demonstrate that DW-FL achieves performance close to centralized training under non-IID data distributions, with significantly improved communication efficiency compared to conventional federated learning methods.

Future work may explore multimodal federated learning integrating medical imaging, genomic data, and clinical text to improve diagnostic accuracy (Borazjani et al., 2024; MedLeak, 2024), as well as cross-age transfer learning that leverages adult datasets for pretraining to enhance pediatric model performance (Li et al., 2020; Rashidi et al., 2023). In addition, combining federated learning with blockchain technology can enable decentralized and auditable collaboration (Nguyen et al., 2023), while real-world multi-center clinical trials are required to validate feasibility in pediatric settings (Rieke et al., 2020; Zhang, 2025).

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