FedP2PAvg: A Peer-to-Peer Collaborative Framework for Federated Learning in Non-IID Scenarios

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Abstract. Federated learning is a decentralized machine learning approach where models are trained collaboratively across multiple devices or nodes holding local data without sharing that data directly. It enables privacy-preserving, scalable, and collaborative machine learning. One of the key challenges in federated learning is its inefficiency in handling scenarios where data is highly imbalanced and non-independent and identically distributed (non-IID) across local nodes, leading to biased global models and slow convergence. This paper introduces a peer-to-peer refinement mechanism combined with FedAvg aggregation to enhance model accuracy in highly imbalanced and non-IID federated learning scenarios. Experiments were conducted on the MNIST, Fashion-MNIST and CIFAR-10 datasets using a Dirichlet distribution with $\alpha = 0.1$ to simulate highly imbalanced and non-IID data scenarios. The results demonstrated that the proposed approach achieved higher accuracy, 98.17% in MNist, 84.35% in Fashion-MNIST and 67.49% in CIFAR-10 while requiring less than half the number of rounds to converge compared to traditional federated learning methods.

Keywords: Federated learning · Computer vision · Neural networks.

1 Introduction

The advancement of technology and the massive collection of data have driven the development of increasingly complex and efficient machine learning algorithms [12]. However, in many cases, this data is distributed across different locations, which complicates the task of training models with such decentralized information [16]. Moreover, sharing this data can compromise the privacy of individuals or organizations involved [20].

Federated learning is a recent paradigm [11] that enables training machine learning models on distributed and decentralized datasets without sharing data directly among participants. It allows multiple entities (e.g., mobile devices, sensors, servers in different locations) to collaborate in training a model while retaining their raw data locally. This approach fosters collaboration between diverse entities while protecting data privacy [4,1] and minimizing communication and centralized storage costs. Federated learning also enhances the efficiency of models [14], as training occurs on edge devices, thereby reducing the load on central servers.

Federated learning, however, also presents several challenges. From an efficiency perspective, while prior distributed learning can reduce costs on the central part of the architecture, communication can become a bottleneck, particularly when considering the scale of connected devices [14]. Collaboration can also be hindered when there is an imbalance in participants' contribution to the collective knowledge [3]. Data heterogeneity, particularly in non-IID scenarios, exacerbates these problems. Bias emerges when dominant devices or clusters with larger datasets disproportionately influence the global model, leading to poor performance in underrepresented groups or classes. Convergence, conversely, can become unstable in scenarios with extreme data imbalances, as inconsistent updates from non-IID data can hinder the optimization process and lead to suboptimal solutions. These challenges are especially pronounced in real-world scenarios such as healthcare federated systems, where data heterogeneity is intrinsic due to variations in population demographics, equipment, and institutional practices [15]. In such domains, data rebalancing or normalization across clients is often infeasible due to strict privacy regulations and lack of access to global statistics.

Although recent surveys, such as [9], have extensively categorized methods to address non-IID federated learning—ranging from data preprocessing and optimization corrections to personalized local adaptation—strategies based on direct peer-level collaboration remain largely unexplored. Specifically, the idea of refining local models through interactions with randomly selected peers has not been sufficiently investigated, despite its potential to mitigate client drift and improve generalization without requiring complex control structures or multiple model instances.

This paper proposes a novel peer-to-peer (P2P) framework for federated learning designed to address the challenges of bias and convergence in highly imbalanced and non-IID data scenarios. The proposed approach, FedP2PAvg, introduces a collaborative training mechanism in which local models are randomly shared with other peers after being trained for a fixed number of epochs for further refinement. This peer-to-peer interaction enables models to incorporate knowledge from diverse distributions before a global aggregation step using FedAvg. By integrating these components, the framework enhances the robustness and accuracy of the global model and improves convergence speed. This methodology highlights the potential of leveraging P2P collaboration to mitigate data imbalance and enhance federated learning in real-world, decentralized environments.

2 FedP2PAvg

FedP2PAvg (*Peer-to-Peer Federated Averaging*) is a novel federated learning framework that combines peer-to-peer collaboration with the standard Federated Averaging (FedAvg) algorithm [11]. The goal is to mitigate the bias and convergence issues that arise in scenarios with highly imbalanced and non-IID (non-identically distributed) data across clients. Instead of relying solely on the traditional cycle of local training followed by centralized model aggregation, FedP2PAvg introduces an additional *peer-to-peer refinement phase* in each global round. In this phase, each client's locally trained model is *shared with a randomly selected peer* for further training on the peer's data before global averaging. By allowing direct knowledge transfer between pairs of clients, the framework enables each model to incorporate information from a more diverse data distribution prior to the global update. This approach is designed to enhance the robustness and generalization of the global model, leading to improved accuracy and faster, more stable convergence even under extreme data heterogeneity. Algorithm 1 outlines the FedP2PAvg procedure in detail[3].

Algorithm 1 FedP2PAvg: Peer-to-Peer Federated Averaging

Input: N (number of client nodes); E (local epochs per round); T (number of global rounds); D_i (local dataset at node i for $i = 1, \dots, N$).
Output: Trained global model W^G.

Initialize global model W^G.
for $t = 1$ to T **do** ▷ Global training rounds
    Server sends W^G to all N clients.
    for each client $i = 1$ to N **in parallel do** ▷ Local training
        $W_i \leftarrow W^G$ // client i receives the global model
        Train W_i on local data D_i for E epochs.
    end for
    for each client $i = 1$ to N **in parallel do** ▷ Peer-to-peer refinement
        Randomly select a peer $j \neq i$.
        Send W_i (model from client i) to peer j.
        On peer j**:** continue training W_i for E additional epochs on D_j.
        Peer j sends the refined model W_i (originating from i) back to the server.
    end for
    $W^G \leftarrow \frac{1}{N} \sum_{i=1}^{N} W_i$ // **FedAvg aggregation**
end for
return W^G.

The design of FedP2PAvg explicitly contrasts with prior peer-to-peer federated learning approaches that focused primarily on communication efficiency. For example, the FedP2P framework proposed by Chou et al. [2] organizes clients into localized P2P networks to reduce reliance on the central server and communication costs. While such decentralized schemes improve scalability, they do not directly address the learning challenges posed by extreme data heterogeneity or class imbalance. FedP2P focuses primarily on reducing communication overhead by organizing clients into local P2P networks, where models are trained and synchronized through Allreduce operations before a final global aggregation.

[3] The source code is available at https://github.com/bjtf/FedP2PAvg.

Instead of group-wise synchronization, FedP2PAvg introduces a peer refinement phase in which each node sends its model to a randomly selected peer for further training on a different local dataset. Unlike FedP2P, which relies on fixed group structures and emphasizes scalability and fault tolerance, FedP2PAvg maintains a centralized global aggregation step and leverages P2P interactions as a mechanism of cross-node knowledge adaptation. In FedP2PAvg, each client's update is enriched by information from two distinct datasets (its own and a peer's) before contributing to the global aggregation. This yields better generalization across diverse client data and improves stability during training.

2.1 Theoretical Foundations

Convergence Guarantee under Non-Convex Objectives.

We now provide a convergence guarantee for FEDP2PAVG in the non-convex case, extending the classical results of FedAvg [11,7].

Let each client $i \in \{1, \ldots, N\}$ have a local loss function $F_i(w) := \mathbb{E}_{\xi_i \sim \mathcal{D}_i}[\ell(w; \xi_i)]$ defined over its local data distribution $\mathcal{D}_i$, where ℓ is a smooth loss function and $w \in \mathbb{R}^d$ denotes the model parameters. The global objective is

$$F(w) := \frac{1}{N} \sum_{i=1}^{N} F_i(w).$$

Assume the following:

- (A1) Each F_i is L-smooth: $\|\nabla F_i(w) - \nabla F_i(w')\| \leq L\|w - w'\|$.
- (A2) Bounded variance: $\mathbb{E}[\|\nabla \ell(w; \xi_i) - \nabla F_i(w)\|^2] \leq \sigma^2$.
- (A3) Bounded gradient: $\mathbb{E}[\|\nabla F_i(w)\|^2] \leq G^2$.
- (A4) The stochastic peer selection is independent and uniform.

In FedP2PAvg, after E local updates, client i sends model w_i to peer $j \neq i$, which continues training for E steps on its own data. Let $\tilde{w}_i$ denote the model after peer refinement. The server receives $\tilde{w}_i$ and aggregates:

$$w^{(t+1)} = \frac{1}{N} \sum_{i=1}^{N} \tilde{w}_i.$$

Let us denote the update direction $\Delta_i = \tilde{w}_i - w^{(t)}$ and define $\Delta := \frac{1}{N} \sum_{i=1}^{N} \Delta_i$. By Taylor expansion and smoothness of F, we have:

$$F(w^{(t+1)}) \leq F(w^{(t)}) + \langle \nabla F(w^{(t)}), \Delta \rangle + \frac{L}{2} \|\Delta\|^2.$$

Taking expectation over stochastic gradients and random peer selection:

$$\mathbb{E}[F(w^{(t+1)})] \leq \mathbb{E}[F(w^{(t)})] - \eta \mathbb{E}[\|\nabla F(w^{(t)})\|^2] + \eta^2 \frac{L}{2} \underbrace{\mathbb{E}[\|\Delta\|^2]}_{\text{bounded by variance + drift}}.$$

Following the standard argument as in [7], and adapting for the double update (own + peer), we can derive:

$$\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[\|\nabla F(w^{(t)})\|^2] \leq \frac{2(F(w^{(0)}) - F^*)}{\eta T} + O(\eta L\sigma^2) + O(\eta^2 G^2),$$

where the $O(\cdot)$ terms are improved relative to FedAvg due to peer refinement that reduces update variance via two-distribution smoothing and implicitly shrinks client-drift (the difference $\|\nabla F_i(w) - \nabla F(w)\|$).

Unbiasedness via Gossip Mixing. Over T rounds, if peer selection is i.i.d. uniform, the induced communication graph (V, E_t) is, in expectation, a connected Erdős–Rényi graph with probability $p = \frac{1}{N-1}$. It follows from gossip learning theory [8] that the average model observed through these peer updates remains an unbiased estimator of the true global optimum in the long term:

$$\mathbb{E}[\Delta_i] \approx \mathbb{E}[\nabla F_i(w) + \nabla F_j(w)] = 2\nabla F(w),$$

preserving the directionality of descent. The stochasticity introduced by random pairing acts as a variance-reducing regularizer and prevents model collapse or domination by any single client. Therefore, FedP2PAvg retains the convergence properties of FedAvg under non-convex settings while improving bias and variance properties through collaborative smoothing.

Variance Reduction and Update Stability. An important theoretical advantage of the peer-to-peer step is the *reduction of variance* in the aggregated model update. In heterogeneous data settings, the gradient updates $\nabla F_i(w)$ across clients can have high variance around the global gradient $\nabla F(w)$ due to differences in data distributions. Averaging many independent client gradients in FedAvg reduces this variance to some extent (central limit effects), but with strongly skewed data, the variance of the average can still be large or dominated by a few outlier clients. FedP2PAvg increases the amount of data and diversity each model update is exposed to, which has an analogous effect to increasing the mini-batch size in stochastic gradient descent. The idea of using information from other clients to reduce update variance is also supported by recent federated optimization research. For example, variance-reduced local SGD methods and control-variate techniques (such as SCAFFOLD) explicitly add correction terms representing other clients' gradients to counter client drift [6]. Our approach attains a similar goal without explicit correction vectors: the act of peer training provides an implicit gradient correction. Each client's model is nudged by a peer's data, serving to regularize the local update. This can be seen as a form of on-the-fly model averaging that happens one step earlier than the central aggregation, inherently dampening the variability of individual client contributions.

Role of Random Peer Selection. A key component of FedP2PAvg's design is the *randomness* in peer selection during the refinement phase. Random peer assignment ensures that, over many rounds, each client's model has the opportunity to be refined by a wide variety of other clients' data. First, it prevents any fixed pairing or clustering of clients that could lead to isolated sub-models or "group drift." If the same pairs of clients always exchanged models, a client with an outlier distribution might only ever see one other distribution, limiting the diversity infusion. Random selection avoids this pitfall by making the communication graph among clients well-connected over time. In essence, the sequence of random peer interactions produces an effective gossip network that, in expectation, is fully mixing. This property is reminiscent of gossip averaging algorithms in distributed optimization, which are known to achieve consensus and convergence even with randomized communication patterns, as long as the expected network connectivity is sufficient [8]. Second, random peer selection introduces stochasticity that can help escape undesirable local minima or stationary points. From an optimization perspective, exposing a model to a random new dataset each round injects a form of perturbation that can jar the model out of overfitting to a particular client's local minimum. This contributes to model robustness. Importantly, the randomness is unbiased: every client has an equal probability of being selected as a peer for any other client. In summary, the stochastic peer selection in FedP2PAvg acts also as a regularizer.

3 Experimental Results

The experiments were conducted using the MNIST, Fashion-MNIST and CIFAR-10 datasets. To assess the performance of the proposed FedP2PAvg framework under highly imbalanced and non-IID conditions, the training data was distributed among ten nodes using a Dirichlet distribution with $\alpha = 0.1$. This setting is a commonly used setting to represent extreme heterogeneity in data distributions.

Each node was trained locally for ten epochs using stochastic gradient descent (SGD) with a learning rate of 0.01 and a momentum of 0.5. The MNIST and Fashion-MNIST datasets were trained over 140 communication rounds, using a network architecture consisting of two convolutional layers with max-pooling, followed by two fully connected layers, and incorporating dropout for regularization. The CIFAR-10 dataset was trained over 300 communication rounds, employing the VGG11 architecture, which features convolutional and pooling layers with ReLU activations, followed by fully connected layers.

We conducted five independent runs for each dataset using the same Dirichlet distribution with $\alpha = 0.1$. Following the methodology outlined by Guo et al. [5], we recorded the maximum test accuracy achieved during the training rounds for each run. The final results are reported as the mean of the maximum accuracies across the five runs. Additionally, we evaluated the number of communication rounds required to reach a threshold accuracy, demonstrating the efficiency of FedP2PAvg in achieving high accuracy with fewer communication rounds.

In FedP2PAvg, peer-to-peer (P2P) communication occurs after the local training phase. During this step, each node refines the model weights of a randomly selected peer for additional epochs. Although this P2P step is crucial for addressing the effects of data imbalance, it adds an overhead that is equivalent to 50% of the total number of communication rounds. The communication rounds reported in this study already include this overhead, ensuring a fair comparison with traditional methods.

The experimental results demonstrate the superiority of FedP2PAvg over baseline methods in both accuracy and communication efficiency. Table 1 presents a consolidated comparison of the proposed method against several state-of-the-art federated learning techniques on CIFAR-10, MNIST and Fashion-MNIST datasets under highly imbalanced non-IID settings ($\alpha = 0.1$). The results show that FedP2PAvg consistently achieves higher accuracy and requires significantly fewer communication rounds to reach target accuracy thresholds compared to classical approaches such as FedAvg and FedProx, as well as more recent methods like FedNova, FedCL, and FedGen. Moreover, while the methods FedDyn and FedDC achieve slightly higher final accuracy on CIFAR-10 (70.79% and 70.53%, respectively), they require over 1500 communication rounds to converge. In contrast, FedP2PAvg reaches 67.49% accuracy in only 200 rounds. At the 400-round mark (equivalent to FedP2PAvg when accounting for its peer communication step), FedDyn and FedDC remain at 65% accuracy. These findings underscore the efficiency of the peer-to-peer refinement strategy in accelerating convergence. Moreover, since FedP2PAvg is a general communication-level mechanism, it could potentially be integrated with algorithms like FedDyn and FedDC to further enhance their performance under extreme heterogeneity. Although the peer-to-peer step adds a secondary communication phase, it reduces the total rounds needed and complements optimization-level methods by improving update diversity and stability.

3.1 Ablation study

To better isolate the effect of the peer-to-peer refinement mechanism, we conducted an ablation study comparing FedP2PAvg with a simplified variant that skips the peer training phase and instead directly averages the locally trained models—effectively reducing to FedAvg under the same local training schedule. The results are illustrated in Figure 1, and confirm that the peer training step is responsible for substantial improvements in both accuracy and convergence speed, particularly in highly heterogeneous settings. Moreover, we extended the comparison to larger client populations (100 clients), where the benefits of FedP2PAvg persist. Regarding communication overhead, we emphasize that the number of bytes transmitted per round is exactly the same across both methods, since the full model is exchanged in either case. The key distinction is that each round of FedP2PAvg includes an additional peer refinement phase, effectively corresponding to two communication steps per global round. However, this does not increase per-message size, only the number of transmissions and Figure 1 already takes it in account since it is doubling the number of epochs considered for the FedP2PAvg. It is worth noting that our evaluation assumes uniform network costs, and that in real-world scenarios, the P2P step may incur additional latency if peer nodes are geographically distant or connected via low-bandwidth links.

Table 1: Comparison of federated learning methods on CIFAR-10 and MNIST with $\alpha = 0.1$. Accuracy values include source citation. Rounds indicate the number required to reach 55% (CIFAR-10), 91% (MNIST), or 70% (Fashion-MNIST) accuracy.

Method	Dataset	Accuracy (%)	Rounds to Threshold
FedAvg	CIFAR-10	58.99 [5]	736
	MNIST	91.13 [18]	400
	Fashion-MNIST	69.94 [13]	—
FedProx	CIFAR-10	59.14 [5]	738
	MNIST	90.69 [18]	146
	Fashion-MNIST	63.81 [13]	—
Moon	CIFAR-10	58.23 [5]	820
DANN	CIFAR-10	58.29 [5]	782
GroupDRO	CIFAR-10	56.57 [5]	835
FedBR	CIFAR-10	64.65 [5]	496
SCAFFOLD	CIFAR-10	43.50 ± 10.50 [19]	—
AFL	CIFAR-10	53.40 ± 11.50 [19]	—
FedNova	CIFAR-10	66.31 ± 0.86 [17]	—
FedDyn	CIFAR-10	65.00 (393) / 70.79 (1.5k) [10]	—
FedDC	CIFAR-10	65.00 (364) / 70.53 (1.5k) [10]	—
FedEnsemble	MNIST	91.60 [18]	132
FedDistill	MNIST	58.03 [18]	—
FedGen	MNIST	95.86 [18]	48
FedCL	MNIST	96.03 [18]	44
FedALC	Fashion-MNIST	72.38 [13]	—
FedP2PAvg (Ours)	CIFAR-10	**67.49 ± 2.44**	**125**
	MNIST	**98.17 ± 0.23**	**16**
	Fashion-MNIST	**84.35 ± 0.23**	**20**

Nevertheless, since peer interactions are parallel and randomized, their practical impact can often be mitigated through architectural optimizations.

3.2 Discussion

The experimental findings confirm that FedP2PAvg consistently outperforms prior federated learning methods, achieving both higher accuracy and faster convergence under extreme data heterogeneity. These results highlight that the peer-to-peer refinement step can effectively tackle the notorious client drift problem, enabling rapid knowledge integration from disparate clients and yielding a superior global model.

Compared to classical federated algorithms, FedP2PAvg demonstrates clear advantages in both final model quality and training efficiency. For instance, *FedAvg* and *FedProx* struggled on CIFAR-10 $\alpha = 0.1$, reaching only about 59% accuracy and requiring over 700 communication rounds to attain 55% accuracy. FedP2PAvg not only boosts the accuracy by nearly 8 percentage points in this challenging setting (reaching $\sim 67.5\%$ vs. $\sim 59\%$), but also slashes the communication rounds needed by an order of magnitude (125 rounds vs. 736+). Even when compared to more sophisticated baselines designed for non-IID data, our method excels.

Beyond the empirical metrics, it is instructive to examine why FedP2PAvg performs so well under extreme non-IID settings. The peer-to-peer refinement strategy in FedP2PAvg provides a theoretically grounded approach to tackling

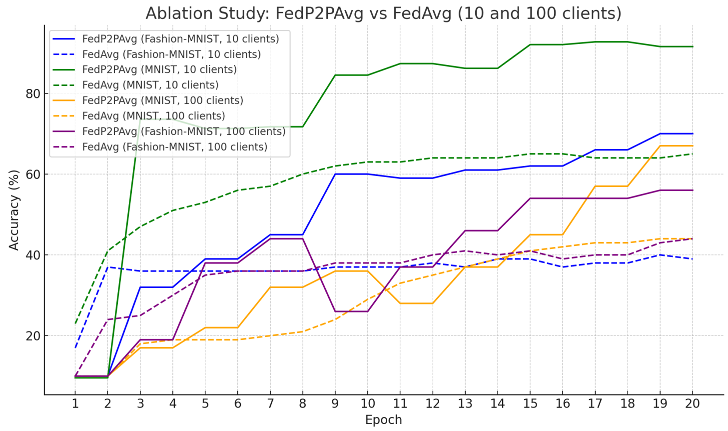

Fig. 1: Ablation study comparing FedP2PAvg and its variant without peer-to-peer refinement, across different datasets and number of clients.

fundamental challenges of federated learning on imbalanced data. By blending ideas from decentralized "gossip" learning and classical FedAvg, the approach benefits from variance reduction and bias correction without requiring additional gradient exchanges. Each peer interaction can be seen as a lightweight form of collaborative training that moves the federated system closer to the ideal scenario where each client's update comes from a more globally representative dataset.

In essence, when a model trained on one client is further trained on a randomly selected peer's data, the resulting update carries information from two distinct distributions. Over many rounds, the sequence of random pairings produces an effectively well-mixed communication graph. No single client or subset of clients can dominate the training since peer selection is unbiased and uniformly random. This stochastic peer mixing acts as a regularizer: it injects a mild perturbation each round (by exposing models to a new data distribution) which helps to shake the training process out of any tendency to overfit to peculiarities of one client's data or to get stuck in local minima.

It is also important to note that real-world applications such as healthcare provide a compelling context for FedP2PAvg, where data is often siloed, highly heterogeneous, and privacy-sensitive. For example, hospitals may hold patient records with varying demographics, equipment, and labeling standards, making model generalization across sites particularly challenging. The peer-to-peer refinement mechanism in FedP2PAvg can help bridge such disparities by facilitating indirect cross-site knowledge sharing. However, the model-sharing process introduces privacy considerations that warrant further attention. Although raw data is never exchanged, sharing intermediate models may still reveal sensitive patterns through inversion or membership inference attacks. Future work should explore privacy-preserving enhancements such as secure aggregation or differential privacy to ensure that the benefits of peer refinement are not offset by privacy risks.

3.3 Limitations

Notwithstanding its benefits, FedP2PAvg also comes with certain trade-offs and limitations. First, the introduction of a peer-to-peer model exchange in each round increases the communication overhead. Each client must transmit its model to a peer and the peer then sends a refined model back to the server, effectively adding an extra communication step per round on top of the standard FedAvg communication. In our implementation this meant roughly 50% more model transmissions in each global round (each client sends one additional copy of its model over the network). While our results show that even considering this overhead the total number of rounds to convergence is greatly reduced (outweighing the per-round overhead), in bandwidth-constrained or high-latency networks this extra communication could be significant. Techniques to compress model updates or to select only a subset of clients for peer exchange in each round might be necessary for better scalability.

Second, FedP2PAvg's effectiveness may depend on the quality of peer selection. We used random peer pairing, which in expectation is fair and unbiased, but randomness can also lead to suboptimal pairings in the short term. For example, it is possible (though unlikely) that a given client is paired with a particularly low-quality or outlier peer several times in a row; in such cases the benefits of peer refinement might temporarily diminish. We did observe a slightly higher variance in FedP2PAvg's performance across runs (see the larger standard deviation in accuracy in Table 1 for our method in CIFAR-10 dataset, 2.44 vs 0.86 for FedNova), which could be attributed to the stochastic nature of the peer exchanges. More sophisticated peer-matching strategies (e.g., ensuring diverse or complementary peers, or gradually adapting peer selection based on past contributions) could potentially further improve robustness, but at the cost of added complexity.

Third, the current FedP2PAvg framework assumes a synchronous training round with participation of all clients and a central server to coordinate the global aggregation. In networks with a very large number of clients or with clients frequently dropping in and out, coordinating pairwise exchanges for every client each round might become difficult. Although peer exchanges are inherently parallel (and could even be done in a decentralized fashion), the server still needs to collect all refined models for aggregation. This could introduce a bottleneck if N (the number of clients) is extremely large, or if clients are spread across unreliable connections. In practice, one might limit the frequency of peer-to-peer refinement (e.g., perform it every few rounds instead of every round) to alleviate load, or resort to clustering clients so that peer exchange happens within smaller groups. These considerations suggest that while FedP2PAvg is highly effective in the tested scale (tens of clients), further work is needed to adapt it to scenarios with hundreds or thousands of clients and harsher network conditions.

4 Concluding Remarks

This study presented FedP2PAvg, a novel framework for federated learning that combines peer-to-peer model refinement with global aggregation to address challenges posed by highly imbalanced and non-IID data distributions. Experimental results on CIFAR-10 and MNIST datasets demonstrated the superiority of FedP2PAvg in terms of accuracy and communication efficiency. The peer-to-peer refinement step proved particularly effective in leveraging nodes' computational resources to train models collaboratively, fostering a sense of shared growth and collaboration within the community of participating nodes. This approach is particularly suited for scenarios where inter-peer communication is feasible, enabling nodes to contribute by training local models and refining models originating from other clients.

Future Directions. Future work can explore hybrid federated learning frameworks integrating FedP2PAvg with other decentralized methods. Exploring personalized federated learning with tailored peer-selection strategies based on data similarity and adaptive pairing could enhance robustness and improve accuracy for minority classes. Additionally, incorporating techniques like model compression could further reduce communication overhead, promoting practical deployment in edge computing environments.

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