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Communication-Efficient FedProx-Binary FedVote for Dual-Task Wi-Fi Fingerprint Indoor Localization

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Abstract

Wi-Fi fingerprinting is a practical solution for wireless indoor localization because it can reuse existing access points without additional positioning infrastructure. Federated learning enables collaborative model training without uploading raw fingerprint data, but standard FedAvg still requires clients to transmit full-precision model updates, resulting in high uplink communication cost. This paper proposes a communication-efficient FedProx-Binary FedVote method for Building-Floor dual-task Wi-Fi fingerprint localization. A lightweight dual-task MLP is first constructed to predict both building and floor labels. To reduce client-to-server communication, a Binary FedVote-style aggregation strategy is adopted, where clients upload only 1-bit update directions instead of 32-bit full-precision updates. To improve robustness under Strong Non-IID data partitioning, a FedProx regularization term is further introduced into local training to reduce client drift and stabilize binary direction voting. Experiments on the UJIIndoorLoc dataset show that, under the Moderate Non-IID setting, Binary FedVote-style reduces the upload communication from about 200.33 MB to about 6.26 MB while maintaining a comparable Dual Accuracy to FedAvg. Under the Strong Non-IID setting,

FedProx-Binary FedVote improves the mean Final Dual Accuracy from 0.6976 to 0.8691 without increasing the 1-bit uplink communication cost.

Keywords: Wi-Fi fingerprinting; federated learning; wireless indoor localization; uplink communication compression; FedVote; Non-IID data

1. Introduction

In wireless network environments such as smart buildings, campuses, hospitals, and shopping malls, indoor localization provides fundamental support for location-aware services, mobile navigation, personnel management, and asset tracking. In outdoor environments, positioning systems such as GPS are widely used, but their performance degrades significantly indoors due to signal blockage and multipath propagation. For this reason, indoor localization often relies on signals that are already available inside buildings[1–3], such as Wi-Fi, Bluetooth, ultra-wideband, or inertial sensor measurements. Among them, Wi-Fi fingerprinting remains attractive because it can make use of existing wireless access points and does not require additional deployment cost.

A typical Wi-Fi fingerprinting system first collects received signal strength indicator (RSSI) values at known locations. A learning model is then trained to map RSSI fingerprints to position-related labels or coordinates[4, 5]. In large indoor environments such as campuses, hospitals, and shopping malls, localization is often required across multiple buildings and multiple floors[6–8]. Therefore, in addition to estimating a physical position, it is also important to correctly identify the building and floor where a user is located. This motivates the Building-Floor dual-task formulation adopted in this paper.

Early Wi-Fi fingerprinting studies mostly used centralized training, where all fingerprints were uploaded to a central server for model construction[9]. Although this paradigm is convenient for model training, it is not always practical in real wireless network environments. Fingerprint data may be

collected by different mobile devices, floors, buildings, or local edge nodes[10]. Directly uploading these data may increase client-to-server uplink traffic in wireless networks. It may also expose information about users' spatial traces or the surrounding wireless environment.

Federated learning provides a feasible solution to this problem by allowing multiple clients to collaboratively train a shared model while keeping raw fingerprint data locally. In a typical federated learning process, each client trains the model using its own local data and uploads model parameters or model updates to the server for aggregation. FedAvg is one of the most widely used aggregation methods[11], in which the server updates the global model by weighted averaging of local client models. However, although federated learning avoids the direct uploading of raw Wi-Fi fingerprints, standard FedAvg still requires clients to transmit full-precision model updates in each communication round. When the number of clients or communication rounds increases, the client-to-server uplink communication cost becomes non-negligible, especially for bandwidth- or energy-constrained wireless clients[12–14].

To reduce the communication cost of distributed and federated learning, existing studies have explored different compression strategies, such as gradient quantization, ternary gradients, sign-based optimization, deep gradient compression, and quantized federated averaging[15–20]. These methods show that model updates or gradients can be represented with fewer bits to reduce communication overhead. Among them, sign-based and voting-based aggregation methods are particularly related to this work, because they replace full-precision update values with low-bit signs or binary representations. Inspired by FedVote, this paper adopts a Binary FedVote-style direction voting strategy for federated Wi-Fi fingerprint localization. Different from uploading 32-bit floating-point

updates, each client only uploads the 1-bit direction of its local model update, and the server obtains the global update direction through weighted voting.

Although Binary FedVote-style aggregation can significantly reduce uplink communication, its stability may be affected by client data heterogeneity. In Wi-Fi fingerprint localization, different clients may correspond to different buildings, floors, or local areas, and their local fingerprint distributions can be highly different[21–23]. Under Strong Non-IID data partitioning, each client tends to optimize the model toward its own local data distribution, which may lead to client drift and inconsistent local update directions. For full-precision aggregation, both the magnitude and direction of local updates can be used during aggregation. In contrast, Binary FedVote-style aggregation only preserves the sign of local updates. Therefore, when the local update directions become inconsistent across clients, the voted global direction may become unreliable.

To improve the robustness of binary direction voting under strong data heterogeneity, this paper introduces a FedProx regularization term into local training. The proximal term restricts the local model from moving too far away from the current global model, thereby reducing client drift and improving the consistency of uploaded binary directions. In this way, FedProx does not directly reduce communication cost, but it stabilizes the 1-bit voting process under Strong Non-IID fingerprint distributions. Since the uploaded information remains binary direction data, the proposed FedProx-Binary FedVote method keeps the same uplink communication cost as Binary FedVote-style while improving localization performance[20, 24].

Based on the above considerations, this paper studies a communication-efficient FedProx-Binary FedVote method for Building-Floor dual-task Wi-Fi fingerprint localization. A lightweight dual-task MLP is used to predict both Building and Floor labels, and Dual Accuracy is adopted to evaluate

whether the two labels are correctly predicted at the same time[6, 8, 25]. Experiments are conducted on the UJIIndoorLoc dataset[26] under Moderate Non-IID and Strong Non-IID settings to evaluate the localization performance, communication cost, and robustness of the proposed method.

Recent studies have applied federated learning to indoor localization and Wi-Fi fingerprinting tasks, including multibuilding and multifloor fingerprint localization, model-reliability-based indoor localization, non-IID fingerprint database analysis, heterogeneity-resilient localization, federated distillation, personalized Wi-Fi fingerprint localization, and privacy-preserving hierarchical localization[8, 25, 27–32]. However, these studies mainly focus on localization accuracy, model reliability, personalization, privacy preservation, or hierarchical localization. Low-bit client-to-server uplink compression and the stability of voting-based aggregation under Strong Non-IID fingerprint distributions remain less explored.

The main contributions of this work are summarized as follows.

(1) We formulate Wi-Fi fingerprint indoor localization as a Building-Floor dual-task federated learning problem. In addition to Building Accuracy and Floor Accuracy, we use Dual Accuracy to evaluate whether both labels are predicted correctly at the same time.

(2) We apply Binary FedVote-style low-bit direction voting to federated Wi-Fi fingerprint localization. Under the Moderate Non-IID setting, it achieves a similar Dual Accuracy to FedAvg while reducing the client-to-server uplink communication from about 200.33 MB to about 6.26 MB.

(3) We design a FedProx-enhanced binary voting mechanism to improve the robustness of low-bit aggregation under Strong Non-IID fingerprint distributions. The proximal regularization reduces client drift and improves the consistency of uploaded binary update directions, thereby stabilizing the voting-based aggregation without increasing the uplink communication cost.

The rest of this paper is organized as follows. Section 2 describes the system model and problem formulation. Section 3 introduces the proposed FedProx-Binary FedVote method. Section 4 analyzes the communication cost. Section 5 presents the experimental results. Section 6 concludes the paper.

2. System Model and Problem Formulation

2.1 Federated Wi-Fi Fingerprint Localization Model

We consider a standard client-server federated learning system for Wi-Fi fingerprint localization. The system contains one central server and K clients. Each client stores a local set of Wi-Fi fingerprints, while the server maintains the global localization model. During training, the server sends the current global model to clients. Each client performs local training and uploads its model update or compressed update information to the server. The server aggregates the uploaded information and updates the global model for the next round.

Let the local dataset of client k be:

$$D_k=(x_i,y_i^b,y_i^f)_{i=1}^{n_k} \tag{1}$$

where x_i is the Wi-Fi RSSI fingerprint of sample i, y_i^b is the Building label, y_i^f is the Floor label, and n_k is the number of samples on client k. In this work, x_i is a 520-dimensional RSSI vector from the UJIIndoorLoc datase[26]t.

The global optimization objective can be written as:

$$\min_{\theta} \sum_{k=1}^{K} \frac{n_k}{n} L_k(\theta) \tag{2}$$

where θ denotes the global model parameters, $L_k(\theta)$ is the local loss on client k, and $n=\sum_{k=1}^{K} n_k$ is the total number of training samples. The goal is not only to optimize the localization performance, but also to reduce the amount of uplink information transmitted from clients to the server.

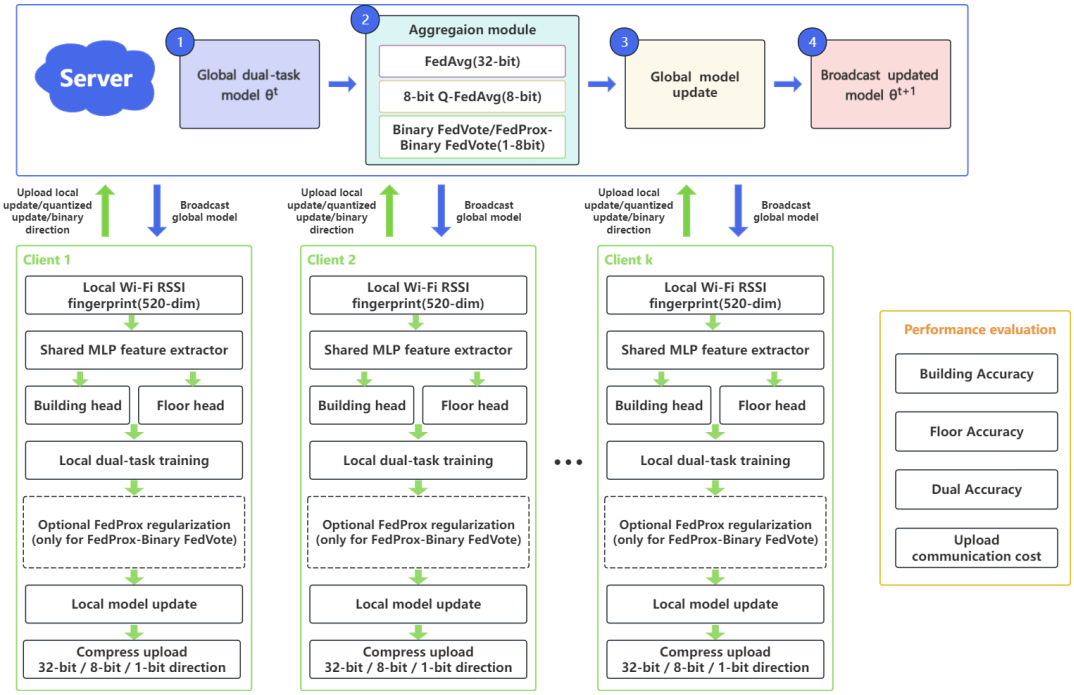


Fig. 1 Overall framework of communication-efficient federated Wi-Fi fingerprint dual-task localization

2.2 Dual-Task Localization Model

The localization model used in this paper is a lightweight dual-task MLP. Similar hierarchical Building-Floor formulations have been considered in multi-building and multi-floor indoor localization studies[6–8]. The model first extracts a shared representation from the RSSI fingerprint. Then two task-specific heads are used to predict the Building and Floor labels, respectively:

$$\mathrm{h}_i = g(x_i;\theta_s) \tag{3}$$

$$\hat{y}_i^b = f_b(\mathrm{h}_i;\theta_b), \quad \hat{y}_i^f = f_f(\mathrm{h}_i;\theta_f) \tag{4}$$

where $g(\cdot)$ is the shared feature extractor, $f_b(\cdot)$ is the Building classifier, and $f_f(\cdot)$ is the Floor classifier.

For client k, the local dual-task loss is defined as:

$$L_k(\theta) = L_{building,k}(\theta) + \alpha L_{floor,k}(\theta) \tag{5}$$

where $L_{building,k}(\theta)$ and $L_{floor,k}(\theta)$ denote the Building and Floor classification losses computed on the local data of client k, respectively. The coefficient α is used to control the contribution of the Floor

classification task. Since Building classification is relatively easier in UJIIndoorLoc, while Floor prediction has a stronger influence on Dual Accuracy, an inappropriate α may lead to task imbalance. Therefore, α is treated as a hyperparameter and determined through sensitivity analysis. In the following experiments, α is fixed to 0.7 because it provides a relatively stable trade-off between Building Accuracy and Floor Accuracy under the adopted model and data partition settings.

We use Building Accuracy, Floor Accuracy, and Dual Accuracy as evaluation metrics. Dual Accuracy is defined as:

$$Acc_{dual}=\frac{1}{N}\sum_{i=1}^{N} I(\hat{y}_i^b=y_i^b,\hat{y}_i^f=y_i^f) \tag{6}$$

where N is the number of test samples and $I(\cdot)$ is the indicator function. A test sample is counted as correct only when both the Building and Floor labels are predicted correctly. For this reason, Dual Accuracy is used as the main performance metric in this paper.

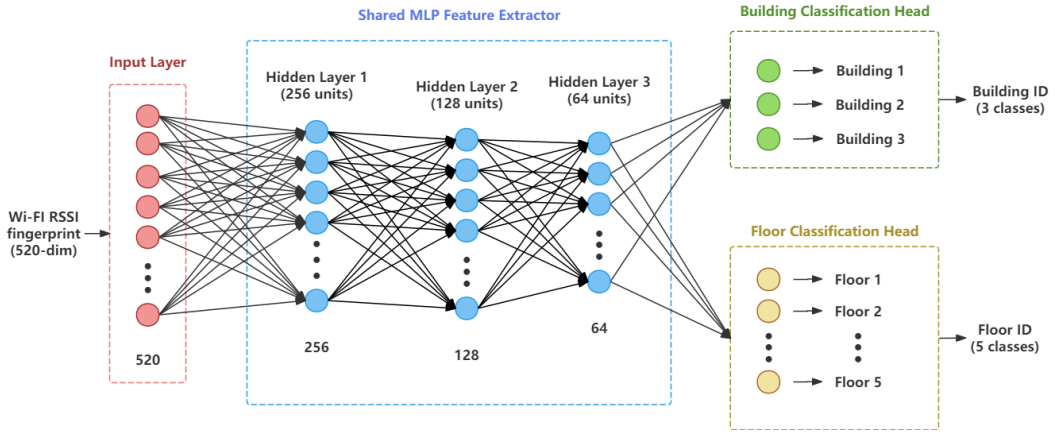


Fig. 2 Architecture of the Building-Floor dual-task MLP

3. FedProx-Binary FedVote for Federated Localization

3.1 FedAvg and 8-bit Q-FedAvg Baselines

FedAvg aggregates local models by weighted averaging. At communication round t, the global model is updated as:

$$\theta^{t+1}=\sum_{k=1}^{K}\frac{n_k}{n}\theta_k^{t+1} \tag{7}$$

where θ_k^{t+1} is the local model after client k completes local training. FedAvg is used as the full-precision federated learning baseline[11]. In the communication analysis, each uploaded parameter is counted as 32 bits.

We also use 8-bit Quantized FedAvg as a compressed communication baseline, following the general idea of update quantization in communication-efficient distributed and federated learning[15, 19] . This baseline is useful because it represents a moderate compression level between full-precision FedAvg and 1-bit direction voting.

3.2 Binary FedVote-Style Direction Voting

Binary FedVote-style aggregation is related to sign-based distributed optimization and voting-based federated aggregation, which use low-bit signs or binary representations to reduce communication[17, 20]. The local update of client k at round t is:

$$\Delta_k^t=\theta_k^{t+1}-\theta^t \tag{8}$$

Instead of uploading Δ_k^t, the client uploads its sign direction. The server obtains the global voting direction by weighted direction voting:

$$v^t=sign(\sum_{k=1}^{K}\frac{n_k}{n}sign(\Delta_k^t)) \tag{9}$$

Here, v^t is the global voting direction and $sign(\cdot)$ is the sign function. Since each parameter only needs a binary direction, the uplink cost is reduced to 1 bit per parameter. In this work, the server updates the global model according to the voted direction and a predefined server update step size η_s, without requiring clients to upload full-precision update magnitudes.

3.3 FedProx-Binary FedVote

Binary FedVote-style is effective in reducing uplink communication cost, but it can be unstable when the client data are highly heterogeneous. In the Strong Non-IID setting, different clients may mainly contain samples from different buildings. Local training can then move each local model toward its own data distribution, and the uploaded directions may conflict with each other.

To reduce this client drift, we add a FedProx regularization term to the local objective[24]. The local training objective becomes:

$$L_k^{prox}(\theta)=L_k(\theta)+\frac{\mu}{2}\|\theta-\theta^t\|^2 \tag{10}$$

where μ is the FedProx coefficient and θ^t is the global model sent by the server at round t. This regularization term restricts the local model from moving too far away from the global model.

The role of the FedProx term in the proposed method is closely related to the reliability of binary direction voting. Under Strong Non-IID data partitioning, each client tends to optimize the model toward its own local data distribution, which may lead to large deviations between local models and the global model, which may lead to large deviations between local models and the global model[21, 22, 24]. For a full-precision aggregation method, both the magnitude and the direction of local updates can be used during aggregation. In contrast, Binary FedVote-style aggregation only preserves the sign of each local update. Therefore, when local update directions become inconsistent across clients, the voted global direction may become unreliable.

By adding a proximal term to the local objective, FedProx restricts each local model from moving too far away from the current global model. This constraint reduces client drift and makes the local update directions more consistent across heterogeneous clients. As a result, the binary signs uploaded by clients become more reliable for server-side voting. In this sense, FedProx does not directly reduce

communication cost, but it improves the stability of the 1-bit voting process under strong data heterogeneity. Since the uploaded information remains binary direction data, the proposed FedProx-Binary FedVote method keeps the same uplink communication cost as Binary FedVote-style while improving localization performance.

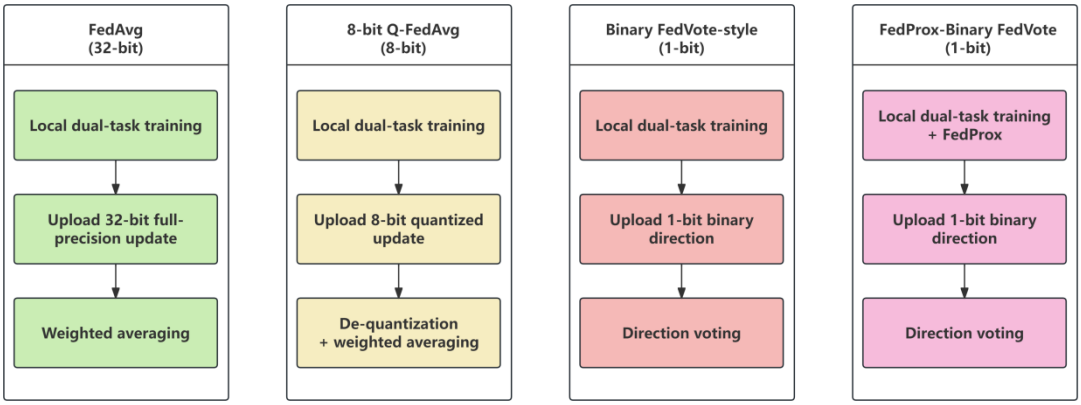


Fig. 3 Aggregation mechanism comparison

3.4 Algorithm Procedure

Algorithm 1 summarizes the training process of FedProx-Binary FedVote. The server initializes a global dual-task MLP and broadcasts it to all clients. Each client performs local training with the FedProx objective, computes the local update direction, and uploads the binary direction to the server. The server then performs direction voting and updates the global model.

Algorithm 1: FedProx-Binary FedVote for Federated Wi-Fi Fingerprint Localization

Input: Client datasets $\{D_k\}_{k=1}^{K}$, initial global model θ^0, communication rounds T, local epochs E, local learning rate η, server learning rate η_s, FedProx coefficient μ, floor loss weight α

Output: Trained global dual-task localization model θ^T

1: Initialize global model θ^0 on the server.

2: for t = 0,1,...,T-1 do

3: Server broadcasts θ^t to all clients

4: for each client k = 1,2,...,K in parallel do

5: Initialize local model $\theta_k^t \leftarrow \theta^t$

6: for local epoch e = 1,2,...,E do

7: Sample a mini-batch from D_k

8: Compute Building loss $L_{building,k}(\theta)$ and Floor loss $L_{floor,k}(\theta)$

9: Compute local task loss $L_k(\theta)=L_{building,k}(\theta)+\alpha L_{floor,k}(\theta)$

10: Compute FedProx loss $L_k^{prox}(\theta)=L_k(\theta)+(\mu/2)\|\theta-\theta^t\|^2$

11: Update local model parameters using Adam

12: end for

13: Compute local update $\Delta_k^t=\theta_k^{t+1}-\theta^t$

14: Extract binary update direction $s_k^t=sign(\Delta_k^t)$

15: Upload s_k^t and local sample size n_k to the server

16: end for

17: Compute global voting direction $v^t=sign(\Sigma_{k=1}^K(n_k/n)s_k^t)$

18: Update global model according to the voted direction and server learning rate η_s

19: end for

20: return θ^T

4. Communication Complexity

We focus on the uplink communication from clients to the server.This bit-level communication accounting is commonly used in communication-efficient federated and distributed learning studies[15, 19, 20]. Suppose the model has P trainable parameters, the number of clients is K, the number of

communication rounds is T, and each parameter is represented by b bits. The total uplink communication cost C is calculated as:

$$C=\frac{P\times b\times K\times T}{8\times 1024^2} \tag{11}$$

The unit of C is MB. In this paper, FedAvg uses 32 bits per parameter, 8-bit Q-FedAvg uses 8 bits per parameter, and both Binary FedVote-style and FedProx-Binary FedVote use 1 bit per parameter.

Table 1 Uplink bit-width of different aggregation methods

Method	**Bits per parameter**	**Description**
FedAvg	32	Full-precision update
8-bit Q-FedAvg	8	Quantized update
Binary FedVote-style	1	1-bit direction voting
FedProx-Binary Fedvote	1	FedProx local regularization + 1-bit direction voting

The compression ratio over FedAvg is defined as:

$$R=\frac{C_{FedAvg}}{C_{method}} \tag{12}$$

where C_{FedAvg} is the uplink communication of FedAvg and C_{method} is the uplink communication of the compared method. Under the same model size, client number, and communication rounds, Binary FedVote-style and FedProx-Binary FedVote can theoretically achieve about 32× uplink compression compared with FedAvg.

5. Experimental Evaluation

5.1 Experimental Setup

Experiments are conducted on the UJIIndoorLoc dataset[26]. Each sample is represented by a 520-dimensional Wi-Fi RSSI fingerprint. In the processed dataset used in this study, the Building task

contains 3 classes and the Floor task contains 5 classes. Therefore, the dual-task MLP uses a 3-dimensional output for Building classification and a 5-dimensional output for Floor classification.

The dataset is divided into 10 clients to simulate a federated indoor localization scenario. Two Non-IID partitions are considered. In the Moderate Non-IID setting, each client mainly contains samples from one Building class, while still keeping a certain proportion of samples from other classes. In the Strong Non-IID setting, each client is more concentrated on a single Building class, which creates a more challenging heterogeneous training condition.Such partition settings are used to simulate statistical heterogeneity across federated clients, which is a common challenge in federated learning[21–23].

The main experiments use 30 communication rounds and one local epoch. The batch size is set to 64, the learning rate is 0.001, and Adam is used as the optimizer with a weight decay of 1e-4. The floor-loss weight α is selected through a sensitivity analysis, as shown in Fig. 5. The setting $\alpha = 0.7$ achieves the best Dual Accuracy in this experiment and provides a stable balance between Floor prediction and dual-task localization. Therefore, α is fixed to 0.7 in the subsequent experiments.

For the Strong Non-IID ablation experiments, five random seeds, namely 42, 43, 44, 45, and 46, are used, and the reported results are averaged to reduce the influence of random initialization and client partitioning.

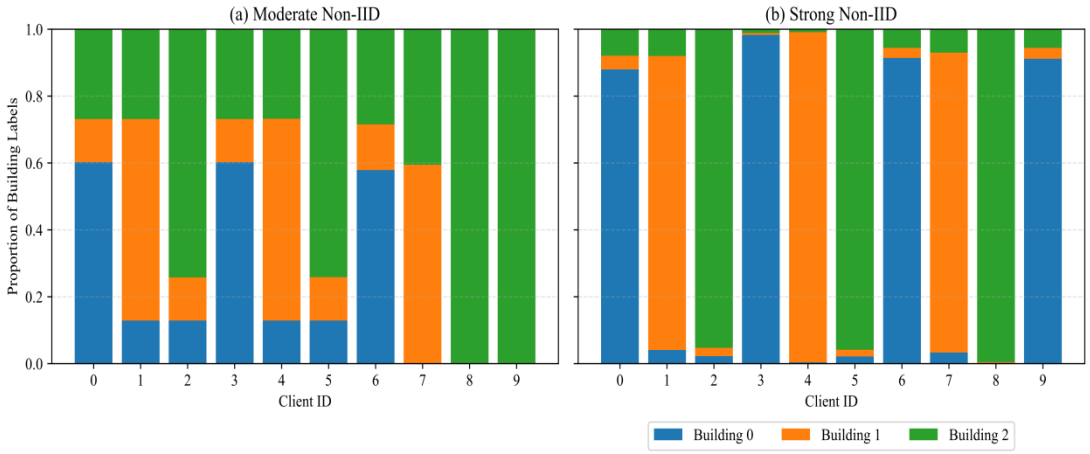


Fig. 4 Building label distributions under Moderate and Strong Non-IID partitions

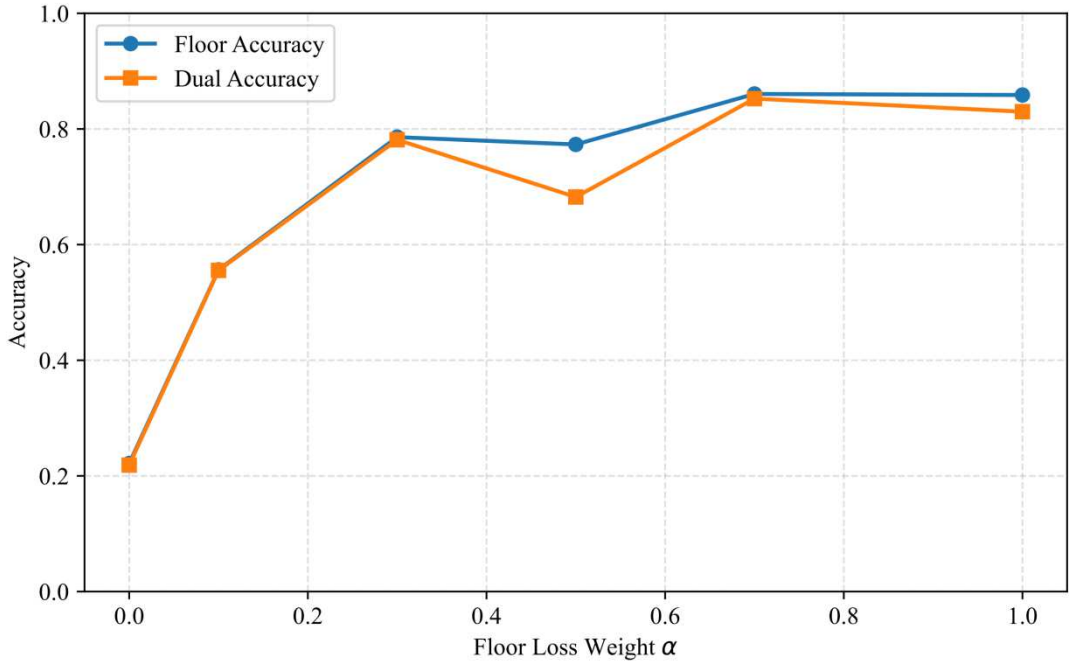


Fig. 5 Sensitivity analysis of the floor-loss weight α

We first use Centralized Dual MLP to verify whether the processed data and the dual-task model are learnable. In federated settings, we compare FedAvg, 8-bit Q-FedAvg, Binary FedVote-style, and FedProx-Binary FedVote. The main evaluation metrics include Building Accuracy, Floor Accuracy, Dual Accuracy, total uplink communication, and the compression ratio over FedAvg.

Table 2 Experimental settings

Parameter	**Value**
Dataset	UJIIndoorLoc
Input feature	520-dimensional Wi-Fi RSSI fingerprint
Building classes	3
Floor classes	5
Number of clients	10
Communication rounds	30
Local epochs	1
Batch size	64
Optimizer	Adam
Local learning rate	0.001
Server update step size η_s	1.0 (FedVote-style methods)
Floor loss weight α	0.7
FedProx coefficient μ	0.001
Evaluation metrics	Building Acc., Floor Acc., Dual Acc., uplink communication

5.2 Baseline Results

The centralized Dual MLP achieves a Building Accuracy of 1.0000, while the Floor Accuracy and Dual Accuracy are both about 0.9127. This result shows that the preprocessing pipeline and the dual-task MLP are reasonable. It also confirms that Building classification is relatively easy on this dataset, while Floor classification is the main factor that limits Dual Accuracy.

FedAvg performs close to the centralized model under IID and Moderate Non-IID settings. Under Strong Non-IID, however, its performance decreases because the local client distributions become more biaseda are a key challenge in federated Wi-Fi fingerprint localization.The performance degradation under Strong Non-IID is further analyzed in Section 5.6.

Table 3 Baseline performance of Centralized Dual MLP and FedAvg

Method	**Data setting**	**Building Accuracy**	**Floor Accuracy**	**Dual Accuracy**	**Uplink Communication**
Centralized Dual MLP	Centralized	1.0000	0.9127	0.9127	N/A
FedAvg	IID	0.9982	0.9109	0.9091	200.33 MB
FedAvg	Moderate Non-IID	0.9964	0.9127	0.9100	200.33 MB

5.3 Communication-Efficient Aggregation Results

Table 4 compares FedAvg, 8-bit Q-FedAvg, and Binary FedVote-style under the Moderate Non-IID setting. FedAvg obtains a Dual Accuracy of about 0.9100 with about 200.33 MB uplink communication. 8-bit Q-FedAvg reduces the communication to about 50.08 MB and keeps a similar Dual Accuracy of about 0.9091. Binary FedVote-style further reduces the uplink communication to about 6.26 MB, while the Dual Accuracy remains around 0.9118.

Table 4 Communication compression performance under the Moderate Non-IID setting

Method	**Upload Precision**	**Dual Accuracy**	**Uplink Communication**	**Compression Ratio**
FedAvg	32-bit	0.9100	200.33 MB	1.00×
8-bit Q-FedAvg	8-bit	0.9091	50.08 MB	4.00×

Binary FedVote-style	1-bit	0.9118	6.26 MB	32.00×

Note: The compression ratio is calculated relative to FedAvg.

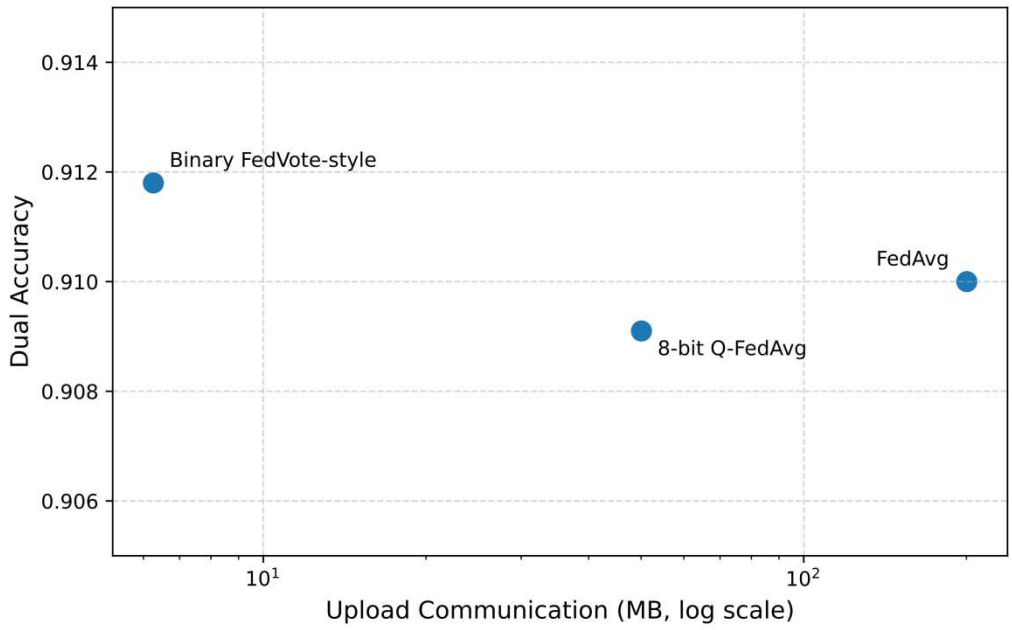


Fig. 6 Trade-off between upload communication and Dual Accuracy under the Moderate Non-IID setting

These results suggest that 1-bit direction voting is sufficient for this dual-task localization problem under Moderate Non-IID. Compared with FedAvg, Binary FedVote-style saves most of the uplink communication without causing a clear loss in Dual Accuracy.

The above results show that Binary FedVote-style is effective under the Moderate Non-IID setting. We next examine whether the main floor-recognition pattern is preserved after using 1-bit direction voting.

5.4 Floor Confusion Analysis

Since the Building classification task is relatively easy in the Moderate Non-IID setting, we further analyze the Floor classification results using confusion matrices. As shown in Fig. 7, the predictions of

both FedAvg and Binary FedVote-style are mainly concentrated near the diagonal, indicating that the two methods can correctly distinguish most Floor labels.

The remaining misclassifications mainly occur between adjacent floors. This is reasonable because Wi-Fi RSSI fingerprints collected from adjacent floors may share similar signal patterns, leading to a higher probability of confusion. Compared with FedAvg, Binary FedVote-style shows a similar floor-recognition pattern, which suggests that the 1-bit direction voting strategy preserves the main discriminative ability for Floor classification while significantly reducing the upload communication cost.

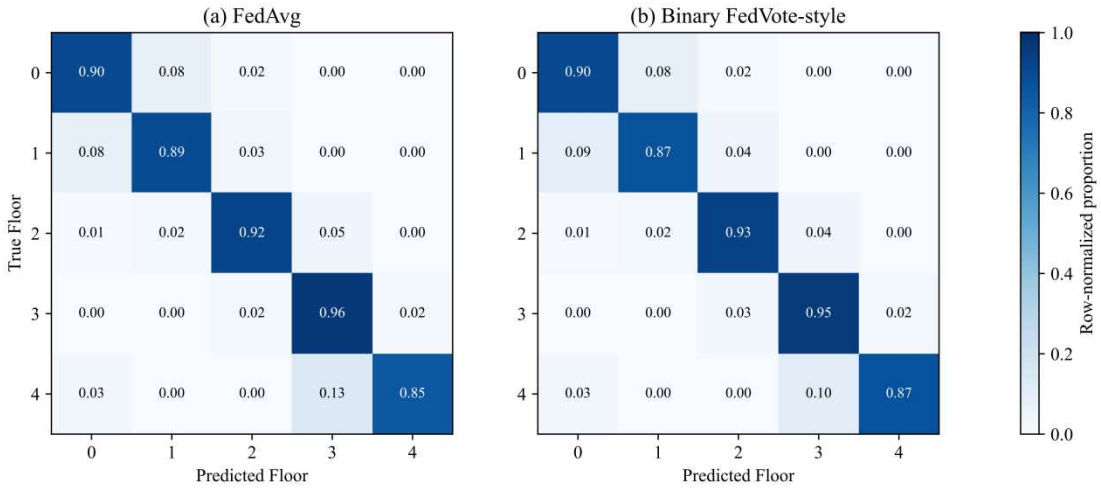


Fig. 7 Floor confusion matrices of FedAvg and Binary FedVote-style under the Moderate Non-IID setting

5.5 Convergence and Communication Rounds

To justify the use of 30 communication rounds, we further conduct 100-round experiments. As shown in Fig. 8 and Fig. 9, both FedAvg and Binary FedVote-style improve rapidly in the early rounds. The test loss decreases sharply within the first several rounds, and Dual Accuracy becomes relatively stable after about 20 communication rounds. After 30 rounds, further training brings only limited improvement. Meanwhile, as shown in Fig. 10, the cumulative upload communication increases almost

linearly with the number of communication rounds. Therefore, 30 rounds are used in the main experiments to ensure stable convergence while avoiding unnecessary uplink communication cost.

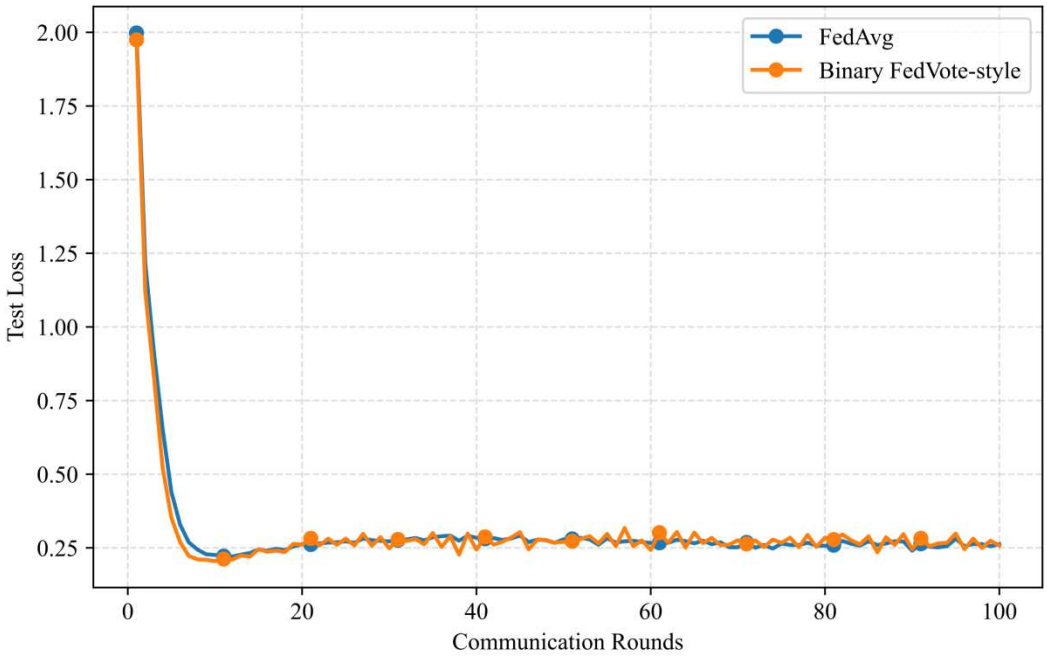


Fig. 8 Test loss convergence curves over communication rounds

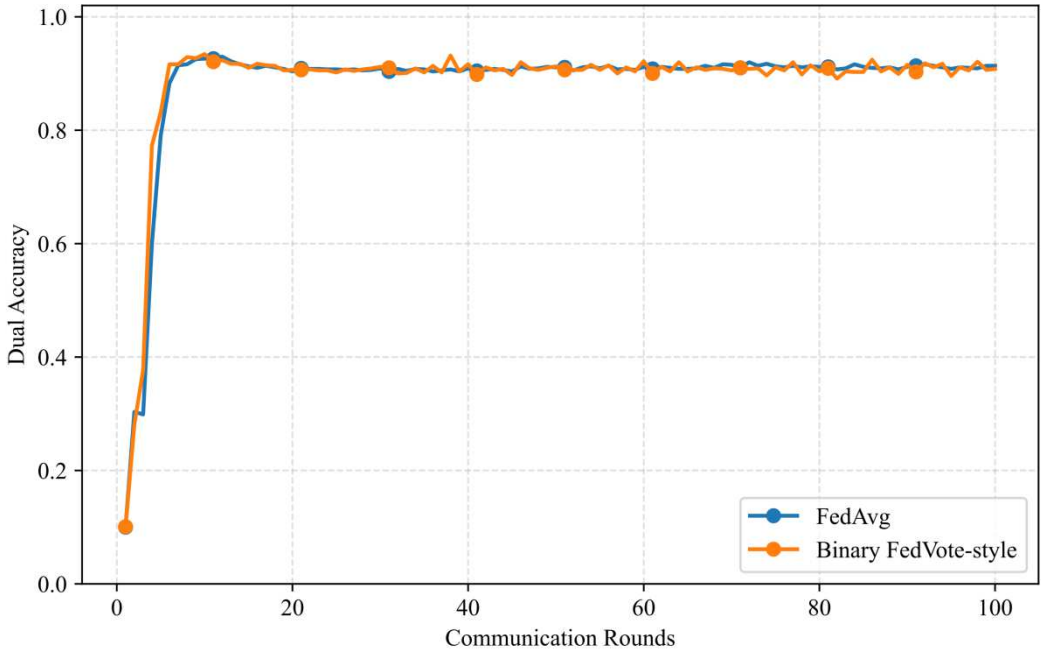


Fig. 9 Dual Accuracy convergence curves over communication rounds

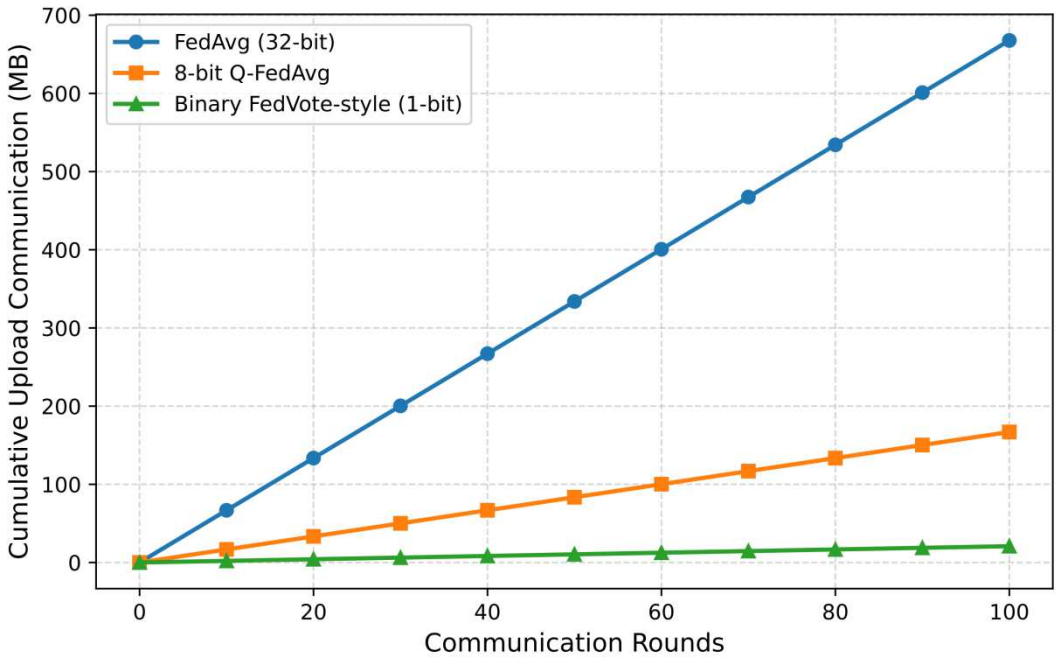


Fig. 10 Cumulative upload communication over communication rounds

5.6 Effect of FedProx under Strong Non-IID

Although Binary FedVote-style achieves a favorable communication-accuracy trade-off under the Moderate Non-IID setting, its performance becomes less stable under the Strong Non-IID setting. In this setting, client data are highly biased toward different Building classes, which may lead to inconsistent local update directions across clients[21, 33]. Since Binary FedVote-style relies on 1-bit direction voting, such direction inconsistency can directly weaken the reliability of the global update.

To further evaluate the stability of different methods under severe data heterogeneity, we conduct experiments with five random seeds, i.e., 42, 43, 44, 45, and 46. The results are reported in Table V. Under the Strong Non-IID setting, FedAvg obtains a mean Final Dual Accuracy of 0.6695 with full-precision 32-bit upload communication. The original Binary FedVote-style achieves a mean Final Dual Accuracy of 0.6976, while reducing the upload communication to 6.2602 MB. This result indicates that low-bit direction voting can greatly reduce upload communication, but it is still sensitive to strong client heterogeneity.

After introducing FedProx regularization, FedProx-Binary FedVote improves the mean Final Dual Accuracy to 0.8691, with a standard deviation of 0.0358. Meanwhile, the upload communication remains 6.2602 MB because the uploaded information is still 1-bit binary direction data. Compared with the original Binary FedVote-style, FedProx-Binary FedVote improves the mean Final Dual Accuracy by 0.1715 without increasing the upload communication cost. This result demonstrates that local regularization is effective in stabilizing low-bit direction voting when client distributions are highly heterogeneous.

Table 5 Performance comparison under the Strong Non-IID setting

Method	**Upload Precision**	**Seeds**	**Mean Final Dual Accuracy**	**Std**	**Upload Communication**
FedAvg	32-bit	42–46	0.6695	0.1175	200.3265 MB
FedVote-style	1-bit	42–46	0.6976	0.0412	6.2602 MB
FedProx-Binary FedVote	1-bit	42–46	0.8691	0.0358	6.2602 MB

Note: The results are averaged over five random seeds, i.e., 42, 43, 44, 45, and 46.

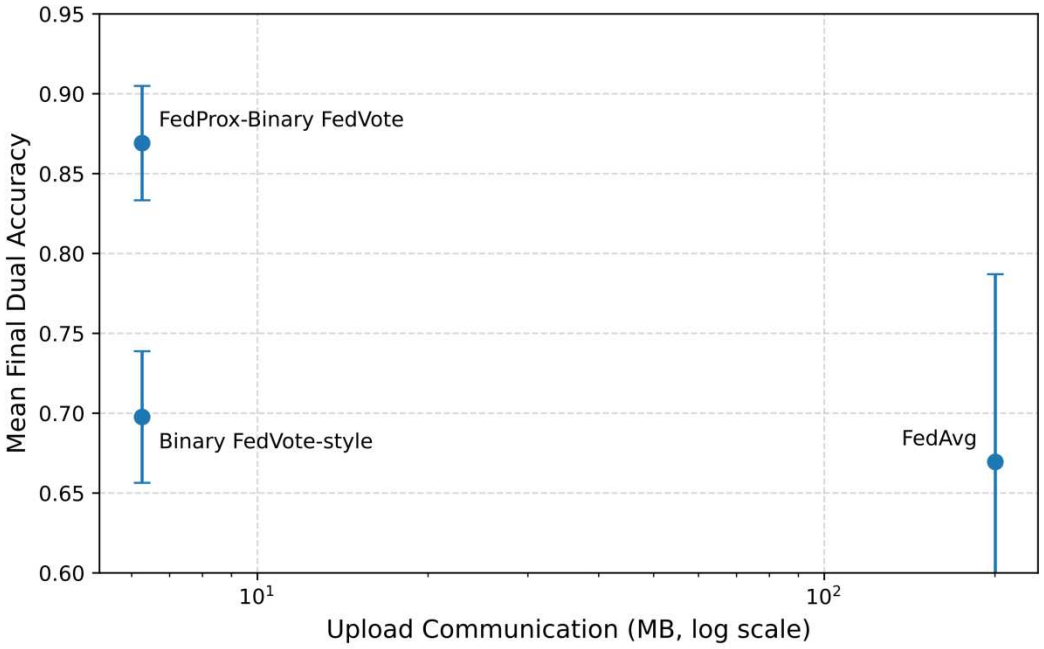


Fig. 11 Trade-off between upload communication and mean Final Dual Accuracy under the Strong Non-IID

6. Conclusion

This paper studied communication-efficient federated learning for Building-Floor dual-task Wi-Fi fingerprint indoor localization. A lightweight dual-task MLP was used to predict both Building and Floor labels. To reduce uplink communication, Binary FedVote-style aggregation was adopted, where each client uploads the 1-bit direction of its local update. To improve stability under Strong Non-IID, FedProx local regularization was added to the client training objective.

Experiments on UJIIndoorLoc show that Binary FedVote-style can reduce the total uplink communication from about 200.33 MB to about 6.26 MB under Moderate Non-IID, while keeping a similar Dual Accuracy to FedAvg. Under Strong Non-IID, averaged over five random seeds, FedProx-Binary FedVote improves the mean Final Dual Accuracy from 0.6976 to 0.8691 without increasing the upload communication cost. These results indicate that the proposed method provides a useful trade-off between localization performance and uplink communication cost.

In future work, this framework can be extended to finer localization outputs, such as coordinate regression or joint Building-Floor-coordinate prediction. It is also worth studying low-bit aggregation under dynamic client participation and more complex heterogeneous data partitions.

Declarations

Funding

No funding was received for conducting this study.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Data availability

The data used in this study are publicly available through the UJIIndoorLoc dataset. The implementation code and additional experimental details are available from the corresponding author upon reasonable request.

Reference

1. Bahl P, Padmanabhan VN (2000) RADAR: an in-building RF-based user location and tracking system. In: Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064). pp 775–784 vol.2

2. Youssef M, Agrawala A (2005) The Horus WLAN location determination system. In: Proceedings of the 3rd international conference on Mobile systems, applications, and services. Association for

Computing Machinery, New York, NY, USA, pp 205–218

3. Zafari F, Gkelias A, Leung KK (2019) A Survey of Indoor Localization Systems and Technologies. IEEE Communications Surveys & Tutorials 21:2568–2599. https://doi.org/10.1109/COMST.2019.2911558

4. Wang X, Gao L, Mao S, Pandey S (2017) CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach. IEEE Transactions on Vehicular Technology 66:763–776. https://doi.org/10.1109/TVT.2016.2545523

5. Wang X, Gao L, Mao S, Pandey S (2015) DeepFi: Deep learning for indoor fingerprinting using channel state information. In: 2015 IEEE Wireless Communications and Networking Conference (WCNC). pp 1666–1671

6. Kim KS, Lee S, Huang K (2018) A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on Wi-Fi fingerprinting. Big Data Anal 3:4. https://doi.org/10.1186/s41044-018-0031-2

7. Etiabi Y, Njima W, Amhoud EM (2023) Federated Learning based Hierarchical 3D Indoor Localization. In: 2023 IEEE Wireless Communications and Networking Conference (WCNC). pp 1–6

8. Gao B, Yang F, Cui N, Xiong K, Lu Y, Wang Y (2023) A Federated Learning Framework for Fingerprinting-Based Indoor Localization in Multibuilding and Multifloor Environments. IEEE Internet of Things Journal 10:2615–2629. https://doi.org/10.1109/JIOT.2022.3214211

9. Lee S, Kim J, Moon N (2019) Random forest and WiFi fingerprint-based indoor location recognition system using smart watch. Hum Cent Comput Inf Sci 9:6. https://doi.org/10.1186/s13673-019-0168-7

10. Kargar-Barzi A, Farahmand E, Taheri Chatrudi N, Mahani A, Shafique M (2024) An Edge-Based WiFi Fingerprinting Indoor Localization Using Convolutional Neural Network and Convolutional Auto-Encoder. IEEE Access 12:85050–85060. https://doi.org/10.1109/ACCESS.2024.3412676

11. McMahan B, Moore E, Ramage D, Hampson S, Arcas BA y (2017) Communication-Efficient Learning of Deep Networks from Decentralized Data. In: Proceedings of the 20th International Conference on Artificial Intelligence and Statistics. PMLR, pp 1273–1282

12. Kairouz P, McMahan HB (2021) Advances and Open Problems in Federated Learning. Foundations and Trends in Machine Learning 14:1–210. https://doi.org/10.1561/2200000083

13. Li T, Sahu AK, Talwalkar A, Smith V (2020) Federated Learning: Challenges, Methods, and Future Directions. IEEE Signal Processing Magazine 37:50–60. https://doi.org/10.1109/MSP.2020.2975749

14. Konečný J, McMahan HB, Yu FX, Richtárik P, Suresh AT, Bacon D (2016) Federated Learning: Strategies for Improving Communication Efficiency. In: arXiv.org.

https://arxiv.org/abs/1610.05492v2. Accessed 16 Jun 2026

15. Alistarh D, Grubic D, Li J, Tomioka R, Vojnovic M (2017) QSGD: Communication-Efficient SGD via Gradient Quantization and Encoding. In: Advances in Neural Information Processing Systems. Curran Associates, Inc.

16. Wen W, Xu C, Yan F, Wu C, Wang Y, Chen Y, Li H (2017) TernGrad: Ternary Gradients to Reduce Communication in Distributed Deep Learning. In: Advances in Neural Information Processing Systems. Curran Associates, Inc.

17. Bernstein J, Wang Y-X, Azizzadenesheli K, Anandkumar A (2018) signSGD: Compressed Optimisation for Non-Convex Problems. In: Proceedings of the 35th International Conference on Machine Learning. PMLR, pp 560–569

18. Lin Y, Han S, Mao H, Wang Y, Dally WJ (2020) Deep Gradient Compression: Reducing the Communication Bandwidth for Distributed Training

19. Reisizadeh A, Mokhtari A, Hassani H, Jadbabaie A, Pedarsani R (2020) FedPAQ: A Communication-Efficient Federated Learning Method with Periodic Averaging and Quantization. In: Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics. PMLR, pp 2021–2031

20. Yue K, Jin R, Wong C-W, Dai H (2024) Federated Learning via Plurality Vote. IEEE Transactions on Neural Networks and Learning Systems 35:8215–8228. https://doi.org/10.1109/TNNLS.2022.3225715

21. Zhu H, Xu J, Liu S, Jin Y (2021) Federated learning on non-IID data: A survey. Neurocomputing 465:371–390. https://doi.org/10.1016/j.neucom.2021.07.098

22. Zhao Y, Li M, Lai L, Suda N, Civin D, Chandra V (2018) Federated Learning with Non-IID Data. https://doi.org/10.48550/arXiv.1806.00582

23. Li Q, Diao Y, Chen Q, He B (2022) Federated Learning on Non-IID Data Silos: An Experimental Study. In: 2022 IEEE 38th International Conference on Data Engineering (ICDE). pp 965–978

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

25. Jeong M, Choi SW, Kim S (2023) A tutorial on Federated Learning methodology for indoor localization with non-IID fingerprint databases. ICT Express 9:548–555. https://doi.org/10.1016/j.icte.2023.01.009

26. Torres-Sospedra J, Montoliu R, Martínez-Usó A, Avariento JP, Arnau TJ, Benedito-Bordonau M, Huerta J (2014) UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems. In: 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN). pp 261–270

27. Park J, Moon J, Kim T, Wu P, Imbiriba T, Closas P, Kim S (2022) Federated Learning for Indoor Localization via Model Reliability With Dropout. IEEE Communications Letters 26:1553–1557. https://doi.org/10.1109/LCOMM.2022.3170878

28. Gufran D, Pasricha S (2023) FedHIL: Heterogeneity Resilient Federated Learning for Robust Indoor Localization with Mobile Devices. ACM Trans Embed Comput Syst 22:125:1-125:24. https://doi.org/10.1145/3607919

29. Etiabi Y, Amhoud EM (2024) Federated Distillation Based Indoor Localization for IoT Networks. IEEE Sensors Journal 24:11678–11692. https://doi.org/10.1109/JSEN.2024.3357798

30. Wu Z, Wu X, Long Y (2022) Multi-Level Federated Graph Learning and Self-Attention Based Personalized Wi-Fi Indoor Fingerprint Localization. IEEE Communications Letters 26:1794–1798. https://doi.org/10.1109/LCOMM.2022.3159504

31. Kumar R, Popli R, Khullar V, Kansal I, Sharma A (2023) Confidentiality Preserved Federated Learning for Indoor Localization Using Wi-Fi Fingerprinting. Buildings 13:2048. https://doi.org/10.3390/buildings13082048

32. Jan M, Njima W, Zhang X (2024) A Privacy-Preserving Indoor Localization System based on Hierarchical Federated Learning. In: 2024 14th International Conference on Indoor Positioning and Indoor Navigation (IPIN). pp 1–6

33. Karimireddy SP, Kale S, Mohri M, Reddi S, Stich S, Suresh AT (2020) SCAFFOLD: Stochastic Controlled Averaging for Federated Learning. In: Proceedings of the 37th International Conference on Machine Learning. PMLR, pp 5132–5143