Towards Accuracy-Aware Client Selection in Federated Learning

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***Abstract*—We proposed a novel accuracy-aware client selection in federated learning (FL) obtained from FL server evaluation in this work. The proposed method solves the uncertainty problem caused by random client selection in vanilla FL by training the highest-performing clients to enhance the global model accuracy. The proposed client selection is investigated based on two well-known datasets for FL, namely MNIST and FMNIST. Based on the comprehensive performance evaluation, the proposed accuracy-aware client selection is able to enhance vanilla FL performance with 4.56% and 5.82% improvement for MNIST and FMNIST datasets, respectively.**

***Index Terms*—Accuracy-aware, client selection, federated learning, heterogeneous data.**

I. INTRODUCTION

Artificial intelligence (AI) has become popular in the last five years due to its high applicability and efficiency in solving various problems in a multidiscipline environment. For instance, AI can improve the internet of things (IoT) sensor lifetime by limiting data transmission to the server and predicting the future sensor value based on its behavior [1]. In most cases, centralized learning is employed, where the data is stored on a server. This server produces the model by using all available dataset instances. However, the centralized data raise privacy issues, specifically for the AI model that requires collaborative learning due to the limited availability of the dataset.

To preserve the privacy of each user, federated learning (FL) is introduced to conduct distributed training without sharing any sensitive information with the server [2]. Moreover, various studies have migrated the approach from centralized to distributed in the last few years. For instance, DDoS detection in a software-defined network (SDN) can be mitigated by applying distributed learning without actually sharing any critical information with the FL server [3]. Furthermore, this technique is more suitable for the continuous learning approach, enabling the AI model to learn different tasks continuously. On the other hand, centralized learning requires higher communication costs to forward the updated model. Despite the slightly lower performance of FL compared to the centralized approach, various technique is proposed to improve the performance of distributed learning [4].

Generally, optimization is done in a heterogeneous environment, driven by various data distributions among FL participants, known as non-independent identically distributed (Non-IID). This data distribution will produce bias and affects the overall performance of FL. To tackle this problem, carefully selecting FL participants is become promising technique. Clients with large numbers of data and classes will produce learning bias compared to users with limited data. In vanilla FL, the client is selected randomly to maximize model generalization. However, random sampling might cause uncertainty because the selection is performed without any additional knowledge.

Various techniques were introduced to tackle the uncertainty of random client selection, such as utilizing the client communication bandwidth to select federated participants carefully [4]. Another approach is based on client resource conditions. For example, the author in [5] proposed a mechanism that collects computing information of the client before conducting the distributed learning. Despite the high performance produced by those two approaches, additional information is required to determine the best possible clients for the training process (e.g., bandwidth, computing resources). Thus, additional communication cost is required to gather that information.

Based on the mentioned studies above, this paper proposed a new client selection for FL by considering the clients' accuracy. Additional communication costs can be mitigated since the user requires no additional information, only the updated local parameter. The major contribution of this paper is detailed as follows:

- Propose an accuracy-aware client selection to mitigate the uncertainty in vanilla FL.
- An extensive evaluation is conducted based on accuracy, F1 score, and federated training time using MNIST and FMNIST datasets.

II. ACCURACY-AWARE CLIENT SELECTION

This paper proposes a novel client selection in distributed learning based on client evaluation accuracy investigated on the FL server. Suppose K is the total number of available participants in FL. Then, all K clients are selected to train and update their local model to the server for the initial training $t = 1$ round. Based on the update parameter, the FL server conducts an evaluation for all participants to determine the representative accuracy. In the following communication round $t > 1$, client selection is made based on the client with the best-performing accuracy. This selection will force the client

TABLE I: Comparative results between random and accuracy-aware client selection with 50 FL participants

Client Selection Method	MNIST Dataset			FMNIST Dataset		
	Accuracy (%)	F1 score (%)	Time (s)	Accuracy (%)	F1 score (%)	Time (s)
Random	80.26	79.64	**440.20**	49.41	47.27	**502.69**
Accuracy-Aware	**83.19**	**81.08**	441.19	**53.78**	**52.79**	503.41

with the highest accuracy to train the global model and helps to improve overall model performance.

The main difference compared to vanilla FL with random client selection is on the first communication rounds. Instead of training a fraction of the participants, all available clients are selected to conduct local training. For the rest of the communication rounds, the training will be conducted based on the evaluation accuracy investigated on the FL server. The evaluation is done by using the FL server dataset. Here, we assume that the FL server covers all types of dataset classes owned by each participant in FL; hence the evaluation results are reliable.

III. Results and Discussion

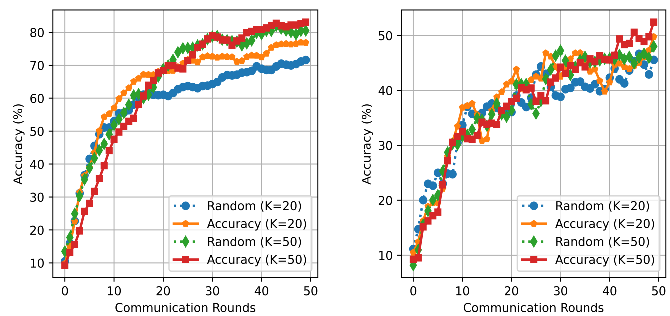
Flower [6] is employed as an FL framework to investigate the proposed accuracy-aware client selection in a heterogeneous environment. A lightweight CNN-based model is utilized to classify MNIST and FMNIST datasets for the FL server and participant. Three metrics are used during the evaluation to show the proposed system's effectiveness: accuracy, F1 score, and training time.

The comparative performance result of the proposed accuracy-aware with random client selection is illustrated in Fig. 1b. Two different sizes of K are investigated with two kinds of datasets. The overall performance of accuracy-aware client selection outperforms the random selection in terms of accuracy and F1 score. For example, the random client selection achieves 71.11% accuracy for the MNIST dataset, whereas the proposed selection provides 75.67% accuracy. Then, based on the FMNIST dataset with 20 participants, the proposed accuracy-aware client selection produces 49.95% accuracy, whereas the random client selection only generates 44.13%. On average, the total performance increment in terms of accuracy by utilizing the proposed client selection is 4.56% and 5.82% for MNIST and FMNIST datasets, respectively.

Furthermore, we also consider the F1 score and overall training time, which are detailed in Table I. The presented findings are based on 50 participants, where the proposed method is superior to random client selection in terms of F1 score. In addition, based on the overall training process, the proposed method slightly prolongs the federation process due to the evaluation and the sorting technique performed every round on the FL server.

IV. Conclusion

This paper introduces a novel client selection based on the accuracy of each participant in the FL process. The proposed model tackles random client selection in vanilla FL that produces uncertainty in the performance. In the accuracy-aware client selection, each local client parameter is evaluated on the server side and sorted in descending order in the first communication round. Then, for the rest communication, the training is conducted based on the best-performing client. Based on the performance evaluation, the proposed client selection can enhance the performance up to 5.82% compared to the random client selection. Finally, the proposed system can compete with random selection regarding training time.



(a) MNIST Dataset (b) FMNIST Datast

Fig. 1: Performance comparison among random and accuracy-aware client selection with 20 and 50 FL participants

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References

[1] M. A. P. Putra, A. P. Hermawan, D.-S. Kim, and J.-M. Lee, "Energy Efficient-based Sensor Data Prediction using Deep Concatenate MLP," in *2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2021, pp. 1–4.

[2] H. B. McMahan, E. Moore, D. Ramage, and B. A. y Arcas, "Federated learning of deep networks using model averaging," *CoRR*, vol. abs/1602.05629, 2016.

[3] A. Zainudin, L. A. C. Ahakonye, R. Akter, D.-S. Kim, and J.-M. Lee, "An efficient hybrid-dnn for ddos detection and classification in software-defined iiot networks," *IEEE Internet of Things Journal*, pp. 1–1, 2022.

[4] P. Kairouz, H. B. McMahan, B. Avent *et al.*, "Advances and open problems in federated learning," 2019. [Online]. Available: https://arxiv.org/abs/1912.04977

[5] T. Nishio and R. Yonetani, "Client selection for federated learning with heterogeneous resources in mobile edge," in *ICC 2019 - 2019 IEEE International Conference on Communications (ICC)*, 2019, pp. 1–7.

[6] D. J. Beutel, T. Topal, A. Mathur, X. Qiu, T. Parcollet, and N. D. Lane, "Flower: A friendly federated learning research framework," *arXiv preprint arXiv:2007.14390*, 2020.