FedHealth 2: Weighted Federated Transfer Learning via Batch Normalization for Personalized Healthcare

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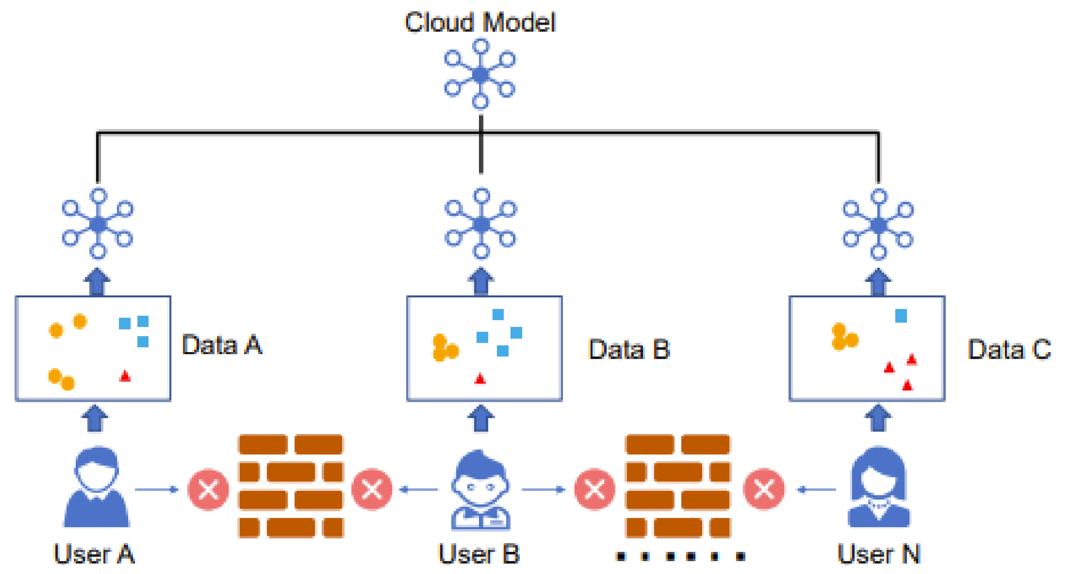
Abstract

The success of machine learning applications often needs a large quantity of data. Recently, federated learning (FL) is attracting increasing attention due to the demand for data privacy and security, especially in the medical field. However, the performance of existing FL approaches often deteriorate when there exist domain shifts among clients, and few previous works focus on personalization in healthcare. In this article, we propose FedHealth 2, an extension of FedHealth [2] to tackle domain shifts and get personalized models for local clients. FedHealth 2 obtains the client similarities via a pretrained model, and then it averages all weighted models with preserving local batch normalization. Wearable activity recognition and COVID-19 auxiliary diagnosis experiments have evaluated that FedHealth 2 can achieve better accuracy (10%+ improvement for activity recognition) and personalized healthcare without compromising privacy and security.

Problem formulation



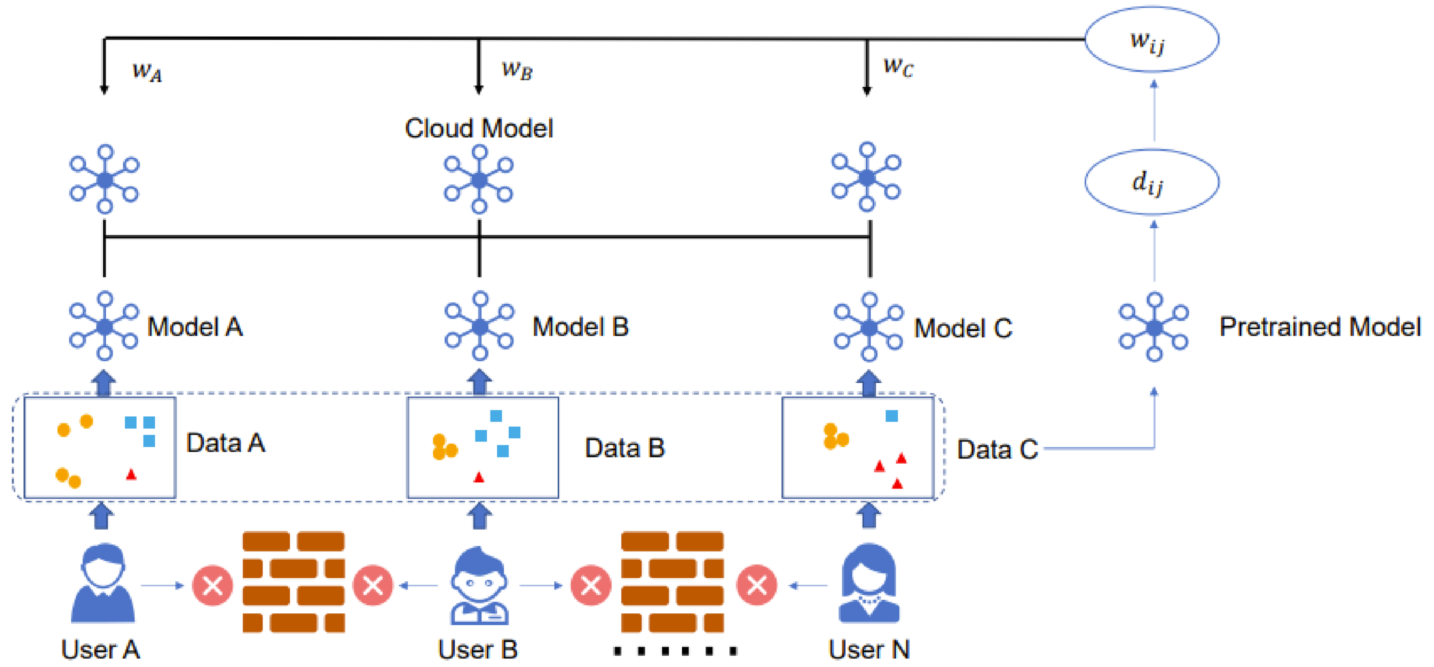
In a FL problem, there are N different clients (organizations or users), denoted as $\{C_1, C_2, \cdots, C_N\}$ and each client has its own dataset, i.e. $\{\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_N\}$. Each dataset, $\mathcal{D}_i = \{(\mathbf{x}_{i,j}, y_{i,j})\}_{j=1}^{n_i}$, contains two parts, i.e. a train dataset $\mathcal{D}_i^{train} = \{(\mathbf{x}_{i,j}^{train}, y_{i,j}^{train})\}_{j=1}^{n_i^{train}}$ and a test dataset $\mathcal{D}_i^{test} = \{(\mathbf{x}_{i,j}^{test}, y_{i,j}^{test})\}_{j=1}^{n_i^{test}}$. Obviously, we have $n_i = n_i^{train} + n_i^{test}$ and $\mathcal{D}_i = \mathcal{D}_i^{train} \cup \mathcal{D}_i^{test}$. All of the datasets have different distributions, i.e. $P(\mathcal{D}_i) \neq P(\mathcal{D}_j)$. Each client has its own model denoted as $\{f_i\}_{i=1}^N$. Our goal is to combine information of all clients to learn a good model f_i for each client on its local dataset $\mathcal{D}_i$ without private data leakage:

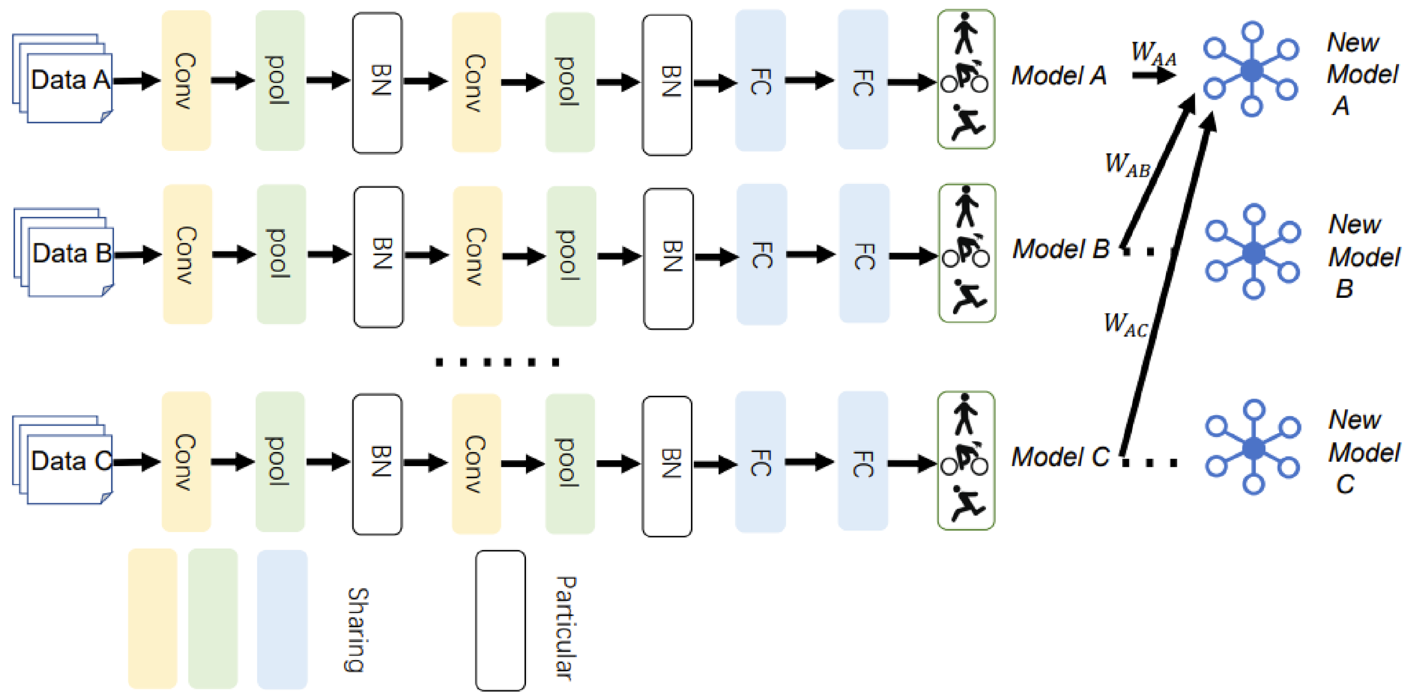
$$\min_{\{f_k\}_{k=1}^N} \frac{1}{N} \sum_{i=1}^{N} \frac{1}{n_i^{test}} \sum_{j=1}^{n_i^{test}} \ell(f_i(\mathbf{x}_{i,j}^{test}), y_{i,j}^{test}), \quad (1)$$

Contributions

- We propose FedHealth 2, a weighted federated transfer learning algorithm via batch normalization for healthcare, which can aggregate the information from different clients without compromising privacy security, and achieve personalized models for clients through weighting models and preserving local batch normalization.
- We show the excellent performance achieved by FedHealth 2 in healthcare applications. Experiments show that FedHealth 2 dramatically improves the recognition accuracy of the local clients' models. At the same time, it reduces the number of rounds and speeds up the convergence to some extent.
- FedHealth 2 is extensible and can be employed in many healthcare applications. Diverse extensions allow it can work in many circumstances. Even if there does not exist a pretrained model, FedHealth 2 can get similarities via FedBN [3] with few rounds.

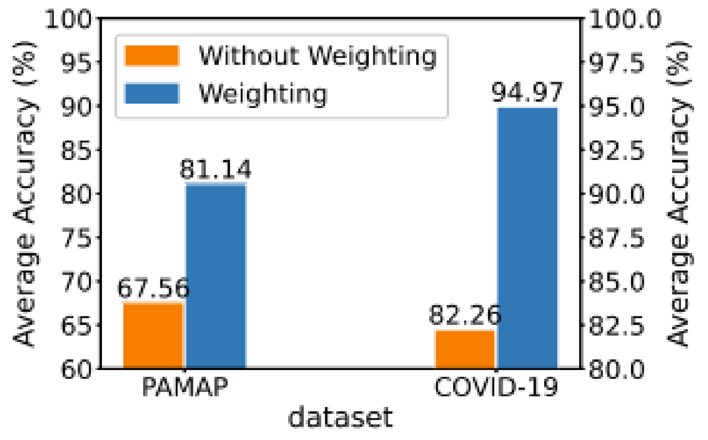
The Proposed Method



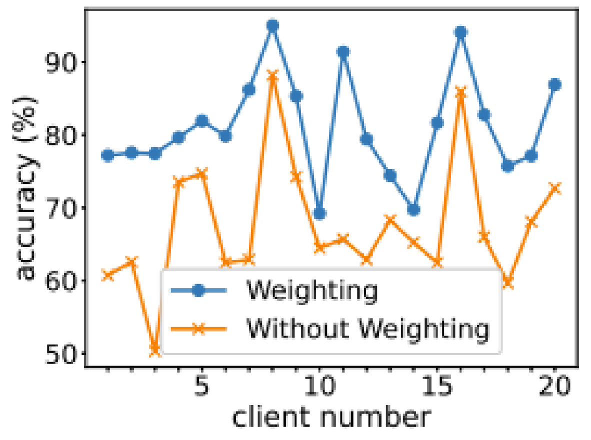


Experiments

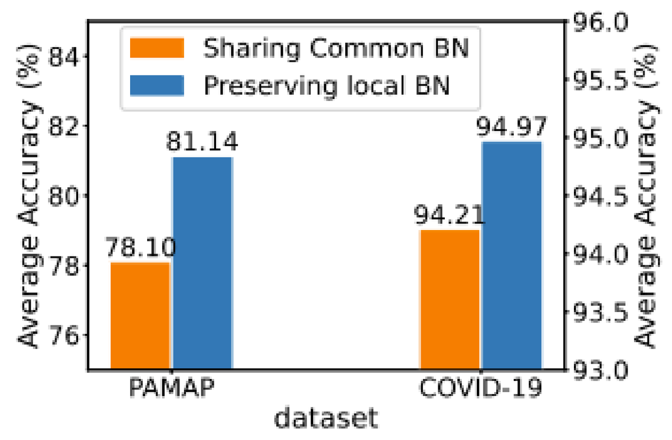
Client	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	avg
Base	**92.86**	17.68	**100.00**	**83.52**	18.78	77.66	**95.05**	17.58	**92.39**	**93.37**	29.12	**84.78**	**98.90**	24.18	**98.91**	**98.90**	41.44	**93.62**	**85.71**	37.02	69.07
FedAvg	60.27	62.36	50.56	73.98	74.27	62.90	64.03	87.78	74.49	64.71	65.24	63.35	68.33	64.79	63.12	85.26	66.21	59.64	67.87	72.46	67.58
FedBN	60.72	62.59	50.34	73.53	74.72	62.44	62.90	88.24	74.27	64.48	65.69	62.90	68.33	65.24	62.44	85.94	65.99	59.64	68.10	72.69	67.56
FedProx	60.50	62.36	50.34	73.98	73.81	61.76	63.57	87.78	74.27	64.71	66.37	63.12	68.33	65.69	62.44	85.49	66.21	59.41	67.87	72.46	67.52
FedPer	48.31	**97.51**	61.40	47.29	58.47	23.98	49.55	91.86	51.24	77.60	89.16	57.92	42.53	49.44	58.60	86.62	77.32	52.38	73.08	**97.52**	64.59
FedHealth 2	77.20	77.55	77.43	79.64	**81.94**	79.86	86.20	**95.02**	85.33	69.23	**91.42**	79.41	74.43	69.75	81.67	94.10	**82.77**	75.74	77.15	86.91	**81.14**
d-FedHealth 2	64.33	77.55	78.33	77.38	79.91	**80.77**	85.52	92.53	86.23	69.23	87.58	80.09	74.66	**70.43**	83.71	93.88	80.50	74.60	78.73	87.13	80.16
f-FedHealth 2	64.11	77.78	69.53	79.86	77.88	74.43	84.62	93.67	74.04	81.00	79.91	71.95	74.21	62.98	78.05	89.57	79.59	68.71	71.95	87.81	77.08



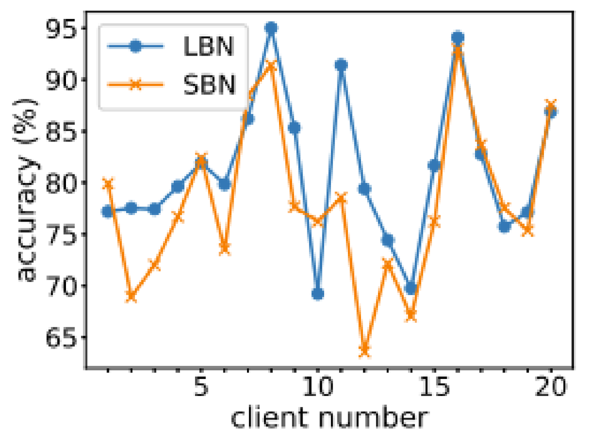
(a) Average Accuracy



(b) Client Acc on PAMAP

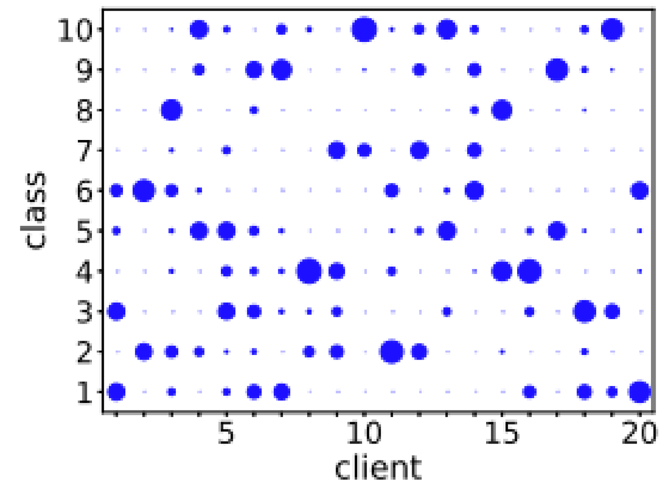


(a) Average Accuracy

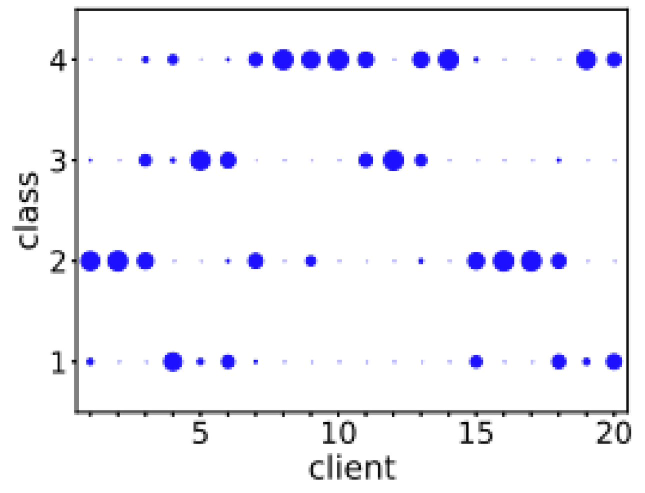


(b) Client Acc on PAMAP

Datasets



(a) PAMAP



(b) COVID-19

References

[1] Chen, Yiqiang, et al. "FedHealth 2: Weighted Federated Transfer Learning via Batch Normalization for Personalized Healthcare." *arXiv preprint arXiv:2106.01009* (2021).

[2] Chen, Yiqiang, et al. "Fedhealth: A federated transfer learning framework for wearable healthcare." *IEEE Intelligent Systems* 35.4 (2020): 83-93.

[3] Li, Xiaoxiao, et al. "Fedbn: Federated learning on non-iid features via local batch normalization." *arXiv preprint arXiv:2102.07623* (2021).

Method	Base	FedAvg	FedBN	FedProx
avg	92.70	86.48	82.26	86.15
Method	**FedPer**	**FedHealth 2**	**d-FedHealth 2**	**f-FedHealth 2**
avg	88.51	94.82	**94.97**	93.5

Table 2: Average accuracy of 20 clients on COVID-19