FedHealth: A Federated Transfer Learning Framework for Wearable Healthcare

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***Abstract*—With the rapid development of computing technology, wearable devices make it easy to get access to people's health information. Smart healthcare achieves great success by training machine learning models on a large quantity of user personal data. However, there are two critical challenges. First, user data often exist in the form of isolated islands, making it difficult to perform aggregation without compromising privacy security. Second, the models trained on the cloud fail on personalization. In this article, we propose FedHealth, the first federated transfer learning framework for wearable healthcare to tackle these challenges. FedHealth performs data aggregation through federated learning, and then builds relatively personalized models by transfer learning. Wearable activity recognition experiments and real Parkinson's disease auxiliary diagnosis application have evaluated that FedHealth is able to achieve accurate and personalized healthcare without compromising privacy and security. FedHealth is general and extensible in many healthcare applications.**

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Activities of daily living are highly related to people's health. Recently, the development of wearable technologies helps people to understand their health status by tracking activities using wearable devices, such as smartphone, wristband, and smart glasses. Wearable healthcare has the potential to provide early warnings to several cognitive diseases, such as Parkinson's[1] and small vessel diseases.[2] Other applications include mental health assessment, fall detection, and sports monitoring.[3] In fact, there is a growing trend for wearable healthcare over the years.

In healthcare applications, machine learning models are often trained on sufficient user data to track health status. Unfortunately, there are two critical challenges in today's wearable healthcare (see Figure 1). First of all, in real life, data often exist in the form of isolated islands. Although there is plenty of data in different organizations, it is not possible to share them due to privacy and security concerns, as shown in Figure 1. This makes it hard to train powerful models using the valuable data. Additionally, recently, China, the United States, and the European Union enforced the protection of user data via different regularizations.[4,5] Hence, the acquisition of massive user data is not possible in real applications.

The other important issue is personalization. Most of the methods are based on a common server model for nearly all users. After acquiring sufficient user data to train a satisfactory machine learning model, the model is then distributed to all user devices on which the daily health information can be tracked. This process lacks personalization. As can be seen, different users have different physical characteristics and daily activity patterns. Therefore, the common model fails to perform personalized healthcare.

In this article, we propose *FedHealth*, the first federated transfer learning framework for wearable healthcare. FedHealth can solve both of the data islanding and personalization problems. Through federated learning[6] and homomorphic encryption,[7] FedHealth aggregates the data from separate organizations to build powerful machine learning models with the users' privacy well preserved. After the cloud model is built, FedHealth utilizes transfer learning methods to achieve personalized model learning for each

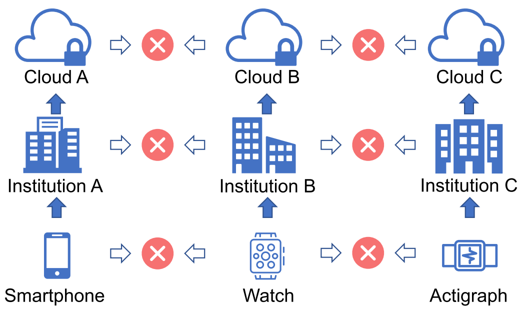

Figure 1. Data islanding and personalization problems in wearable healthcare.

organization. The framework can incrementally update. FedHealth is extensible and can be deployed to many healthcare applications to continuously enhance their learning abilities in real life.

Our contributions are as follows.

1. We propose FedHealth, the first federated transfer learning framework for wearable healthcare, which aggregates the data from different organizations without compromising privacy security, and achieves relatively personalized model learning through knowledge transfer.
2. We show the excellent performance achieved by FedHealth in smartphone-based human activity recognition. Experiments show that FedHealth dramatically improves the recognition accuracy compared to traditional learning approaches.
3. FedHealth is extensible and can be the standard framework for many healthcare applications. Specifically, we design a FedHealth system and apply it in Parkinson's disease auxiliary diagnosis with the users' privacy well preserved and good performance achieved in the real situation.

RELATED WORK

Wearable Healthcare

Certain activities in daily life reflect early signals of some cognitive diseases.[8] For instance, the change of gait may result from small vessel disease or stroke. A lot of researchers pay attention to monitor users' activities using body-worn sensors,[9] through which daily activities and sports activities can be recognized. With the development of wearable technology, smartphone, wristbands, and smart glasses provide easy access to this information.

It is noteworthy that traditional healthcare applications often build the model by aggregating all the user data. However, in real applications, data are often separate and cannot be easily shared due to privacy issues.[4] Moreover, the models built by applications lack the ability of personalization.

Federated Transfer Learning

Federated machine learning was first proposed by Google,[10] where they trained machine learning models based on distributed mobile phones all over the world. The key idea is to protect user data during the process. Federated learning has the ability to resolve the data islanding problems by privacy-preserving model training in the network.

Transfer learning aims at transferring knowledge from existing domains to a new domain. The key idea is to reduce the distribution divergence between different domains. To this end, there are mainly two kinds of approaches: instance reweighting[11] and feature matching.[12] Recently, deep transfer learning methods have made considerable success in many application fields. FedHealth is mainly related to deep transfer learning. Most of the methods assume the availability of training data, which is not realistic. FedHealth makes it possible to do deep transfer learning in the federated learning framework without accessing the raw user data. Therefore, it is more secure.

Federated transfer learning considers scenarios where neither samples nor features have much in common. Recently, more researchers start to focus on this field. According to,[13] Liu et al. proposed a secure federated transfer learning system in a two-party privacy preserving setting, which is more focused on data security. And some researchers proposed federated domain adaptation approaches that extended domain adaptation to federated setting constraints to tackle data privacy and domain shift. Although the research work is fast growing, federated transfer learning faces many challenges to apply in practical application.[13] Our work is the first federated transfer learning framework tailored for wearable healthcare applications and it can be extended with various transfer learning methods.

PROPOSED FEDHEALTH FRAMEWORK

Problem Definition

We are given data from N different users (organizations), denote the users by $\{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_N\}$ and the sensor readings they provide by $\{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_N\}$. Conventional methods train a model $\mathcal{M}_{\mathrm{ALL}}$ by combining all the data $\mathcal{D} = \mathcal{D}_1 \cup \mathcal{D}_2 \cup \cdots \cup \mathcal{D}_N$. All the data have different distributions. In our problem, we want to collaborate all the data to train a federated transfer learning model $\mathcal{M}_{\mathrm{FED}}$, where any user $\mathcal{S}_i$ does not expose its data $\mathcal{D}_i$ to each other. If we denote the accuracy as $\mathcal{A}$, then the objective of FedHealth is to ensure the accuracy of federated learning is close to or superior to that of conventional learning denoted by

$$\mathcal{A}_{\mathrm{FED}} - \mathcal{A}_{\mathrm{ALL}} > \Delta \tag{1}$$

where Δ is an extremely small nonnegative real number.

Overview of the Framework

FedHealth aims to achieve accurate personal healthcare through federated transfer learning without compromising privacy security. Figure 2 gives an overview of the framework. Without loss of generality, we assume there are three users (organizations) and single server, which can be extended to the more general case. The framework mainly consists of four procedures. First, the cloud model on the server is trained based on public datasets. Then, the cloud model is distributed to all users where each of them can train their own model on their data. Subsequently, the user model can be uploaded to the cloud to help training a new cloud model by model aggregation. Finally, each user can train personalized models by utilizing the cloud model and data and local data. In this step, since there is large distribution divergence between server data and user data, transfer learning is performed to make the model more tailored to the user (right part in Figure 2). It is noteworthy that all the parameter-sharing processes do not

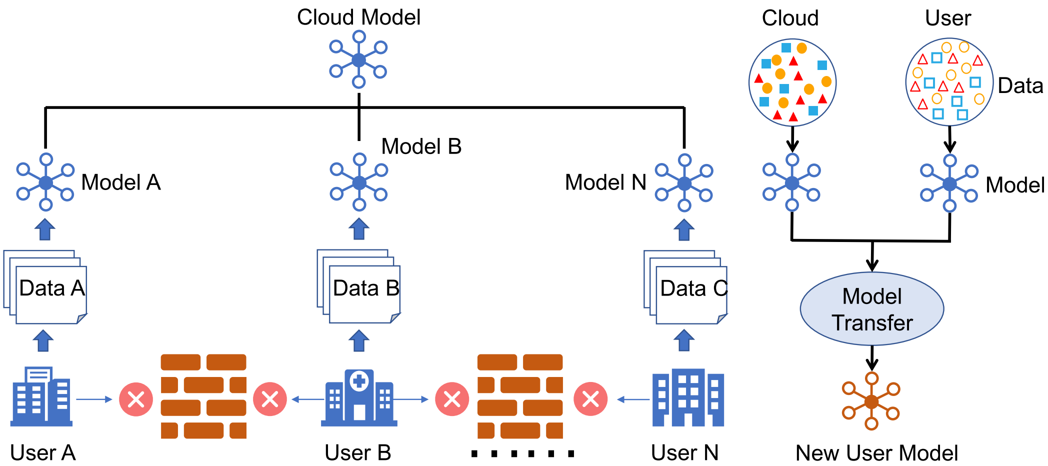

Figure 2. Overview of the FedHealth framework. "User" represents organizations.

involve any leakage of user data through homomorphic encryption.[7]

The federated learning paradigm is the main computing model for the whole FedHealth framework. It deals with model building and parameter sharing during the entire process. After the server model is learned, it can be directly applied to the user. This is just what traditional healthcare applications do for model learning. It is obvious that the samples in the server are having highly different probability distribution with the data generated by each user. Therefore, the common model fails in personalization. Additionally, user models cannot easily be updated continuously due to the privacy security issue.

Federated Learning

FedHealth adopts the federated learning paradigm[6] to achieve encrypted model training and sharing. This step mainly consists of two critical parts: cloud and user model learning.

In FedHealth, we adopt deep neural networks to learn both the cloud and user models. Deep neural networks perform end-to-end feature learning and classifier training by taking the raw inputs of the user data as inputs. Let f_S denote the server model to be learned, then the learning objective becomes

$$\arg\min_{\Theta} \mathcal{L} = \sum_{i=1}^{n} \ell(y_i, f_S(\mathbf{x}_i)) \tag{2}$$

where $\ell(\cdot,\cdot)$ denotes the loss for the network, e.g., cross-entropy loss for classification tasks. $\{\mathbf{x}_i, y_i\}_{i=1}^{n}$ are samples from the server data with n their sizes. Θ denotes all the parameters to be learned, i.e., the weight and bias.

After acquiring the cloud model, it is distributed to all the users. As we can see from the "wall" in Figure 2, the direct sharing of user information is forbidden. This process uses homomorphic encryption[7] to avoid information leakage. Since the encryption is not our main contribution, we will show the process of additively homomorphic encryption using real numbers. The encryption scheme of the weight matrix and bias vector are following the same idea. The additively homomorphic encryption of a real number a is denoted as $\langle a \rangle$. In additively homomorphic encryption, for any two numbers a and b, we have $\langle a \rangle + \langle b \rangle = \langle a + b \rangle$. Therefore, the parameter sharing can be done without leaking any information from the users. Through federated learning, we can aggregate user data without compromising privacy security.

Technically, the learning objective for user u is denoted as

$$\arg\min_{\Theta^u} \mathcal{L}_u = \sum_{i=1}^{n^u} \ell(y_i^u, f_u(\mathbf{x}_i^u)). \tag{3}$$

After all the user model f_u is trained based on the shared cloud model, it is uploaded to the server for aggregation. It has been evaluated that with shared initialization, averaging the models can achieve good performance in loss reduction in the approach of FederatedAveraging[14]. Thus, following[14], we use model average to

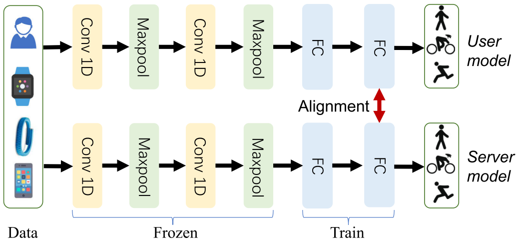

Figure 3. Transfer learning process of FedHealth.

align user models, K user models are averaged for the cloud model update in each training round. Note that we simply average user models here, we will further study the influence of specific model parameters on the average in the future. The updated cloud model is denoted as

$$f_S'(w) = \frac{1}{K}\sum_{k=1}^{K} f_{u_k}(w) \tag{4}$$

where w are parameters of the network and K is the number of users. After adequate rounds of iteration, the updated server model f_S' has better generalization ability. Subsequently, new users can take part in the next training round of server model, thus FedHealth has the capability for incremental learning.

Transfer Learning

Federated learning solves the data islanding problem. Therefore, we can build models using all the user data. Another important factor is the personalization. Even if we can directly use the cloud model, it still performs poor on a particular user. This is due to the distribution difference between the user and the cloud data. The common model in the server only learns the coarse features from all users, while it fails in learning the fine-grained information on a particular user.

In this article, FedHealth uses transfer learning to build a personalized model for each user (organization). Recall that features in deep neural networks are highly transferable in the lower levels of the network since they focus on learning common and low-level features. The higher layers learn more specific features to the task.[15] In this way, after obtaining the parameters of the cloud model, we can perform transfer learning on the user to learn their personalized models.

Figure 3 presents the process of transfer learning for a specific convolutional neural network (CNN). Suppose the network is composed of two convolutions layers (conv1, conv2), two max-pooling layers (pool1, pool2), two fully connected layers (fc1, fc2), and one softmax layer for classification. The network is designed for human activity recognition where the input data are the activity signals for a user and the output is his/her activity classes.

In model transfer, we think that the convolution layers aims at extracting low-level features about activity recognition. Thus, we keep these layers along with the max-pooling layers frozen, which means we do not update their parameters in backpropagation. As for the fully connected layers fc1 and fc2, since they are at higher level, we believe they focus on learning specific features for the task and user. Therefore, we update their parameters during training. The softmax serves as the classification function, which can be formulated as

$$y_j = \frac{e^{z_c}}{\sum_{c=1}^{C} e^{z_c}} \tag{5}$$

where z_c denotes the learned probability for class C, and y_j is the final classification result.

FedHealth adapts the inputs from different domains by replacing fc2 with an alignment layer. We regard the public datasets as the source domain. Given the network from the server and user, we add a correlation alignment[16] layer before the softmax layer to further adapt the domains. This alignment function is used to align the second-order statistics between the inputs. Formally, the loss of correlation alignment is computed as follows:

$$\ell_{\mathrm{CORAL}} = \frac{1}{4d^2}\|C_S - C_T\|_F^2 \tag{6}$$

where $\|\cdot\|_F^2$ denotes the squared matrix Frobenius norm and d is the dimension of the embedding features. C_S and C_T are the covariance matrices of the source and target features computed by.[16] Let η denote the tradeoff parameter. The cross-entropy loss is calculated with the source and target data. Therefore, the loss for the user model is computed by

$$\arg\min_{\Theta_u} \mathcal{L}_u = \sum_{i=1}^{n} \ell(y_i, f_u(\mathbf{x}_i)) + \sum_{i=1}^{n_u} \ell(y_i^u, f_u(\mathbf{x}_i^u)) + \eta \ell_{\mathrm{CORAL}}. \quad (7)$$

Learning Process

The learning procedure of FedHealth is presented in Algorithm 1. Note that this framework works continuously with the new emerging user data. FedHealth can update the user model and cloud model simultaneously when facing new user data. Therefore, the longer the user uses the product, the more personalized the model can be. Other than transfer learning, other popular methods such as incremental learning can also be embedded in FedHealth for personalization.

Algorithm 1. The learning procedure of FedHealth

Input: Data from different users $\{\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_N\}$, η
Output: Personalized user model f_u

1: Construct an initial cloud model f_S with public datasets using (2)
2: Distribute f_S to all users
3: Train user models using (3)
4: Update all user models to the server using homomorphic encryption. Make models aggregation by using (4). Then the server takes this aggregation model as the updated cloud model f'_S.
5: Distribute f'_S to all users, then perform transfer learning on each user to get their personalized model f_u using (7)
6: Repeat the above procedures with the continuously emerging user data

The entire framework can also adopt other machine learning methods other than deep neural networks. For instance, the gradient boosting decision tree can be integrated into the framework to harness the power of ensemble learning. These lightweight models can be deployed to computation restricted wearable devices. This makes FedHealth more general to real applications.

EXPERIMENTS

Datasets

We adopt a public human activity recognition dataset called UCI Smartphone.[17] This dataset contains 6 activities collected from 30 users with smartphones on the waist. Nine channels of accelerometer and gyroscope data are collected at a constant rate of 50 Hz. There are 10 299 instances in total.

In order to construct the problem situation in FedHealth, we extracted five subjects (Subject IDS 26 $\sim$ 30) and regarded them as the isolated users, which cannot share data due to privacy security. Data on the remaining 25 users are used to train the cloud model. Henceforth, the objective is to use the cloud model and all the five isolated subjects to improve the activity recognition accuracy on the five subjects without compromising the privacy. In short, it is a variant of the framework in Figure 2 where there are give users.

Implementation Details

On both the server and the user end, we adopt a CNN for training and prediction. The network is composed of two convolutional layers, two pooling layers, and three fully connected layers. The network adopts a convolution size of 1×9. It uses minibatch stochastic gradient descent (SGD) for optimization. During training, we use 70% of the training data for model training, whereas the rest 30% is for model evaluation. We fix $\eta = 0.01$ and $K = 5$. We set the learning rate to be 0.01 with batch size of 64 and training epochs fixed to 80. The accuracy of user u is computed as $\mathcal{A}_u = \frac{|\mathbf{x}:\mathbf{x}\in\mathcal{D}_u \wedge \hat{y}(\mathbf{x})=y(\mathbf{x})|}{|\mathbf{x}:\mathbf{x}\in\mathcal{D}_u|}$, where $y(\mathbf{x})$ and $\hat{y}(\mathbf{x})$ denote the true and predicted labels on sample $\mathbf{x}$, respectively.

We follow[7] for homomorphic encryption in federated learning. During transfer learning, we freeze all the convolutional and pooling layers in the network. Only the parameters of the fully connected layers are updated with SGD. To show the effectiveness of FedHealth, we compare its performance with traditional deep learning (NoFed), where we record the performances on each subject using the initial server model only, and other traditional machine learning methods. The hyperparameters of all the comparison methods are tuned using cross-validation. For the fair study, we run all the experiments five times to record the average accuracies.

Classification Accuracy

The activity classification accuracy for each subject is shown in Table 1. FedHealth achieves

Table 1. Classification accuracy (%) of the test subject.

Subject	KNN	SVM	RF	NoFed	FedHealth
P1	83.8	81.9	87.5	94.5	**98.8**
P2	86.5	96.9	93.3	94.5	**98.8**
P3	92.2	97.2	88.9	93.4	**100.0**
P4	83.1	95.9	91.0	95.5	**99.4**
P5	90.5	98.6	91.6	92.6	**100.0**
AVG	87.2	94.1	90.5	94.1	**99.4**

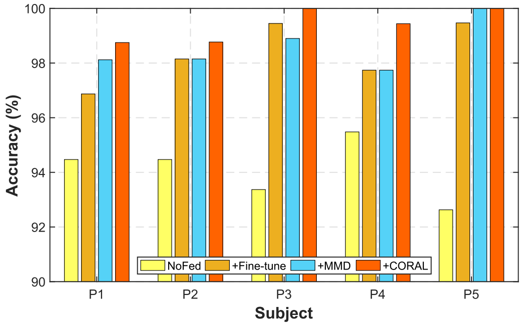

Figure 4. Extending FedHealth with other transfer learning methods.

the best classification accuracy on all users. Compared to NoFed, it significantly improves the average results by 5.3%. This is because federated learning can indirectly utilize more information from distributed data to train a better model, and through transfer learning, models become more personalized to the characteristics of each user. Compared to the traditional methods (KNN, SVM, and RF), FedHealth also greatly improves the recognition results. In short, it demonstrates the effectiveness of the FedHealth framework.

The results also show that for activity recognition, the deep methods (NoFed and FedHealth) achieve better results than traditional methods. This is due to the representation capability of deep neural networks, whereas traditional methods rely on hand-crafted feature learning. Another advantage of deep learning is that the models can be updated online and incrementally without retraining, whereas traditional methods require further incremental algorithms. This property is extremely valuable in federated transfer learning where model reuse is important and helpful.

Evaluation of Extensibility

In this section, we analyze the extensibility of FedHealth with different transfer learning approaches. We compare its performance with two methods: 1) fine-tuning, which only fine-tunes the network on each subject without explicitly reducing the distribution divergence between domains; and 2) transfer with maximum mean discrepancy (MMD),[12] which replaces the alignment loss with MMD loss. The comparison results are shown in Figure 4.

We can see that other than the alignment loss, FedHealth can also achieve promising results using fine-tuning or MMD. The results of transfer learning significantly outperform no transfer by 4% on average accuracy. This indicates that the transfer learning procedure of FedHealth is highly effective and extensible. Therefore, FedHealth is general and can be extended in many applications by integrating other transfer learning algorithms. Moreover, the federated learning procedure can also be extended using other encryption methods, which can be the future research.

APPLICATION IN AUXILIARY DIAGNOSIS OF PARKINSON'S DISEASE

Parkinson's disease usually distinguished with some motor symptoms, thus it is possible to utilize wearable healthcare methods to help diagnosis.[1] Besides, patient data are a privacy-sensitive issue that requires federated learning to address. Thus, we make an application of FedHealth in the auxiliary diagnosis of Parkinson's disease, which can be deployed in hospitals. After the user model is trained in hospital (user side), patients can download it into their smartphones and update in the next visit. They can make self-test and get real-time feedback to acquire disease status conveniently.

Parkinson's Disease Dataset

We developed a smartphone application to collect patients' acceleration and gyroscope signals in the symptom tests at rate of 50 Hz. Five symptom tests including arm droop, balance, gait, postural tremor, and resting tremor are

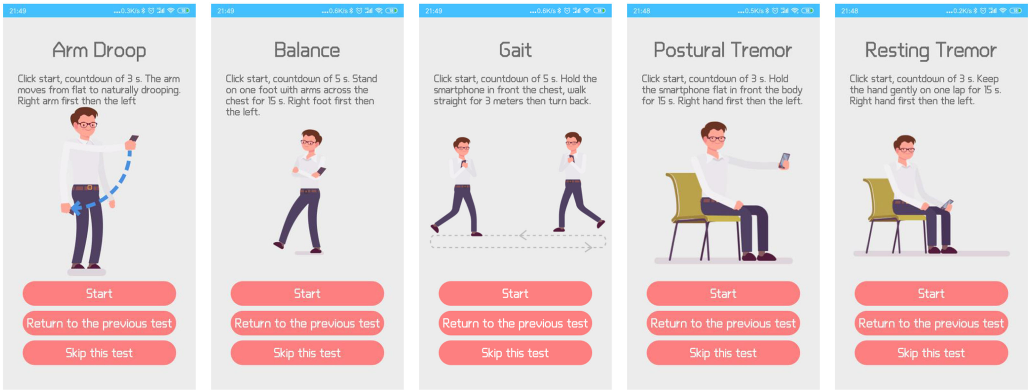

Figure 5. Main interfaces of symptom tests in smartphone application.

provided in series. For each test, symptoms can be ranked into five levels from normal to severe. The detailed description and the interfaces of these tests are shown in Figure 5. During the collection process, a Parkinson's disease therapist is around to rate the symptoms. We collected sensor data with more than 130 patients age from 19 to 87 years old participated. In the following evaluation, we carried experiments on test data of arm droop and postural tremor from where two classes with relatively adequate data are selected.

Classification Performance

We evaluate the classification accuracy and macro F1 score on the collected dataset. Data are collected from three hospitals, we randomly selectly 70% from each hospital as public dataset, and 30% as three users and we fixed $K = 3$. Comparison results are shown in Table 2. Also, we provide the results of ideal scenario with the proposed approach but where all data been stored in one location to see the upper bound of the model performance. From the results, we can see that FedHealth achieves the best average classification accuracy that significantly outperforms the best comparison method by 21.6% and 16.8% in two datasets and the best classification accuracy and mean-F1 score on almost all users, and it narrows the gap with the ideal situation. This indicates that through federated transfer learning FedHealth can achieve effective symptom classification in the real application.

Table 2. Classification accuracy (%) and mean-F1 (shown in the bracket) of each subject in arm droop and postural tremor test.

Arm Droop test						
Subject	KNN	SVM	RF	NoFed	FedHealth	Upper bound
P1	36.0 (0.32)	40.4 (0.38)	44.9 (0.41)	49.4 (0.49)	**75.0 (0.75)**	88.6 (0.88)
P2	64.0 (0.64)	61.8 (0.62)	57.3 (0.47)	68.5 (0.68)	**93.2 (0.93)**	100.0 (1.00)
P3	**85.7 (0.86)**	72.5 (0.72)	67.0 (0.64)	70.3 (0.70)	84.8 (0.84)	89.1 (0.89)
AVG	61.9 (0.61)	58.2 (0.57)	56.4 (0.51)	62.7 (0.62)	**84.3 (0.84)**	92.6 (0.92)
Postural Tremor test						
Subject	KNN	SVM	RF	NoFed	FedHealth	Upper bound
P1	50.4 (0.44)	47.4 (0.37)	59.0 (0.58)	47.5 (0.41)	**85.3 (0.81)**	87.0 (0.86)
P2	59.5 (0.58)	58.3 (0.58)	51.8 (0.52)	61.2 (0.61)	**70.9 (0.67)**	87.3 (0.86)
P3	64.3 (0.64)	52.3 (0.50)	51.1 (0.51)	58.0 (0.58)	**68.4 (0.68)**	75.1 (0.75)
AVG	58.1 (0.55)	52.7 (0.48)	54.0 (0.54)	55.6 (0.53)	**74.9 (0.72)**	83.1 (0.82)

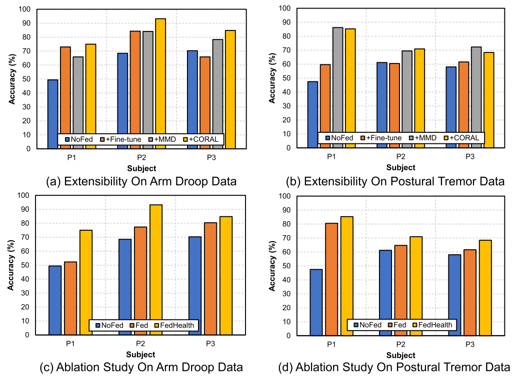

Figure 6. Extensibility with alternative transfer learning methods and ablation study on Parkinson's disease data.

Extensibility With Alternative Transfer Learning Methods

Consistent with the experiment settings in "Evaluation of Extensibility," extensibility results on arm droop and postural tremor test data are shown in Figure 6(a) and (b). We can see that FedHealth can achieve satisfying results with fine-tune or MMD in most cases, this indicates that FedHealth is effective and extensible with other transfer learning algorithms in the real application.

Ablation Study

We further provide the ablation study to evaluate the two main components of federated learning and transfer learning. We use Fed to denote the averaged model without personalized transfer learning. Results are shown in Figure 6(c) and (d). Results show that both federated learning and transfer learning make important contributions to the performance of FedHealth. Comparing Fed with NoFed, we can see model with federated settings can improve the classification accuracy, which indicate the effectiveness of federated learning. Further comparing Fed with the proposed federated transfer learning framework FedHealth, we can see that combined with transfer learning, each user model can achieve better performance on classification. This is because: 1) with federated learning, the server can take advantage of more information from multiple users indirectly to get a more generalized cloud model; 2) with transfer learning, users can utilize the cloud model to get a more personalized user model.

DISCUSSIONS

In this section, we discuss its potential to be extended and deployed to other situations with possible solutions.

1. FedHealth with incremental learning. Incremental learning has the ability to update the model with the gradually changing time, environment, and users. In contrast to transfer learning that focuses on model adaptation, incremental learning makes it possible to update the model in real time without much computation when new user data arrive.

2. FedHealth to be applied in more applications. This article mainly focuses on the possibility of federated transfer learning in healthcare via activity recognition and Parkinson's disease auxiliary diagnosis. In more real situations, FedHealth can be deployed to more healthcare applications, such as elderly care, fall detection, cognitive disease detection, etc. We hope that through FedHealth, federated learning can become federated computing, which can become a new computing model in the future.

CONCLUSIONS AND FUTURE WORK

In this article, we propose FedHealth, the first federated transfer learning framework for wearable healthcare. FedHealth aggregates the data from different organizations without compromising privacy security and achieves relatively personalized model learning through knowledge transfer. Experiments and applications have evaluated the effectiveness of the framework. We also present a detailed discussion for its potential from specific technical improvements to healthcare applications. FedHealth opens a new door for future research in wearable healthcare. In the future, we plan to extend FedHealth with incremental learning to achieve more personalized and flexible healthcare.

ACKNOWLEDGMENTS

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