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FEDERATED UNSUPERVISED AND SEMI-SUPERVISED TRANSFER LEARNING FOR ADDRESSING SCARCITY AND IMBALANCED HUMAN ACTIVITY RECOGNITION

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Abstract. *There are many researchers who use deep learning to investigate human activity recognition (HAR). However, deep learning requires a lot of labeled data to train the model. Human activity recognition data is typically imbalanced; it is collected from different sensors, and human movements vary according to time, lifestyle, health conditions, and so on. This paper proposes a novel framework named FUP-ST&DS-USA that integrates federated unsupervised preprocessing with semi-supervised transfer learning and adaptive symmetry uncertainty to generate high-quality labels for the unlabeled and imbalanced data. The proposed method can represent data with fewer features and can generate high-quality pseudo-labels for unlabeled data. It can also capture different types of imbalanced data: intra-client class imbalance, inter-client class imbalance, and dataset size imbalance by generating synthetic data based on the density of minority classes. Experiments on two real-world datasets, UCI and OpenPose Human Activity Recognition, demonstrate the effectiveness of the proposed framework in generating high-quality pseudo-labels with a high mask rate and low impurity rate. The FUP-ST&DM-UAS framework achieves 93% and over 96% on the UCI and OpenPose datasets, respectively, in terms of precision, recall, F1-score, and accuracy, outperforming state-of-the-art techniques.*
Keywords: Semi-supervised learning, Federated learning, Human activity recognition, Adaptive symmetry uncertainty

1. **Introduction.** Human activity recognition (HAR) is a technique used to track human activities, commonly applied to detecting the behavior of elderly people living alone. To collect HAR data, sensor data such as gyroscope and accelerometer readings, camera images, or video are used. The primary benefit of HAR lies in its ability to detect threats to safety, health, and emergency situations [1]. Smart sensing-based HAR has garnered increasing attention from academia and industry in the past few years. Sensor-based HAR has its own distinct features and issues: 1) Privacy of patients. Data collected by sensors

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contains sensitive information related to patient privacy and security [2]; 2) Types of imbalance data. Imbalanced data can arise due to various factors, such as age, gender, habits, and lifestyle. There are several types of imbalances: intra-client class imbalance [3], inter-client class imbalance [4], and differences in the quantity of data across clients [5]; 3) Label scarcity. The data must be labeled by experts, but the labeling process is time-consuming and costly [6,7].

Previous HAR studies have addressed some of the aforementioned problems, but few have attempted to tackle all of these challenges within a single framework. Machine learning techniques such as CNNs [8], Markov transition fields [9], and generative adversarial networks (GANs) [10] can be employed to centrally label patient movements without compromising patient privacy. VFDTs [11] is a framework for online learning that uses unlabeled data to update models without requiring data to be labeled. In this work [1], the authors combined semi-supervised learning with active transfer learning to label data without the need for manual labeling and, at the same time, reduce query requests. SimCLR [12] used a self-supervised learning paradigm to align features in the temporal dimension of human activity recognition. A proposed innovation system [13] selects the most informative data for expert labeling to reduce labeling costs by combining active learning and semi-supervised learning. In addition, Qi et al. [14] proposed a framework that enhances the privacy of clients while exploiting the complementarity of human movements to detect patient falls.

Many researchers have proposed solutions to address the issue of label scarcity in human activity recognition within federated learning frameworks. However, these solutions often do not mitigate the uneven distribution of data among clients, class imbalance within a single client, or the varying quantities of data per client. One common strategy [15] involves combining active learning and label propagation with federated learning to annotate unlabeled sensor data. Another approach [2] leverages semi-supervised learning to design an online personalization framework for human activity recognition, addressing privacy, labeling, and imbalance between clients. Additionally, personalized semi-supervised learning has been proposed to adapt models with limited or no labeled data [16].

The proposed framework, named FUP-ST&DS-USA, combines federated unsupervised preprocessing and semi-supervised transfer learning to leverage the strengths of these techniques. Federated unsupervised preprocessing reduces the dimensionality of unlabeled data at the client and preserves privacy without the need to share data. To enhance labeling, semi-supervised transfer learning is used to transfer knowledge from a pre-trained data (small labeled dataset) to clients to help label a large amount of unlabeled data, while improving the learning process and generalization. The integration of these techniques helps to build a synergistic framework able to handle annotated data, different types of imbalanced data, and the privacy of patients. This makes the architecture particularly well-suited for decentralized applications in the real world. The proposed framework is evaluated with two datasets, UCI HAR and OpenPose HAR, with various performance metrics. The quality of labeled data is measured by mask rate and impurity rate and yields good results. The results demonstrate that the proposed work using a simple multilayer perceptron outperforms time series techniques like CNN, LSTM, and GRU in terms of the number of parameters, total network overhead, and total training time. The contributions made in this paper are as follows.

- We propose a framework named FUP-ST&DS-USA to leverage semi-supervised transfer learning by mitigating label scarcity, data imbalance among classes within single clients, and varying dataset sizes.

- It produces a high-quality label for human activity by measuring mask rate and impurity rate without needing an extensive amount of labeled data.
- Two real datasets are used to evaluate the proposed work; the results show that FUP-ST&DS-USA achieves high performance metrics in terms of F1-score, precision, recall, etc., while requiring significantly less in terms of the number of parameters, total network overhead, and total training time.

2. **Related Work.** This section describes the most common issues that human activity recognition faces, which affect the performance of federated learning.

2.1. **Unsupervised preprocess for dimensionality reduction.** Unsupervised learning plays an important role in reducing the dimensionality of unannotated data without relying on labeled data, especially in the field of human activity recognition. There is little research on dimensionality reduction for unlabeled data. Hurtik et al. proposed F-transform and (k)PCA to reduce the dimensionality of unlabeled images, which reduces computation and frame complexity [17]. Liu et al. proposed an unsupervised model using a variational auto-encoder to perform dimensionality reduction of unlabeled text. The proposed model improves accuracy by 3.7% and 0.21% compared with other dimensionality reduction techniques [18]. Lim and Park integrated Maximum Margin Criteria (MMC) and Linear Discriminant Analysis (LDA) for dimensionality reduction to reduce overfitting in high-dimensional data. The semi-supervised technique utilizes a similarity graph to reduce dispersion within classes and increase distance between classes [19]. To reduce running time and improve performance, Niu et al. [20] proposed a robust unsupervised dimensionality reduction method using an adaptive bipartite graph. The approach constructed a bipartite graph with a small number of anchor points and sample points while preserving the local geometric structure of the data. Manongga et al. [21] proposed an unsupervised learning approach (K-means clustering) to determine the correlation of each feature. Then, supervised learning was employed to connect the dominant features with the risk of stunting. This research used machine learning to highlight important features, such as indicators of maternal health and sanitation coverage, that are associated with stunting.

2.2. **Federated imbalance data.** Federated imbalanced data can take many forms, such as inter-client class imbalance, intra-client class imbalance, and varying dataset sizes among clients in federated learning [22]. Each form of imbalanced data is explained below.

Inter-client class imbalance refers to the uneven distribution of classes across different clients. For example, client 1 is predominantly class A, while client 2 is predominantly class B [3].

Intra-client class imbalance occurs when, within a single client dataset, there is an uneven distribution of the dataset among classes. It negatively affects the performance of the system and introduces bias towards the more represented classes [3,22,23].

Clients' dataset sizes vary significantly, with some clients having large amounts of data collected using many sensors, while others have much smaller datasets [5,22].

In our previous work, Taha et al. [24] proposed FUP-DS2MOTE-USA, which captures various types of imbalanced data and locally preprocesses the data. The experiments showed that the proposed framework reduces computational complexity and ensures client privacy. Shuai et al. [25] proposed a balanced federated learning approach capable of learning from both underrepresented and overrepresented classes. Their local update technique rectifies class imbalance and ensures that the local model learns in a manner similar to uniformly distributed data. Cheng et al. [26] proposed protoHAR, a method that decouples representations and classifiers to capture label and data distributions among clients.

The method corrects class data representation using a global prototype that is shared among clients, facilitating knowledge transfer while maintaining client security. Sarkar et al. [27] proposed a new technique called Fed-Focal Loss, which addresses class imbalance in clients by modifying the cross-entropy loss used in well-classified examples. Wu et al. [28] designed FedHome based on federated learning to provide precise and personalized health monitoring. To balance data among clients, the authors used a generative convolutional autoencoder (GCAE) to generate synthetic samples for minority classes.

2.3. **Scarcity data.** Presotto et al. [15] proposed FedHAR, which combines federated learning with active learning and label propagation to label sensor data for human activity recognition. The proposed methods were applied to two datasets: the WISDM and MobiAct datasets. However, the authors did not consider significant types of imbalanced sensor data, particularly human movements, which vary according to factors such as time, habits, and mood. Trotta et al. [6] incorporated federated learning with a self-organizing map (SOM) to detect patient activity. Dimensionality reduction was used to reduce the SOM size and enable efficient operation on constrained IoT devices. Trotta et al. incorporated federated learning with a self-organizing map (SOM) to detect patient activity. Dimensionality reduction was used to reduce the SOM size and enable efficient operation on constrained IoT devices. The main limitation of the proposed method is that it takes a long time and is more complex for the labeling process. Sarkar et al. [29] introduced GraFeHTy, an innovative method for semi-supervised classification of human activities. The framework utilizes a graph convolution network (GCN) to train the local model at the client in a federated setting, and then transmits the model results to the server for aggregation to update the global model. The proposed method is extremely time-consuming. Tashakori et al. [16] designed a personalization framework for devices with limited or no labels. Personalized auto-encoders are generated by the hyper network during training, enabling learning from user data representations. Yu et al. [2] proposed personalized FedHAR, combining federated learning with semi-supervised learning to overcome the concept drift and convergence instability issues in the online federated learning process. The limitations of the proposed framework are the data quality of the client and the scalability of FedHAR. Che et al. [30] proposed a new approach named FedTriNet, aimed at generating high-quality pseudo-labels for unlabeled data with two learning stages. In the first phase, labeled data is used to pre-train FedTriNet. The second stage generates pseudo-labels that help in learning the model. The proposed model has two limitations: computational overhead and the quality of the pseudo-labels. In this work, Ma et al. [31] proposed federated semi-supervised sleep, which significantly boosts performance by sharing task knowledge contained in the relationships among sleep stages. The method faces issues related to the integrated model of federated learning across institutions, which could affect overall model performance. Sattler et al. [32] proposed a framework, named FedAUX, which is modified to federated distillation. It utilizes unlabeled auxiliary data to extract maximum utility, which enhances performance and is used to pre-train the model. The proposed framework faces problems in the pre-training model that affect the scalability and efficiency of the system.

3. **Methodology.** Building on previous work [24], this paper proposes a framework named FUP-ST&DS-USA. This framework addresses the limitations identified in earlier research, particularly those related to the scarcity of labels when clients have limited labeled data. By referencing and expanding upon the earlier work, this study aims to advance the field and offer deeper insights into the challenges affecting human activity

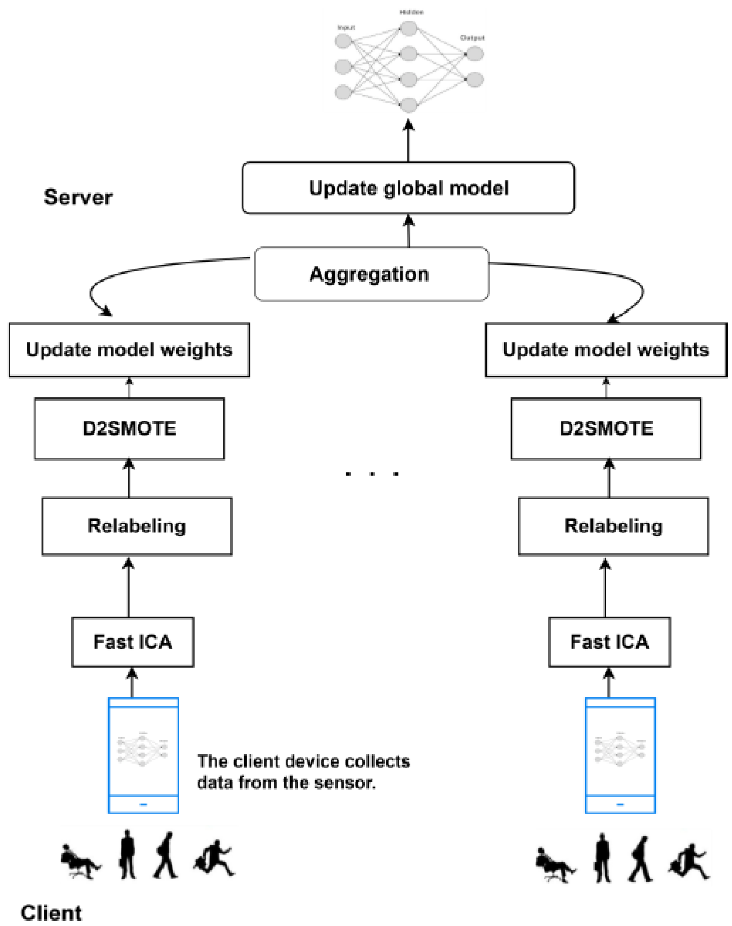


FIGURE 1. The steps for relabeling data in the FUP-ST&DS-USA framework

recognition with federated learning. The procedure of the FUP-ST&DS-USA framework is presented in Figure 1.

3.1. **Client side: Federated preprocessing for unlabeled data and rebalancing imbalanced data.**

3.1.1. *Federated unlabeled preprocessed data.* Unsupervised learning techniques are used to extract relevant features and meaningful attributes from unannotated data, especially in complex datasets like human activity recognition. Supervised learning cannot provide a mapping for unseen data because it relies on the classes of data to make inferences. Meanwhile, unsupervised techniques like clustering, ICA (independent component analysis), and PCA (principal component analysis) can be utilized to reduce the dimensionality of unlabeled data [33,34]. These techniques produce new data while preserving the original information and relationships between features without any prior knowledge of the target variables [35].

ICA is an unsupervised technique used for feature extraction, producing new information that does not carry any label-related information. It focuses on finding a linear transformation of the data such that the transformed data is as close to being statistically independent as possible [36]. In the context of human activity recognition (HAR), where data often comes from multiple sensors placed at different positions on the human body, ICA can handle unlabeled data and reduce the dimensionality of the data. This leads to a reduction in the computational cost and an enhancement in the performance of the frameworks.

ICA was chosen over other techniques because of its ability to extract relevant information (independent components, where HAR is non-iid) and reduce the dimensionality of noise and real medical data. This attribute is beneficial in HAR, unlike clustering techniques that are not proficient with high-dimensional data or non-linearly separable features. ICA is suitable for local computation under a federated learning environment. In contrast, PCA assumes a linear correlation between features, which is not true for all datasets, making it an inappropriate choice for capturing the HAR dataset.

3.1.2. *Semi-supervised transfer learning.* In FUP-ST&DS-USA, clients have limited labeled data (split into validation and training) with a large amount of unlabeled data. Semi-supervised transfer learning is used to relabel data at the client side. Each client has two models: the deep neural network-based basic model (DNN) and a transferred correct classifier model. Figure 2 presents the architectures of the DNN and the correct classifier model. The basic model consists of 2 layers, with 128 and 64 units, using ReLU in the two layers and Softmax in the output layer (with 6 and 4 units for the UCI and OpenPose datasets, respectively) to avoid overfitting and ensure the system learns from unseen data. The correct classifier is built by freezing the two layers of the basic model, with 2 output units (correct and incorrect).

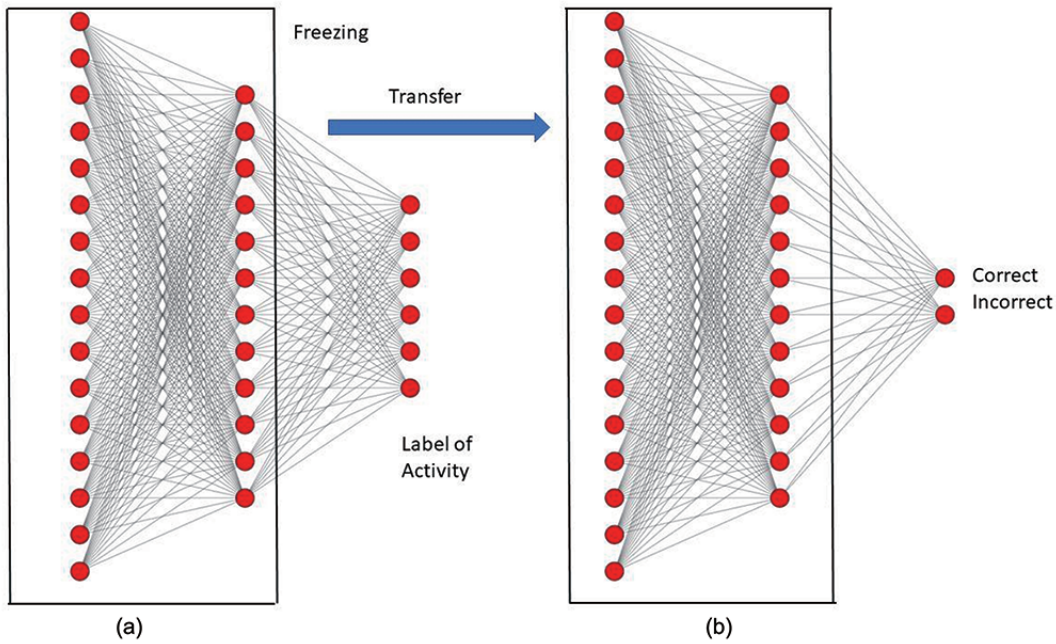


Figure 2. (a) Basic model; (b) correct classifier model

The client begins learning the DNN with labeled training data, and then passes the information to the transferred correct classifier. The validation set is then fed into the learned basic model to generate the correct dataset by comparing the actual output with the predicted values of the validation set. The correct classifier is trained with the correct dataset. This process allows the model to learn more and makes it easier to annotate unlabeled data. Next, input the unlabeled data to the correct classifier; the resulting classifier outputs correct or incorrect, allowing comparison of probabilities based on current model knowledge. First, if the probability of the correct classifier exceeds its threshold value, a pseudo-label is assigned to this sample. Second, this sample is added to the training dataset. Incorrectly high-probability samples are discarded. This process is repeated for each client until no samples are incorrect. Figure 3 demonstrates the steps for relabeling data at client sides.

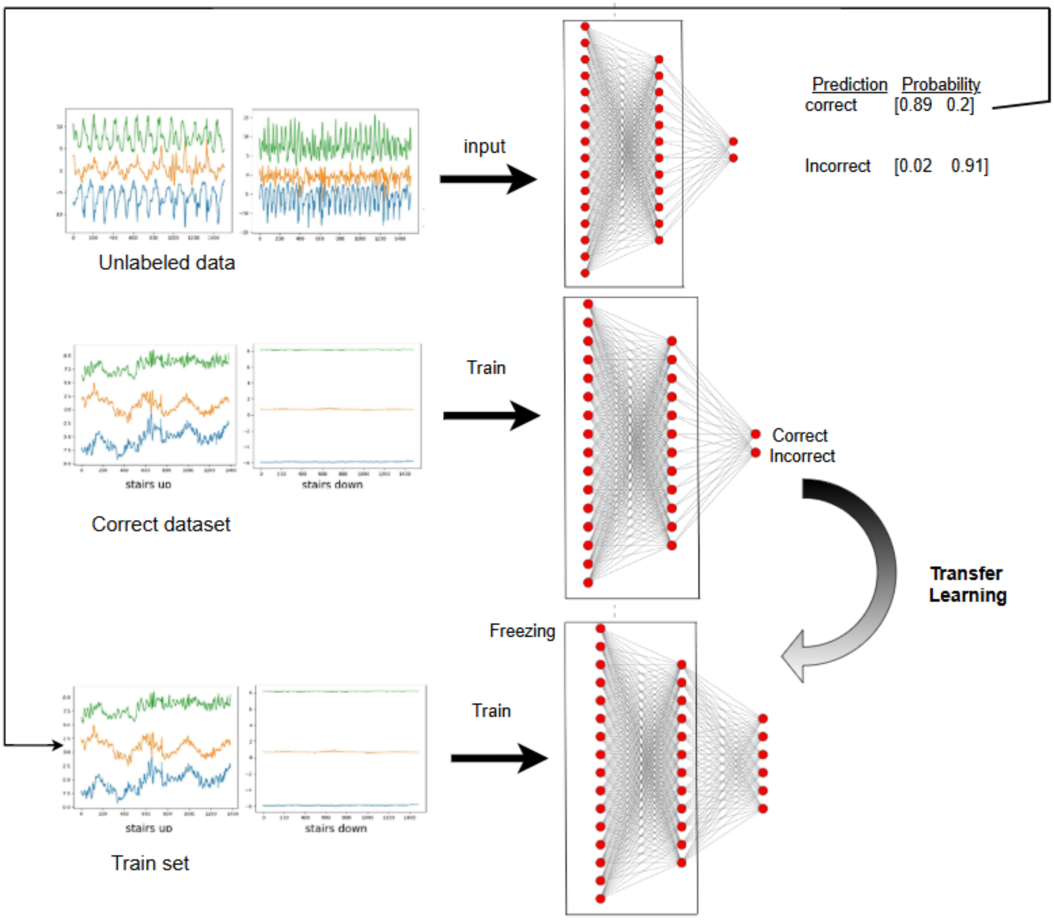


Figure 3. The steps for relabeling data in the FUP-ST&DS-USA framework

3.1.3. *The density-sensitive synthetic minority oversampling technique (D2SMOTE).* An imbalanced dataset refers to a situation where one or more classes are overrepresented compared to others. This issue is common in medical applications, especially in the analysis of human activities. It can lead to bias, causing poor performance in the classification of the minority class [37]. SMOTE is a popular method used to address this issue by generating new samples for the minority class, thus reducing the bias toward the majority class and improving system performance [38,39].

A modification of the original SMOTE method that takes account of the examination of areas where classes overlap is called the density-sensitive synthetic minority oversampling technique (DS2MOTE). A DS2MOTE approach is presented, motivated by our earlier research [24]. The new method considers both the spatial relationship between samples of the minority and majority classes, as well as the density of the minority class. The proposed method improves the model's sensitivity towards minority classes and enhances the overall performance of the system. It also improves the system's ability to distinguish between classes with overlapping areas by generating synthetic samples in the regions where misclassification may occur.

After preprocessing, each client applies D2SMOTE to a small label to balance data and then applies after generating pseudo label. This is a mathematical model of the framework.

Given dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, where x_i are feature vectors and y_i are the corresponding labels, and a class distribution $\{c_1, c_2, \ldots, c_k\}$, the goal is to balance the class distribution through a two-step process:

1) During Pretraining (with training label data)

2) On client data after pseudo label

Let D_j denote the dataset of client j where $j = 1, 2, \ldots, K$ (K is total number of clients). Each user has dataset D_j contents of small label dataset l_j and large unable dataset U_j, such that

$$D_j = l_j \cup U_j$$

where

- $l_j = \{(x_{j,i}, y_{j,i}) | i = 1, 2, \ldots, m_j\}$ is the labeled data for client j, with $x_{j,i}$ representing the input features (output of ICA) and $y_{j,i}$ is label of data.
- $U_j = \{x_{j,k} | K = 1, 2, \ldots, n_j\}$ is the unlabeled data for client j.
- Initial label data: each client j has a small label dataset $l_j = \{(x_{j,i}, y_{j,i}) | i = 1, 2, \ldots, m_j\}$ is the labeled data for client j, with $x_{j,i}$ representing the input features (output of ICA) and $y_{j,i}$ is label of data. The labeled data is divided into training and validation set l_j^{train} and l_j^{val}.
- Unlabeled data: The client also holds an unlabeled dataset $U_j = \{x_{j,k} | K = 1, 2, \ldots, n_j\}$, where only features $x_{j,k}$ are available.

Step 1: Identify the minority class: let $Y_{minority}$ be the underrepresented class. The dataset can be divided into

$$D_{\min} = \{x_i \in X | Y_i = Y_{minority}\}$$
$$D_{maj} = \{x_i \in X | Y_i \neq Y_{minority}\}$$

Step 2: Calculate density: compute the density for each sample in $D_{\min}$ using the average distance to the K-nearest neighbors using Equation (1):

$$D_{density}[i] = \frac{1}{K} \sum_{j=1}^{K} d(x_i, x_j), \quad x_i \in KNN(x_i, D_{\min}) \tag{1}$$

where $d(x_i, x_j)$ is the Euclidean distance between samples.

Step 3: Identify nearest neighbors: for each sample in $x_i \in D_{\min}$, find the nearest neighbors from $D_{\min}$: Let $Y_{nearest}$ be the set of K_{nn} nearest neighbors for x_i.

Step 4: Generate synthetic samples.

For each $y_i \in D_{\min}$:

1) Determine the number of synthetic samples N_{synth} based on the density:

$$N_{synth} = \text{function of } D_{density}[i]$$

2) For each j from 1 to N_{synth}: Randomly select $Y_{nearest}$. Generate synthetic samples using Equation (2):

$$Y_{synth}[j] = Y_{minority}[i] + r(Y_{nearest} - Y_{minority}[i]) \tag{2}$$

where r is a random value in $[0, 1]$.

Step 5: Pseudo-labeled data.

A trained model f_j is used (in Equation (3)) to assign pseudo-labels $\widehat{y^i}$ to the unlabeled dataset U_j based on a confident threshold τ.

$$\widehat{y^i} = f_j(x_i) \text{ if } \max(p(f_i(x_i))) > \tau \tag{3}$$

where $p(f_j(x_i))$ is the prediction probabilities from the model for input x_i.

The pseudo-labeled data can be represented as

$$U'_j = \left\{ \left(x_i, \widehat{y^i} \right) : \widehat{y^i} \text{ is confident} \right\}$$

Apply D2SMOTE on pseudo label data with same steps.

Merge Datasets

After generating synthetic samples, merge the datasets:

- Combine Labeled Data

Let l_j^{train} be the initial labeled training data:

$$L_j^{final} = l_j^{train} \cup Y_{synth} \cup U_j'$$

3.1.4. *Update model.*

1) The basic model is a deep neural network (DNN) that initially learns from the labeled dataset. It is responsible for capturing the core features of the data, which can later be transferred to other models for specific tasks.

   The architecture of the basic model is designed to be robust enough to extract meaningful features while ensuring efficient training on relatively small datasets.

2) The correct classifier is a specialized model derived from the basic model. It is designed to identify which predictions made by the basic model are correct or incorrect, thus creating a dataset of "correct" and "incorrect" predictions. This information is crucial for labeling the unlabeled data and generating pseudo-labels with high confidence.

   The correct classifier model is constructed by freezing specific layers of the pre-trained basic model and adding a new output layer that predicts whether a sample's prediction is correct or incorrect. By freezing the first few layers of the basic model, the correct classifier can focus on learning from the already extracted features, allowing it to specialize in distinguishing between correct and incorrect predictions without modifying the core feature extraction layers.

3.2. **Server side: Addressing inter-client imbalance through symmetric uncertainty with adaptive threshold.** The concept of symmetry of uncertainty [40] in client selection states that there is equal uncertainty in both cases on whether to include or exclude a given client. In other words, client may provide valuable information for server, but there is also uncertainty as to whether their inclusion actually increases predictive power or if they are redundant or noisy. It all depends on the degree of imbalance in the client's dataset is. Equation (4) provides the formula for computing SU.

$$SU(X,Y) = 2\frac{IG\left(\frac{X}{Y}\right)}{H(X)H(Y)} \tag{4}$$

Hence, in this specific context, $IG(X/Y)$ denotes the amount of information gain related to feature X, which is treated as an attribute that is unrelated to the class attribute Y. $H(X)$ signifies the entropy of feature X, while $H(Y)$ represents the entropy of feature Y [41].

4. **Implementation and Evaluation.** Two different datasets – the HAR OpenPose and the Human Activity Recognition with Smartphones (UCI HAR) dataset [42] – were used to assess the proposed methodology. The PC used for this research had an Intel(R) Core (TM) i7-10750H CPU and 24GB of RAM. Each dataset was divided into labeled and unlabeled data. 70% of the unlabeled dataset was distribute among clients, while the labeled dataset was spilt into 10% for training, validation and testing the global model on the server.

4.1. **Human Activity Recognition with Smartphones (UCI HAR) dataset.** The UCI HAR dataset is organized into 6 activities based on its 561 features. These characteristics represent a variety of sensor readings and lifestyle-related indicators that are important for analyzing human movement. The activities are WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, and LAYING. The dataset was collected by having participants wear a Samsung Galaxy S II smartphone around their waist. This device recorded 3-axial angular velocity and 3-axial linear acceleration data at a steady 50 Hz rate.

4.2. **OpenPose dataset.** This dataset could include video recordings of patients performing various activities such as standing, walking, squatting, and jumping. By capturing detailed human movements, these videos can be analyzed into 36 features. The purpose of this dataset is to analyze human movements and track individuals through the videos.

4.3. **Model network.** The neural network is designed with one input layer, three hidden layers, and a single output layer. The size of the input layer corresponds to the number of components derived from LDA. The two hidden layers have neuron counts of 128, and 64, in that order. Batch normalization and dropout are applied following each layer, with dropout rates of 0.2 for the first two hidden layers and 0.1 for the third. ReLU is the activation function chosen for all hidden layers. The output layer uses a linear activation function for label classification. A learning rate of 0.001 is set, and the model is optimized using Stochastic Gradient Descent (SGD). Random search was utilized in the experiments to determine the hyperparameters of the model, such as batch size (32 for UCI and OpenPose datasets), number of epochs (10), and dropout rate. Table 1 displays the hyperparameter settings for the UCI and OpenPose datasets.

Table 1. Hyperparameter setup of the proposed model

Parameters	UCI HAR dataset	OpenPose dataset
Train ratio	90%	90%
Test ratio	10%	10%
ICA components	50	10
Learning rate	0.001	0.001
Batch size	32	32
Communication round	10	10
Optimizer	Adam	Adam
Basic model architecture	2 dense layers (128, 64 units); Dropout $(0.2, 0.1)$	2 dense layers (128, 64 units); Dropout $(0.2, 0.1)$
Activation function of hidden layer and output layer	ReLU, Softmax	ReLU, Softmax
Batch size	32	32
Activation function (Hidden/Output)	ReLU, Softmax	ReLU, Softmax

4.4. **Performance metric.** To evaluate FUP-ST&DS-USA for human activity labeling, it is essential to use rigorous performance criteria that accurately capture the model's efficacy. Several factors are considered, such as the F1-score, accuracy, precision, recall, and Matthews correlation coefficient (MCC), to measure the efficacy of the system. While accuracy provides a broad indication of the model's overall performance, precision and recall are crucial for evaluating its capacity to accurately detect human movement. The F1-score, which balances precision and recall, is particularly useful when the HAR dataset suffers from various types of imbalances, data scarcity, and noise generated from pseudo-labeling. In multi-class classification scenarios, the Matthews correlation coefficient offers a more nuanced understanding of the model's performance by taking account of true positives, false positives, true negatives, and false negatives. By integrating these parameters, researchers can ensure a comprehensive evaluation of model performance, ultimately leading to more trustworthy diagnostic tools in HAR.

5. Results and Discussion.

5.1. Overall performance metrics of FUP-ST&DS-USA. In this semi-supervised learning framework, transfer learning can significantly aid in improving the performance of the current model by transferring useful knowledge from the base model to the correct classifier. This concept allows the model to capture general patterns and relationships

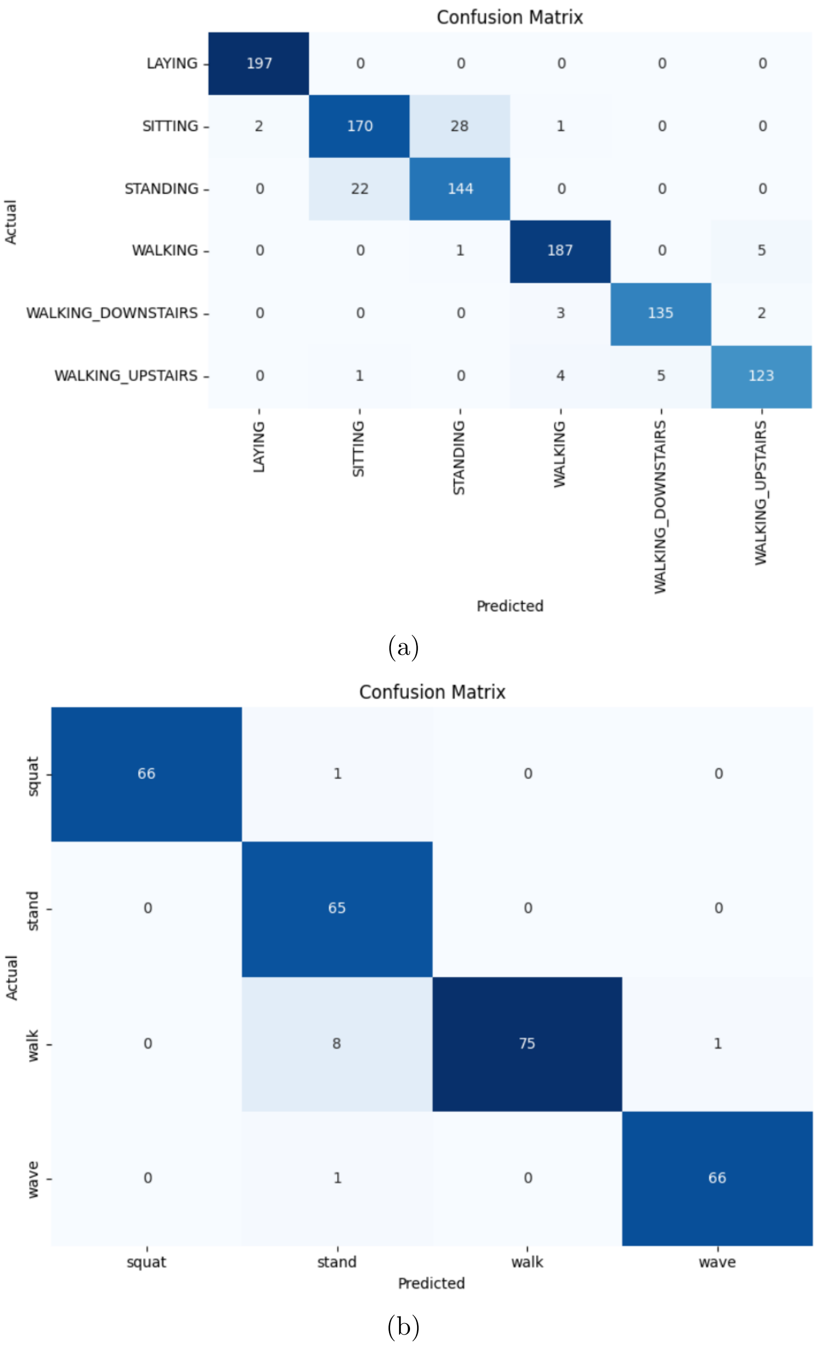


FIGURE 4. Confusion matrix: (a) UCI HAR; (b) OpenPose HAR

Table 2. Performance metrics of UCI HAR

Class	Precision (%)	Recall (%)	F1-score (%)
LAYING	99	100	99
SITTING	88	85	86
STANDING	83	87	85
WALKING	96	97	96
WALKING_DOWNSTAIRS	96	96	96
WALKING_UPSTAIRS	95	92	94

Table 3. Performance metrics of OpenPose HAR

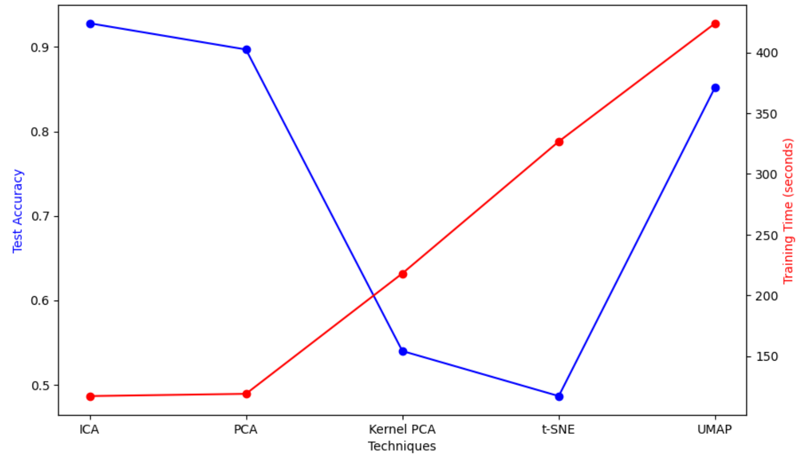
Class	Precision (%)	Recall (%)	F1-score (%)
Squat	100	99	99
Stand	87	100	93
Walk	100	89	94
Wave	99	99	99

between features by first training a base model on a small set of training data and then re-training it on the client's labeled and pseudo-labeled data. However, the model may perform poorly due to noise, imbalanced data, or limited labeled data. Through the use of transfer learning, the correct classifier is built by freezing the initial layers of the base model to preserve the learned knowledge and use it to create a correct dataset. This is demonstrated in Figure 4 and Tables 2 and 3. The proposed base model and correct classifier allow the model to dynamically adapt its understanding based on previously generated outputs to generate the correct dataset.

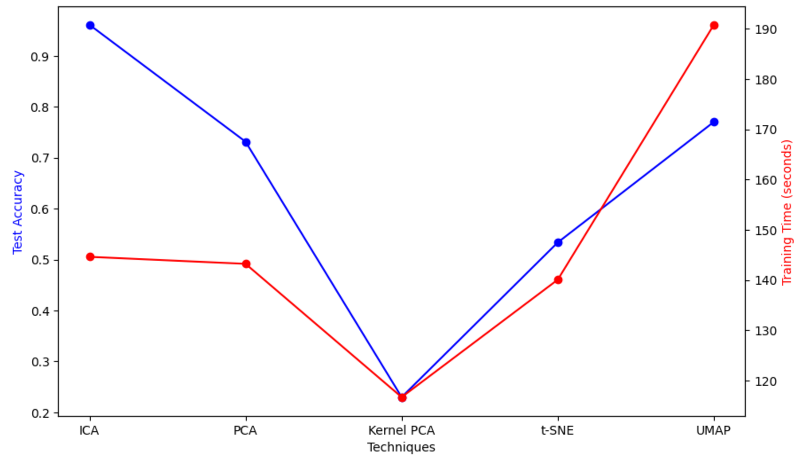
The framework, in combination with D2SMOTE, can enhance the learning of minority classes because it relies on class density to address the degree of imbalance. Furthermore, uncertainty systems with adaptive theory should filter out clients that participate in global model updates to prevent the negative impact of imbalanced data on certain clients.

5.2. **The impact of unsupervised preprocessing techniques.** To evaluate the impact of unsupervised techniques for dimensionality reduction in human activity recognition (HAR), ICA, PCA, Kernel PCA, t-SNE, and UMAP were compared in terms of test accuracy and training time on the UCI and OpenPose HAR datasets. The experimental results (in Figure 5) show that ICA outperformed the others in accuracy (92.81% and 96.11%) while maintaining a moderate training time (117.05 seconds and 144.62 seconds). PCA demonstrated that it is a good choice when speed is crucial. In contrast, UMAP performed poorly in terms of accuracy (85.24% and 77.03%) and required more training time, making it less ideal for time-sensitive applications. Kernel PCA and t-SNE took significantly longer to train, with much lower accuracy. Overall, ICA stands out as a suitable option, as it strikes a balance between computational time and accuracy.

5.3. **Impact of transfer learning on the performance of the framework.** Transfer learning can help improve the performance of the human activity recognition framework by applying pre-trained models to labeled data. Using transfer learning, the framework can capture patterns and characteristics from labeled data that are similar to unlabeled data to help the model label unlabeled data. This section compares FUP-ST&DS-USA with the baseline model (without transfer learning). In the baseline model, the clients have a single model to handle labeled and unlabeled data in every communication round. The correct classifier is not found, and the client is directly trained with a small labeled dataset,



(a)

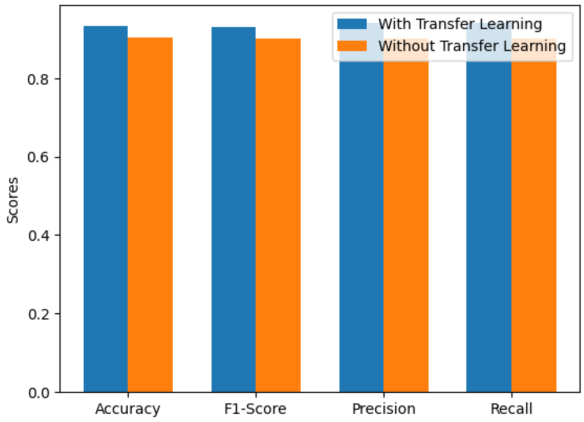


(b)

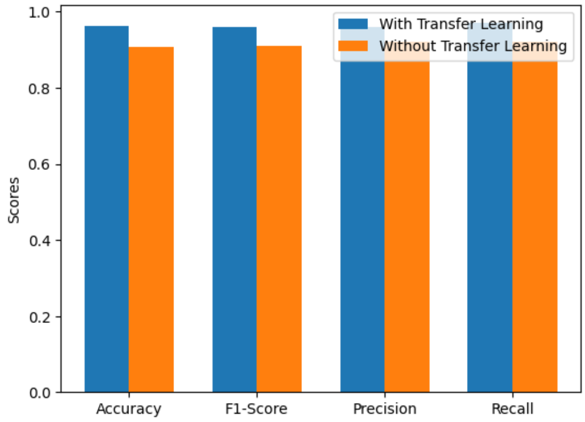
FIGURE 5. Comparison of test accuracy and training time for different techniques: (a) UCI HAR and (b) OpenPose HAR

and then uses the same model to predict unlabeled data. If the prediction probability exceeds the threshold, the pseudo-label is combined with the training set. In UCI HAR, the improved model with transfer learning shows improvements of 3.22%, 3.33%, 4.44%, and 4.44% for accuracy, F1-score, precision, and recall, respectively, while in OpenPose, the improvements in accuracy, F1-score, precision, and recall are 5.84%, 5.49%, 4.35%, and 5.43%, respectively. The enhancement in system performance as a result of transfer learning transfers knowledge from labeled to unlabeled data, allowing the model to train and converge faster and more accurately to make predictions. All the enhancements can be tracked using Figure 6.

5.4. **Comparison of MLP with time series techniques.** The combination of independent component analysis (ICA) with a multi-layer perceptron (MLP) is more effective in capturing relevant features and reducing dimensionality for the human activity recognition (HAR) dataset compared to convolutional neural networks (CNNs), long short-term memory (LSTM), and gated recurrent units (GRU). Although CNN, LSTM, and GRU can extract features without preprocessing techniques, this is not always ideal because these models require a large number of parameters, leading to higher network overhead and increased computational complexity. It is clear from Figure 7. More layers mean

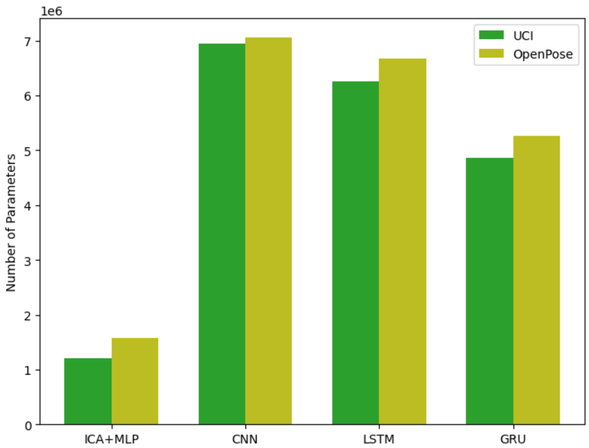


(a)

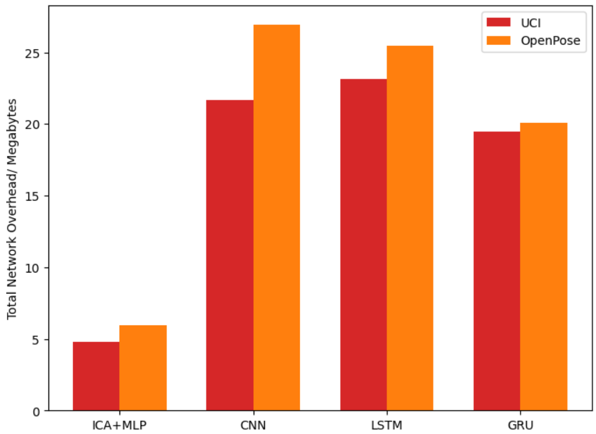


(b)

FIGURE 6. Comparison of metrics with and without T.L: (a) UCI HAR; (b) OpenPose HAR



(a)



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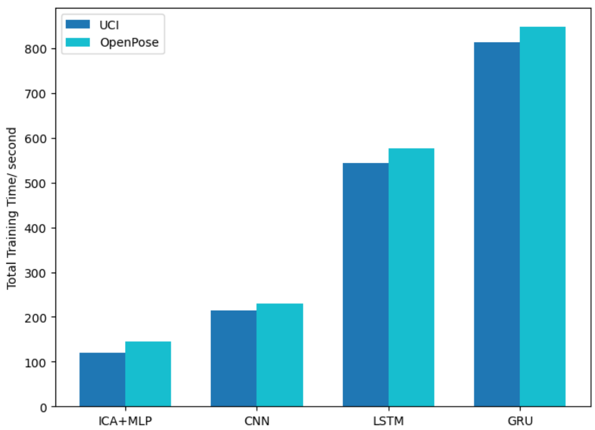
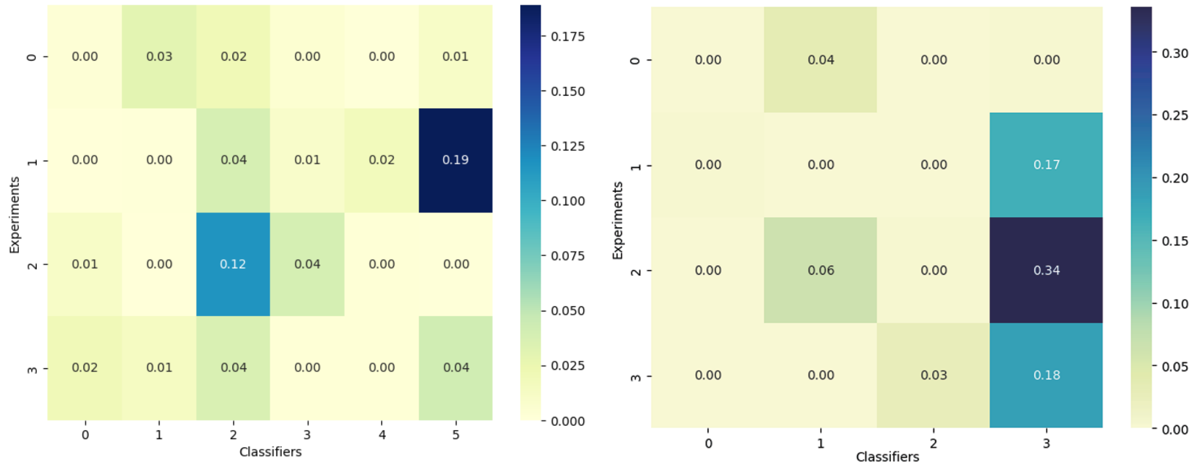
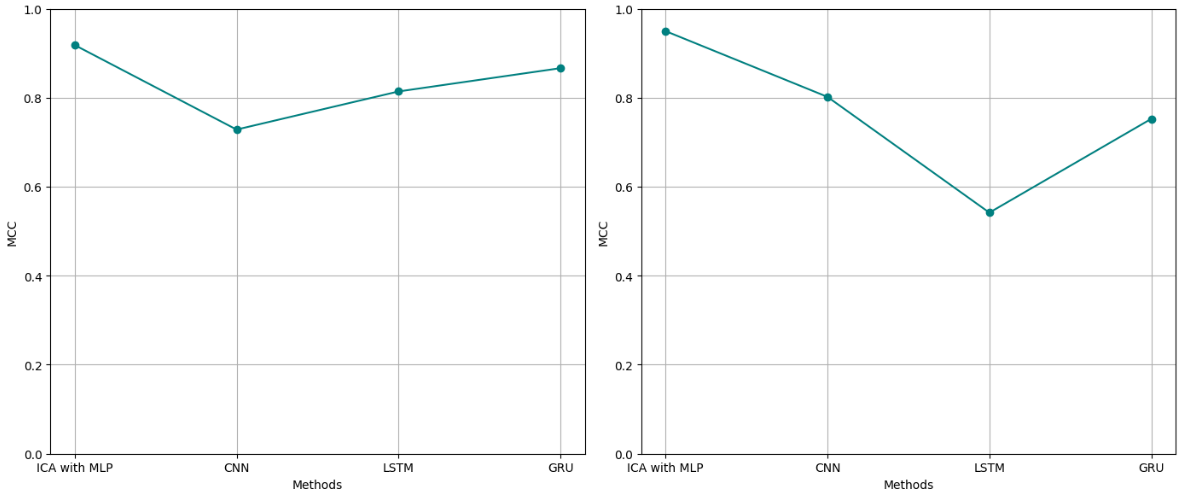


(c)

FIGURE 7. Comparison of UCI HAR and OpenPose HAR: (a) Number of parameters; (b) total network overhead; (c) total training time



(a)



(b)

FIGURE 8. (a) False positive rate for UCI and OpenPose HAR; (b) Matthews correlation coefficient for UCI and OpenPose

more parameters to update, more computation, and a more complex system. In contrast, introducing ICA before applying MLP simplifies the framework.

Additionally, Figures 8(a) and 8(b) demonstrate improvement in other performance metrics, such as the false positive rate (FPR) and Matthew's correlation coefficient (MCC), when utilizing ICA with MLP for the HAR dataset. A lower FPR indicates fewer false positives, while a higher MCC reflects better overall performance of the framework.

5.5. **Balancing the quality and quantity of FUP-ST&DS-UAS pseudo-labels with confidence thresholds.** The mask rate and impurity are used to balance the quantity and quality of the pseudo-labels, aiming to improve the reliability of the framework and generate confident pseudo-labels. The results as shown in Figure 9 demonstrate that FUP-ST&DS-USA can label data with high quality, achieving a balance between good model generalization, reducing noise from inaccurate labels, and maintaining high performance.

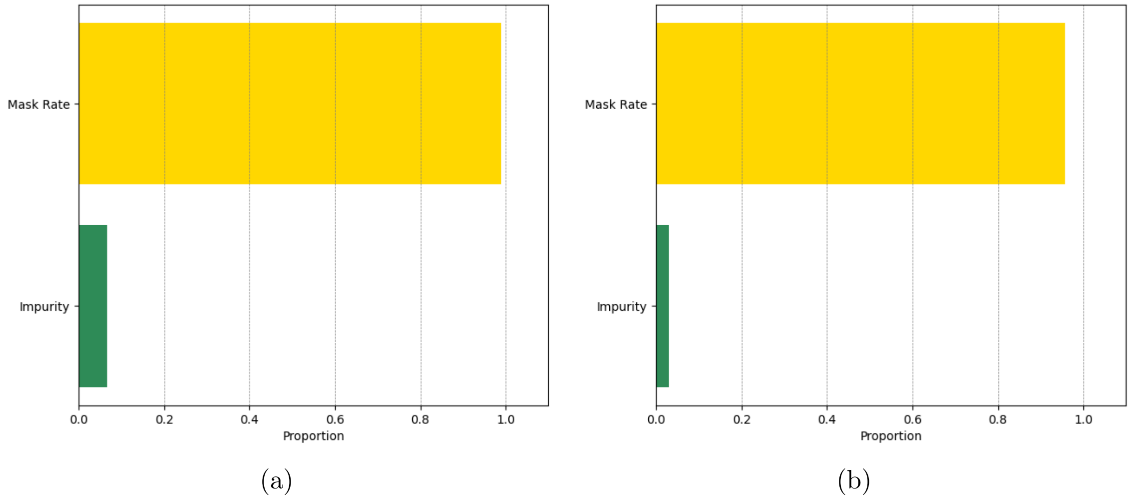


FIGURE 9. Mask rate and impurty rate for (a) UCI and (b) OpenPose HAR

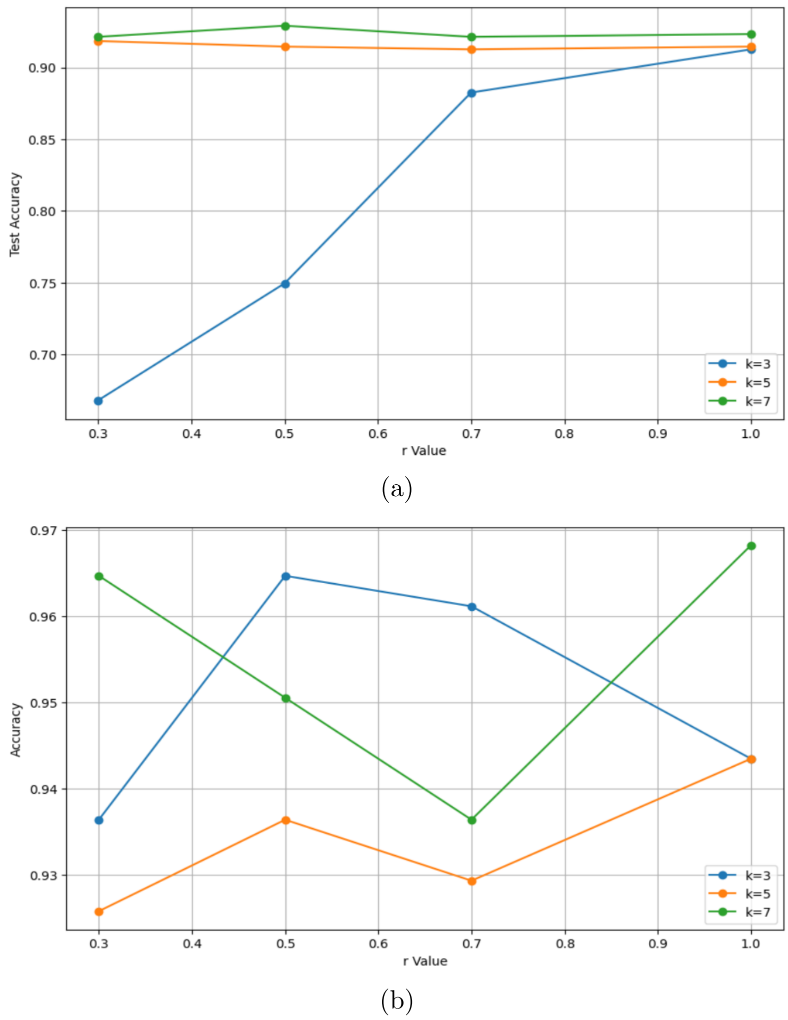


FIGURE 10. Relationship between k and r with accuracy for (a) UCI HAR and (b) OpenPose HAR

5.6. **Parameter sensitivity analysis of D2SMOTE.** In this section, we study the effect of two parameters, k and r of D2SMOTE on the performance of FUP-ST&DS-USA, as shown in Figure 10. The range of k is from 3 to 10; it controls the diversity of synthetic sets generated. When k is large, it means the synthetic samples are more diverse, but it also increases the risk of overfitting or class overlap. Meanwhile, r is a random value between 0 and 1; it determines the exact position of new synthetic samples that lie between X_i and X_j. It controls the separable distance of X_{new} from the original sample or neighboring sample. The experiments show that increasing r, to produce more synthetic data, can enhance the accuracy of the framework. The parameter k indicates how many neighbors are considered when generating synthetic data for the minority class. The values of k help to produce diverse data and mitigate the imbalance issue. We choose appropriate values of r and k to strike a balance between enhancing accuracy and avoiding overfitting. Higher values of r and k can better handle class imbalance and reduce the introduction of noise in the generated samples.

6. **Conclusion.** In this paper, an innovative framework named FUP-ST&DS-USA is proposed to address the issues of imbalanced data types and unlabeled data in the human activity recognition dataset. The framework integrates semi-supervised transfer learning with sampling theory to tackle these challenges. The proposed framework is tested using two real-world datasets, UCI and OpenPose HAR datasets. Future work will focus on non-independent and identically distributed data (non-IID) and client privacy. The results show that the proposed framework enhances accuracy, F1-score, and other performance metrics for imbalanced and unlabeled data. Furthermore, our method requires less complexity and time to train, while generating high-quality labels for sensitive data.

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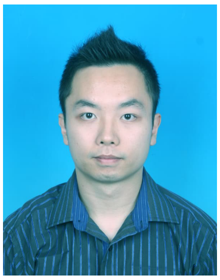

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