Semi-supervised Federated Learning for Activity Recognition

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ABSTRACT
The proliferation of IoT sensors and edge devices makes it possible to use deep learning models to recognize daily activities locally using in-home monitoring techniques. Recently, federated learning systems that use edge devices as clients to collect and utilize IoT sensory data for human activity recognition have been commonly used as a new way to combine local (individual-level) and global (group-level) models. This approach provides better scalability and generalisability and also offers higher privacy compared with the traditional centralised analysis and learning models. The assumption behind federated learning, however, relies on supervised learning on clients. This requires a large volume of labelled data, which is difficult to collect in uncontrolled IoT environments such as remote in-home monitoring.

In this paper, we propose an activity recognition system that uses semi-supervised federated learning, wherein clients conduct unsupervised learning on autoencoders with unlabelled local data to learn general representations, and a cloud server conducts supervised learning on an activity classifier with labelled data. Our experimental results show that using autoencoders and a long short-term memory (LSTM) classifier, the accuracy of our proposed system is comparable to that of a supervised federated learning system. Meanwhile, we demonstrate that our system is not affected by the Non-IID distribution of local data, and can even achieve better accuracy than supervised federated learning on some datasets. Additionally, we show that our proposed system can reduce the number of needed labels in the system and the size of local models without losing much accuracy, and has shorter local activity recognition time than supervised federated learning.

CCS CONCEPTS
• Computer systems organization → Client-server architectures; • Computing methodologies → Semi-supervised learning settings.

KEYWORDS
Edge Computing, Federated Learning, Human Activity Recognition, Unsupervised Learning, Semi-supervised Learning

1 INTRODUCTION
Modern smart homes are integrating more and more Internet of Things (IoT) technologies in different application scenarios. The IoT devices can collect a variety of time-series data, including ambient data such as occupancy, temperature, and brightness, and physiological data such as weight and blood pressure. With the help of machine learning (ML) algorithms, these sensory data can be used to recognize people’s activities at home. Human activity recognition (HAR) using IoT data has the promise that can significantly improve quality of life for people who require in-home care and support. For example, anomaly detection based on recognised activities can raise alerts when an individual’s health deteriorates. The alerts can then be used for early interventions [5, 11, 25]. Analysis of long-term activities can help identify behaviour changes, which can be used to support clinical decisions and healthcare plans [10].

An architecture for HAR is to deploy devices with computational resources at the edge of networks, which is normally within people’s homes. Such “edge devices” are capable of communicating with sensory devices to collect and aggregate the sensory data, and running ML algorithms to process the in-home activity and movement data. With the help of a cloud back-end, these edge devices can form a federated learning (FL) system [38], which is increasingly used as a new system to learn at population-level while constructing personalised edge models for HAR. In an FL system, clients jointly train a global Deep Neural Network (DNN) model by sharing their local models with a cloud back-end. This design enables clients to use their data to contribute to the training of the model without breaching privacy. One of the assumptions behind using the canonical FL system for HAR is that data on clients are labelled with corresponding activities so that the clients can use these data to train supervised local DNN models. In HAR using IoT data, due to the large amount of time-series data that are continuously generated from different sensors, it is difficult to guarantee that end-users are capable of labelling activity data at a large scale. Thus, the availability of labelled data on clients is one of the challenges that impede the adoption of FL systems in real-world HAR applications.

In centralised ML, unsupervised learning on DNN such as autoencoders [4] has been widely used to learn general representations from unlabelled data. The learned representations can then be utilised to facilitate supervised learning models with labelled data. A recent study by van Berlo et al. [34] shows that temporal convolutional networks can be used as autoencoders to learn representations on clients of an FL system. The representations can help with training of the global supervised model of an FL system. The resulting model’s performance is comparable to that of a fully supervised FL. Building upon this promising result, we propose a semi-supervised FL system that realises activity recognition using time-series data at the edge, without labelled IoT sensory data on clients. Apart from the alleviation of the efforts of labelling local data, since the edge clients in our design only conduct unsupervised learning locally, it is not affected by the possible non-independent and identically distributed (Non-IID) labels, which may negatively affect the performance of the global model [39] and are considered as one of the challenges in supervised FL [17, 20].

In our proposed design, clients locally train autoencoders with unlabelled time-series sensory data to learn representations. These local autoencoders are then sent to a cloud server that aggregates them into a global autoencoder. The server integrates the resulting global autoencoder into the pipeline of the supervised learning
process. It uses the encoder component of the global autoencoder to transform a labelled dataset into labelled representations, with which a classifier can be trained. Such a labelled dataset on the cloud back-end server can be provided by service providers without necessarily using any personal data from users (e.g., open data or data collected from laboratory trials with consents). Whenever the server selects a number of clients, both the global autoencoder and the global classifier are sent to the clients to support local activity recognition.

We evaluated our system through simulations on different HAR datasets, with different system component designs and data generation strategies. We also tested the local activity recognition part of our system on a Raspberry Pi 4 model B, which is a low-cost edge device. With the focus on HAR using time-series sensory data, we are interested in answering the research questions as follows:

- **Q1.** How does HAR using semi-supervised FL perform in comparison to using supervised FL?
- **Q2.** How does HAR using semi-supervised FL perform with Non-IID data in comparison to using supervised FL?
- **Q3.** How do the key parameters of semi-supervised FL, including the number of labels on the server and the size of learned representations, affect the performance of HAR?
- **Q4.** How efficient is HAR using semi-supervised FL on low-cost edge devices?

Our experimental results demonstrate several key findings:

- Using simple autoencoders as local models and a long short-term memory model as a global classifier, our system can achieve similar accuracy to that of a supervised FL.
- Our system is not affected by Non-IID data since it does not need labels in local model training. In some Non-IID cases, it can even achieve higher accuracy than supervised FL does.
- By only conducting supervised learning in the cloud, our system can significantly reduce the needed number of labels without losing much accuracy.
- By using simple local autoencoders, our system can significantly reduce the size of local models. This can potentially contribute to the reduction of upload traffic from the clients to the server.
- The processing time of our system when recognising activities on low-cost edge devices is acceptable for real-time applications and is significantly lower than that of supervised FL on some datasets.

## 2 RELATED

As one of the key applications of IoT that can significantly improve the quality of people’s lives, HAR has attracted an enormous amount of research. Many HAR systems have been proposed to be deployed at the edge of networks, thanks to the evergrowing computational power of different types of edge devices.

### 2.1 HAR at the edge

In comparison to having both data and algorithms in the cloud, edge computing [30] instead deploys devices closer to end users of services, which means that data generated by the users and computation on these data can stay on the devices locally. Modern edge devices such as Intel Next Unit of Computing (NUC) [1] and Raspberry Pi [2] are capable of running DNN models [8, 29] and providing real-time activity recognition [6, 21] from videos. Many deep learning models such as long short-term memory (LSTM) [13–15] or convolutional neural network (CNN) [14] can be applied at the edge for HAR. For example, Zhang et al. [36] proposed an HAR system that utilised both edge computing and back-end cloud computing. One implementation of this kind of HAR edge systems was proposed by Cao et al. [5], which implemented fall detection both at the edge and in the cloud. Their results show that their system has lower response latency than that of a cloud based system. Quer-alta et al. [25] also proposed a fall detection system that achieved over 90% precision and recall. Uddin [33] proposed a system that used more diverse body sensory data including electrocardiography (ECG), magnetometer, accelerometer, and gyroscope readings for activity recognition.

These HAR systems, however, send the personal data of their users to a back-end cloud server to train deep learning models, which poses great privacy threats to the data subjects. Servia-Rodriguez et al. [29] proposed a system in which a small group of users voluntarily share their data to the cloud to train a model. Other users in the system can download this model for local training, which protects the privacy of the majority in the system but does not utilise the fine trained local models from different users to improve the performance of each other’s models. To improve the utility of local models and protect privacy at the same time, we apply federated learning [23] to HAR at the edge, which can train a global deep learning model with constant contributions from users but does not require the users to send their personal data to the cloud.

### 2.2 HAR with federated learning

McMahan et al. [23] proposed federated learning (FL) as an alternative to traditional cloud based deep learning systems. It uses a cloud server to coordinate different clients to collaboratively train a global model. The server periodically sends the global model to a selection of clients that use their local data to update the global model. The resulting local models from the clients will be sent back to the server and be aggregated into a new global model. By this means, the global model is constantly updated using users’ personal data, without having these data in the server. Since FL was proposed, it has been widely adopted in many applications [19, 35] including HAR. Sozino [31] proposed an FL based HAR system and they demonstrated that its performance is comparable to that of its centralised counterpart, which suffers from privacy issues. Zhao et al. [38] proposed an FL based HAR system for activity and health monitoring. Their experimental results show that, apart from acceptable accuracy, the inference time of such a system on low-cost edge devices such as Raspberry Pi is marginal. Feng et al. [12] introduced locally personalised models in FL based HAR systems to further improve the accuracy for mobility prediction. Specifically, HAR applications that need both utility and privacy guarantees such as smart healthcare can benefit from the accurate recognition and the default privacy by design of FL. For example, the system recently proposed by Chen et al. [9] applied FL to wearable healthcare, with a specific focus on the auxiliary diagnosis of Parkinson’s disease.
Existing HAR systems with canonical FL use supervised learning that relies on the assumption that all local data on clients are properly labelled with activities. This assumption is difficult to be satisfied in the scenario of IoT using sensory data. Compared to the existing FL based HAR systems, we aim to address this issue by utilising semi-supervised machine learning, which does not need locally labelled data and can additionally avoid possible Non-IID problems in labels.

2.3 Semi-supervised learning

Semi-supervised learning combines both supervised learning that requires labelled data and unsupervised learning that does not use labels when training DNN models. One technique of semi-supervised HAR is to first train a model with labelled data through supervised learning and then transfer the resulting model to another domain that does not have labelled data, which is refer to as transfer learning. For example, Khan and Roy [18] use transfer learning to recognise unseen activities in a domain that does not have labels. Similarly, Zhang and Ardakanian [37] use transfer learning for occupancy estimation in a semi-supervised fashion.

Another commonly used technique is autoencoders [4], which uses unsupervised learning to train models with unlabelled data in order to extract the key features (i.e., representations) of data. The resulting autoencoders can then be plugged into the pipeline of supervised learning to train a model on the representations of labelled data. This technique has been widely used in centralised ML such as learning time-series representations from videos [32], learning representations to compress local data [16], and learning representations that do not contain sensitive information [22]. In many HAR systems, autoencoders have demonstrated the ability to support semi-supervised time-series activity prediction. Sagheer and Kotb [28] use LSTM-autoencoders [32] for unsupervised time-series event prediction including bike rent demands and air quality. Their experimental results show that autoencoders trained with unlabelled data can increase the performance of models trained with labelled data. Saeed et al. [27] show that, in HAR, training autoencoders with unlabelled time-series data to extract useful representations can help improve the performance of down-stream tasks including supervised learning.

Traditional centralised ML has benefited from semi-supervised learning, which has not gained enough attention in FL. Preliminary results from the recent work by van Berlo et al. [34] show promising potential of using autoencoders to implement semi-supervised FL. Compared to their work, we focus on FL based HAR and systematically investigate how different design considerations of semi-supervised FL affect its performance, how it performs with Non-IID data, and how efficient its local activity recognition is when running on low-cost edge devices.

3 METHODOLOGY

Our goal is to implement HAR using an FL system, without having any labelled data on the edge clients. We first introduce the long short-term memory model [15], which is a powerful technique for analysing time-series data for HAR. We then introduce autoencoders, which are the key technique for deep unsupervised learning. We finally demonstrate the design of our proposed semi-supervised FL system and describe how unsupervised and supervised learning models are used in our design.

3.1 Long short-term memory

The long short-term memory (LSTM) belongs to recurrent neural network (RNN) models, which are a class of DNN that processes sequences of data points such as time-series data. At each time point of the time series, the output of an RNN, which is referred to as the “hidden state”, is fed to the network together with the next data point in the time-series sequence. An RNN works in a way that, as time proceeds, it recurrently takes and processes the current input and the previous output (i.e., the hidden state), and generates a new output for the current time. Specifically for LSTM, Fig. 1 shows the network structure of a basic LSTM unit, which is called an LSTM cell. At each time t, it takes three input variables, which are the current observed data point X_t, the previous state of the cell C_{t−1}, and the previous hidden state h_{t−1}. For the case of applying LSTM to HAR, X_t is a vector of all the observed sensory readings at time t. h_t is the hidden state of the activity to be recognised in question.

LSTM can be used in both supervised learning and unsupervised learning. For supervised learning, each X_t of a time-series sequence has a corresponding label Y_t (e.g., activity class at time point t) as the ground truth. The hidden state h_t can be fed into a “softmax classifier” that contains a fully-connected layer and a softmax layer. By this means, such an LSTM classifier can be trained against the labelled activities through feedforward and backpropagation to minimise the loss (e.g., Cross-entropy loss) between the classifications and the ground truth. For unsupervised learning, LSTM can be trained as components of an autoencoder, which we will describe in detail in Sec. 3.2.
3.2 Autoencoder

An autoencoder [4] is a type of neural network that is used to learn latent feature representations from data. As shown in Fig. 2, different from supervised learning that aims to learn a function \( f(X) \rightarrow Y \) from input variables \( X \) to labels \( Y \), an autoencoder used in unsupervised learning tries to encode \( X \) to its latent representation \( h \) and to decode \( h \) into a reconstruction of \( X \), which is presented as \( X' \). Ideally, \( X' \) is supposed to be as close to \( X \) as possible, based on the assumption that the key representations of \( X \) can be learned and encoded as \( h \). As the dimensionality of \( h \) is lower than that of \( X \), there is less information in \( h \) than in \( X \). Thus the reconstructed \( X' \) is likely to be a distorted version of \( X \). The goal of training an autoencoder is to minimise the distortion, i.e., minimising a loss function \( L(X, X') \), thereby producing an encoder that can capture \( X \)'s most useful information in its representation \( h \).

As mentioned Sec. 3.1, LSTM can also be used as components of an LSTM-autoencoder [32] to encode time-series data. As shown in Fig. 3, an LSTM cell is used as the encoder of an autoencoder and takes a time-series sequence as its input. The final hidden state \( h_3 \) is the representation of \( X_3 \) in the context of the sequence \((X_1, X_2, X_3) \). As the hidden state of the LSTM encoder is based on both the input observation and the previous hidden states, the representation generated in this way compresses information of both the features in the observation and the time-series sequence. The decoder, which is another LSTM cell, reconstructs the original sequence in a reversed order. Thus, the goal of an LSTM-autoencoder is to minimise the loss between the original and the reconstructed sequences.

Since our system runs unsupervised learning locally at the edge and supervised learning in the cloud, we consider both simple autoencoders and LSTM-autoencoders in our proposed system, in order to understand how the location where time-series information is captured (i.e., in supervised learning or unsupervised learning) affect the performance of our system.

3.3 System design

In a canonical FL system, as in a client-server (CS) structure, a cloud server periodically sends a global model to selected clients for updating the model locally. As shown in Fig. 4, in each communication round \( t \), a global model \( w^g_t \) is sent to three selected clients, which conduct supervised learning on \( w^g_t \) with their labelled local data. The resulting local models are then sent to the server, which uses the federated averaging (FedAvg) algorithm [23] to aggregate these models into a new global model \( w^g_{t+1} \). The server and clients repeat this procedure through multiple communication rounds between them, thereby fitting the global model to clients’ local data without releasing the data to the server.

In order to address the lack of labels on clients in HAR with IoT sensory data, our proposed system applies semi-supervised learning in an FL system, in which clients use unsupervised learning to train autoencoders with their unlabelled data, and a server uses supervised learning to train a classifier that can map encoded representations to activities with a labelled dataset.

As shown in Fig. 5, in each communication round, the server sends a global autoencoder \( w^{ag}_t \) to selected clients. In order to update \( w^{ag}_t \) locally, clients run unsupervised learning on \( w^{ag}_t \) with their unlabelled local data and then send the resulting local autoencoders to the server. The server follows the standard FedAvg algorithm to generate a new global autoencoder \( w^{ag}_{t+1} \), which is then plugged into the pipeline of supervised learning with a labelled data.
We evaluated our system through simulations on different human activity datasets with different system designs and configurations. In addition we evaluated the local activity recognition algorithms of our system on a Raspberry Pi 4 model B. We want to answer research questions as follow:

- Q1. How does HAR using semi-supervised FL with different system designs (i.e., autoencoders and classifiers) perform in comparison to using supervised FL?
- Q2. How does HAR using semi-supervised FL perform with Non-IID data in comparison to using supervised FL?
- Q3. How do the key parameters of semi-supervised FL, including the size of labelled samples on the server and the size of learned representations, affect the performance of HAR.
- Q4. How efficient is HAR using semi-supervised FL on low-cost edge devices.

### 4.1 Datasets

We used three different human activity datasets that contain time-series sensory data in our evaluation. The datasets have different numbers of features and activities with different durations and frequencies.

The Opportunity (Opp) dataset [7] contains short-term and non-repeated kitchen activities of 4 participants. The Daphnet Freezing of Gait (DG) dataset [3] contains Parkinson’s Disease patients’ freezing of gaits incidents collected from 10 participants, which are also short-term and non-repeated. The PAMAP2 dataset [26] contains household and exercise activities collected from 9 participants, which are long-term and repeated. The data pre-processing procedure in our evaluation is the same as described by Hammerla et al. [14]. Table 1 shows detailed information about the used datasets after being pre-processed.

| Dataset | Activities | Features | Classes | Training | Testing |
|---------|------------|----------|---------|----------|---------|
| Opp     | Kitchen    | 79       | 18      | 651k     | 119k    |
| DG      | Gait       | 9        | 3       | 792k     | 81k     |
| PAMAP2  | Household  | 52       | 12      | 473k     | 83k     |

### 4.2 Simulation setup

We simulated a semi-supervised FL that runs unsupervised learning on 100 clients to locally update autoencoders and runs supervised learning on a server to update a classifier. In each communication round $t$, the server selects $100 \cdot C$ clients to participate in the unsupervised learning, and $C$ is the fraction of clients to be selected. Each selected client uses its local data to train the global autoencoder $w^t_{\text{ae}}$ with a learning rate $l_{ra}$ for $e_a$ epochs. The server conducts supervised learning to train the classifier $w^t_{\text{c}}$ with a learning rate $l_{rs}$ for $e_r$ epochs. For each individual simulation setup, we conducted 64 replicates with different random seeds.

Based on the assumption that a server is more computationally powerful than a client in practice, we set the learning rates $l_{ra}$ and $l_{rs}$ as 0.01 and 0.001, respectively. Similarly, we set the numbers of epochs $e_a$ and $e_r$ as 2 and 5, because an individual client is only supposed to run a small number of epochs of unsupervised learning and a server is capable of doing more epochs of supervised learning. The reason for setting $e_r = 5$ is to keep the execution time of our simulations reasonable.
Figure 5: System structure of our semi-supervised FL system. A server and three clients follow the standard FL procedure to update a global autoencoder $w^a_{t}$ to $w^a_{t+1}$. Then the server uses the encoder of $w^a_{t+1}$ to encode the labelled dataset $D$ on the server into a labelled representation dataset $D'$. It then conducts supervised learning on a classifier $w^s_{t}$ with $D'$ and generates a new classifier $w^s_{t+1}$.

Require: $K$: number of clients; $C$: fraction of clients; $D = (X, Y)$: labelled dataset in the format as $(features, label)$

1: initialise $w^a_{0}$, $w^s_{0}$ at $t = 0$
2: for all communication round $t$ do $S_t \leftarrow$ randomly selected $K \cdot C$ clients
3: for all client $k \in S_t$ do
4: \hspace{1cm} $w^a_{t+1} \leftarrow \text{LocalTraining}(k, w^a_{t})$ \hspace{0.5cm} ☐ on client $k$
5: end for
6: $w^a_{t+1} \leftarrow \sum_{k \in S_t} \frac{n_k}{n} w^a_{t+1}$ \hspace{0.5cm} ☐ FedAvg on the server
7: $X' \leftarrow w^a_{t+1}.\text{encoder}(X)$
8: $D'_t \leftarrow (X', Y)$
9: $w^s_{t+1} \leftarrow \text{CloudTraining}(D'_t, w^s_{t})$ \hspace{0.5cm} ☐ on the server
10: end for

Figure 6: Algorithm of semi-supervised FL. $n_k$ and $n$ are the numbers of unlabelled samples on client $k$ and on all selected clients, respectively. $\text{LocalTraining}$ is unsupervised learning on the global autoencoder $w^a_{t}$ on a client. $\text{CloudTraining}$ is supervised learning on the classifier $w^s_{t}$ on the server.

4.2.1 Autoencoders and classifiers. In order to answer Q1, we designed two schemes with different autoencoders and classifiers. One scheme uses an LSTM-autoencoder to capture time-series information in local unsupervised learning and uses a simple classifier that has a fully connected (FC) layer and a softmax layer, which we refer to as LSTM-FC. Another scheme uses a simple autoencoder to learn representations only from individual samples in unsupervised learning and uses a classifier that has an LSTM cell with its output hidden states connected to an FC layer and a softmax layer, which we refer to as FC-LSTM.

We adopted the bagging (i.e., bootstrap aggregating) strategy similar to Guan and Plötz [13] to train our models with random batch sizes and sequence lengths. In both schemes, we used the mean square error (MSE) loss function for autoencoders and the cross-entropy loss function for classifiers. We used the stochastic gradient descent (SGD) optimiser in the training of all models. All the deep learning components in our simulations were implemented using PyTorch libraries [24].

simulation in an acceptable range. Nevertheless, we believe that this parameter on the server can be set as a larger number in real-world applications where more powerful clusters and graphics processing units (GPUs) can be deployed to accelerate the convergence of performance.
4.2.2 IID and Non-IID local data. We first split a training dataset into a labelled training dataset and an unlabelled training dataset (see Sec. 4.2.3 for details). We then used two strategies to generate local training data for clients from the unlabelled training dataset in order to answer Q2. In both strategies, the number of allocated samples for each client, i.e., \( n_k \), equals to \( \frac{n^o}{100} \), where \( n^o \) is the number of samples in the original training dataset shown in Table 1.

To generate IID local training datasets, we divided the unlabelled training dataset into 100 divisions. For a client to be allocated \( n_k \) samples, its local training data evenly distribute in these divisions. In each division, a time window that contains \( \frac{n^o}{100} \) continuous samples is randomly selected as the client’s sample fragment in this division. The sample fragments from all divisions are then concatenated as the local training dataset for the client in the IID scenario.

For Non-IID local training datasets, we randomly located a time window with length \( n_k \) in the unlabelled training dataset and used the samples in the time window as the local training dataset for the client in the Non-IID scenario. By this means, the local training dataset of each client can only represent the distribution within a single part in the unlabelled dataset.

4.2.3 Label ratio and compression ratio. For Q3, we adjusted two parameters to control the amount of labelled data and the size of representations. For an original training dataset that has \( N^l \) time-series samples with labels, we adjusted the label ratio \( r^l \in (0, 1) \) and took \( r^l \cdot N^l \) samples from it as the labelled training dataset on the server. We used the rest of the samples, without using their labels, as the unlabelled training dataset to generate local data for clients. Since the samples are formed as time-series sequences, to avoid breaking the activities by directly taking random samples from the sequences, we first divided the entire training set into 100 divisions. We then randomly sampled \( 100 \cdot r^l \) divisions and concatenated them as the labelled training dataset on the server. The rest of the divisions were used for generating unlabelled data for clients. For a training dataset whose observations have \( N^f \) features, we adjusted the compression ratio \( r^f \in (0, 1) \) and used the rounded value of \( r^f \cdot N^f \) as the size of the representation when training autoencoders.

4.3 Edge device setup

Apart from simulations, to answer Q4, we evaluated the local activity recognition part of our system on a Raspberry Pi 4 Model B. The specifications of the device are shown in Table 2.

| CPU            | Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz |
|----------------|---------------------------------------------------|
| RAM            | 4GB LPDDR4-3200 SDRAM                             |
| Storage        | SanDisk Ultra 32GB microSDHC Memory Card          |
| OS             | Ubuntu Server 19.10                              |

Table 2: System specifications of Raspberry Pi 4 Model B.

Compared with supervised FL, on the one hand, our system introduces local autoencoders that encode samples into representations before feeding them into classifiers, which costs additional processing time. On the other hand, encoded representations have smaller sizes than original samples do, which reduces the processing time of classifiers. To understand how these two factors affect the overall local processing time, we tested both supervised FL and our system on the Raspberry Pi and compared their performances. We divided the testing datasets into one-second-long sequences and measured the overall processing time of the trained models (i.e., autoencoders + classifiers) on each sequence, in order to calculate the overhead for each one-second time window.

4.4 Metrics

We evaluated the performance of the global autoencoder and the classifier with the test datasets at the end of every other communication round. We first used a time window to select 5000 samples each time. As the sampling frequency in the processed datasets is approximately 33Hz, this time window represents activities in about 2.53 minutes. We then applied the global autoencoder on the samples in the time window to encode them into a sequence of labelled representations. The classifier was applied to the sequence of representations to recognise the activities, which were then compared with the ground truth labels. We calculate the accuracy in the time window, which is the fraction of correctly classified representations among all representations. The accuracies from different time windows are averaged as the accuracy of the system. In each communication round \( t \), we calculate the average value from 64 simulation replicates and its standard error.

5 RESULTS

We find that our proposed semi-supervised FL system can achieve comparable accuracy to that of the supervised FL system and is not affected by Non-IID data. It can also reduce the needed amount of labelled data of the entire system and the size of local models without losing much performance, and has marginal local activity recognition time a low-cost edge device.

5.1 Analysis of autoencoders and classifiers

We first look at how the choices of autoencoders on the clients and classifiers on the server affect the accuracy of our system in order to understand which of them should be used to learn the time-series information in human activities. Fig. 7 shows the accuracies of the scheme FC+LSTM and the scheme LSTM+FC, with \( r^l = \{0.75, 0.125\} \) and \( r^f = 0.5 \), on different datasets. As the round of communications increases, the accuracies of all schemes go up and converge. The accuracies of the FC+LSTM schemes, i.e., using a simple autoencoder to learn representations locally and using an LSTM classifier for supervised learning in the cloud, are higher (or converge faster) than those of the LSTM+FC schemes that deploy more complex LSTM autoencoders locally and run supervised learning with a simple softmax classifier in the cloud. On the Opp and DG datasets, FC+LSTM can achieve acceptable accuracies using only 1/8 labels compared with the supervised FL. In the rest of our analyses of our results, we only show the accuracies of the FC+LSTM scheme of our system.

The experimental results show that, when implementing semi-supervised FL system for HAR, using simple autoencoders that only
compress feature-wise information has better performance than using a more complex LSTM-autoencoder that compresses both feature-wise and time-series information. Due to the compression effectiveness of autoencoders and the fixed size of representations, trying to compress both types of information may lead to the loss in both of them. Therefore, time-series information should be kept in the form of representation sequences and be processed by RNN such as LSTM during supervised learning on the server.

5.2 Performance with Non-IID data
We set both $r_f$ and $r_l$ to 0.5 and evaluated our system with both IID and Non-IID local training data. Our system is not supposed to be affected by the Non-IID distributions of labels since it does not use any labels. What we are interested in knowing is how its performance compares with that of the supervised FL with Non-IID data.

As shown in Fig. 8, the converged test accuracy of the supervised FL with Non-IID data is significantly lower than that with IID data on both DG and PAMAP2 datasets. As a client only has a continuous period of data from the training datasets, different clients may have different distributions over the activity labels they have. The LSTM classifiers locally trained by the supervised FL are thus affected by the labels on each client. In contrast, our semi-supervised FL only learns general representations through training autoencoders and does not use any labels. It has avoided such effectiveness from the skewed distribution in local labels, which is the major source of "Non-IIDness" [17]. As shown in Fig. 8, on the Opp and DG datasets, there is no significant differences between the test accuracies of our system with IID and Non-IID data. The difference between the accuracies of our system on the PAMAP2 dataset is from feature distribution skew [17] and is marginal compared with the difference between the accuracies of the supervised FL. In addition, it is worth to note that on the DG dataset with Non-IID data, the accuracy of our system is even higher than that of the supervised FL that uses 100% more labels and more complex local models than our system does.

Our finding indicates that, unlike supervised FL, our system is not affected by Non-IID local training data. In addition, its performance may surpass that of supervised FL. This suggests that learning general representations instead of fitting models to labels locally may be a useful approach to address the challenges caused by local Non-IID data, which commonly exist in real-world FL applications. In this paper we only focus on the application of HAR using RNN. We leave the research questions on whether this approach works on other FL applications such as image recognition using CNN for our future research.

5.3 Analysis of label ratio
Our system requires that the server has a labelled training dataset for the supervised learning on the classifier. We changed the label ratio $r_f = \{0.75, 0.125\}$ and $r_l = 0.5$. The combination of a simple autoencoder and an LSTM classifier (i.e., FC+LSTM) has higher accuracy or faster convergence than the combination of an LSTM autoencoder and a softmax classifier (i.e., LSTM+FC). The best converged accuracy of FC+LSTM is comparable to that of the supervised FL system.

![Figure 7: Test accuracy with different autoencoder and classifier combinations, with $r_f = \{0.75, 0.125\}$ and $r_l = 0.5$. The combination of a simple autoencoder and an LSTM classifier (i.e., FC+LSTM) has higher accuracy or faster convergence than the combination of an LSTM autoencoder and a softmax classifier (i.e., LSTM+FC). The best converged accuracy of FC+LSTM is comparable to that of the supervised FL system.](image)
Figure 8: Test accuracy with IID and Non-IID local training data, with $r^l, r^f = 0.5$. On the Opp and DG datasets, the Non-IID data has little effectiveness on our semi-supervised system as it does not use any labels in local training. The accuracy with Non-IID data is even higher than that of the supervised FL with Non-IID data on the DG dataset.

Figure 9: Test accuracy with different label ratio $r^l = \{0.75, 0.5, 0.25, 0.125\}$, with $r^f = 0.5$. The converged accuracies on the Opp and DG datasets are almost the same and close to that of the supervised FL. On the PAMAP2 dataset, our system needs more labels to converge to an acceptable test accuracy than on the other datasets.

5.4 Analysis of compression ratio

We also investigate how the compression ratio $r^f$ of autoencoders affects the accuracy of our system. It is an important factor that can affect the number of parameters and the size of local models. These local models are regularly uploaded from the clients to the server over network, hence their sizes affect the outbound traffic. We use different $r^f = \{0.75, 0.5, 0.25, 0.125\}$ and keep the $r^l = 0.5$.

Fig. 10 demonstrates that, on the Opp dataset, our system can compress an original sample into a representation whose size is only $1/8$ of the original sample and achieve comparable accuracy to that of the supervised FL. On the DG dataset, which only has 9
features in its original samples, our system can achieve comparable accuracy by generating representations whose size is \(1/4\) of the original sample. Similar to the result in Fig. 9, the accuracies on the PAMAP2 dataset are more sensitive to the change of \(r_f\) than the other datasets do.

Our system’s ability to compress samples into representations can reduce the size of local models that are uploaded from the clients to the server, which may lead to lower network traffic. For example, the supervised FL scheme in our experiments uses a model containing one LSTM cell whose hidden size is 256 and a FC layer. For \(N_f\) input features and \(N_c\) classes, the overall number of parameters of the model is \(4\cdot(256N_f^2+256^2)\cdot256N_c = 2^{10}N_f^2 + 2^8N_c^2 + 2^{18}\). With a compression ratio \(r_f = 0.25\), the number of parameters of the autoencoder in our system is \(2\cdot N_f \cdot \text{round}(0.25N_f)\). Thus, for the Opp dataset and the DG dataset, the local models in our system have around 3.2k parameters and 36 parameters, compared to around 348k parameters and around 272k parameters that the supervised FL models have. We believe that such a significant reduction in the number of parameters can contribute to the improvement of outbound network traffic.

### 5.5 Running time at the edge

We evaluated the local activity recognition using both supervised FL (LSTM) and our system (FC-LSTM) with \(r_f = 0.5\) on the Raspberry Pi. As shown in Fig. 11, the processing time of our system is close to that of the supervised FL on the Opp dataset, and is significantly lower (\(p < 0.001\)) on the DG and PAMAP2 datasets. Although the autoencoder in our system inevitably causes extra processing time as it increases the length of the local pipeline, its generated representations have 50% fewer data than original samples do. This reduction of the amount of input data to the classifier leads to a shorter overall processing time than that of the supervised FL.

Combined with the results of Sec. 5.4, our experimental results show that running unsupervised learning on simple models such as autoencoders can reduce the size of local models and the size of input data to classifiers. This can potentially improve not only the outbound network traffic, but also the efficiency of local activity recognition.

### 6 DISCUSSION

Our experimental results show that HAR with semi-supervised FL can achieve comparable accuracy to that of supervised FL. We now discuss how these results can contribute to the system design of FL systems and possible research topics.

### 6.1 FL Servers can do more than FedAvg

In canonical FL systems, servers only hold global models and use the FedAvg algorithm to aggregate received local models into new global models. This design consideration is due to the privacy concerns of having personal data on the servers. Our findings suggest that running supervised learning with a small amount of labelled data on the servers can alleviate individual users from labelling their local data. Therefore, we suggest that FL systems may consider maintaining datasets that do not contain private information on their servers to support semi-supervised learning. Apart from implementing the FedAvg algorithm in every communication round, servers can conduct more epochs of supervised learning than individual clients can do, since they have more computational resources and fewer power constraints than clients do. This can help the performance of the models converge faster.

### 6.2 Learning useful representations, not bias

Our results indicate that semi-supervised FL is not affected by Non-IID data because it does not use any labels locally. Its performance can even be better than that of a supervised FL that uses more labels and has more complex local models. This sheds light on a new solution, which is different from data augmentation or limiting individual contributions from clients [17], to address the Non-IID data issue in FL. Although, our work focuses on semi-supervised FL where no labels are available on clients, we suggest that supervised FL can also consider learning general representations apart from the mappings from features to labels, and use the learned representations to help alleviate the bias caused by Non-IID data.

Another possible application of semi-supervised FL is to defend against malicious users who attack the global model through data poisoning [17]. Labels of local data are a common attack vector in FL. Adversaries can manipulate (e.g., flipping) the labels in their local data to affect the performance of their local models, thereby affecting the performance of the global model. Such an attack will be removed if we do not use local labels. We suggest that security researchers in FL should consider semi-supervised FL as a possible scheme to defend from data poisoning attacks.

### 6.3 Smaller models via unsupervised learning

In supervised FL, as the complexity of an ML task goes up, the size of the model of the task increases. This eventually leads to increasing numbers of parameters and increasing network traffic when uploading local models to the server. Semi-supervised FL keeps supervised learning tasks that require complex models on the server and only uploads trained autoencoders from clients to the server. Our experimental results suggest that the performance of semi-supervised FL can still converge to an acceptable level even if we use high compression rates and simple autoencoders, which help with reducing a significant amount of model parameters. The compression rate can be considered as a system parameter that can be tuned to reduce the size of models, along with the key representations can be learned and the performance of the system can be guaranteed. This makes our system suitable in scenarios that have demanding network conditions. Although in this paper, we only focus on the application of HAR and simple autoencoders, such effects may exist in other applications with different types of autoencoders, which should be further investigated.

### 7 CONCLUSIONS

HAR using IoT sensory data and FL systems can empower many real-world applications including processing the daily activities and the changes to these activities in people living with long-term conditions. The difficulty of learning from population data and at the same time, constructing personalised models limits the scalability and generalisability of the machine learning applications for HAR in real-world and uncontrolled environments. In this paper,
we propose a semi-supervised FL system to enable HAR in IoT environments. By training simple autoencoders through unsupervised learning on FL clients, and training LSTM classifiers through supervised learning on an FL server, our system can achieve comparable accuracy to that of a supervised FL system but does not require any locally labelled data. In addition, it is not affected by Non-IID local data and has simpler local models with smaller size and faster processing speed.

Our future research plans are to investigate fully unsupervised FL systems that can support anomaly detection through analysing the difference between local and global models. We believe that such systems will enable many useful real-time applications in HAR where useful labels are rare or extremely difficult to collect.

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