Toward Crowdsourced Transportation Mode Identification: A Semisupervised Federated Learning Approach

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***Abstract*—Privacy-preserving transportation mode identification (TMI) is among the key challenges toward future intelligent transportation systems. With recent developments in federated learning (FL), crowdsourcing has emerged as a promising cost-effective data source for training powerful TMI classifiers without compromising users' data privacy. However, existing TMI approaches have relied heavily on the availability of transportation mode labels, which is often limited in real-world applications. While recent semisupervised studies have partially addressed this issue by assigning pseudolabels to unlabeled data, such practice often degrades classification performance as more unlabeled data are incorporated. In response to this issue, we present a semisupervised FL scheme for TMI termed mean teacher semisupervised FL (MTSSFL). MTSSFL trains a deep neural network ensemble under a novel semisupervised FL framework, achieving highly accurate and privacy-protected crowdsourced TMI without depending on the availability of massive labeled data. MTSSFL introduces consistency updating to insert the global model in the gradient updates of the local models that only have unlabeled data to improve their training. We also devise *mean-teacher-averaging*, a secure parameter aggregation mechanism that further boosts the global model's TMI performance without requiring additional training. Our extensive case studies on a real-world data set demonstrate that MTSSFL's classification accuracy is merely 1.1% lower than the state-of-the-art semisupervised TMI approach while being the only one to satisfy FL's privacy-preserving constraints. In addition, MTSSFL can achieve high accuracy with less training overhead due to the proposed semisupervised learning design.**

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I. Introduction

TRANSPORTATION mode identification (TMI) aims to infer transportation modes from users' mobility data. As a core application of intelligent transportation systems (ITSs), accurate TMI can help address a variety of transportation-related problems, such as public transportation planning, route recommendations, and traffic signal optimization [1]. With recent developments in data-driven analysis, particularly in machine and deep learning algorithms, Internet of Things (IoT)-enabled ITSs have attracted significant research interest due to their capacity for capturing massive quantities of data [2]. The widespread presence of global positioning system (GPS) sensors in modern smartphones and wearable devices has streamlined the acquisition of diverse user trajectories, paving the way for IoT-enabled TMI [3].

Training highly accurate deep learning models primarily requires immense amounts of data. Data crowdsourcing seeks to alleviate this issue by allowing multiple users to collectively generate large data sets in a distributed manner [4]. A centralized server is always set to receive the crowdsourced data and train them. These data are usually transmitted to the centralized server in unprocessed forms; however, information implied by the data may have a strong connection to the users' privacy, which raises a privacy concern; for instance, GPS trajectories are tied to users' location and transportation history. There exist techniques for addressing such privacy concerns, including encrypted evaluation, data anonymization, and noise injection [5]. Nevertheless, the computational complexity of such methods often prohibits their use in real-world applications [6], with noise injection possibly degrading the performance of deep learning models over time.

Federated learning (FL) provides a privacy-preserving framework for deep learning to realize the benefits of crowdsourcing [7]. It allows users to share their data without jeopardizing their privacy, provided that the data are only stored and used locally. Users only need to intermittently share their local model gradient updates with the centralized server, which, in turn, manages the collective training process. Concretely, the centralized server trains the global model by aggregating the local models' gradients and subsequently broadcasts the updated model parameters to all users. Each user uploads their local model to the server and then downloads the global model to perform offline inference with the cloud-distributed model. FL has rapidly sparked tremendous interest within the IoT-enabled ITS community due to its privacy-preserving nature and the efficient use of computing power provided by edge devices. Successful applications can be seen in urban traffic forecasting [8], [9], rail traffic control [10], vehicular networking [11], and others. Following this trend, we envision that FL will also be successful for crowdsourced TMI; however, some practical concerns need to be addressed first.

Existing TMI research typically employs machine or deep learning models in fully supervised settings, thereby assuming the availability of sufficient GPS trajectories labeled by transportation mode at training time [12]–[15]. This assumption, however, cannot hold for real-world crowdsourced TMI applications. Even though GPS sensors can readily capture user movement without requiring human intervention, they have no knowledge of the corresponding transportation mode labels: these would have to be provided by the users themselves to ensure correctness. Nonetheless, manual annotation is both time consuming and labor-intensive for users. While FL offers a variety of incentive and reward mechanisms, they can impose a significant financial or computational burden on task publishers in real crowdsourcing systems [16], [17]. Therefore, large volumes of unlabeled trajectories are often left unused, despite being no less useful than their labeled counterparts.

To close the research gap in existing FL-based approaches for crowdsourced TMI, we propose a novel semisupervised FL scheme toward FL-based crowdsourcing TMI tasks. Particularly, we devise a semisupervised FL framework, mean teacher semisupervised FL (MTSSFL), to address the issues caused by the lack of labeled data in crowdsourced TMI. Concretely, MTSSFL leverages *consistency updating*, which we introduce to include the global model in the gradient updates of local models that only possess unlabeled data. Such a teacher–student learning scheme, in conjunction with existing pseudolabeling approaches, can considerably improve the local models' training on their own unlabeled data. Furthermore, we propose *mean-teacher-averaging* to replace conventional secure parameter aggregation mechanisms, in order to form a better global model without requiring additional training. Additionally, specific to the TMI task, we devise an ensemble of spatial–temporal deep neural networks for feature extraction from GPS trajectory data and achieve TMI. The main contributions of this article are summarized as follows.

1) We propose MTSSFL, a new FL-based semi-supervised learning scheme that incorporates an ensemble-learning-based TMI model. MTSSFL can effectively address the model training issues caused by the few labeled data typically available for crowdsourced, privacy-preserving TMI. The involved semisupervised FL approach of MTSSFL can also serve as a generic solution to other proper applications.
2) We introduce consistency updating, a novel approach for training local models that only possess unlabeled data guided by the centralized model trained on few labeled data.
3) We design an exponential moving average (EMA)-based secure parameter aggregation mechanism termed *mean-teacher-averaging* to improve the global model without additional training.
4) We conduct extensive case studies to assess the performance of MTSSFL on IID and non-IID data. We also investigate its robustness to different hyperparameter configurations, and provide guidelines into hyperparameter selection.

The remainder of this article is organized as follows. Section II summarizes related work in TMI and semisupervised learning. Section III defines the problems of GPS-based TMI and semisupervised FL for TMI. Section IV details our data preprocessing techniques applied to raw GPS trajectory data, as well as the proposed TMI model and MTSSFL framework. Section V conducts a comprehensive series of case studies to demonstrate the effectiveness of the proposed approach and investigate its sensitivity to hyperparameter variations. Section VI discusses the traits regarding security and privacy, (S&P) and generalization ability of MTSSFL. Finally, Section VII concludes this article.

II. Related Work

A. Transportation Mode Identification

Contemporary TMI approaches can be broadly categorized into machine- and deep-learning based. Their input data sources include but are not limited to GPS, accelerometer, and gyroscope sensors, often combined with geographic information system (GIS) information such as proximity to bus or metrostations [18]. Among the above, GPS sensors are arguably the most popular sources due to their rich spatial–temporal information, easy acquisition, and lower communication costs [19]. As such, we focus on GPS-based works in the remainder of this section.

Feature extraction and classification are two main subtasks in the GPS-trajectory-based TMI approaches. The design of feature extraction can be regarded as a distinguishing factor among different TMI approaches. Zheng *et al.* [12] proposed a two-step identification scheme that has been widely adopted in utilizing GPS trajectory for TMI [20], [21]. In this scheme, trajectories are first partitioned into single-transportation-mode segments based on domain knowledge. Subsequently, a set of hand-crafted features is extracted for each segment and fed to machine learning models for classification.

More recently, the success of deep neural networks in research areas, such as computer vision and natural language processing, has led to their adoption for TMI. In this direction, Dabiri and Heaslip [13] trained convolutional neural network (CNN) ensembles, while Jeyakumar *et al.* [22] employed recurrent neural networks with the long short-term memory (LSTM) module to exploit the temporal dependencies within GPS trajectories and improve identification accuracy. Yu [19] leveraged a deep LSTM ensemble to cope with the few-shot data problem.

B. Privacy-Preserving Transportation Mode Identification

Since GPS trajectory analysis may reveal individuals' personal information, the issue of privacy preservation in TMI has gradually attracted increasing attention [23]. Traditional approaches to privacy-preserving TMI have typically been based on cryptography [24], [25]. However, the required data encryption technology can be computationally expensive, especially on large-scale data. On the other hand, with the ever-growing restrictions brought forth by data privacy regulations (e.g., general data protection regulation[1]), third-party organizations such as mobile communications operators are not allowed to collect or share users' personal data [26]. Since performing machine learning at scale usually requires sharing massive amounts of data among multiple public organizations or private companies, such regulations challenge the feasibility of existing approaches.

The emerging (FL) paradigm greatly breaks through this dilemma, whose decentralized learning strategy that enables data can be trained locally at different organizations without exchange [27]. FL also achieves the tradeoff between model performance and privacy preserving, and great successes have been witnessed in various studies [28], [29]. Liu *et al.* [30] proposed an FL framework for traffic flow prediction, who first introduced FL to ITS research. Zhu *et al.* [31] devised an FL-based approach for TMI considering the non-IID data of GPS trajectories.

C. Semisupervised Deep Learning

Recent years have witnessed a wide adoption of semisupervised deep learning approaches aiming to jointly train neural networks on few labeled and massive unlabeled data, spanning research areas such as computer vision, and natural language processing problems. These approaches can be divided into roughly three categories [32].

The first category combines unsupervised pretraining with supervised fine-tuning [33]. Concretely, the pretraining phase trains the classifier on unlabeled data in an unsupervised manner; fine-tuning then trains the supervised component of the model on the available labeled data. The second category indirectly constructs semisupervised algorithms based on latent features extracted from the model [34]. After the classifier is trained on the available labeled data in a supervised manner, the inference is performed on the unlabeled data. The predicted labels are then manually assessed, and the correctly classified ones are added to the training set for model training. While labeled and unlabeled data are both used in the previous two approaches, the model is ultimately trained in a supervised manner. The third category of semisupervised approaches involves training models in a truly semisupervised fashion. As one of the representatives of this category, Lee [35] devised "pseudolabels" for unlabeled data by selecting the class having the maximum predicted probability as pseudoground truth. Laine and Aila [36] proposed an approach based on the moving average of the predicted labels in each training iteration, aiming to construct a better target. The target is then used to estimate the unsupervised loss and update the model. Following [36], Tarvainen and Valpola [37] proposed a promising approach termed *mean teacher*, which averages model weights instead of label predictions.

In the field of TMI, Yazdizadeh *et al.* [38] and Dabiri *et al.* [21] recently proposed two semisupervised deep learning approaches based on generative adversarial networks (GANs) and convolutional autoencoders. Yu [19] instead trained a semisupervised LSTM ensemble on different views of the data. While these semisupervised approaches have been shown to be effective, they may not be able to satisfy several FL requirements [39]. First, in FL systems, the optimization objectives among the local models differ due to the relatively different distributions of their respective trained data. The averaging aggregation at the central server can contribute to develop a generic model from these local models effectively, mitigating these isolated training processes' negative effect to a certain extent. However, in semisupervised learning contexts, especially for those involved with dummy labels [35], the data distribution differences among different clients are more significant and intricate. The conventional updating and averaging approaches of FL are incapable of capturing these information timely, which makes it difficult to maintain the consistency between the client models and global models; this is a big challenge for semisupervised FL. Second, the assumption of imbalanced label distributions for semisupervised learning has not been well studied in the FL context where most of them only considered mild conditions. Particularly, extreme conditions (e.g., only a small number of labeled data can be utilized or the labeled data only exist at the central server) were not involved in the previous researches. Last but not least, some of the state-of-the-art semisupervised approaches were only designed and evaluated on simple classification tasks (e.g., [40]–[42]), which might not be applicable to practical and complex ones such as the investigated crowdsourcing TMI tasks in this work. Considering the traits of FL under few labeled data and the requirement of crowdsourcing tasks, in this article, we propose a novel semisupervised FL framework for crowdsourced TMI based on the *mean teacher* approach [37] to fill the research gap.

III. PRELIMINARIES

In this section, we first formulate the task of GPS-based TMI. We then delve into the problems of crowdsourced FL and learning from non-IID data.

A. GPS-Based Transportation Mode Identification

In this work, TMI is performed on features extracted from GPS trajectories. The latter are represented as chronologically ordered sequences of discrete GPS records, with each record (or point) being defined by the following four attributes: 1) *latitude* (lat); 2) *longitude* (lng); 3) *timestamp*; and 4) *label*.

Following the established TMI research [12], [13], [19], we aim to identify the following five transportation modes: 1) *walk*; 2) *bus*; 3) *bike*; 4) *driving*; and 5) *train*. All GPS trajectories are first partitioned into segments such that each corresponds to exactly one transportation mode. Since raw GPS trajectories are ill-suited for training machine or deep learning models [12], we then preprocess them into motion

[1]https://gdpr-info.eu/

and other features following standard TMI practice [12], [13], [19], as will be detailed in Section IV-A.

Let $\mathcal{F}_i$ denote the calculated features of the ith GPS point in a segment. We can then reform GPS segment k of length T as $\text{GPS}_k = \{\mathcal{F}_1, \mathcal{F}_2, \ldots, \mathcal{F}_T, \text{label}_k\}$, where label_k is the corresponding transportation mode of the segment. Our aim is to train a deep learning classifier to classify GPS_k, $\forall k$, by transportation mode. This is formulated as

$$\text{GPS}_k[\mathcal{F}_1, \mathcal{F}_2, \ldots, \mathcal{F}_T] \xrightarrow{f(\cdot)} \text{GPS}_k[\text{label}_k] \tag{1}$$

where $f(\cdot)$ denotes the classification function learned by the classifier model.

B. Semisupervised Federated Learning

1) Crowdsourced Federated Learning Framework: In this work, we propose an FL framework for crowdsourced TMI. We use the term "publisher" to refer to the initiator of the crowdsourcing task, who also owns a central server. We refer to the local (distributed) entities as "workers." Let q denote the total number of workers; we then have the set of workers $\mathcal{C} = \{C_1, C_2, \ldots, C_q\}$. Each worker C_i uses their respective database D_i to store their sensed GPS trajectories, resulting in the database set $\mathcal{D} = \{D_1, D_2, \ldots, D_q\}$. In FL, worker C_i uses their locally stored data to train their local model $M_i \in \mathcal{M} = \{M_1, M_2, \ldots, M_q\}$, where the learned parameters of M_i are denoted by ϕ_i.

This work assumes that both the publisher and the workers are reliable and low-latency communicators. Both are also considered to be honest, which means that they will strictly execute FL protocols and will not try to infer other entities' data from the shared model parameters. Additionally, this work assumes that the security level of uploading channels is higher than that of broadcasting channels [5].

2) IID and Non-IID Data: Each worker is likely to have more data corresponding to some transportation modes than others. This will inevitably lead to a skewed local class distribution, i.e., nonindependent and identically distributed (non-IID) data. Previous research indicated the deviating FL performance on IID and non-IID data, where the latter usually renders the FL systems to develop inferior training performance due to the data imbalance among different clients [43]. To explore how non-IID data affect the classification performance of our approach, we introduce the metric R to measure the level of non-IID. Specifically, the class distribution of database D_i belonging to worker C_i is defined as $P_i = [p_1, p_2, \ldots, p_c] \in \mathbb{R}^c$, where p_j is the fraction of the jth class in D_i and c denotes the total number of classes. R can be defined as

$$R = \frac{1}{2} \sum_{1 \le i < o \le q} \|P_i - P_o\|_1 \frac{1}{q(q-1)/2} \tag{2}$$

where $\|\cdot\|_1$ denotes the L_1 norm, $\|P_i - P_o\|_1$ is the variation distance, and $q(q-1)/2$ corresponds to the total number of worker pairs. Note that the first factor $(1/2)$ is merely used to ensure $R \in [0, 1]$. We obtain $R = 0$ when each worker has a uniform class distribution, i.e., $P_i = [(1/c), (1/c), \ldots, (1/c)]$, while $R = 1$ means that each worker only has trajectories belonging to one transportation mode class.

IV. Methodology

In this section, we introduce the proposed scheme for crowdsourced TMI. We start by presenting the data preprocessing approach adopted to handle raw GPS data. Next, we detail the employed TMI model. Finally, we elaborate on the proposed semisupervised FL framework.

A. Representation of TMI Data Features

Raw GPS data preprocessing is the prerequisite procedure of GPS-trajectory-based TMI, which consists of two steps, namely, GPS trajectory preprocessing and data feature representation.

1) GPS Trajectory Preprocessing: Raw GPS trajectories are usually denoted as chronologically ordered series of GPS records. To segment each trajectory by transportation mode, we follow the trajectory segmentation algorithm introduced in [12], which has since been widely used in the transportation literature [19], [21]. This segmentation method is based on the intuition that the transportation mode separating any other two has to be *walk*. For instance, if a user traveling by train intends to board a bus, they are bound to walk from the former to the latter. As such, this method first classifies each GPS point as *walk* or *nonwalk* according to velocity and acceleration thresholds before forming single-transportation-mode segments by aggregating adjacent points with the same predicted label. Using the same thresholds defined by [12], we split all trajectories into a total of T^* single-transportation-mode segments $\{\text{GPS}_1, \text{GPS}_2, \ldots, \text{GPS}_{T^*}\}$.

2) Motion Feature Extraction: We follow established TMI research [12], [13], [19] in extracting three pointwise motion-related features, i.e., speed, acceleration, and jerk. To do so, we first calculate the relative distance between every two consecutive GPS records using the Vincenty Formula [44], which can be denoted as

$$d_i = \text{Vincenty}\big(\text{lat}_i, \text{lng}_i; \text{lat}_{i+1}, \text{lng}_{i+1}\big). \tag{3}$$

Based on d_i, we can then estimate speed s_i, acceleration a_i, and jerk j_i for the ith GPS point as follows:

$$s_i = \frac{d_i}{\Delta t_i}, \quad 1 \le i \le T, \quad s_T = s_{T-1} \tag{4a}$$

$$a_i = \frac{s_{i+1} - s_i}{\Delta t_i}, \quad 1 \le i \le T, \quad a_T = 0 \tag{4b}$$

$$j_i = \frac{a_{i+1} - a_i}{\Delta t_i}, \quad 1 \le i \le T, \quad j_T = 0 \tag{4c}$$

where T is the number of GPS records in a GPS segment. In this way, a motion feature vector $x_i \equiv \mathcal{F}_i = (d_i, s_i, a_i, j_i)$ can be extracted for the ith GPS point. These 4-channel feature vectors are then stacked into a tensor for each trajectory segment and used as input to the TMI model detailed in the sequel.

B. TMI Model

In this work, we build our TMI model based on DNNs and ensemble learning techniques. The ensemble learning technique can deal with the bias and variance developed

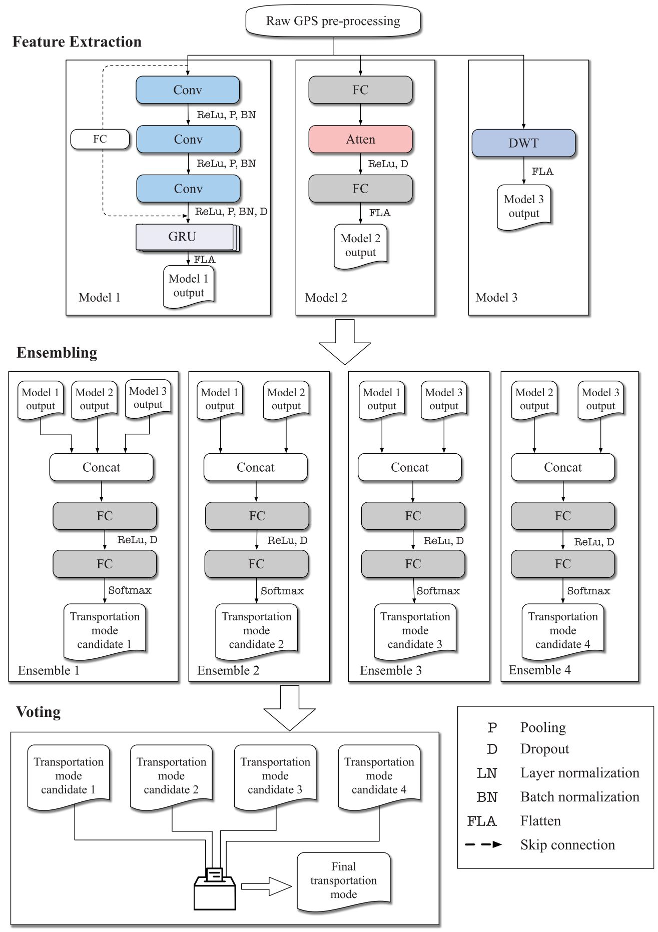

Fig. 1. Framework of TMI model.

by conventional single-model networks and develop high-accuracy prediction by fusing multiple submodels, while the training of an ensemble model might be relatively costly since more than one network are required to be trained on the same data set [45]. The FL-based crowdsourcing can greatly improve the training efficiency on an ensemble model by distributed learning, which makes the best use of the advantages and circumvents the disadvantages of ensemble learning. Thus, we consider an ensemble model as the configured model for MTSSFL in the investigated crowdsourcing TMI task. The framework of the devised TMI model is shown in Fig. 1. It incorporates three procedures, namely, *feature extraction*, *ensembling*, and *voting*. Particularly, we employ three submodels for feature extraction, i.e., Models 1 to 3. We elaborate on the three submodels and the ensemble and voting procedures of our model in the sequel.

1) Model 1: This submodel first employs three convolution layers with skip connections to capture the spatial features within the input motion features $\mathbf{X}$. The layers' output channels are set to 32, 64, and 128, respectively. The kernel sizes and strides for all three convolution layers are set to 3 and 1, respectively. Each convolution is followed by a max-pooling operation with size 2.

Next, we stack eight layers of gated recurrent units (GRUs) with hidden size 16 to exploit the temporal dependencies within the input data. As a simplified variant of the LSTM module, the GRU adopts a stack of gating units and cell states to process and control the input information [8], [46]. There are two types of gating units, i.e., the update gate z and the reset gate r. The operations performed in each layer can be written as

$$r_t = \sigma\left(W^{(r)}\mathbf{X}_t + U^{(r)}h_{t-1}\right) \tag{5}$$

$$z_t = \sigma\left(W^{(z)}\mathbf{X}_t + U^{(z)}h_{t-1}\right) \tag{6}$$

$$h'_t = \tanh(W\mathbf{X}_t + r_t \odot U h_{t-1}) \tag{7}$$

$$h_t = z^t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \tag{8}$$

where $\mathbf{X}_t$ is the input of each GRU layer, $t \in T$, and weight matrices $W^{(z)}$, $W^{(r)}$, $U^{(z)}$, and $U^{(r)}$ connect $\mathbf{X}_t$ and h_{t-1} to the two gates. Finally, h'_t is the intermediate activated output, while h_t denotes the final output.

2) Model 2: This submodel incorporates an attention module between two linear layers, In this work, following the one proposed in [47], the attention module incorporates a stack of multihead attentional layers, each of which computes the attention using a scaled dot-product attention mechanism. The orchestra of multihead enables the model to collectively involve knowledge learned from multiple representation subspaces. The processes can be formulated as

$$\mathbf{X}^A = \text{concat}(hd_1, hd_2, \ldots, hd_{n^*})W^O \tag{9}$$

where

$$hd_i = \text{softmax}\left(\frac{QW_i^Q\left(KW_i^K\right)^T}{\sqrt{d_k}}\right)VW_i^V \tag{10}$$

where Q, K, and V are the query, key, and value, which serve as the input of the self-attention mechanism in [47], and the mechanism requires that they are all $\mathbf{X}$; $d_k = (hidd_a/n^*)$ denotes the dimension of keys where hidd_a denotes the hidden size of the attention module, which is set to 128; softmax denotes the softmax activation function; hd_i denotes each attentional head and n^* is the number of heads; $\text{concat}(\cdot)$ represents the concatenation operation; W^O, W^Q, W^K, and W^V are the corresponding weight matrices. Considering the tradeoff between model performance and training overload, the number of heads and hidden size is set to 8 and 30, respectively.

3) Model 3: To better analyze the data characteristics, a wavelet representation-based feature extracting approach named discrete wavelet transform (DWT) is adopted in Model 3 to further exploit the hidden time-domain feature from the feature vectors. Specifically, DWT employs discrete wavelets $\psi_{a,b}(t)$ to convolve the input, which can be defined as

$$\psi_{a,b}(t) = \frac{1}{2^a}\psi\left(\frac{t}{2^a} - b\right), \; a, b \in \mathbb{Z} \tag{11}$$

where $\psi(t)$ is predefined mother wavelet, a denotes the oscillatory level, and b denotes the shifted position of DWT. Given a time sequence signal $x(t)$, DWT transforms the input by $\psi_{a,b}(t)$ into the following signal, which can be formulated as:

$$d_{a,b}(x(t), \psi(t)) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}^*(t)dt = \left\langle x(t), \psi_{a,b}(t)\right\rangle \tag{12}$$

where $\psi^*_{a,b}(t)$ is the complex conjugate of $\psi_{a,b}(t)$. Additionally, DWT can be interpreted regarding a multiresolution decomposition of the input signal. Specifically, following the inference in [48], given a decompsition level M, a hierarchical framework can be built as:

$$\begin{aligned} s(t) &= \sum_a^M \sum_b d_{a,b}(x(t), \psi(t)) 2^{-a/2} \psi\left(\frac{t}{2^a} - b\right) \\ &\quad + \sum_b A_{M,b} 2^{-M/2} \varphi\left(\frac{t}{2^M} - b\right) \\ &\triangleq \sum_a^M D_a(t) + A_M(t) \end{aligned} \tag{13}$$

where $A_{M,b} = \langle x(t), \varphi_{M,b}(t)\rangle$ denotes the approximation coefficient at level M and $\varphi(t)$ represents a companion scaling function. We can utilize (13) to decompose the signal $x(t)$ into a detailed signal $D_a(t)$ and an approximation signal $A_M(t)$.

In this work, since we emphasize more on the general trend of GPS trajectory characteristics, the detailed signals are omitted, and only the approximation signal $A_M(t)$ of the preprocessed quarternary feature (i.e., $x_i = (d_i, s_i, a_i, j_i)$) is reserved. The *daubechies* mother wavelets are used to decompose the feature, following [48]. Finally, we can obtain the tensor of quarternary feature $\mathbf{X} \in \mathbb{R}^{T\times n\times 4}$ and the tensor after DWT $\mathbf{X}^{dwt} \in \mathbb{R}^{T\times n\times 1}$, with the latter forming the output of Model 3.

4) Ensemble and Voting: Multiview ensemble learning (MEL) is a type of semisupervised learning aiming to train different learning models with different views of the original data [49]. In the feature extraction stage, we constructed three submodels to learn different latent representations of the input. Following the concept of MEL, we create four ensembles by concatenating the outputs of the three submodels as:

$$\mathbf{X}^{E1} = \text{concat}\left(\mathbf{X}^{M1}, \mathbf{X}^{M2}, \mathbf{X}^{M3}\right) \tag{14}$$

$$\mathbf{X}^{E2} = \text{concat}\left(\mathbf{X}^{M1}, \mathbf{X}^{M2}\right) \tag{15}$$

$$\mathbf{X}^{E3} = \text{concat}\left(\mathbf{X}^{M1}, \mathbf{X}^{M3}\right) \tag{16}$$

$$\mathbf{X}^{E4} = \text{concat}\left(\mathbf{X}^{M2}, \mathbf{X}^{M3}\right) \tag{17}$$

where $\mathbf{X}^{M1}$, $\mathbf{X}^{M2}$, and $\mathbf{X}^{M3}$ are the outputs of the three submodels; $\mathbf{X}^{E1}$, $\mathbf{X}^{E2}$, $\mathbf{X}^{E3}$, and $\mathbf{X}^{E4}$ denote the four ensemble tensors for corresponding ensembles. After a series of linear transformation of the ensemble tensor, we use a softmax function to estimate the probability that a trajectory segment pertains to a certain transportation mode for each ensemble, and further obtain the transportation mode by

$$\text{mode}_{\text{pred}} \leftarrow \arg\max\ \text{softmax}\left(\mathbf{X}^{o,i}\right) \tag{18}$$

where $\mathbf{X}^{o,i}$ denotes the linear transformed tensor of each ensemble.

Finally, we use a voting strategy to decide the final transportation mode classification from the predictions of the four ensembles. Specifically, we regard the inferred transportation mode of each ensemble as a *candidate*. A hard voting procedure [50] is adopted, in which we select the final class as the one with the largest sum of votes among the classes predicted by the four candidates. In the case of a tie, we consider the transportation mode classification provided by Ensemble 1 as the final classification, since Ensemble 1 is trained on more inputs and is thus expected to be more reliable than the others.

As shown in Fig. 1, we adopt batch normalization followed by dropout with rate 0.5 to ensure training stability. We use the rectified linear unit (ReLU) function to activate all hidden layers. Note that all model hyperparameters are selected following standard deep learning practice, i.e., via grid search based on model performance on the validation set.

5) Submodel Design Principles: We construct the above three submodels based on the following intuition. Model 1 incorporates convolution layers and recurrent GRU modules to extract both spatial and temporal correlations of the transformed trajectory data. The combination of CNN and RNN has been demonstrated to be effective in exploiting the spatial–temporal correlations in traffic data [22], [51]. Models 2 and 3 are instead tailored to time-series feature learning, each producing different latent representations due to the nature of the attention mechanism and DWT. Particularly, for Model 2, the adopted attention mechanism enables to "attend" to the parts that are relevant to the current part of the data since arbitrary parts of time series can be more important at different time steps, which overcomes the limitation of GRU adopted in Model 1 that encode everything into one or more hidden layers of fixed size. For Model 3, the adopted DWT, as a signal decomposition technique, can extract frequency-domain data features of the input motion feature vectors. Compared with other frequency-domain processing techniques, DWT is also capable of developing a relatively stable spectrum when handling temporally nonstationary signals [52], which is applicable to the input motion feature vectors of our model. Given that each of the three submodels has strengths that the others do not, and although it is uncertain which one is the most discriminative for TMI, ensembling them aggregates their predictions and ensures that their collective knowledge is utilized toward the final decision making.

C. Mean Teacher Semisupervised Federated Learning

In this article, we propose a semisupervised FL framework, MTSSFL, to solve the massive unlabeled data problems in data collaboration of FL for crowdsourced TMI. In this section, we introduce the proposed framework by first presenting the architecture, participants, and communication protocol. Then, we elaborate on the proposed model optimization and aggregating algorithms of MTSSFL. Finally, we describe the designs for the privacy protection and trustworthiness of MTSSFL.

1) Architecture, Participants, and Communication Protocol: As illustrated in Fig. 2, MTSSFL is a framework designed for privacy-protected FL data collaboration. There are three main entities in MTSSFL, namely, publisher, workers, and third-party evaluator. The publisher intends to train a powerful model; however, it only possesses a small amount of labeled GPS trajectory data in its own central server. Therefore, the publisher publishes a crowdsourcing TMI task. Workers receive the task and process the local model training to serve

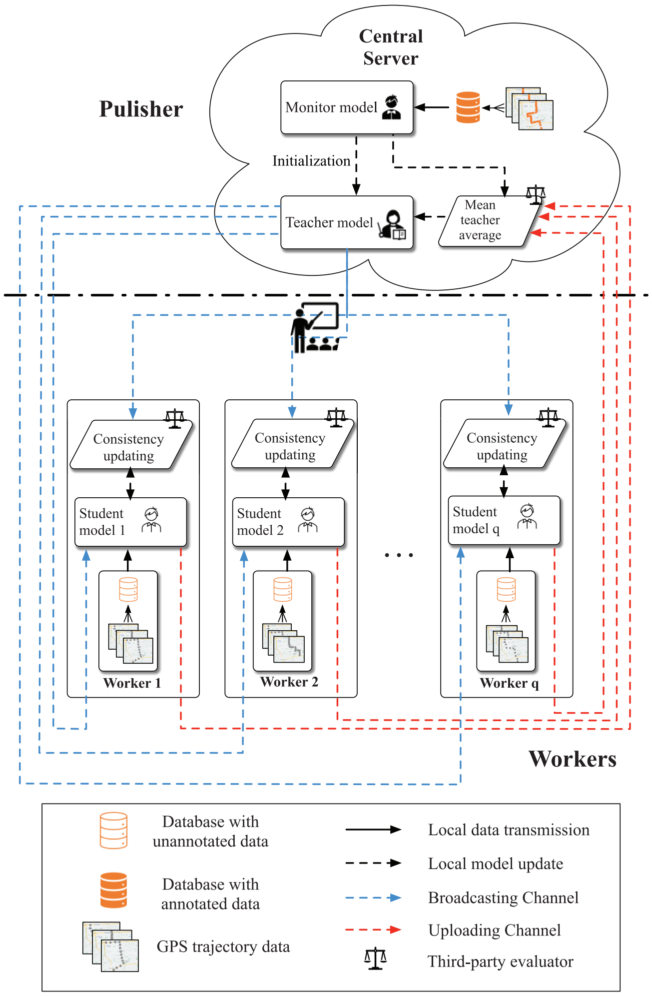

Fig. 2. Framework overview of the proposed MTSSFL.

the data collaboration with the publisher and other workers; however, each of them only possesses a set number of GPS trajectory data that is unlabeled. The third-party evaluator is independent of other participants, which is assumed to be trustworthy. The security of training and data is critical in FL-based crowdsourcing task [53], [54]; therefore, the independently trained TMI model from different participants and the data for training will be first assessed by the third-party evaluator before any aggregation or collaboration.[2] In this work, since all the data and participants are assumed to be benign, we consider all the evaluations are passed in our simulations. To successfully achieve the training goal under such biased data distribution, MTSSFL introduces a novel semisupervised learning scheme. Specifically, MTSSFL regards the local models owned by workers as *student models*, and the global model on the central server as *teacher model*. We additionally introduce the *monitor model* on the central server to train with the labeled data. Terming it "monitor" is because trained with the labeled data can guarantee itself obtain the best training effect compared to the student models of workers, like a student who has the best learning ability in a class. The teacher model is not trained directly but updated by the aggregation of the monitor model and student models. Therefore, while the teacher and monitor models are both on the central server, they are of different functionality and cannot be conflated. Furthermore, since the communication and computation overhead by aggregation is minuscule compared with the training and data transmission process [55], a benefit of this design is that the development of the teacher model will not introduce extra computation burden.

[2]The technical detail of the operation of the third-party evaluator is out of the scope of this article since it is not an influential factor of the investigated semisupervised FL performance. Related investigation will be included in future work.

Algorithm 1: MTSSFL Communication Protocol

Initialization:

Central server pre-trains the monitor model with labeled data, and update the pre-trained model parameter to the teacher model.

Iteration:

The central server distributes the copies of the teacher model to all workers, and each worker trains its copies with unlabeled data using the *pseudo-labeling*, and consistency-updating approaches.

Each worker uploads the updated model parameters to the central server. The central server aggregates the model parameters from the teacher model, student models, and the monitor model using the *mean-teacher-averaging* approach and updates the teacher model's parameters with the aggregation result.

The communication protocol between the entities is demonstrated in Algorithm 1. In the following sections, we will give details to the involved approaches, i.e., *consistency updating* and *mean-teacher-averaging*.

2) Consistency Updating: Before presenting the proposed *consistency-updating* approach, we first briefly introduce the pseudolabeling approach. Pseudolabeling is a popular approach in the semisupervised learning community, which is a process of using the model trained on the labeled data to make predictions on the unlabeled data, filtering the samples based on the classification results, and reinputting them into the model for training [35]. Particularly, the pseudolabeling approach considers the training balance between labeled data and unlabeled data, which defines a loss function as

$$J = \frac{1}{B}\sum_{m=1}^{B}\sum_{i=1}^{c} J\left(y_i^m, \hat{y}_i^m\right) + \alpha(t)\frac{1}{B'}\sum_{m=1}^{B'}\sum_{i=1}^{c} J\left(y_i'^m, \hat{y}_i'^m\right) \quad (19)$$

where B and B' denote the size of minibatch in labeled and unlabeled data, respectively; $\hat{y}_i^m$ and $\hat{y}_i'^m$ are the output of m samples in labeled and unlabeled data, respectively; y_i^m and $y_i'^m$ are the labels of m samples in labeled and unlabeled data, respectively; $\alpha(t)$ is a balancing weight.

In the condition of data collaboration defined in this article, it is hard to directly adopt the pseudo-labeling approach due to that local student models cannot access the labeled data for pretraining. In this context, we proposed *consistency-updating* approach. Specifically, we follow the pseudolabel generation as proposed in [35] to develop the pseudolabels for unlabeled data.[3] Moreover, to fine-tune the student models in the data collaboration condition, we incorporate the loss developed by the teacher model when updating the local student models. A consistency cost J_{con} is introduced to measure the distance between the prediction of student model and teacher model on unlabeled data using L2 loss, which can be formulated as

$$J_{\text{con}} = \frac{1}{c}\sum_{i=1}^{c}\left(\dot{f}\left(x_i'^m\right) - f\left(x_i'^m\right)\right)^2 \tag{20}$$

where $\dot{f}$ and f denote the teacher and student TMI model, respectively; $x_i'^m$ is the unlabeled data. Furthermore, we can define a final loss function J_s for the student model's update by combining (20) and the second half of the (19), which can be formulated as

$$J_s = \frac{1}{B'}\sum_{m=1}^{B'} J_{\text{con}} + \frac{1}{B'}\sum_{m=1}^{B'}\sum_{i=1}^{c} J\left(y_i'^m, f\left(x_i'^m\right)\right). \tag{21}$$

3) Mean-Teacher-Averaging: In this work, we proposed a mean-teacher-averaging as a secure parameter aggregation mechanism for the TMI models based on the approach proposed in [37]. Tarvainen and Valpola [37] proposed an EMA-based approach to update the model parameter of the teacher model at communication round t, which can be defined as

$$\dot{\phi}_t = \delta\dot{\phi}_{t-1} + (1-\delta)\phi_t \tag{22}$$

where $\dot{\phi}$ and ϕ are the parameters of teacher model and student model, respectively; and δ is a smoothing coefficient. The adoption of EMA makes $\dot{\phi}_t$ react more significantly to the most recent learned parameters, which can guarantee a satiating training effect [37].

We extend this method into a model parameter aggregation method applicable to FL. Specifically, we first use the naive FedAvg [56] to aggregate model updates of student and monitor models, which can be formulated as

$$\phi_{\Sigma,t} = \frac{1}{1+q}\left(\sum_{i=1}^{q}\phi_{i,t} + \ddot{\phi}_t\right) \tag{23}$$

where q denotes the number of student models (i.e., workers); $\ddot{\phi}$ is the model parameter of monitor model; and ϕ_Σ represents the aggregated parameters from student and monitor models by FedAvg. Subsequently, we incorporate ϕ_Σ by (23) into (22), and finally, obtain the aggregation mechanism for MTSSFL as

$$\dot{\phi}_t = \delta\dot{\phi}_{t-1} + (1-\delta)\phi_{\Sigma,t}. \tag{24}$$

Note that appropriate selection of the smoothing coefficient is vital when training the teacher model. We empirically found that a default value of $\delta = 0.1$ works well in practice; Section V-C3 includes a hyperparameter sensitivity test for δ and provides guidelines into setting its value based on application requirements.

To summarize, the entire working process of MTSSFL is shown as Algorithm 2.

Algorithm 2: MTSSFL Training

Input: workers $\mathcal{C} = \{C_1, C_2, \ldots, C_q\}$; number of communication rounds (global epochs) E; cloud mini-batch size (for monitor model) B; local mini-batch size (for student models) B'; number of local epochs E_l[4]; learning rate η; gradient optimizer $\mathcal{L}(\cdot)$ for TMI model; gradient optimizer $\mathcal{L}_{con}(\cdot,\cdot)$ for TMI model used for *consistency-updating* as per Eq. (21); smoothing coefficient δ; volunteer ratio μ.
Output: Teacher model parameters $\dot{\phi}$.

CentralServer:
  Initialization:
    initialize and pre-train monitor model parameters $\ddot{\phi}$
    update teacher model parameters $\dot{\phi}$ with $\ddot{\phi}$
  Iteration:
    for *round* $t = 1, 2, \ldots, t \in E$ **do**
      broadcast $\dot{\phi}_t$ to workers
      for *epoch* $t = 1, 2, \ldots, t \in E_l$ **do**
        $\ddot{\phi}_t \leftarrow$ MU $(\ddot{\phi}_{t-1}, B)$
      wait until all $\phi_{i,t}$, $i \in q$ are received
      randomly select a ratio (μ) of volunteers to participate in this round of aggregation
      $\dot{\phi}_{t+1} \leftarrow$ MTA $(\phi_{i,t}, \ddot{\phi}_t, \dot{\phi}_t, \delta, q)$

Worker:
  Initialization:
    initialize student model parameters ϕ_i
  Iteration:
    for *round* $t = 1, 2, \ldots, t \in E$ **do**
      foreach *worker* $C \in \mathcal{C}$ ***in parallel*** **do**
        receive $\dot{\phi}_t$ from central server
        for *epoch* $t = 1, 2, \ldots, t \in E_l$ **do**
          $\phi_t \leftarrow$ CU $(\phi_{t-1}, \dot{\phi}_t, B')$
        upload ϕ_t to central server

Approach MU (ϕ_t, B) **:**
  // Model update
  foreach *batch* $b = 1, 2, \ldots, b \in B$ **do**
    $\phi_{t+1} \leftarrow \phi_t - \eta \cdot \mathcal{L}(\phi_t)$

Approach CU $(\phi_{t-1}, \dot{\phi}_t, B)$ **:**
  // Consistency update
  foreach *batch* $b = 1, 2, \ldots, b \in B$ **do**
    $\phi_t \leftarrow \phi_{t-1} - \eta \cdot \mathcal{L}_{con}(\phi_{t-1}, \dot{\phi}_t)$

Approach MTA $(\phi_{i,t}, \ddot{\phi}_t, \dot{\phi}_{t-1}, \delta, q)$ **:**
  // Mean-teacher average
  $\dot{\phi}_t = \delta\dot{\phi}_{t-1} + \frac{1-\delta}{1+q}(\sum_{i=1}^{q}\phi_{i,t} + \ddot{\phi}_t)$

V. Case Studies

To fully assess the performance of the proposed MTSSFL framework in identifying the transportation modes with massive unanotated data, a series of comprehensive case

[3] Interested readers can refer the detailed process of pseudolabeling in the reference.

[4] The numbers of epochs for the monitor model and student models are set the same (i.e., E_l) to reduce macroscopic communication latency between publisher and workers.

studies is carried out with a real-world data set. First, we compare the proposed scheme with previous transportation mode models in the literature. Subsequently, the performance of the proposed scheme on non-IID data is investigated. Then, we investigate the performance sensitivity of the proposed scheme to the hyperparameters of MTSSFL. Finally, a study on the performance of the proposed scheme with fewer local iterations is conducted.

A. Experimental Setup

1) Data Set Description: MTSSFL is evaluated on Geolife [12], [57], an open data set of real-world GPS trajectories by Microsoft Research Asia. It contains a total of 17 621 trajectories collected by 182 users over 2090 days, with a total traveled distance of 1 292 951 km. Among these users, only 69 have labeled parts of their trajectories by transportation mode. The labeled trajectories are considered as ground truth and preprocessed as per Section IV-A. Even though a total of eleven transportation modes is labeled, not all of them are sufficiently represented in the data set. As such, we follow the data set authors' recommendations in only considering the five most prominent transportation modes (see Section III-A). We also perform data augmentation by flipping the input motion features along the temporal dimension as in [58]. Finally, a total of $T^* = 16,370$ single-transportation-mode GPS trajectory segments are obtained based on the available ground-truth labels. Note that although evaluation on at least one more data set would be ideal, we are not aware of any other data set of similar or larger size that contains densely sampled GPS trajectories labeled by transportation mode.

To train the TMI models involved in the proposed scheme in a semisupervised manner, we first partition the original data set into two data sets using a 17:3 ratio. The second data set is used as the testing set and serves the purpose of evaluating the identification accuracy of the monitor model when assessing MTSSFL. We further partition the first of the two data sets into a percentage of unlabeled data[5] and labeled data, with the proportion of unlabeled and labeled data being denoted by γ and $1-\gamma$, respectively; in other words, we use hyperparameter γ to control the percentage of unlabeled data in the training set. In MTSSFL, the labeled data are assigned to the monitor model, while the unlabeled data are uniformly distributed among the student models. Note that $\gamma = 0$ effectively corresponds to using all labels in fully supervised learning. In this case, we only report the identification accuracy of the monitor model when evaluating MTSSFL, since no data are distributed to the student models.

2) Experimental Settings: Our simulations were conducted on a server equipped with eight NVIDIA GeForce RTX 2080 GPUs and an Intel Xeon E5-2620 v4 CPU. All neural networks were developed using PyTorch v1.6.

3) MTSSFL Configuration: Unless otherwise stated, we set the number of workers $q = 20$, the number of communication rounds (i.e., global epochs) $E = 100$, and the number of local epochs $E_l = 5$. We also select the minibatch size for the monitor and student models as $B = 256$ and $B' = 50$, respectively. All models in MTSSFL are trained using the Adam optimizer [59] with learning rate $\eta = 0.0005$. We also set the smoothing coefficient for mean-teacher-averaging $\delta = 0.2$, the volunteer ratio $\mu = 0.5$, and the proportion of unlabeled data $\gamma = 0.5$. Note that all baselines' hyperparameters are selected according to their corresponding literature.

[5]The transportation mode labels of this data subset are discarded.

TABLE I
COMPARISON OF TMI METHODS

Method	Accuracy	Semi-supervised	Secure crowdsourcing
MLP	33.1%	–	–
SVM	47.0%	–	–
KNN	54.9%	–	–
CNN	83.6%	–	–
LSTM	81.7%	–	–
SPL	72.5%	✓	–
SGAN	83.1%	✓	–
SECA	73.2%	✓	–
STS	59.1%	✓	–
ELSTM	90.3%	✓	–
MTSSFL	89.2%	✓	✓

4) Baselines: We evaluate MTSSFL against a series of established TMI baselines. Specifically, we consider the following fully supervised machine and deep learning models: 1) multilayer perceptron (MLP) [19]; 2) k-nearest neighbors (KNNs) [19]; 3) support vector machine (SVM) [19]; 4) CNN [13]; and 5) LSTM [60]. We also include the following state-of-the-art semisupervised TMI approaches: 6) semisupervised convolutional autoencoder (SECA) [21]; 7) semipseudo-label (SPL) [21]; 8) semisupervised GAN (SGAN) [38]; 9) ensemble-based LSTM (ELSTM) [19]; and 10) semi-two-steps (STSs) [21]. It is worth mentioning that, since models 1)–5) are not designed for semisupervised learning, we only use labeled data to train them.

B. Identification Accuracy

1) Results: The comparison of identification accuracy is shown in Table I. It is evident the proposed scheme outperformed the traditional machine and deep learning baselines while performing comparably to the state-of-the-art semisupervised frameworks. The inferior performance of the conventional machine learning approaches, MLP, SVM, and KNN can be attributed to their shortage in handling complex nonlinearity of data features. Nevertheless, we can observe a satisfying result obtained by CNN and LSTM, which implies their capacity of capturing spatial correlation information and long-term temporal correlation information from the data, respectively, regardless of user data privacy. Among the semisupervised *state-of-the-arts* approaches, the proposed scheme scores the second. Compared to STS, SGAN, and SECA, ELSTM and the proposed scheme achieve higher accuracy, thanks to the learning capability of the ensemble design. The difference between the proposed scheme and the first-performing ELSTM method is due to the difference in network size that the number of our employed neurons is only approximately a third of the latter's. Meanwhile, considering the distributed configuration of

TABLE II
SENSITIVITY OF TMI ACCURACY TO PERCENTAGE OF UNLABELED DATA

Method	Accuracy (%)					
	$\gamma = 0.99$	$\gamma = 0.95$	$\gamma = 0.90$	$\gamma = 0.80$	$\gamma = 0.50$	$\gamma = 0$ (Supervised)
SPL	50.9	56.0	61.8	68.6	72.5	75.4
SGAN	68.4	77.7	80.5	82.1	83.1	83.8
SECA	52.0	56.1	62.9	69.3	73.2	76.8
STS	50.7	53	50.6	54.4	57.7	59.1
ELSTM	84.8	86.5	89.0	90.0	90.8	91.5
MTSSFL	82.4	83.1	85.7	87.3	89.2	91.4
MTSSFL-non-IID	82.3	82.5	85.7	86.9	89.0	91.3

the proposed scheme, the actual performance gap could be even smaller.

2) Accuracy for Different Percentages of Unlabeled Data: To evaluate MTSSFL against the selected baselines when different percentages of unlabeled data are available at training time, we vary $\gamma \in \{0.99, 0.95, 0.9, 0.8, 0.5, 0\}$. According to the results reported in Table II, we observe that MTSSFL achieved 82.4% accuracy when only 1% of training data are labeled, i.e., $\gamma = 0.99$. Accuracy only declined by 6.8% compared to when $\gamma = 0.5$. We note that although ELSTM attained the highest classification accuracy for all percentages of unlabeled data, it was not designed with FL in mind and thus, cannot provide secure crowdsourcing. Achieving the third best overall results, SGAN scored an accuracy of 83.1% for $\gamma = 0.50$; yet it only achieved 68.4% accuracy when $\gamma = 0.99$, demonstrating significant performance degradation when labeled data were scarce.

3) Accuracy on Non-IID Data: As discussed in Section III-B2, non-IID data are commonly encountered in crowdsourcing applications. Therefore, we additionally study the proposed scheme's performance on non-IID data. We construct a non-IID data set based on (2), where $R = 1$. Our simulation results are shown in Table II *MTSSFL-non-IID*. We find that, regardless of the percentage of unlabeled data γ, the proposed scheme performed similarly on both IID and non-IID data. This indicates that MTSSFL is indeed robust to non-IID data.

C. Performance With Different MTSSFL Hyperparameters

1) Number of Workers q: The default number of workers in our simulations is set to $q = 20$. However, in real-world crowdsourced TMI, the number of workers is expected to be very large. To examine the performance of the proposed scheme with a larger number of workers, we conduct a series of simulations with $q \in \{20, 30, 40, 50, 100\}$.[6]

From the results shown in Fig. 4(a), it is evident that the number of workers has a negative correlation with the accuracy of the proposed scheme on both IID and non-IID data. This is not surprising, as more workers mean more model parameters to be learned and more unlabeled data to be used in training; this makes performing the required aggregation algorithms more challenging for the centralized server. We can draw the same conclusion from the convergence curves shown in Fig. 3(a) and (d), where larger numbers of workers resulted in slower training convergence. Nonetheless, it is important to note that the accuracy degradation was not significant. In the case of 100 workers, only a 0.9%–1% accuracy reduction was observed.

2) Fraction of Volunteers μ: In the above tests, the fraction of volunteers participating in a communication epoch was empirically set to $\mu = 0.5$. It is interesting to investigate the impact of different μ on the proposed scheme's performance. In this experiment, we evaluate classification accuracy by varying $\mu \in \{0.1, 0.2, 0.5, 0.8, 1\}$.

The simulation results are shown in Figs. 3(b) and (e) and 4(b). It appears that higher volunteer fractions negatively affect the convergence speed of the global model, yet the impact on the final classification accuracy is negligible: the difference between the highest accuracy and the lowest accuracy is merely 0.3% (IID) and 0.8% (non-IID), respectively. This implies that a properly selected fraction of volunteers can somewhat improve model performance, while too many may slow down convergence.

3) Smoothing Coefficient δ: The proposed secure parameter aggregation mechanism of MTSSFL, termed emphmean-teacher-averaging, uses smoothing coefficient δ to control the EMA when training the global model. Here, we examine the training impact of different values for δ by varying $\delta \in \{0.1, 0.2, \ldots, 0.9\}$.

According to the learning curves shown in Fig. 3(c) and (f), it appears that the higher the value for δ, the faster training converges. However, Fig. 4(c) shows that the final accuracy decreased as δ increased, with the best value for δ on IID and non-IID data being 0.2 and 0.3, respectively. The above tradeoff has a significant implication for MTSSFL's real-world applicability: system operators will be able to either increase δ to accelerate convergence, or use relatively smaller values for δ when maximizing classification accuracy is the main target.

4) Local Iterations E_l: It is rather challenging to guarantee both high accuracy and low latency in the crowdsourced TMI. Latency may occur due to two factors: one is the latency of workers, which is excluded from the scope of this study based on our assumption in Section III-B1. The other is the workers' training time consumption. In this work, we empirically set the default number of local training epochs $E_l = 5$. To further investigate whether the proposed scheme can meet the requirements of crowdsourced TMI in fewer training iterations, we also evaluate its performance with fewer local training epochs, i.e., we test $E_l \in \{1, 2, 3, 4, 5\}$.

[6]Simulations are limited to $q \leq 100$ due to the data set's moderate size.

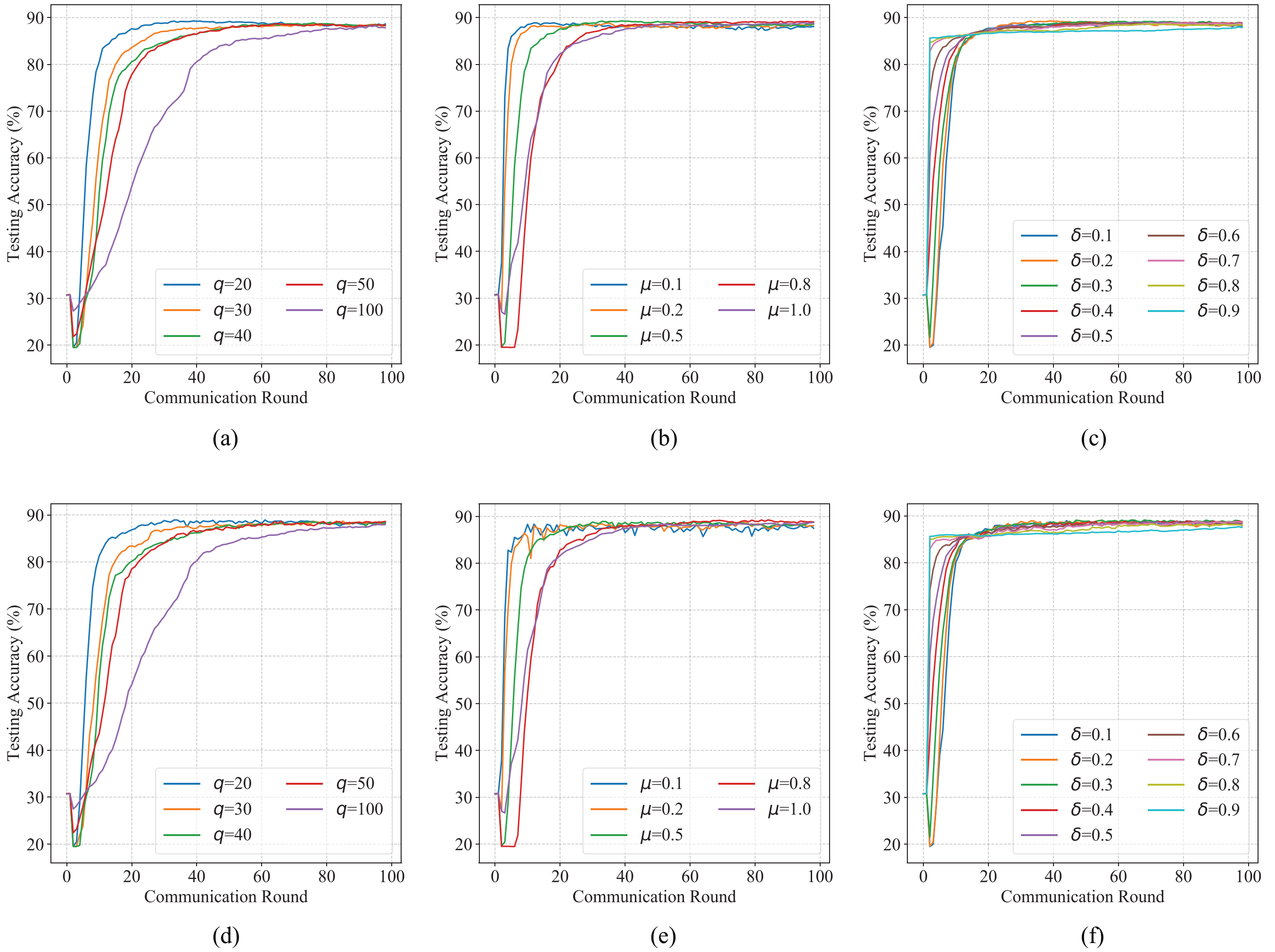

Fig. 3. Learning curves of MTSSFL for different hyperparameter settings. (a) q values (IID data). (b) μ values (IID data). (c) δ values (IID data). (d) q values (non-IID data). (e) μ values (non-IID data). (f) δ values (non-IID data).

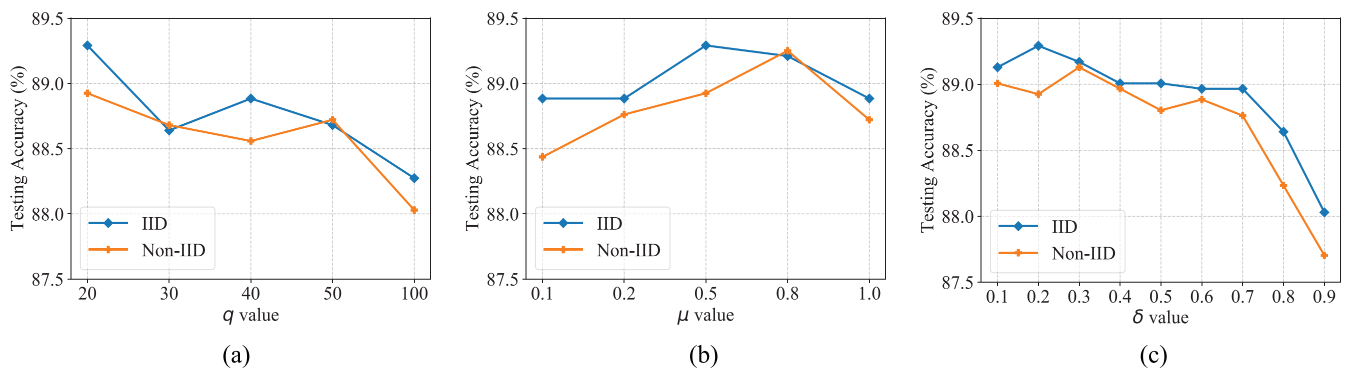

Fig. 4. Accuracy of MTSSFL for different hyperparameter settings. (a) Accuracy for different q values. (b) Accuracy for different μ values. (c) Accuracy for different δ values.

The corresponding simulation results are shown in Fig. 5 and Table III. It is evident that the performance of MTSSFL did not deteriorate when decreasing E_l. In fact, $E_l = 1$ resulted in nearly the same accuracy and convergence speed as $E_l = 5$. However, the former led to a 75.6% reduction in training time. This reduction can be attributed to the proposed consistency-updating scheme performing fewer iterations. Thus, for time-critical scenarios, training time can be reduced without significantly compromising TMI accuracy by employing fewer local training iterations.

In summary, the learning curves presented in Figs. 3 and 5 show that MTSSFL can achieve the satisfying convergence performance under different conditions even though the convergence speed may differ, which demonstrates the convergence robustness of MTSSFL.

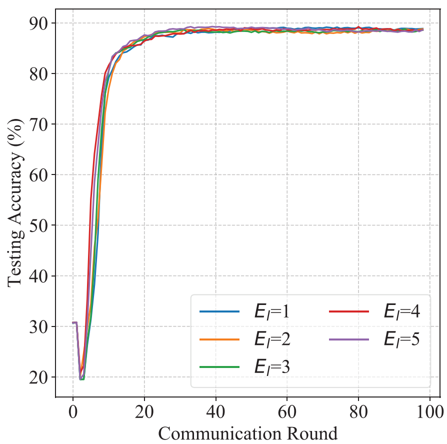

Fig. 5. Learning curves of MTSSFL for different numbers of local epochs.

TABLE III
ACCURACY AND TRAINING TIME OF MTSSFL FOR DIFFERENT NUMBERS OF LOCAL EPOCHS

E_l	Accuracy (%)	Training time (s)
1	89.1	750 ± 30
2	88.9	1480 ± 30
3	88.8	1920 ± 45
4	88.3	2620 ± 70
5	89.2	3110 ± 80

Note: Deviations are due to fluctuations in the performance of the computing device.

VI. SECURITY AND PRIVACY, AND GENERALIZATION DISCUSSION ON MTSSFL

A. Security and Privacy

The FL nature can guarantee MTSSFL with good TMI performance of the collaborative model without involving any data exchange among the workers. Furthermore, MTSSFL also allows workers only having unlabeled data to contribute to training the global model without accessing the central server's labeled data. While in-depth S&P issues such as defense against malicious attackers are out of the scope of this article, MTSSFL incorporates the following advantages in terms of S&P.

1) *Resiliance:* In MTSSFL, the amount of unlabeled data involved in training is equal for each worker regardless of how much data they actually have. For example, in real-world scenarios, different workers may generate different numbers of GPS trajectories due to factors, such as frequency of travel or online connectivity. This leads to a mismatch in the amount of data they possess and can therefore be used for training. For workers who contribute significantly more data during training, if their data are adversarially mixed with malicious or low-quality data, the teacher model may easily be poisoned, and its TMI performance may suffer. To mitigate this issue, we set the constraint that the amount of data involved in training is equal for each worker. Furthermore, in Section III-B1, we assume that the security of uplink channels is higher than that of downlink broadcasting channels. In MTSSFL, the two channels (denoted in Fig. 2 by blue and red dotted lines, respectively) are set up to use different frequency bands or time slots, while the frequency bands also change dynamically to protect the model transmission from eavesdropping attacks.
2) *Trustworthiness:* To preserve the contribution of each worker and enhance trustworthiness during crowdsourcing, an authorized third-party evaluator is involved in examining the model updating, performance evaluation, and aggregation processes of MTSSFL. The workers that are tested to be anomalous will be disqualified from the crowdsourcing. It is also worth mentioning that as illustrated in Fig. 2, the third-party evaluator operates locally, thereby reducing additional communication overhead and avoiding possible malicious attacks during transmissions.

In this work, we focus on the semisupervised FL performance of MTSSFL, and we will further investigate the above S&P factors in future work.

B. Generalization

In this work, MTSSFL is proposed to solve the lack of labeled data problems, which is a realistic problem in crowdsourcing TMI tasks. However, this problem is not peculiar to the crowdsourcing TMI tasks, which also exists in other tasks. Thus, the proposed framework can be used for a broader range of semisupervised FL. For those applications which have, but not limited to, the following characteristics, MTSSFL are well suited.

1) *Expensive Data Labeling:* Unlike some simple classification tasks, the manual labeling of transportation mode to raw GPS data can be very expensive since it requires massive expert knowledge. However, ideally, supervised learning is more advised since massive data with exact labels usually develop more ideal training results [61]. MTSSFL can be considered in the cases where the manual labeling is indeed unattainable.
2) *Stable and Timely Communication (Data Transmission):* As can be seen from the communication protocol of MTSSFL in Algorithm 2, the data transmission between the central server and workers is relatively frequent due to the design of the consistency update approach. For applications running in unstable or inferior network environments, the possible straggling effects may degenerate the framework's overall efficiency.
3) *Semisupervised Classification Task:* As a semisupervised learning approach, MTSSFL is designed for TMI, which is a classification task. For these "semisupervised classification" tasks, MTSSFL can be directly applied. However, for "semisupervised regression" tasks where the output variable is real valued (e.g., missing data imputation) [62], a specific variant of MTSSFL is required to handle them, which is out of the scope of this article.

VII. SUMMARY AND FUTURE WORK

In this article, we proposed a novel semisupervised FL approach for TMI to address a *de facto* problem that hinders the realization of crowdsourced TMI: the fact that only a small number of labeled data (owned by the central server) can be used in model training, while the distributed workers only possess their sensed (unlabeled) data. To this end, we first introduced a deep ensemble-learning-based TMI scheme to exploit the spatial–temporal relationships within GPS trajectory data. We then proposed a semisupervised FL framework, MTSSFL, tailored to the aforementioned problem. To train the distributed models having only unlabeled data at the workers' end, we proposed an approach named consistency updating to get the central model trained with labeled data involved in the worker models' training process, under a "teacher-monitor-student" triad. Furthermore, to improve the classification performance without the need for further training, we proposed an EMA-based approach named *mean-teacher-averaging* for model aggregation. In addition, we introduced a series of privacy and security design of MTSSFL. Our extensive case studies on a real-world GPS trajectory data set showed that the proposed scheme outperformed established TMI approaches while protecting data privacy, performing comparably to the state of the art with only marginally lower classification accuracy. We also find the capacity of the proposed scheme for handling non-IID data. By studying the influence of different hyperparameters on the model performance, we demonstrated the outstanding training efficiency of the proposed scheme, which can benefit the crowdsourced task.

In future work, we will further investigate in-depth privacy and security mechanisms for crowdsourced TMI. We will also extend MTSSFL to other domains to consolidate its universality and address other potential issues related to semisupervised FL.

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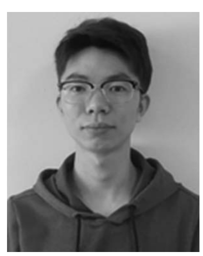

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