Vehicular Intelligence at the Edge: A Decentralized Federated Learning Approach for Technology Recognition

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***Abstract*—In the evolving landscape of vehicular networks, the need for robust, scalable, and decentralized learning mechanisms is paramount. This paper introduces a novel Decentralized Federated Learning (DFL) framework for wireless technology recognition in vehicular networks, essential for intelligently allocating spectrum resources in Multi-Radio Access Technology (Multi-RAT) scenarios. In contrast with centralized learning at the base station level, our approach leverages Roadside Units (RSUs) for model training and aggregation, eliminating central server dependency and enhancing resilience to single points of failure. Each vehicle trains a Convolutional Neural Network (CNN) for wireless technology recognition using the Fourier transform of In-phase and Quadrature (IQ) samples collected from a specific combination of technologies. The proposed framework is comprised of two steps. First, Centralized Federated Learning (CFL) is employed at the RSU level to create an aggregated model, considering the users' connectivity status. Second, DFL is utilized to establish a global model at each RSU by sharing models with neighboring RSUs. This approach not only preserves data privacy and security but also optimizes learning by leveraging local computations and minimizing the need for extensive data transmission. Our experimental analysis validates the viability of this approach in providing a scalable and resilient solution for technology recognition in vehicular networks. Our results indicate that DFL surpasses its centralized counterpart by 30% in sparse deployments with low connectivity rates.**

***Index Terms*—Decentralized Federated Learning, multi-RAT, Technology Recognition, Vehicular Networks**

I. Introduction

The exponential growth of wireless networks and the increasing demand for high-speed data have driven the need for more efficient and scalable wireless communication systems [1]. As the demand for high-speed data and efficient communication systems grows, integrating multiple Radio Access Technologies (RATs) has emerged as a pivotal strategy, enabling the harmonious coexistence of different wireless standards. Multi-RAT scenarios aim to leverage the strengths of each technology to ensure optimal performance, coverage, and user experience. However, this integration is not without challenges, as it involves complex management of the shared spectrum and coordination of various technologies in a unified manner [2].

Dynamic spectrum sharing allows multiple technologies to utilize the same frequency bands simultaneously or in a coordinated manner, preventing interference and ensuring quality of service. This approach facilitates coexistence and optimal utilization of the spectrum among diverse RATs, such as Wi-Fi, 5G New Radio Unlicensed (NR-U), and Unlicensed Long Term Evolution (LTE-U) [3]. Wireless technology recognition can enhance spectrum sharing further by detecting the presence of signals in the spectrum and identifying the specific types of technologies being used. This capability enables sophisticated spectrum sharing mechanisms [4].

Two primary Vehicle-to-everything (V2X) communications technologies, Intelligent Transport Systems G5 (ITS-G5) and Cellular Vehicle-to-Everything (C-V2X), have emerged as frontrunners in facilitating vehicular connectivity. Sharing the 5.9 GHz spectrum, these technologies must coexist harmoniously to satisfy the stringent requirements of transport services in terms of latency, reliability, and coverage [5]. This coexistence poses significant challenges due to potential interference, necessitating sophisticated technology recognition strategies [6].

Technology recognition in multi-RAT scenarios is typically achieved through signal processing techniques and machine learning methods. These methods analyze the signals in the spectrum, their characteristics, patterns, and other features to determine the technology or RAT in use [7]. In the context of vehicular intelligence, multi-RAT scenarios and spectrum sharing have become even more crucial. As vehicles move, they may need to switch between wireless technologies, ensuring uninterrupted communication. This becomes more crucial with the advent of autonomous vehicles [8].

Deep learning has emerged as a powerful tool for technology recognition, offering significant improvements over traditional methods. Neural networks can learn intricate patterns in data without explicit feature engineering. In the context of wireless signal recognition, these models can be trained on

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raw In-phase and Quadrature (IQ) signal data or pre-processed spectral features, learning to distinguish between different types of signals and communication standards effectively [9].

Applying deep learning in technology recognition is particularly advantageous in environments with high signal overlap and interference, as is common in multi-RAT scenarios. These models can adapt to new and evolving signal types, making them highly suitable for dynamic spectrum sharing and management. However, most current state-of-the-art technology recognition algorithms are based on Centralized Learning (CL) paradigms, where data from various sources are collected and processed in a central location [10]. This approach, while effective in specific contexts, raises concerns regarding scalability, latency, and privacy, as it requires the aggregation of large volumes of potentially diverse data from multiple edge devices across the network. Furthermore, CL may not be entirely suitable for scenarios requiring real-time processing at the edge devices, such as vehicular networks.

This highlights the need for more decentralized approaches, such as Federated Learning (FL), that can provide a more scalable, efficient, and privacy-enhancing solution for technology recognition in wireless networks [11]. Centralized Federated Learning (CFL), a subset of FL, enables collaborative model training across multiple devices, with a central server orchestrating the learning process. Consequently, CFL addresses some of the critical limitations of CL approaches, such as robustness and generalization, while enhancing the robustness and generalization capabilities of the model.

While CFL offers significant advantages in technology recognition within wireless networks, it has drawbacks. One of the primary challenges is managing communication overhead and latency, especially when edge devices are geographically dispersed or have varying computational capabilities. Aggregating and updating the global model from numerous local models can be bandwidth-intensive and slow, potentially leading to model convergence and update delays. Moreover, CFL is impractical in sparse deployments where only a small portion of edge devices are connected simultaneously.

Decentralized Federated Learning (DFL) mitigates these challenges by further distributing the learning process. In contrast to CFL, where a central server is required for aggregation and coordination, DFL allows edge devices to directly communicate and share model updates with each other or indirectly through a decentralized framework. The decentralized architecture eliminates the dependency on a central server and diminishes communication bottlenecks, improving stability and security. Additionally, DFL can potentially improve efficiency in managing non-Independent and Identically Distributed (IID) data by enabling localized model training, reflecting each node's unique data distributions [12]. Fig. 1 compares the various learning schemes for a vehicular network.

Aiming to address the inherent challenges of data heterogeneity and communication constraints, we introduce a new decentralized framework for technology recognition in multi-RAT vehicular networks. The considered system model integrates various communication technologies, including C-V2X PC5, ITS-G5, LTE, 5G NR, and Wi-Fi, to establish a robust and flexible vehicular network. Each user device employs a Convolutional Neural Network (CNN) for wireless technology recognition using the Fast Fourier Transform (FFT) of IQ samples.

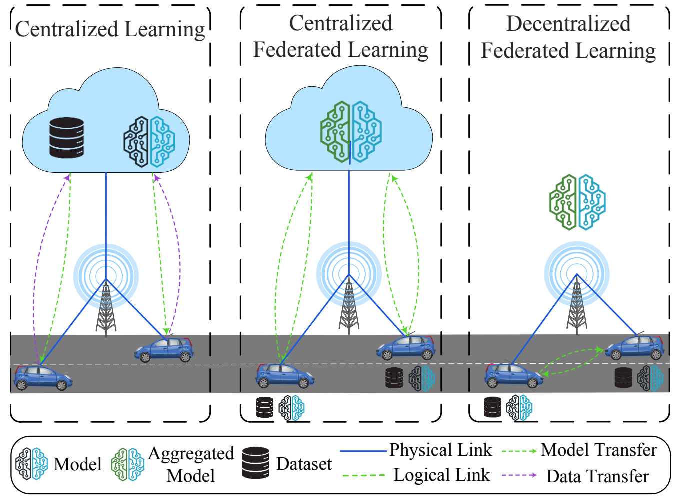

Fig. 1. Overview of the CL, CFL, and DFL approaches. In all scenarios, the physical link is established between vehicles and the RSUs, while the logical link can vary depending on the scenario.

Our proposed framework comprises two steps. First, CFL is employed at the RSU level to create an aggregated model with respect to edge devices' connectivity status. Second, a global model is established at each RSU by sharing models with neighboring RSUs. The framework enables edge devices connected through different RSUs to share model weights, facilitating the creation of a generalized and resilient wireless technology recognition model.

The key contributions of this work can be outlined as follows:

- We propose a novel DFL framework for technology recognition within vehicular networks. Our framework eliminates the reliance on centralized servers, fostering a collaborating model weight sharing among edge devices via RSUs and addressing the challenge of intermittent device connectivity.
- Our study considers a system model incorporating edge devices with diverse technologies, including Wi-Fi, LTE, NR, ITS-G5, and C-V2X PC5. This inclusion underlines the versatility of our framework in modern vehicular networks with heterogeneous communication capabilities.
- Through an empirical analysis, we evaluate the efficacy of our DFL-based approach against CFL using real-world data. This evaluation considers various scenarios with differing numbers of edge devices and connectivity conditions. Results illustrate that our proposed approach outperforms CFL in scenarios of low connectivity.

II. Related Work

FL has emerged as a pivotal approach in distributed machine learning, offering significant advantages for applications that involve classification and signal processing. For instance, Shi et al. [13] explore the application of FL in signal modulation recognition, addressing the limitations of deep learning methods that require a large amount of data. By adopting a distributed learning approach, the authors achieve an acceptable recognition rate across 11 modulation schemes and enhance privacy protection and data security.

Further addressing challenges such as class imbalance and varying noise conditions, authors in [14] propose an FL-based automatic modulation classification method. This method is designed to maintain privacy without significantly compromising performance, addressing the issues of data leakage and suboptimal performance. The simulation results suggest that the proposed solution achieves an average accuracy gap of less than 2% compared to centralized classification methods. Similarly, Qi et al. [15] introduce federated incremental learning to manage heterogeneous local datasets in modulation classification effectively. Their approach enhances the federated averaging algorithm's efficiency by treating private classes of local users as incremental classes, thereby facilitating incremental learning.

In the setting of vehicular networks, the study in [16] investigates the spectrum scarcity caused by the rapid expansion of intelligent vehicles. It presents an innovative federated transfer learning framework that leverages Unmanned Aerial Vehicles (UAVs) for modulation classification in cognitive radio systems while ensuring spectrum efficiency and reliability. Experiment results underscore the superiority of FL-based methods over centralized approaches regarding classification accuracy.

Finally, an FL-based framework for technology recognition is introduced in [17], aiming to overcome the drawbacks of centralized training. The authors propose a model where users independently train a local CNN model on their data, subsequently aggregating the model weights through a central server. This method notably excels in efficiency and privacy protection, outperforming centralized approaches while ensuring robust performance across various network conditions.

Distinct from the CFL architectures discussed in preceding studies, our work introduces a decentralized topology. This novel approach not only preserves the data privacy and security benefits inherent in FL but also tackles the challenges posed by intermittent connectivity, single points of failure, and network bottlenecks. Specifically designed for the dynamic and mobile environment of vehicular networks, where connectivity is often sporadic, our system facilitates continuous learning and model improvement. By enabling local aggregations at the RSU level and allowing for model updates without direct central server connectivity, our method represents a significant advancement over traditional FL techniques, which typically depend on consistent network connectivity for model aggregation and updates.

III. System Model and Problem Formulation

We consider a vehicular network comprising edge devices (mainly vehicles and mobile user equipment) equipped with various communication technologies, including Wi-Fi, LTE, NR, ITS-G5, and C-V2X PC5. The network consists of N edge devices, denoted as the set $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$, each embedded with one or more of the aforementioned communication technologies. These devices are dispersed over a geographical area, such as a highway, and interact with M RSUs, represented by the set $\mathcal{R} = \{r_1, r_2, \ldots, r_M\}$ through a short-range link.

RSUs, interconnected via a backhaul link, play a pivotal role by facilitating the communication and aggregation of FL model updates among the edge devices. The connection status of each edge device v_i $(i = 1, 2, \ldots, n)$ to an RSU at any given time is modeled as a Bernoulli random variable X_i with success probability p, encapsulating the mobility and intermittent connectivity of vehicles to RSUs. The equation representing this connectivity can be expressed as

$$X_{ij} = \begin{cases} 1 & \text{if edge device } v_i \text{ is within range of } j\text{-th RSU} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Edge devices are tasked with capturing and processing IQ samples from signals transmitted by different RATs, identifying and labeling them using a neural network detailed in Section IV. The L-point FFT of these IQ samples, expressed by

$$S(k) = \sum_{i=0}^{L-1} (I(i) + jQ(i)) \cdot e^{-\frac{2\pi j}{L} ki}, \forall\, k = \{0, 1, ..., L-1\}, \tag{2}$$

serves as the input for the technology recognition model. Here, $I(i)$ and $Q(i)$ denote the in-phase and quadrature-phase components of the IQ samples at the i-th point, respectively, and $S(k)$ is the FFT result at the k-th frequency bin. This process effectively transforms time-domain IQ samples captured in a specific Time Resolution Window (TRW) into their frequency-domain representation.

Consequently, each edge device forms a local private dataset $\mathcal{D}i$ through capturing, transforming via FFT, and augmenting IQ samples. The device participates in the learning process by training a local technology recognition model with weights w_i on $\mathcal{D}i$, with the aim of minimizing a global loss function. This function, $\mathcal{L}$, is a weighted sum of local loss functions and can be expressed as

$$\min_{\mathbf{w}} \mathcal{L}(\mathbf{w}) = \min_{\mathbf{w}} \sum_{i=1}^{N} \frac{|\mathcal{D}_i|}{|\mathcal{D}|} \mathcal{L}_i(\mathbf{w}_i, \mathcal{D}_i), \tag{3}$$

where $\mathcal{L}_i$ is the loss function of the $i-th$ device's model, $|\mathcal{D}_i|$ is the number of samples in the dataset of $i-th$ device, and $|\mathcal{D}| = \sum_{i=1}^{N} |\mathcal{D}_i|$.

Fig. 2 depicts the proposed DFL framework. Initially, edge devices update their models at the RSU level using CFL. Subsequently, RSUs collaborate with neighboring units to

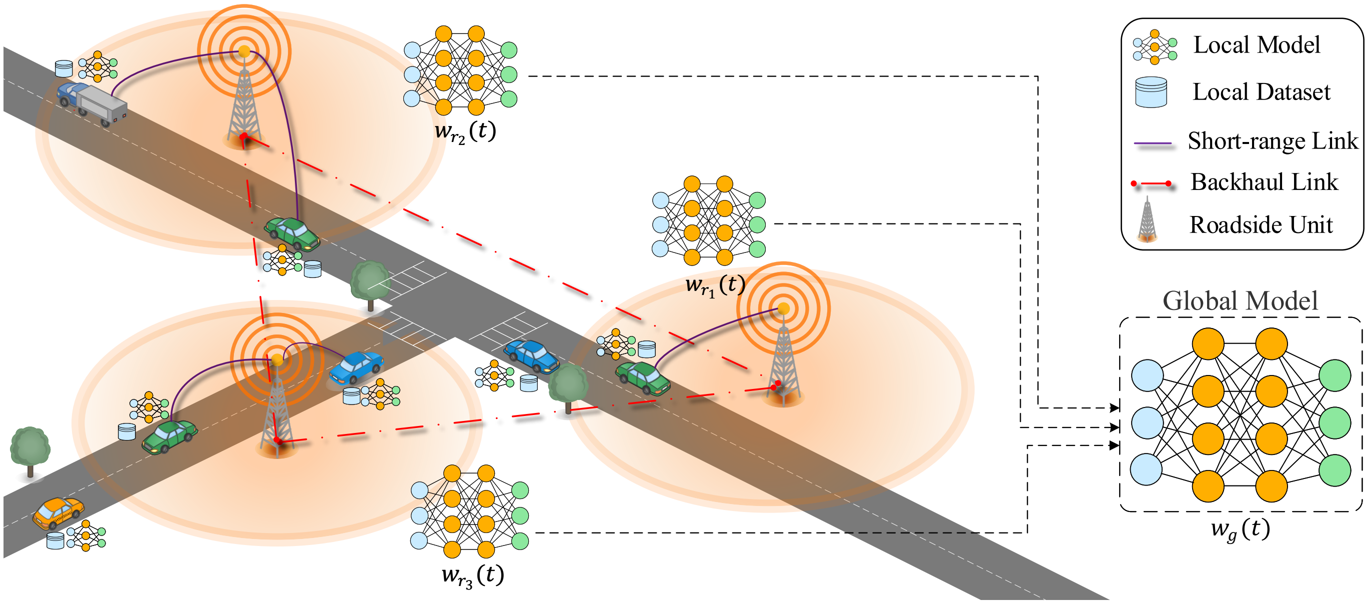

Fig. 2. Framework of the proposed DFL scheme. Model training is done at the edge device level, and model aggregation is done at two levels: a) device-to-RSU and b) RSU-to-RSU. CFL is employed at the RSU level in the first level to create an aggregated model. In the second level, DFL establishes a global model at each RSU by sharing models with neighboring RSUs.

train a shared global model through a structured peer-to-peer network, exchanging model updates to achieve decentralized aggregation. Each device i (if connected to an RSU) updates its model $\mathbf{w}_i$ using its local data $\mathcal{D}_i$ and then shares these updates with the RSU, facilitating a collaborative and efficient learning process across the network.

IV. Methodology

The technology classification within the vehicular network utilizes a CNN-based architecture inspired by the model described in [7]. This architecture incorporates three convolutional layers, each designed to capture different levels of feature abstraction. To manage complexity, max pooling follows each convolutional layer, reducing the dimensions of the feature maps. After feature extraction, the classification is done by two densely connected layers, where a softmax classifier outputs the probability estimation of the technology type.

This CNN-based model is deployed across edge devices within the vehicular network with the same parameters, serving as the local technology recognition model. It is designed to be lightweight yet practical, catering to the on-device computational constraints while achieving high classification accuracy. By leveraging DFL, the model benefits from a diverse and rich dataset from other edge devices, enhancing its generalization capabilities and robustness to varying channel conditions while mitigating the risk of a single point of failure. This decentralized approach ensures that the network remains resilient and the learning process continuous, even if some nodes or communication links fail.

RSUs act as pivotal nodes in the DFL framework, aggregating local model updates from edge devices within their vicinity. The aggregation for an RSU r_j during a specific round t is expressed as

$$\mathbf{w}_{r_j}(t) = \frac{1}{|V_{r_j}(t)|} \sum_{v_i \in V_{r_j}(t)} \mathbf{w}_{v_i}(t), \tag{4}$$

where $\mathbf{w}_{r_j}(t)$ denotes the aggregated weights at RSU r_j, $\mathbf{w}_{v_i}(t)$ indicates the weight vector of device v_i after local training, and $V_{r_j}(t)$ represents the set of devices connected to RSU r_j at round t. The subsequent model update process for the next round is obtained by

$$\mathbf{w}_{r_j}(t+1) = \mathbf{w}_{r_j}(t) + \eta \sum_{v_i \in V_{r_j}(t)} \Delta \mathbf{w}_{v_i}(t), \tag{5}$$

with $\Delta \mathbf{w}_{v_i}(t)$ being the update from device v_i at round t, and η symbolizing the learning rate.

The aggregation process within the proposed framework occurs at two levels: local device-to-RSU aggregation and global RSU-to-RSU aggregation through the backhaul links. The local aggregation at an RSU is conditioned on the presence of devices within its proximity. In contrast, the global aggregation is a function of the RSU's ability to communicate with other RSUs. The global aggregated weights at each round t, denoted $\mathbf{w}_g(t)$, are obtained by

$$\mathbf{w}_g(t) = \frac{1}{M} \sum_{j=1}^{M} \mathbf{w}_{r_j}(t). \tag{6}$$

This hierarchical aggregation process, outlined in Alg. 1, allows for decentralized learning to take place. RSUs serve as intermediary nodes, facilitating model updates between edge devices and achieving the global model. This setup eliminates

Algorithm 1 Overview of the DFL approach for Technology Recognition

Input: Number of communication rounds (T)
Output: Global model w_g

Initialize global model $w_g(0)$ with random weights
for $t = 0$ to $T - 1$ **do**
  Level 1: Aggregation at RSU level
  for edge device $v_i \in V_{r_j}(t)$ **do**
    Capture IQ samples
    Apply FFT to obtain D_i
    for RSU $r_j \in \mathcal{R}$ **do**
      if $X_{ij} = 1$ **then**
        Receive global parameters $w_g(t)$ from r_j
        Compute local gradient and update $w_{v_i}(t+1)$
        Transmit local weights to r_j
      else
        Compute local gradient and update $w_{v_i}(t+1)$
      end if
    end for
  end for
  Level 2: Aggregation at system level
  for RSU $r_j \in \mathcal{R}$ **do**
    Aggregate the received parameters at RSU-level $w_{r_j}(t+1)$ using (5)
    Transmit the aggregated model to other RSUs and form the global model $W_g(t+1)$ using (6)
  end for
end for

the need for direct communication between all devices, reducing the communication overhead. Additionally, it ensures that the learning process is scalable and can accommodate a large number of vehicles and RSUs, which is essential in vehicular networks.

V. Numerical Analysis

This section presents the performance evaluation of our decentralized technology recognition solution deployed within a simulated vehicular network environment. We utilize the publicly available IQ sample dataset [18] collected from multiple RATs using the Smart Highway Testbed [19]. This dataset was collected with a sampling rate of 20 Msps within 44 μs TRW. We consider 80% of the samples for the training dataset and the other 20% for the testing dataset, which is used to assess the performance of our aggregated model throughout various rounds.

The training data is initially distributed across different edge devices at the start of each communication round to foster a realistic simulation. Each device is assigned a distinct set of IQ samples, limited to two specific classes. This distribution scheme reflects the varied capabilities found in real-world devices such as vehicles and smartphones, with each type capable of identifying and labeling combinations of signals from different RATs. For instance, contemporary smartphones are equipped to detect and classify signals from Wi-Fi, LTE, and NR, while devices dedicated to ITS applications can process and label C-V2X PC5 and ITS-G5 signals.

This approach not only simulates a diverse and realistic vehicular network environment but also allows for evaluating the decentralized scheme across different configurations of devices and RSUs, each harboring unique combinations of signal classes, as outlined in Table I.

Each device intentionally introduces a Gaussian noise of differing power levels to its dataset before applying the FFT to simulate and account for different channel conditions and unforeseen scenarios. This step ensures that our model training and subsequent evaluations reflect the practical challenges inherent in real-world networks. The training procedure is iterative, with each round initiating with local model updates at the device level, followed by aggregation at the RSUs. The aggregation is computed by averaging the weights of the local model weights. Devices positioned out of the RSU range perform local training but are excluded from the aggregation process until they re-enter the effective range of an RSU. The mobility of the edge devices is modeled using the Bernoulli process of (1). Finally, local model training is done within five epochs using the Adam optimizer, with a learning rate set at 0.001 and a batch size of 256 samples.

TABLE I
DIFFERENT NUMBER OF DEVICES AND THEIR CLASS COMBINATIONS USED THROUGHOUT THE SIMULATION.

Number of devices	Number of RSUs	Classes per device
7	2	LTE & 5G NR C-V2X PC5 & ITS-G5 WiFi & LTE WiFi & 5G NR C-V2X PC5 & LTE C-V2X PC5 & 5G NR ITS-G5 & WiFi
11	3	LTE & 5G NR x2 C-V2X PC5 & ITS-G5 x2 WiFi & LTE x2 WiFi & 5G NR x2 C-V2X PC5 & LTE C-V2X PC5 & 5G NR ITS-G5 & WiFi
14	4	LTE & 5G NR x2 C-V2X PC5 & ITS-G5 x2 WiFi & LTE x2 WiFi & 5G NR x2 C-V2X PC5 & LTE x2 C-V2X PC5 & 5G NR x2 ITS-G5 & WiFi x2

Fig. 3 illustrates the testing accuracy curves for the proposed DFL-based technology recognition for different settings of Table I with the connectivity rate of 50% compared against CFL with full connectivity as baseline. We can observe that the accuracy of the aggregated DFL model is slightly lower than that of the CFL model. Specifically, after convergence, the accuracy of the DFL model is approximately 7% lower than its CFL counterpart. The observed marginal reduction can be primarily attributed to intermittent connectivity, as only half of the devices participate in model aggregation at every round.

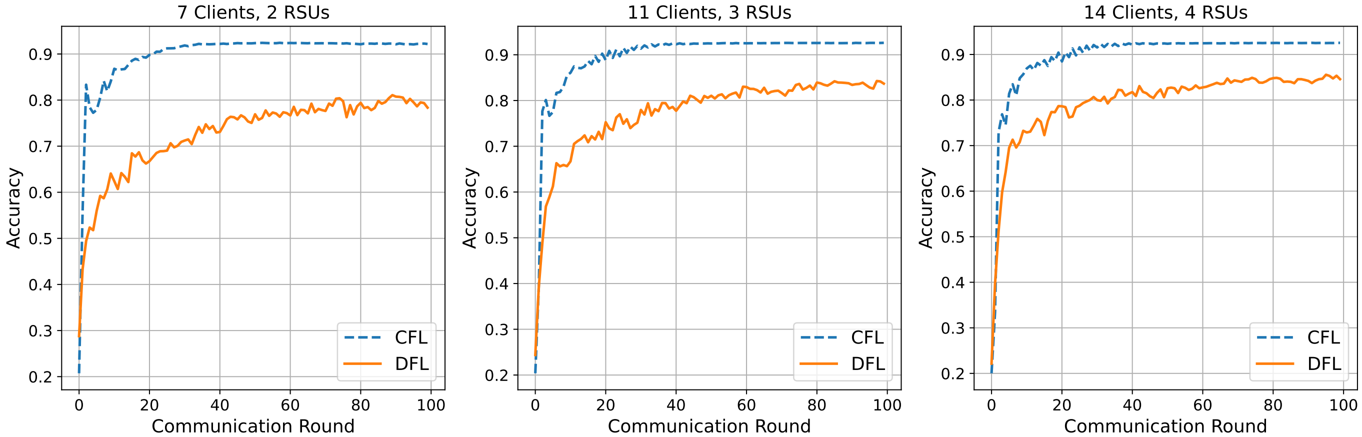

Fig. 3. Comparison of the aggregated model accuracy in CFL and DFL schemes across various device size scenarios reveals two prominent trends. The accuracy performance of DFL improves with the increase in devices and RSUs. However, DFL's convergence is slower than CFL, regardless of the number of devices and RSUs involved.

This contrasts with the CFL scheme, in which all edge devices participate in learning. Furthermore, as the number of devices and RSUs increases, the accuracy of the DFL scheme slightly improves, whereas in the FL scheme, the accuracy remains the same.

Additionally, Fig. 3 demonstrates that the convergence rate of DFL is slower compared to CFL. This observation holds true across different device sizes, highlighting a trade-off inherent to the decentralized nature of DFL. While DFL offers advantages in terms of resilience and scalability, owing to its lack of reliance on centralized coordination for model updates, this benefit comes at the expense of a more gradual convergence. The slight noise in the accuracy curve of the DFL can be linked to the variance in model updates due to the decentralized aggregation process. Factors such as intermittent connectivity and the non-IID nature of data across devices further accentuate these fluctuations.

In our subsequent experiments, we aim to investigate the impact of connectivity on performance. We define three levels of connectivity: low connectivity ($p = 0.1$), medium connectivity ($p = 0.5$), and high connectivity ($p = 0.9$). The results, as depicted in Fig. 4, suggest that the model accuracy improves as p increases, indicating a higher chance of devices being within an RSU range. Under low connectivity conditions, the sparse interactions between devices and RSUs lead to slower model convergence and diminished accuracy. This effect stems from the reliance on isolated local datasets and fewer aggregations, while more connectivity results in more frequent and substantive device-RSU model exchanges. The exposure of the aggregated model to a broader spectrum of data accelerates the convergence rate and enhances accuracy.

Furthermore, the significant advantage of DFL in low connectivity scenarios is highlighted in Fig. 4. While both approaches experience challenges in achieving maximum accuracy, the accuracy of the DFL surpasses that of the CFL by 30%. The proposed approach is more resilient as the distributed aggregation process accommodates sparse connectivity. However, as connectivity improves, the gap between DFL and CFL narrows, with both models exhibiting substantial gains in accuracy and equal performance. The marginal difference in model performance between the high and medium connectivity suggests an optimal connectivity threshold. Despite this equal performance in higher connectivity scenarios, DFL holds a distinct advantage in terms of system reliability and resilience, specifically through its inherent capacity to mitigate the risks associated with a single point of failure.

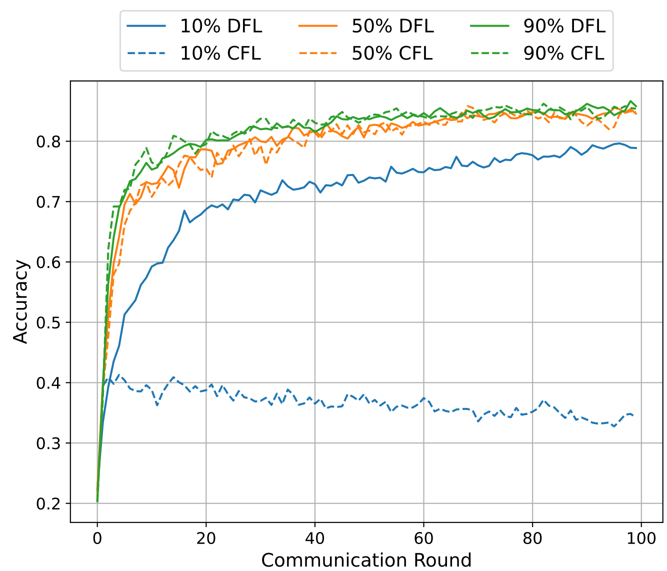

Fig. 4. Impact of connectivity probability on aggregated model accuracy for both CFL and DFL. Here, a setting with 14 devices and 4 RSUs is used. DFL shows a significant improvement in low connectivity and equal performance in medium and high connectivity settings.

At medium connectivity, devices already have a significant opportunity to participate in model aggregation, substantially improving accuracy and learning efficiency. Connectivity beyond this point only offers marginal improvements, as the model is already approaching its optimal learning capacity based on the available data and network interactions. Hence, moderate levels of connectivity are sufficient for DFL to leverage the advantages of distributed learning without the severe penalties seen in lightly connected environments. This offers a critical perspective on RSU deployment in real-world scenarios, as full connectivity is not required for models to achieve sufficient performance.

VI. Conclusion

This paper has presented a novel DFL framework for technology recognition in vehicular networks, demonstrating its efficacy in a dynamic and mobile environment. Our approach successfully integrates a range of advanced communication technologies within edge devices, catering to the diverse and evolving needs of modern vehicular networks. The use of RSUs as intermediate aggregators of model updates plays a crucial role in increasing the overall reliability and robustness of the system, as it mitigates the risk associated with a single point of failure. The experimental analysis underscores the potential of DFL in managing large-scale, distributed learning tasks in vehicular networks. Specifically, the results suggest an accuracy gain of 30% in settings with low connectivity.

Our approach offers a promising direction for other real-world applications within V2X communications where decentralized data processing and decision-making are critical. Extending this framework to different use cases, such as network selection and vertical handover management, could provide valuable insights into decentralized approaches' broader applicability and effectiveness in vehicular networks. Additionally, exploring advanced algorithms for more efficient decentralized data aggregation and model synchronization among edge devices, particularly in scenarios characterized by high mobility and fluctuating connectivity, is another valuable area of research.

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