Entropy-based Client Selection Mechanism for Vehicular Federated Environments

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Abstract. *Autonomous driving requires machine learning models to be trained at the edge for improved efficiency and reduced communication latency. Federated learning (FL) allows knowledge sharing among all devices, but Not Independent and Identically Distributed (non-IID) scenarios with biased device data distributions can lead to statistical heterogeneity and lower classification accuracy. This paper proposes an entropy-based client selection approach for vehicular federated learning environments that aims to address the challenges posed by non-IID data in vehicular networks. The proposed method is compared to a random selection mechanism in both IID and non-IID scenarios, as well as in a scenario with random client drops. The results show that the entropy-based selection method outperforms the random selection method in all compared metrics, particularly in non-IID scenarios.*

Keywords: Federated Learning, Vehicular Networks, Client Selection, Entropy

1. Introduction

The market for Connected and Autonomous Vehicles (CAVs) is anticipated to reach 166 billion dollars by 2025, and some sources indicate that it may transcend 200 billion dollars. In order to increase their safety, vehicles are increasingly reliant on advanced technologies such as processing, sensors, and communication [Damaj et al. 2021]. CAVs are designed to enhance driving safety, traffic efficiency, and the utilization of public resources such as roads, highways, and public transportation, as well as CAVs become a interest topic for both academia and industry [Pilz et al. 2021]. CAVs also issue warnings or take action during risky events or maneuvers, allowing drivers to be relieved of the stressful task of driving and providing them with physical and mental relaxation [Lobato et al. 2023].

CAVs are equipped with a set of onboard sensors, such as high-resolution cameras, RADAR, Light Detection And Ranging (LIDAR), Global Positioning System (GPS), Inertial Measurement Unit (IMU), and ultrasonic sensors [Shladover 2021, Schiegg et al. 2020]. However, regardless of the technology used, onboard sensors are limited by the CAV's Field-of-View, and by obstacles from other moving vehicles or roadside objects. Notwithstanding, extensive sensor data sharing raises alarming privacy concerns, as these data reveal confidential information about the vehicle, the driver, and the occupants. Furthermore, when data is uploaded to the cloud, it may be intercepted and misused by malicious parties [Barros et al. 2021, Lobato et al. 2022].

Federated Learning (FL) gained popularity in the context of CAVs applications due to its privacy-preserving property, since this method allows CAVs to conduct machine learning tasks without compromising the privacy of sensitive data, making it an attractive option for those applications [Du et al. 2021]. FL ensures the privacy of vehicle data by only transmitting local models to the cloud for aggregation, CAVs use FL to share their model parameters rather than their sensor data, and the models are aggregated at cloud servers to produce an accurate global model [AbdulRahman et al. 2020, Wahab et al. 2021]. This allows for real-time analysis of sensor data and predictions to be made without the need for transmitting sensitive data to a cloud server, not only increasing the efficiency of models accuracy and predictions but also ensuring the privacy of the data being collected [Agarwal et al. 2021].

However, while FL enables the sharing of knowledge among all devices while ensuring the privacy, FL applied in CAVs is subject to several challenges related to non-IID data scenarios, where data from different sources are not independent or have different statistical distributions. The diverse CAVs behaviors and sensing data, as well as large heterogeneity in different CAVs' local sensor data lead to statistical heterogeneity of datasets, resulting in lower classification accuracy [Luo et al. 2021]. Additionally, the number of model aggregation required in FL can cause high communication overhead [Liu et al. 2022]. Often only a subset of clients could be selected to put into training in each round due to the communication bottleneck, which is called the client selection problem. A client is considered significant or relevant if the data it has, and consequently the local model updates it shares, enhance the functionality of the global model [Nagalapatti and Narayanam 2021]. In order to effectively use FL applied in CAVs is crucial to address these challenges by developing novel techniques that can handle non-IID data without compromising classification accuracy [Nguyen et al. 2022].

To address the challenges of non-IID data and high communication overhead in FL for CAVs applications, we propose an entropy-based client selection mechanism where the participant CAVs are selected based on their data distribution heterogeneity. Entropy measures the randomness or unpredictability of a system, while heterogeneity refers to the diversity or variability of data across different sources. The mechanism prioritizes CAV with more diverse and representative data, by only selecting a subset of CAV that have the better suited data for model training. The proposed mechanism only selects the clients that have a higher than a threshold entropy score while ensuring high classification accuracy. Compared to baseline mechanism that rely on random CAV selection, our entropy-based selection mechanism provides a more targeted and effective selection of CAV for local model training, leading to a improved global model accuracy in 5%. Furthermore, the proposed mechanism handles with non-IID data by prioritizing devices with more diverse data, resulting in more representative models that can better handle CAVs applications.

The remainder of this paper is structured as follows. Section 2 discuss the related works. Section 3 presents the operation of the proposed client selection mechanism. Section 4 shows a comparative study about different client selection mechanisms in the CAV scenario. Finally, Section 5 describes the conclusion of this paper and present some future work directions.

2. Related Work

Li et al. developed an effective and privacy-preserving sample selection solution for FL to obtain models with high accuracy and fast convergence speed when there are low-quality or even erroneous data [Li et al. 2021]. The proposed solution considers multiple factors that influence the model performance and both the clients' data privacy and the server's task privacy. The authors proposed a set of novel techniques to first select relevant clients before training and then dynamically select clients and their samples with greater importance to the global model, with the aims to reduce the cost for data selection. However, the authors consider only the static scenario.

Huang et al. proposed a stochastic client selection algorithm, which jointly considers the cumulative effect of participants and selection fairness to obtain a trade-off between the convergence time and accuracy [Huang et al. 2022]. The authors also proposed a client selection sub-problem in a solvable form based on empirical observations. Empirically, numerical and real data-based experiments are conducted to substantiate the effectiveness of the proposed solutions.

Liu Yi et al. proposed a novel FL model called FedGRU that uses Federated Averaging (FedAvg) as the core of the secure parameter aggregation mechanism to collect gradient information from different organizations, the filtering of clients participating in the training is not considered for this algorithm. Therefore, the client selection still remains an open challenging in the vehicular field. The proposed model only discussed the reduction of communication overhead without considering the quality of the data [Liu et al. 2020].

Shi et al. demonstrated that accurately quantifying the quality features of training samples and their impact on the model is crucial for optimal sample selection in federated learning. To achieve this while maintaining data privacy, private set intersection (PSI) is a powerful cryptography technique that can be used. However, integrating PSI into federated learning algorithms requires careful implementation and tuning due to its increased computational time, communication overhead, and complexity [Shi and Li 2022].

Cho et Al. demonstrated a novel framework called Power-Of-Choice, a communication and computation-efficient client selection framework that flexibly spans the trade-off between convergence speed and solution bias. The work achieves 3 times faster convergence and 10% higher accuracy [Jee Cho et al. 2022]. Yonetani and Nishio proposed a new FL protocol called FedCS that addresses the issue of training inefficiency when some clients have limited computational resources or poor wireless channel conditions. FedCS allows the server to aggregate as many client updates as possible to accelerate performance improvement in ML models. However, the authors only address the mobile scenario [Nishio and Yonetani 2019].

We deduced from the schemes mentioned above that a client selection mechanism is necessary to fully enable the CAV scenario's. The analyzed mechanisms did not consider the quality of the data collected by the CAVs, which could compromise the selection of the most relevant clients and those that best represented the model. In addition, some approaches rely on a more controlled and specific environment to operate satisfactorily, and most of the approaches not considered client selection in a vehicular scenario.

3. Entropy-Based Client Selection

This section describes the entropy-based client selection mechanism, which uses the data entropy value of each CAV for client selection. The cloud server chooses the best ranked CAV in the total pool of participants and executes the training utilizing their local models. At the end of each global round, the edge server aggregates the local models and transmits the updated global model to all vehicles.

3.1. System Model

Entropy-based client selection has the potential to significantly impact the effectiveness of FL in vehicular networks across multiple applications. In traffic prediction, selecting clients based on their data entropy can improve the accuracy of models by ensuring that the training data is representative of the entire vehicular network. For intelligent and autonomous driving systems, selecting clients with high entropy can enhance the safety and efficiency of the system by capturing the heterogeneity of driving behaviors and conditions. Anomaly detection can benefit from entropy-based client selection by identifying vehicles with rare and unusual patterns in the network. Finally, for network optimization, selecting clients with high entropy can improve the efficiency and reliability of network performance by capturing variations in connectivity and latency. Thus, entropy-based client selection is a critical research challenge that can have significant impacts on the development of FL in vehicular networks.

Entropy is a fundamental concept in information theory to measure the degree of randomness or disorder present within a system. It also serves as a metric of uncertainty or unpredictability in a message or data stream. Entropy is quantified in bits, providing a means of assessing the amount of information contained within a message. The entropy of each client's can be calculated as a measure of randomness or uncertainty in the data. The use of entropy-based client selection can enable FL algorithms to identify the most relevant and diverse data for learning models that capture the heterogeneity of vehicular networks. By selecting clients with high entropy, FLs algorithms can ensure that the learned models are representative of the entire network and capture the variations in driving behavior, traffic patterns, and network connectivity. Therefore, entropy-based client selection is a critical research challenge that can impact the development of FL in vehicular networks.

$$H(X) = -\sum_{x} P(x) \log P(x) \tag{1}$$

To calculate the entropy, we use the formula described in Equation 1, where H(X) is the entropy of the dataset, P(x) is the probability of observing a particular value x in the dataset, and log is the natural logarithm. Clients whose datasets have a high level of entropy are selected because they contain diverse and informative data that can improve the performance of the federated learning model.

3.2. Mechanism Operation

To implement the entropy client selection, we introduce a parameter θ that controls the minimum entropy score that a client must have in order to be included in the selected subset. The θ value is obtained by calculating the median or mean entropy score across

Algorithm 1: FedAvg with Entropy-Based Client Selection

Input : C_t: the fraction of clients participating in round t, K: the total number of clients, θ: the entropy threshold, T: number of rounds, E: number of local epochs

Output: Global model $\mathbf{w}^*$

Initialize global model $\mathbf{w}_0$;
for $t = 1$ **to** T **do**
  Entropy-Based Client Selection;
  Compute entropy scores for all clients using validation set;
  Sort clients in descending order of entropy scores;
  Select top $m = \lfloor C_t \cdot K \rfloor$ clients whose entropy scores exceed θ;
  Local Model Training;
  for $i \in SelectedClients$ **do**
    $\mathbf{w}_i \leftarrow$ LocalUpdate($\mathbf{w}_{t-1}$, i, E);
  Global Model Aggregation;
  $\mathbf{w}_t \leftarrow FedAvg(\{\mathbf{w}_i\}_{i \in SelectedClients})$;
return $\mathbf{w}^* = \mathbf{w}_T$;

all clients. We also assume that the entropy scores for each client have already been computed using a held-out validation set or other method. Algorithm 1 illustrates the operation of the mechanism. At the start of the training, we compute the entropy scores of all clients' models and select the top m clients with the highest entropy scores to participate in training, where m is determined based on the fraction of clients C_t and the total number of clients K. However, if a client's entropy score is below the threshold θ, it will not be included in the selected subset.

With the selected clients, we can now train the FL model using the chosen clients' data. The weights of the model are updated after each round of training. Once the model is trained, it is evaluated on a test dataset to determine its performance. The evaluation results can be compared with the performance of the model trained using other selection criteria, such as random selection or selection based on data size.

We designed the entropy-based client selection model diagram involving entropy calculation, local training and testing of the model and aggregation and update of the global model, as illustrated in Figure 1. It is assumed that each vehicle (client) in the network will get a random subset of the data, mainly distributed in two ways, IID or non-IID. Each communication round consists in 5 steps. The procedure consists in sending the current global model state to the clients involved, receiving the entropy of the data in each client and only training the local models in the clients that meet the θ threshold. Then, the server will aggregate the local updates provided by the selected clients into a updated global model.

The process starts when the global model is broadcasted to all participants by the server (1). After each client received the global model, all clients will send their calculated entropy of their own data (2) to the server, which will select the best-suited ones by ranking from best to worst. In this experiment, the dataset in non-IID scenario was split using the Dirichlet distribution. The entropy calculation was done using the scipy library in Python. Then, the selected ones will do the local training (3), which may take different times for different clients, depending on local training data, and when finished they will send the local models to the server to be aggregated (4). Finally, the server generates the new global model based on aggregating the collected local models and sends the updated global model (5).

In this model, we implemented the predominantly used FL algorithm for aggregation called FedAvg. The aggregation is made in (3), as shown in Figure 1, where the server receives the minimum number of models from different clients and averages the local models to compute the updated global model.FedAvg assumes that all clients are willing to join each communication round for FL training.

While our entropy-based client selection approach shows promising results in mitigating the impact of non-IID data on vehicular FL, it is essential to acknowledge the potential challenges associated with the proposed mechanism. Firstly, the mechanism assumes that clients are honest and will accurately report the entropy of their data. However, in a real-world scenario, some clients may be malicious and intentionally report incorrect entropy values, which could affect the selection process and compromise the overall accuracy of the model. Finally, it requires a threshold value to determine the percentage of clients selected for training, and this value may need to be adjusted based on the specific characteristics of the dataset and the network environment.

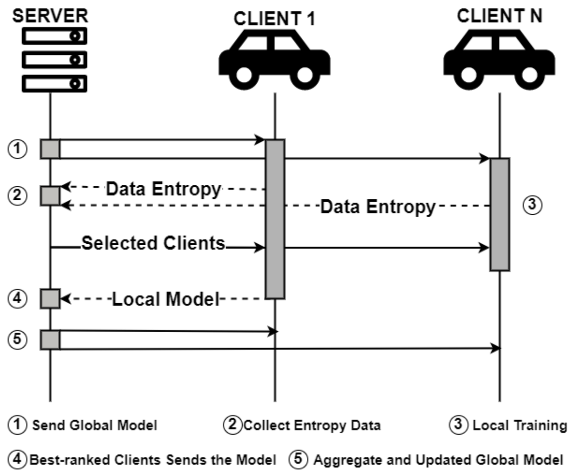


Figure 1. Entropy-Based Client Selection Model

4. Evaluation

This Section presents the evaluation of the proposed entropy-based client selection mechanism for FL in CAVs environments. The simulations were performed using a PyTorch-based framework[1] and the Fashion-MNIST (FMNIST) dataset[2]. In addition, we describe the scenario, including IID, non-IID, and random client drop. We also discuss the obtained results regarding the train loss, accuracy, and Area Under the Curve (AUC) score.

[1] `https://github.com/TsingZ0/PFL-Non-IID`

[2] `https://deepobs.readthedocs.io/en/stable/api/datasets/fmnist.html`

4.1. Simulation Description and Evaluation Metrics

we conducted simulations using a Pytorch-based framework to evaluate the effectiveness of the proposed client selection. The framework is based on Pytorch, which contains the FedAvg algorithm with the FMNIST dataset and a CNN model. The dataset was partitioned between 20 clients in two modes, standard IID and non-IID using Dirichlet distribution, allowing for varied and heterogeneous data distributions among clients. We compared the entropy-based selection with a random selection method of clients in the FedAvg algorithm. The random selection serves as a baseline method that does not consider the quality or diversity of clients' data, and simply selects a random subset of clients to participate in each round of training. By comparing the performance of the two methods, we can assess the impact of the entropy ranking on the convergence speed and accuracy of the global model. Although the original dataset used is related to the state-of-the-art (FMNIST), the concept behind entropy-based client selection can be applied to various types of data, including sensor data and driving behavior data in vehicular scenarios.

Parameters	Value
Total Participant Clients	20 vehicles
Percentage Selected	25%
Number of Rounds	50 Rounds
Learning Rate	0.001
Rate of Client Dropout	20%
Number of Epochs	5
Network Model	CNN
Batch Size	10
θ	0.25

Table 1. Simulation parameters for entropy-based selection model

Each client in the vehicular FL environment sends its own data entropy information to the server. Based on the calculated data entropy, the server selects the top 25% of clients to participate in the model training process, based on the θ threshold defined earlier. Consequently, this choice balances model representativeness and communication overhead, which ensures a diverse representation of data while keeping the communication costs manageable. This selection method is designed to reflect a real scenario and prevent the selection of clients with little data variation. The resulting train loss, accuracy, and AUC score are collected and compared to evaluate the performance of the proposed method. The AUC score is a suitable evaluation metric as it provides a comprehensive view of classifier performance, considering the trade-off between true positive rate and false positive rate across all classification thresholds, and is insensitive to class imbalance.

The simulation ran on a machine equipped with an Intel Core i7-9700 @ 3.00 GHz. For the FedAvg with entropy selection, the learning rate was fixed in 0.001, batch size defined to 10 and 50 global rounds each with 5 epochs. For the client dropout scenario, the rate of the client dropout was set at 0.2, so 20% of the selected clients will randomly drop out of the training.

4.2. Simulations Results

In non-IID scenarios represented in Figure 2, the proposed method achieved a higher accuracy and AUC score compared to the random selection approach, which can be attributed to the fact that our method selects clients with diverse data distributions, thereby reducing the impact of biased data on the training process. This suggests that selecting clients based on data entropy can effectively address the challenge posed by non-IID data in vehicular FL environments. The lower train loss also indicates that the proposed approach can achieve better convergence during training. However, it is worth noting that the proposed method may require more communication overhead to collect entropy information from all clients, which may be a limitation for large-scale federated learning systems. Overall, the results obtained highlight an important finding for vehicular networks, particularly in scenarios where non-IID data is prevalent.

Table 2. Performance metrics of random client selection mode.

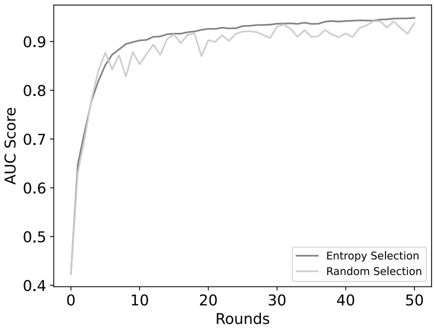
Metric	IID	Client Dropout IID	Non-IID	Client Dropout non-IID
Test Accuracy	0.7159	0.7091	0.7026	0.6849
Train Loss	1.0693	1.1628	0.9972	1.0443
AUC Score	0.9380	0.9064	0.9380	0.9064

Tables 2 and 3 further demonstrates the advantage of the entropy-based selection method over random selection. In particular, the entropy-based selection method achieves a higher score than random selection in all three metrics measures, even in the scenarios with client dropout.

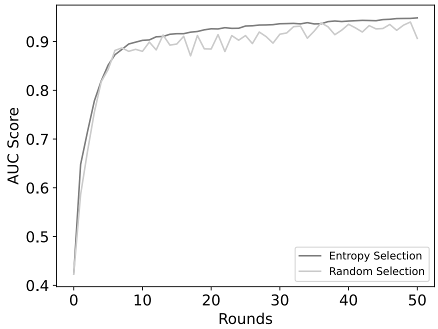
Table 3. Performance metrics of entropy client selection mode.

Metric	IID	Client Dropout IID	Non-IID	Client Dropout non-IID
Test Accuracy	0.7323	0.7301	0.7121	0.7103
Train Loss	0.7862	0.8081	0.7862	0.8081
AUC Score	0.9841	0.9840	0.9485	0.9474

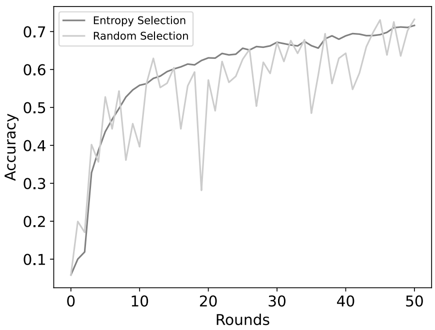
The large oscillations in the metrics during the rounds in non-IID scenarios, both in normal and random client dropout, for the random selection approach are due to the fact that the randomly selected clients have highly unbalanced and diverse data distributions. As a result, some clients may have much better data quality than others, leading to large variations in the training performance during each round. This can cause the model to overfit on some clients while underfitting on others, resulting in unstable and inconsistent performance over time. The entropy-based selection approach helps to mitigate this issue by selecting clients with more diverse and balanced data distributions, which leads to more stable and consistent performance during training.



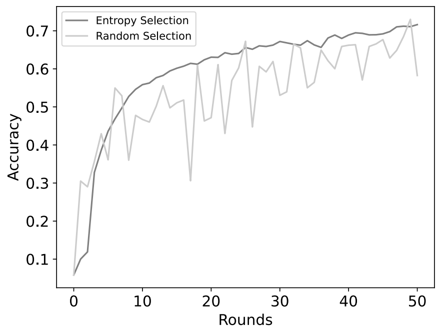
(a) AUC Score Normal Scenario



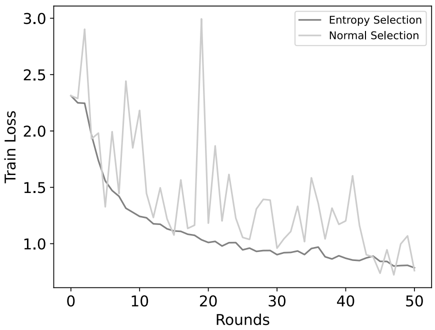
(b) AUC Score Dropout Scenario



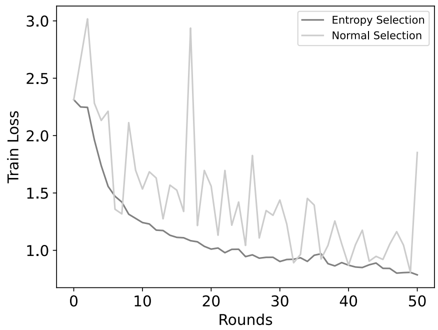
(c) Accuracy Normal Scenario



(d) Accuracy Dropout Scenario



(e) Train Loss Normal Scenario

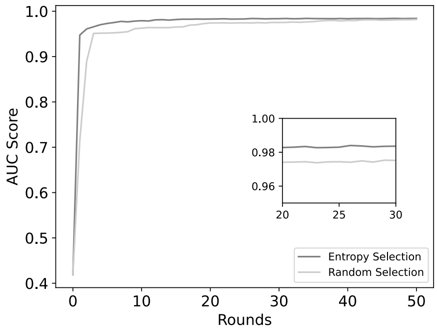


(f) Train Loss Dropout Scenario

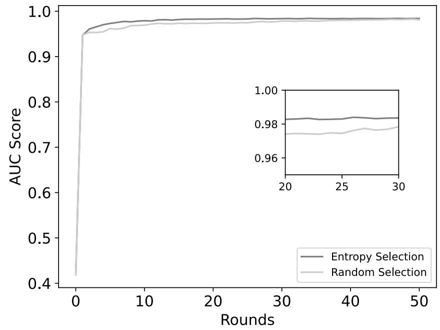
Figure 2. Accuracy, Train Loss, and AUC score in Non-IID data scenario

Regarding the random client drop scenario, the entropy-based selection method also performs better than the random selection method, following a similar pattern to the normal scenario. The entropy-based selection method consistently achieves better metrics and converges faster than the random selection method in all cases, especially in non-IID data scenarios, which are crucial for vehicular networks.

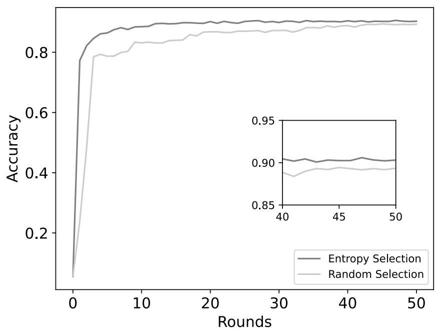
These findings show that the suggested entropy-based selection strategy can improve performance and stability while working with non-IID data, indicating that the proposed client selection could greatly improve the performance of vehicular federated learning by selecting higher quality data for the training of the model. In the IID scenario,



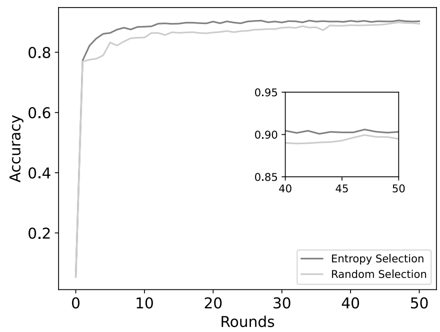
(a) AUC Score Normal Scenario



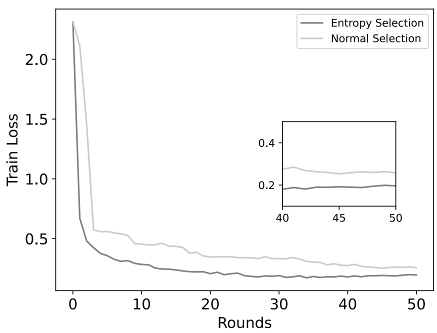
(b) AUC Score Dropout Scenario



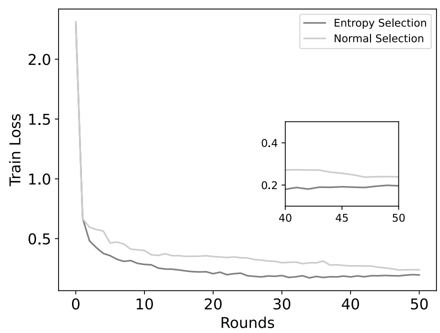
(c) Accuracy Normal Scenario



(d) Accuracy Dropout Scenario



(e) Train Loss Normal Scenario



(f) Train Loss Dropout Scenario

Figure 3. Accuracy, Train Loss, and AUC score in IID data scenario

presented in 3, both selection methods perform similarly across all three metrics, with a slight advantage for the entropy-based selection method when dealing with data that follows an IID distribution.

5. Conclusions and Future Work

We described an entropy-based client selection mechanism for FL in CAVs environments. The proposed mechanism aims to enhance the performance and accuracy of the global model by selecting CAVs with high-quality data. The client selection mechanism based on the entropy of their data indicates the diversity of information, which can improve the overall performance of the global model. Simulation results show that the proposed entropy-based selection mechanism outperforms other client selection mechanism, such as random selection in terms of model performance by 34% lower train loss, 6% higher AUC score and increased accuracy by 5%.

As future work, we plan to investigate the application of our mechanism in in more complex vehicular federated learning scenarios. Additionally, we aim to integrate our method into existing federated frameworks, such as Flexe [3], to evaluate the network capabilities of the client selection mechanism.

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