PC-SSL: Peer-Coordinated Sequential Split Learning for Intelligent Traffic Analysis in mmWave 5G Networks

Khaled Bedda*[1], Mostafa M. Fouda‡§[2], and Zubair Md Fadlullah¶[3].
*Department of Computer Science, Lakehead University, Thunder Bay, ON, Canada.
‡Department of Electrical and Computer Engineering, Idaho State University, Pocatello, ID, USA.
§Center for Advanced Energy Studies (CAES), Idaho Falls, ID, USA.
¶Department of Computer Science, Western University, Ontario, London, ON, Canada.
Emails: [1]kbedda@lakeheadu.ca, [2]mfouda@ieee.org, [3]zfadlullah@ieee.org.

***Abstract*—Fifth Generation (5G) networks operating on mmWave frequency bands are anticipated to provide an ultra-high capacity with low latency to serve mobile users requiring high-end cellular services and emerging metaverse applications. Managing and coordinating the high data rate and throughput among the mmWave 5G Base Stations (BSs) is a challenging task, and it requires intelligent network traffic analysis. While BSs coordination has been traditionally treated as a centralized task, this involves higher latency that may adversely impact the user's Quality of Service (QoS). In this paper, we address this issue by considering the need for distributed coordination among BSs to maximize spectral efficiency and improve the data rate provided to their users via embedded AI. We present Peer-Coordinated Sequential Split Learning dubbed PC-SSL, which is a distributed learning approach whereby multiple 5G BSs collaborate to train and update deep learning models without disclosing their associated mobile users data, i.e., without privacy leakage. Our proposed PC-SSL minimizes the data transmitted between the client BSs and a server by processing data locally on the clients. This results in low latency and computation overhead in making handoff decisions and other networking operations. We evaluate the performance of our proposed PC-SSL in the mmWave 5G throughput prediction use-case based on a real dataset. The results demonstrate that our proposal outperforms conventional approaches and achieves a comparable performance to centralized, vanilla split learning.**

***Index Terms*—Throughput prediction, mmWave 5G networks, split learning.**

I. Introduction

Recently, Fifth generation (5G) cellular networks emerged to support Ultra-Reliable Low-Latency Communication (URLLC), massive Machine Type Communication (mMTC), and enhanced Mobile Broadband (eMBB) services. The high bandwidth in 5G networks can be attributed to the new radio (NR) specifications, which encompass a wide range of frequencies, including low-band through mid-band to high-band, particularly mmWave frequency spectrum. These services open the way for a wide range of intriguing applications, including Internet of Things (IoT), autonomous driving, Augmented/Virtual Reality (AR/VR), and ultra-high resolution and high-responsive metaverse applications. While the majority of commercial 5G services deployed globally in 2019 utilized mid-band and low-band frequencies for 5G systems, mmWave-enabled 5G BSs started to be commercially deployed [1].

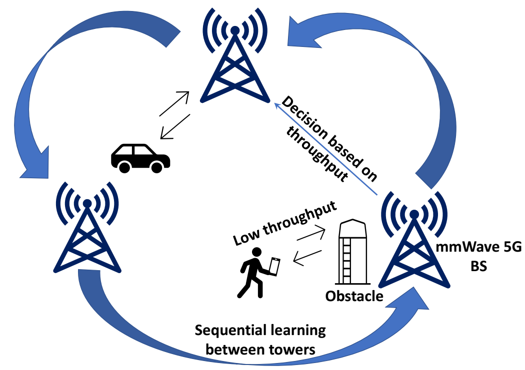

Fig. 1. A typical scenario of the netwrok traffic analysis problem based on user's mobility and location in mmWave 5G networks.

5G mmWave technology offers higher data transfer rates and lower latency, opening up a plethora of new application fields and use-cases. However, The signal intensity, signal-to-noise ratio (SNR), the distance between the device and the base station, and the number of devices connected to the network are all essential variables that affect the throughput of 5G mmWave networks, making it challenging to estimate [2], [3]. Conventional, centralized traffic analysis methods for forecasting 5G mmWave throughput include gathering and analyzing network data, which may be both time-consuming and privacy-violating.

The ultra-high bandwidth of mmWave 5G, which may theoretically reach up to 20 Gbps, opens up interesting new possibilities for supporting a wide range of current and future applications that require high bandwidth. However, many technical challenges exist involving mmWave radios that include directionality, limited range, and high sensitivity to obstructions, making the design and management of 5G services based on mmWave radio difficult. Also, it might be challenging to establish and maintain a solid communication link with user equipment (UE), especially when the UE moves around, as depicted in Fig. 1. Given these challenges, it is hard to carry out a real-time network traffic analysis and make proactive decisions regarding bandwidth allocation, load balancing, user handoff, and so forth in a seamless manner. In other words, even though the development of mmWave 5G networks has the potential to transform the telecommunications sector, adopting the mmWave frequencies confronts significant barriers, such as limited coverage area and increased path loss [3]–[5]. As a consequence, a key challenge in mmWave 5G network design is how to accurately predict the network throughput [6]. While conventional machine learning models have been employed to address this issue, they typically demand the exchange of vast amounts of data between devices and Base Stations (BSs), posing privacy and security concerns.

To address the 5G mmWave BSs distributed coordination [7], in this paper, we present a split learning approach since this concept allows data to be incorporated into the deep learning models locally on BSs without violating privacy of the mobile users that they serve. In particular, we explore the use of split learning for throughput prediction in mmWave 5G networks, and demonstrate its potential to improve network performance while maintaining user-privacy. Split learning is an emerging machine learning technique allowing multiple parties to train deep learning models to allow them to learn cooperatively without granting access to data [8]. By keeping the client data on the device and processing it locally, split learning can preserve the privacy of sensitive data while enabling efficient model training. This approach significantly reduces the amount of data that needs to be shared between the user device and the central server, making it ideal for applications in which data privacy is a concern. In the context of mmWave 5G networks, split learning can be leveraged to predict network throughput while maintaining user-privacy, as the data remains on the device and is not shared with the network operator or other users. By enabling network operators to predict throughput more accurately and allocate resources more efficiently, we envision a peer-coordinated sequential split learning technique, referred to as PC-SSL, in this paper. Also, we evaluate the performance of PC-SSL that indicates its ability to help optimize the performance of 5G mmWave networks and support the deployment of new and innovative applications by means of effective throughput prediction without privacy-outage and with low communication overheads.

The remainder of this paper is structured as follows. The recent, related reseach work are surveyed in section II. Our considered system model is presented in section III. This section also contains a formal description of the research problem we address in this work. Next, our proposed method is presented in section IV followed by its performance evaluation in section V. Section VI provides concluding remarks and future research directions.

II. Related Work

Several research work on throughput prediction in 5G networks have appeared in the recent literature that employed machine learning and deep learning methodologies [9]. Researchers in [10] established a technique for estimating the cellular link throughput for end-users and evaluating the efficacy of network slices [11]. To achieve this, they conducted a measurement study to investigate real-world scenarios, including driving in urban, suburban, and rural areas and experiments in crowded/congested environments. Then, they developed machine learning models that utilize lower-level metrics (which portray the radio environment) to forecast the attainable throughput. On the other hand, the work in [12] designed a deep-learning-based Transport Control Protocol (TCP) approach for a disaster 5G mmWave network. Their model learns about the node's mobility and signal strength and predicts the network is disconnected and reconnected, which helps adjust the TCP congestion window. Their work aims to provide network stability and higher network throughput. Next, in [13], researchers designed a deep learning-based framework to design and optimize a 5G air-to-ground network. They deployed two deep neural networks, to predict the user throughput and to optimize the throughput deployment parameters, respectively.

While conducting research on intelligent 5G throughput prediction using deep learning models, other researchers have also focused on the development of distributed 5G intelligent systems that prioritize privacy preservation. Several research works were carried out by employing split learning and Federated Learning (FL) in 5G intelligent applications [14], [15]. The work in [16] conceptualized a secure framework based on blockchain and FL that leverages smart contracts to prevent unreliable and malicious participants from participating in the FL process. The system automatically identifies such participants through the execution of smart contracts, and thus mitigates the risk of poisoning attacks. Additionally, they incorporated local differential privacy techniques to safeguard against membership inference attacks. In [17], researchers introduced a novel hybrid threat detection approach using split-machine learning that leverages both machine learning and human intelligence to detect cyber threats. Their work focused on analyzing Distributed Denial of Service (DDoS) attacks based on their temporal and threshold behavior across various network communication protocols.

While machine and deep learning models have been used in distributed frameworks in the aforementioned research work, there remains an open area for coordinating 5G mmWave BSs in a distributed yet intelligent manner to carry out network traffic analysis to forecast throughput prediction while preserving the desired privacy of the network traffic data.

III. Problem Description and System Model

In this section, we present our motivation and a formal description of the research problem, followed by our considered system model.

The motivation behind our work is to introduce a decentralized technique of split learning to make every client (i.e., 5G BS) capable of making accurate generalized decisions without the need for communication with a centralized server. Furthermore, we may conclude from the relevant work discussed in section II that there is a research gap in distributed learning systems in terms of throughput prediction in a 5G network system choosing a use-case based on traffic analysis of mmWave 5G networks. Moreover, previous studies did not

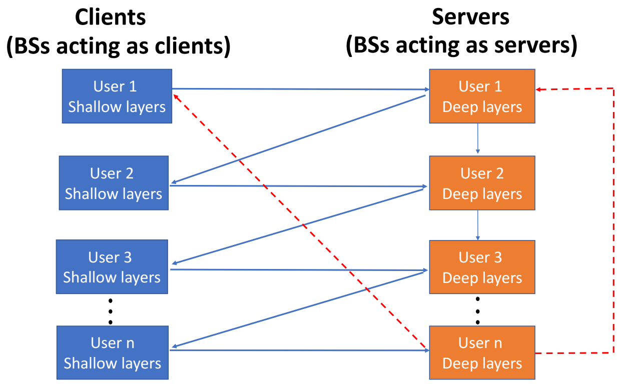

Fig. 2. Peer-coordinted Split learning architecture. Note that during a time-round, a BS assumes the role of a server while other BSs serve as a client, and this is repeated for all the BSs in the considered 5G network. Also, note that the users refer to the participating BSs which aim to perform decentralized coordination for analyzing the network traffic with privacy-preservation. This simple yet powerful concept lays the foundation for a peer BS-coordinated split learning mechanism.

take into account user-privacy while developing optimization models for traffic analysis in 5G networks. In Fig. 1, we depict a typical scenario of our use case. The BSs perform the sequential split learning training process to be up-to-date in terms of deep learning model weights. The deep learning model at each BS analyzes every connected user's data based on the location and mobility, and then predicts the throughput for that user. Based on the throughput, an intelligent decision could be made. For example, in the figure, the pedestrian is shown to suffer from low throughput due to obstacles, a scenario in which the user-device could change the BS it is connected to based on its location and mobility.

Based on the described scenario and problem setting, Fig. 2 illustrates the architecture of our peer-coordinated split learning system model. The training flows sequentially till the last user, and then the last user closes the circle by making the first user the next user. Every process between the user's client and its server indicates a conventional local training process. On the other hand, every process between the user's server and the next user's client represents a vanilla peer-to-peer split learning process. This process is described as follows. Assume that we have the neural network model denoted by $M(x : \theta)$, where x refers to the input and θ refers to the model parameters. In a peer-to-peer paradigm, the L layers of the model are split into L_s and L_d layers, denoting shallow and deep layers, respectively. The client-end has the sub-model of L_s, and the server-side comprises the submodel $L - L_d$. Then, a process called data smashing takes place at the client-end, which transfers the input x into the feature representation $H = h(x)$, where H denotes the features vector represented by $A(F(x : \theta_s))$. Here, A refers to the activation function of the last layer in the L_s layers, and F represents the submodel of M. Then, the feature vector is sent to the server, where the output of the server is represented by $Y = A(F(H : \theta_d))$ such that Y in our aforementioned problem setting denotes the throughput of the considered 5G network system.

IV. Proposed Method

In this section, we introduce our suggested decentralized technique, which is based on the network system model spatial parameters, along with user traffic and mobility, for commercial 5G mmWave networks. For further information on the communication setup and system under consideration, readers should refer to the work in [6]. We explain the dataset processing, the deep learning model used for training, and our proposed peer-coordinated sequential split learning architecture, referred to as PC-SSL, in the remainder of this section.

A. Dataset Preparation

Before delving into the technicalities of the deep learning approach for networks, we introduce the data set adopted for our considered use-case. We consider the Lumos5G dataset, which is a collection of network performance data for over 100 commercial mmWave 5G BSs in the United States [6]. The dataset includes a range of features related to network performance, including signal strength, signal-to-noise ratio, channel quality, and network load. The dataset was collected using a custom data collection framework developed by Lumos Networks that includes a set of mobile measurement units to verify the network performance at various locations around each BS. Table I describes the locations from which data are collected. The dataset covers a range of different scenarios and use cases, including indoor and outdoor environments, static and mobile devices, and different levels of network congestion. Overall, the Lumos5G dataset represents a valuable resource for researchers and practitioners interested in studying mmWave 5G network performance and developing new approaches for network performance prediction. Table II summarizes the data statistics while Table III presents the data attributes. In the data processing phase, we cleaned the data and applied preliminary processing (normalization and discretization) alongside feature selection. For our classification task, we selected the thresholds for the achievable throughput as follows: 0-150 Mbps as low throughput, 150-700 Mbps as medium throughput, and above 700 Mbps as high throughput.

B. Selection of Deep Learning Model for Throughput Prediction

Next, we provide the details of our choice of the centralized deep learning model for throughput prediction given the system model described in Section III. We selected a deep neural network (DNN), from a variety of potential machine and deep learning models, due to its current adoption in the communication networks intelligence field with lightweight performance characteristics. A DNN is a feed-forward neural network architecture comprising dense layers which are fully connected. For details of the considered DNN, readers are recommended to refer to the coauthors' earlier work [18].

C. Vanilla Split Learning Baseline vs Proposed Sequential Split Learning Algorithm

Split learning was first introduced in [8]. Algorithm 1 shows the stages of updating and training the neural network in

TABLE I
INFORMATION ABOUT THE DATA COLLECTION AREAS.

Area	**The intersection**	**Airport**	**Bank Stadium Loop**
Description	Outdoor 4-way traffic intersection	Indoor mall-area with shopping booths	Loop with railroad crossings, traffic signals, and open park restaurants
Num. of Trajectories	12	2	2
Trajectory Length	232 to 274 m	324 to 369 m	1300 m

TABLE II
SUMMARY OF THE DATA STATISTICS USED IN THE STUDY.

Data Points	563,840 (per-sec. throughput w/ feature) samples
Mobility Modes	Walking (331 km), Driving (132 km), Stationary
Data	$38,632$ GBs of data downloaded over 5G
Duration	6 months

TABLE III
DATA FIELDS AND DESCRIPTIONS.

Field	**Description**
	Raw values
Latitude & longitude	UE's spatial coordinates
User's mobility/activity	Indicates whether the user is walking, standing, or driving.
Moving speed	UE's moving speed reported by Android API
Compass direction	The horizontal direction of travel of the UE with respect to the North Pole (also referred to as azimuth bearing) and its accuracy
	Post-processed values
Throughput	Downlink throughput reported by iPerf 3.7
Radio type	Indicates whether the UE is connected to 5G or 4G
Cell ID	Identifies the tower the user is connected to
Signal strength	Signal strength of LTE (rsrp, rsrq, rssi) and 5G (ssrsrp, ssrsrq, ssrssi)
Horizontal handoff	UE switches from one 5G panel (cell ID) to another
Vertical handoff	UE switches between radio types (e.g., 4G to 5G)
UE-Panel distance	Distance between the UE and the panel it is connected to
Positional angle (θ_p)	Angle between UE's position relative to the line normal to the front-face of the 5G panel
Mobility angle (θ_m)	Angle between the line normal to the front-face of the 5G panel and UE's trajectory

the vanilla split learning approach. The algorithm works by splitting the model between the server and user-devices (i.e., BSs in our case), where the server holds the global model parameters and user-devices hold their own local model parameters. The algorithm iterates over a fixed number of iterations T, and for each iteration, it randomly selects a subset of user-devices to update their local model parameters. The split ratio r determines the proportion of user-devices that will update their local model parameters during each iteration. If a user-device is selected to update its local model parameters, it computes the local gradient of the loss function with respect to the model parameters based on its own data and sends the gradient to the server. The server updates the global model parameters using the received gradients and transmits the updated parameters back to the user-device. If a user-device is not selected to update its local model parameters, it sends a random batch of its data to the server to be used for updating the global model parameters. The algorithm combines the updated model parameters from all user-devices using the average function to obtain the final global model parameters.

Next, we present our proposed PC-SSL, i.e., the unique split learning algorithm where the peer BSs engage in distributed coordination. The steps of Algorithm 2 elucidate the main differences between our proposal and the vanilla algorithm (i.e., the baseline). Looking into the proposed PC-SSL in Algorithm 2, we observe that in every iteration, we loop on the number of BSs, and every BS is considered a server and client. During the learning process, every BS updates its server from its client and then commences a peer-to-peer split learning process with the next BS client in the stack. After that, the BS acting as the server updates its server weights and its client BSs' weights; then the next BS's server weights are updated and this process is repeated. The learning process is carried out sequentially in a closed loop where every BS receives updates from the previous one and starts the peer-to-peer mechanism with the subsequent BS.

V. PERFORMANCE EVALUATION

To evaluate the performance of our proposed PC-SSL, we present two comparisons between every BS's model in the two approaches of standalone (every BS trains on its own data only in a centralized manner) and sequential learning. First, we compare the accuracy of every BS in the two approaches as illustrated in Figs. 3, 4, and 5. As shown in the figures, the split learning models yield better performance than the centralized ones.

Algorithm 1: Vanilla SplitNN Algorithm (baseline).

Input : $(x, y) \in D$, batch size B, number of epochs E, learning rates α_c, α_s

Output: Trained client and server models

Initialize client and server models f_c and f_s randomly;
for *each epoch* $e \in [1, E]$ **do**
  Divide the data into batches $D_1, D_2, ..., D_{|D|/B}$;
  for *each batch* $D_i \in D$ **do**
    The client computes the gradients $\nabla_c L(f_c(x_i; \theta_c), y_i)$ and sends them to the server;
    The server aggregates the gradients from all clients, updates the server model parameters, and sends the updated model parameters to the clients;
    The client updates its own model parameters using the server's updated model parameters;
  end
  The server updates its own model parameters using the updated model parameters from the clients;
end
return Trained client and server models f_c and f_s;

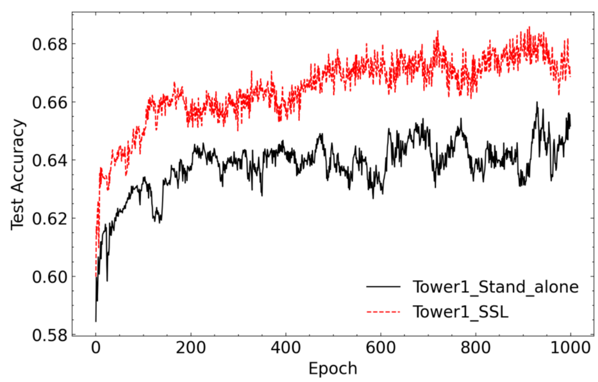

Fig. 3. Comparison of the first tower model in the standalone and sequential learning approaches.

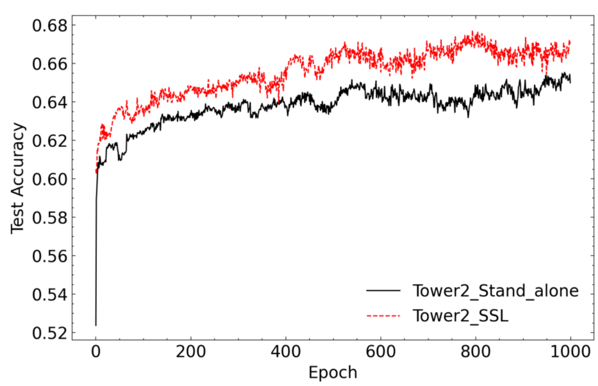

Fig. 4. Comparison of the second tower model in the standalone and sequential learning approaches.

Then, we illustrate the accuracy performance of every BS in the sequential model and the server performance of the vanilla split learning model as depicted in Fig. 6. According to these results, the performance of our proposed split learning model is close to the vanilla model.

Algorithm 2: Proposed Peer-Coordinated Sequential Split Learning (PC-SSL) Algorithm.

Input : $(x, y) \in D$, batch size B, number of epochs E, learning rates α_c, α_s , Stack of BSs or Towers T[Servers, Clients], number of BSs n

Output: Trained client and server models

Initialize client and server models f_c and f_s randomly;
for *each epoch* $e \in [1, E]$ **do**
  Divide the data into batches $D_1, D_2, ..., D_{|D|/B}$;
  for *each batch* $D_i \in D$ **do**
    for *each BS/tower t in T[Servers, Clients]* **do**
      $Client_i$ computes the gradients $\nabla_c L(f_c(x_i; \theta_c), y_i)$ and sends them to the server;
      $Server_i$ completes the forward pass and compute the gradients;
      $Client_i$ updates its model parameters.;
      $Server_{i+1}$ updates its model parameters.;
      $Client_{i+1}$ updates its model parameters.;
    end
  end
end
return Trained stack of clients and servers models f_c and f_s;

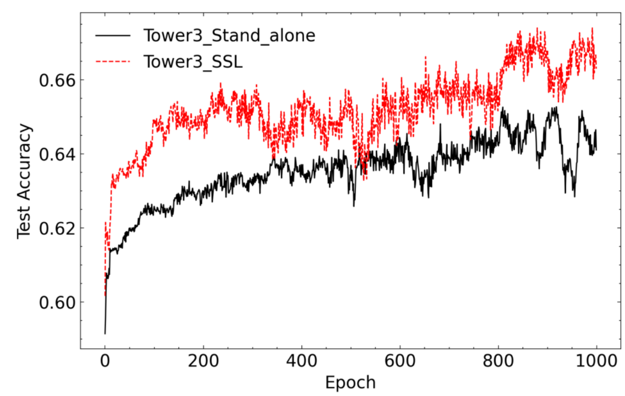

Fig. 5. Comparison of the third tower model in the standalone and sequential learning approaches.

We then evaluate each model of the BSs in both standalone and PC-SSL scenarios alongside the centralized model with the baseline, vanilla split learning. We employ accuracy, precision, and F1-score as evaluation metrics. Table IV presents the results of these metrics in a micro-analysis methodology for all three classes. The results demonstrate the same findings in the comparison figures aside that the results for the low throughput class are higher than the other classes which helps the system to be more accurate in predicting the low throughput scenarios and make an intelligent decision to avoid the low throughput in high-throughput applications, such as high-resolution video streaming.

TABLE IV
METRICS RESULTS SUMMARY OF ALL MODELS.

Models		Metrics								
		Accuracy			Precision			F1-score		
SSL models	BS1	**0.825**	0.749	0.756	**0.802**	0.5	0.624	**0.778**	0.462	0.674
	BS2	**0.822**	0.778	0.753	**.795**	0.581	0.612	**0.776**	0.48	0.682
	BS3	**0.823**	0.759	0.757	**0.787**	0.526	0.622	**0.779**	0.454	0.679
Standalone models	BS1	**0.820**	0.733	0.747	**0.825**	0.467	0.614	**0.761**	0.468	0.66
	BS2	**0.809**	0.747	0.743	**0.777**	0.493	0.60	**0.759**	0.415	0.668
	BS3	**0.8**	0.742	0.738	**0.77**	0.483	0.60	**0.747**	0.448	0.649
	Central	**0.823**	0.77	0.78	**0.78**	0.549	0.666	**0.783**	0.506	0.699

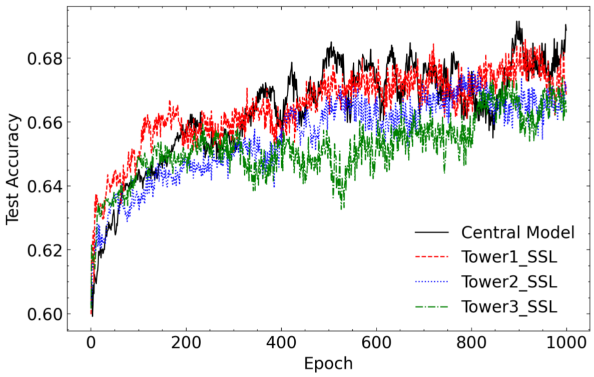

Fig. 6. Comparison of the central model in the standalone approach and all BSs in the sequential learning approach.

VI. CONCLUSION AND FUTURE WORK

This work presented a novel approach for a decentralized split learning method with a use-case of mmWave 5G network throughput prediction that is both privacy-preserving and distributed. The proposed sequential split learning framework enables each 5G base station to learn from a larger pool of user data (e.g., user location, mobility, traffic patterns, application types, and so forth), leading to more accurate and generalized decisions based on data-driven techniques with minimal need to establish communication with a central base station. This approach also ensures that the user-privacy is not compromised. The key contribution of this work is developing a decentralized methodology of split learning which is a self-contained decision-making system that does not rely on a centralized server, allowing for intelligent decisions based on user-mobility and traffic analysis in the considered 5G network. Our research findings indicate the efficacy of data-driven models in a spatial, multi-tenant system without the need for additional computation and processing at a central node. Future research directions may include expanding the dataset to include more devices and signal types for broader IoT and metaverse applications. Additionally, the work could be extended beyond traffic analysis and, depending on user-mobility and positional parameters to temporal analysis based on user's history.

ACKNOWLEDGMENT

The work has been partly supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) (RGPIN-2020-06260) and the National Science Foundation (NSF) under Award No. 2210252.

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