Hybrid Architectures for Distributed Machine Learning in Heterogeneous Wireless Networks

Zhipeng Cheng, Student Member, IEEE, Xuwei Fan, Student Member, IEEE, Minghui Liwang, Member, IEEE, Minghui Min, Member, IEEE, Xianbin Wang, Fellow, IEEE, and Xiaojiang Du, Fellow, IEEE

Abstract—The ever-growing data privacy concerns have transformed machine learning (ML) architectures from centralized to distributed, leading to federated learning (FL) and split learning (SL) as the two most popular privacy-preserving ML paradigms. However, implementing either conventional FL or SL alone with diverse network conditions (e.g., device-to-device (D2D) and cellular communications) and heterogeneous clients (e.g., heterogeneous computation/communication/energy capabilities) may face significant challenges, particularly poor architecture scalability and long training time. To this end, this article proposes two novel hybrid distributed ML architectures, namely, hybrid split FL (HSFL) and hybrid federated SL (HFSL), by combining the advantages of both FL and SL in D2D-enabled heterogeneous wireless networks. Specifically, the performance comparison and advantages of HSFL and HFSL are analyzed generally. Promising open research directions are presented to offer commendable reference for future research. Finally, primary simulations are conducted upon considering three datasets under non-independent and identically distributed settings, to verify the feasibility of our proposed architectures, which can significantly reduce communication/computation cost and training time, as compared with conventional FL and SL.

I. INTRODUCTION

The past decade has witnessed the expeditious evolution of communication and computing technologies, and their innovative applications in many emerging fields such as the Internet of Vehicles and E-health, where massive amount of data is generated, exchanged, and utilized. This development brings both technical challenges and great opportunities for a wide range of machine learning (ML)-based applications, since ML holds considerable promise to fast decisions and inferences without human intervention [1], [2]. Besides, device-to-device (D2D) communications enable multi-layer heterogeneous wireless networks are becoming one of main components of 5G/6G networks, where the complicated network topologies could impose great challenges to the implementations of ML [3].

Securing abundant training data and computation resources is the fundamental requirement of ML. Traditional ML is generally centralized where massive data are collected and transmitted from local devices to centralized data centers associated with remote cloud servers. Disregards its advantages such as high accuracy and efficiency, centralized ML faces the following deficiencies:

- Frequent transmission of big training data is challenging even for the wired links, let alone the dynamic wireless links, while also incurs heavy energy consumption on local devices.
- Centralized ML is unconducive to rapid model deployment. Besides, it suffers from unsatisfying scalability in large-scale networks, especially when the model requires frequent retraining.
- Centralized ML is privacy-unfriendly, since many applications may involve lots of private information, e.g., pathological pictures in E-health [2]. Under these circumstances, local devices (e.g., patients) may be unwilling to provide privacy-sensitive data due to ever-growing privacy concerns, which can result in a dilemma between model training and privacy protection.

A. Preliminaries of Distributed ML

To reconcile the demand for ML model training and privacy protection, a straight idea is to conduct the model training by distributed data owners to avoid sharing raw data, which facilitates distributed ML architectures. Specifically, federated learning (FL) [4] and split learning (SL) [5] represent two bright peals. Specifically, FL and SL implement distributed ML from different perspectives, while the corresponding learning architectures are depicted in Fig. 1.

Training process of FL: Regarding a typical FL scheme, a set of smart devices termed as clients can participate in the iterative model training. At the beginning of each iteration, each client receives a global model from a parameter server, then conducts local training to update the model by performing stochastic gradient descent on its local training data. After the completion of local training, multiple clients upload the corresponding model parameters to the FL server in parallel (step 1). Then, the FL server aggregates (e.g., FedAvg $\text{Avg}()$) the overall received model parameters into a new global model, which will be broadcasted to clients (step 2) for the next training round. Specifically, each client only exchanges the model parameters with the FL server, which can thus prevent privacy disclosure to some extent.

Training process of SL: Regarding a typical SL training process, an ML network is firstly split into two subnetworks via cutting in the middle layer of the network. Generally, the subnetwork associated with input layer is deployed on the clients’ side, and the one related with output layer will be deployed at an SL server. In each iteration, a client first starts training by performing forward propagation; and then, the activation data, i.e., the output of cut layer of the client (with label data), will be transmitted to the SL server (step
combining both FL and SL architectures, to guarantee the training performance in heterogeneous wireless networks.

- **Client heterogeneity:** Clients generally have heterogeneous computation/communication/energy capabilities. Each client in FL requires more computation/energy resources to support the complete model training. Besides, since the stability of wireless links of clients are essential to guarantee successful model transmissions (e.g., the size of a large complete model can reach 1 GB [6]), FL prefers clients with sufficient computation/energy/communication resources. SL architecture can generally support clients with constrained on-board computation/energy resources since each client only has to train a partial model, which, however, can incur heavy communication overhead. Moreover, imbalanced and non-independent and identically distributed (non-IID) data on clients may dramatically impact training performance. To this end, exploring the combination of FL and SL architectures to make full use of clients’ heterogeneous capabilities and resources presents another major significance.

- **Optimization target heterogeneity:** Typically, model test accuracy and convergence speed represent the key optimization targets of distributed ML [3]. Besides, when distributed ML is implemented in heterogeneous networks, common indicators such as data rate, throughput, delay, and energy consumption also represent major concerns of ML, which complicates problems such as client scheduling and resource allocation [7]. Thus, it is significant to improve distributed ML architectures according to the characteristics of heterogeneous networks while realizing multiple targets optimization.

Given the above discussed major challenges and limitations of conventional FL and SL in heterogeneous networks, this article is motivated to propose two comprehensive architectures via analyzing the combination of FL and SL. Our main contributions are highlighted below:

- A new hybrid split FL (HSFL) architecture is firstly proposed by integrating the split architecture into FL. Then, the hybrid federated SL (HFSL) is introduced, which unifies federated architecture with SL. Advantages and performance comparisons of the two novel learning architectures are analyzed in detail.

- Open research directions are comprehensively discussed to identify the challenges and opportunities of our proposed architectures, for future implementations.

- Primary simulations are conducted to verify the feasibility of our proposed architectures on three datasets, under highly non-IID data settings.

## II. Related work

Several initial works have been devoted to exploring the combination of FL and SL, as well as the corresponding performance improvement. For HSFL, [6] proposed a decentralized FL mechanism (i.e., gossip learning) based on FL model splitting in a D2D network, where each FL client only transmits model segmentations to neighboring clients.
However, this work only considers the D2D network. For HFSL, [8] proposed a parallel SL framework, where all the clients’ subnetworks are synchronized. In each training round, all the clients send all the gradients back to the server, and the server averages the gradients and transmits them back to the clients. Although this method enables SL with parallelism during clients’ model update process, it still depends on a single server and thus results in poor scalability, especially in large-scale networks. [9] proposed a SplitFed framework where the clients’ model parameters are also averaged with a dedicated server. Besides, the subnetwork at the server side is updated by averaging the gradients of each client. However, unsatisfying scalability represents one of the key drawbacks of SplitFed, upon considering the increasing number of clients [10]. Therefore, [10] decided to deploy edge servers as coadjuvants to alleviate the communication and computation load of the SL server; then each edge server can interact with one or several clients to exchange gradients; while the SL server can further calculate averaged gradients and update the subnetworks at edge servers. [11] put forward similar ideas by deploying multiple FL servers to handle groups of clients. Additionally, they have made comprehensive experiments on Raspberry Pi devices. Although these works have made certain contributions, none of them have comprehensively discussed the implementations on integrating FL and SL in heterogeneous networks while evaluating the performance associated with different architectures.

III. HYBRID ARCHITECTURES FOR DISTRIBUTED ML

A. Architecture of HSFL

According to previous discussions, FL clients may undergo heavy communication costs since each of them has to transmit a complete model to the server, especially when considering large size models over unstable wireless links. Besides, in typical FL, the model of a client is no longer useful in updating the global mode when facing with transmission failures, e.g., only part of the corresponding model has been successfully transmitted to the server. Promoted by the basic idea of SL and to overcome the drawbacks of FL, we consider splitting the model from a different perspective, namely, the number of model parameters. Then, a comprehensive HSFL architecture is proposed as inspired by [6], in a multi-layer heterogeneous network, as depicted in Fig. 2(a), which consists of D2D clients, cellular clients, edge servers, and the main server. Key modules of HSFL are detailed below.

**Model splitting:** The model is firstly split into \( M \) segments with equal data size where each segment is identified by a unique identification number. \( M \) represents a hyperparameter that can be different for various FL models. More importantly, the larger \( M \) is, the smaller model granularity and higher transmission efficiency could be reached. Considering different communication conditions, an appropriate value of \( M \) can ensure a good trade-off between transmission capacity and communication efficiency. Although each client can set \( M \) by itself theoretically, to facilitate model aggregation/storage, all clients will use the same value of \( M \).

**Model transmission and aggregation at clients:** Each client first evaluates the wireless channel quality and transmission capacity, to determine the number of segments that can be transmitted successfully. Any specific segments for transmission can be randomly chosen or specified by the receiver, while different clients can transmit the same segments. Specifically, for D2D clients, suppose that each client can communicate with its neighboring clients within one hop, it will send/receive at least one segment to/from each neighbor. Two paradigms associated with model transmission and model aggregation are applied for D2D clients and cellular clients, respectively, as given in Fig. 2(a). On the right side, cellular clients can transmit model segments to the edge server in parallel, for example, client 1 sends segment 1 to the edge server while client 2 sends segments 2 and 3. On the left side of Fig. 2(a), D2D clients transmit model segments to their neighboring clients sequentially in a decentralized manner, while the last D2D client can send the aggregated model to the edge server. Specifically, edge servers or D2D clients proceed with segment-wise model aggregation, where
the model segments are aggregated individually. For example, edge servers aggregate segment 1 of \( W_{E,B} \) by averaging all the received segments 1.

**Horizontal/Vertical model aggregation at edge servers:** Vertical aggregation and horizontal aggregation are considered in HSFL to improve communication efficiency. For vertical model aggregation, the model transmission and aggregation can be repeated for multiple rounds to obtain multiple model replicas, which thus reduces the communication cost between edge servers and main server [3]. Then, the model will be transmitted to the main server for a wide-range global aggregation. Horizontal aggregation between edge servers can be regarded as a special D2D communication process from the edge server level, which can further reduce the total model size transmitted to the main server and thus alleviate communication costs. Moreover, horizontal aggregation can be used for model parameter sharing, which greatly accelerates local model training; while mitigating the influence of non-IID data distributions among clients.

**B. Architecture of HFSL**

Fig. 2(b) illustrates the proposed HFSL architecture, where the main principle is to parallelize SL training and average the model weights over multiple clients by applying FL. Similar to HSFL, both D2D clients and cellular clients are considered.

When HFSL is implemented over multiple D2D clients, clients can be clustered into several clusters, e.g., based on their communication/computation capabilities. Then, the ML model is split into multiple subnetworks and distributed to the clients within each cluster. As shown on the left side of Fig. 2(b), the model is split into 4 and 3 subnetworks for two clusters, respectively. Then, the forward propagation starts at the client (e.g., client 1) with the input layer while ending at the client (e.g., client 4) with the output layer. Next, the back propagation starts in reverse order. Thus, each D2D cluster can be regarded as a hyper FL client which trains a complete model, i.e., \( W_1, W_2 \). The models can be transmitted by the clients to the edge server/neighboring cluster for averaging aggregation. In the next training round, the training starts with different clients under a new model splitting setting. Apparently, the training process is sequential within each D2D client cluster, and parallel over different clusters.

For cellular clients, we borrow ideas from [8]–[11], and integrate them into the proposed HFSL. As shown by the right side of Fig. 2(b), the ML model is split into two subnetworks \( C \) and \( H \), where each client trains the same subnetwork \( C \) in parallel while the subnetwork \( H \) is deployed at edge server \( B \). When multiple clients forward the activation results to the server in parallel, the edge server \( B \) first copies the model to obtain multiple model copies to conduct forward propagation and back propagation for different clients in parallel. The number of model copies should be equal to the number of clients, e.g., two copies for clients \( A \) and \( B \). Then, the gradients will be sent back to the clients for updating the corresponding subnetwork parameters, \( C_A \) and \( C_B \), while the server can update parameters \( H_1 \) and \( H_2 \). Then, the clients can send the updated model parameters to the edge server in parallel. Finally, the edge server can aggregate the model copies of edge server \( B \) with \( H_B \), and \( C_B \) of the two clients. \( C_B \) will be sent back to the clients for the next training round. Notably, the number of cellular clients associated with each edge server should be optimized so that to alleviate the model storage cost of the edge server. Similarly, edge server \( B \) can further send the complete model parameter \( W_{E,B} \) to the main server for wide-range global aggregation. Besides, horizontal model aggregation can also be done between the edge servers in HFSL, which is omitted here.

**C. Comparison of HSFL and HFSL**

**Connections and differences:** Although HSFL and HFSL are both concrete implementations of the combination of FL and SL architectures, they have connections and differences. First, the core architecture of HSFL is FL, namely, all the clients should train a complete ML model, while only have to transmit partial (or complete) model parameters. Model splitting based on the number of model parameters can be considered as a special case of SL. Differently, the core architecture of HFSL is SL, that is, each client only trains a certain part of the model, while the federated architecture aims to realize parallel training and multi-layer model aggregation. Therefore, HFSL and HSFL essentially represent two different architectures, but can both be implemented in heterogeneous networks. Generally, HSFL and HFSL are interrelated and can be organically combined to form a more complex architecture.

**Performance discussion:** To achieve better performance comparison regarding different learning architectures, we quantify the communication (comm.)/computation (comp.) cost of clients for a simple analytical analysis. Without losing generality, we mainly consider cellular clients, since it is challenging to compare the performance of different architectures under the same parameter settings for D2D clients. Besides, it is hard to find general settings for decentralized FL and SL. Assuming that there are \( N \) clients, the total training data size is \( D \) where each client has the same training data size \( D/N \). The overall model data size is \( |W| \). The model is split into two subnetworks for SL and HSFL, the size of the split layer is \( b \), and the size of forward propagation or back propagation over the split layer can be calculated by \( bD/N \) [12]. The fraction of model size with clients is \( \gamma \) and \( (1 - \gamma) \) with the server. For HSFL, the model is equally divided into \( M \) segments, while each client transmits \( m \) segments to the server at one training round. The computation cost, i.e., floating point of operations (FLOPs) of training a complete model is denoted by \( F \); and the size of allocated computation load fraction at the client is \( \lambda \). Thus, the total computation cost is \( NF \) for FL and HSFL, while it is \( N\lambda F \) for SL and HSFL. Correspondingly, HSFL reduces the total communication cost of FL from \( 2N|W| \) to \( N2m|W|/M \), while HSFL raises the communication cost of SL from \( N(2bD/N + \gamma|W|) \) to \( N2(bD/N + \gamma|W|) \), which, however, greatly reduces the training time through parallelization (as shown in the simulation).

**Key advantages:** According to the above-discussions, the advantages of HSFL and HFSL are summarized as follows:

- **Training cost reduction:** Compared with FL/SL, HSFL/HFSL can greatly reduce the communication cost
and training time, while HSFL works better for training large size models, rather than HFSL, upon considering a large number of clients.

- Communication efficiency improvement: Spectrum can be efficiently reused as benefited by in-band D2D communication mode with an appropriate resource sharing scheme.
- Data-efficient training: HSFL can alleviate the loss caused by possible model transmission failures, while take good use of the local models trained by clients. In addition, HFSL can facilitate more clients with limited computation resources to participate in each global training round, thanks to the property of parallelism. Besides, D2D communications and multi-layer hybrid network architecture will greatly expand the client coverage of the servers, and more training data can be efficiently utilized.
- Good adaptation in time-varying network topology: Based on the hybrid network architecture, HSFL and HFSL can adapt well to the dynamic network environment (e.g., caused by the mobility of clients), and achieves good stability during the training process.
- High privacy protection: HSFL and HFSL enable clients to train or transmit partial models, which thus reduce the possibility of privacy disclosure incurred by malicious attacking or eavesdropping.

IV. OPEN RESEARCH DIRECTIONS

This section discusses interesting research directions of the proposed HSFL and HFSL architectures, some examples are discussed as below.

Model splitting and resource allocation: For HSFL, an applicable splitting scheme, e.g., the value of \( M \), can greatly improve the transmission efficiency and reduce client dropout rate. Particularly, considering a D2D network where the wireless links among clients are random and dynamic, how to determine a reasonable \( M \) represents a noteworthy problem, e.g., designing a dynamic model splitting scheme. For HFSL, the structural characteristics of the model can impose higher complexity and additional challenges to the model splitting problem, especially in D2D networks. For example, the model of HFSL can be divided into multiple subnetworks and assigned to different D2D clients, where subnetworks and D2D clients are regarded as two directed graphs. In this case, the subnetwork allocation problem over a D2D network is formulated as a subgraph isomorphism problem [13], which is generally NP-complete and greatly calls for low-complexity and responsive solution designs. Besides, since different model segments (layers) may leave various impacts on training performance, highly depending on the local data set of each client. Thus, model splitting scheme for HSFL and HFSL should be well concerned. Specifically, problems such as reward transfer among different clients and the secondary distribution of internal reward in client clusters under HSFL/HFSL should be well concerned.

Multiple ML tasks scheduling: Thanks to the innovative and diverse on-board sensors, client devices can collect various types of data. Besides, benefit from the enhanced multi-core computing processors, a client can participate in multiple ML model training processes simultaneously [7]. Therefore, when performing multiple ML training tasks at one time, it is significant to determine appropriate learning architectures (i.e., FL, SL, HSFL, or HFSL) and resource scheduling schemes regarding diverse learning tasks’ requirements and clients’ status, to ensure the learning performance. This topic also offers a practical and interesting research direction.

Privacy-oblivious data sharing: Although avoiding raw data sharing (e.g., in case of privacy disclosure) represents the basic intention of distributed ML, several clients are somehow allowed to offload training data to a trusted client in many scenarios. For example, clients are willing to share photos with their families and friends, rather than strangers. This privacy-oblivious data sharing process can involve more training data. For example, clients with limited power supply can offload training data to others in supporting model training. Besides, data sharing can also realize client dimensionality reduction in HSFL and HFSL, which thus enables better optimizations. To avoid high-risk privacy disclosure, data sharing strategies need to be further studied, such as measuring the relationship
Fig. 3. Test accuracy of CL, FL, SL, HSFL, and HFSL over the training rounds, with four clients upon considering three datasets: a) MNIST; b) Fashion-MNIST; c) MedMNIST.

| TABLE I |
| --- |
| PERFORMANCE COMPARISON OF DIFFERENT ARCHITECTURES FOR DIFFERENT DATA SETS IN ONE GLOBAL ROUND. |

### MNIST

| Architectures | Client network | Server network | Total comm. cost (MB) | Total comp. cost (FLOPs) | Test accuracy | Training time (Second) |
| --- | --- | --- | --- | --- | --- | --- |
| CL | N/A | cov2d(32, (5,5)) + cov2d(64, (3,3)) + dense(30976, 128) + dense(128, 64) + dense(64, 10) | N/A | N/A | 99.05% | 5.02 |
| FL | cov2d(32, (5,5)) + cov2d(64, (3,3)) + dense(30976, 128) + dense(128, 64) + dense(64, 10) | N/A | 60.94 | 1.07 x 10^8 | 96.83% | 50.83 |
| SL | cov2d(32, (5,5)) + cov2d(64, (3,3)) | dense(30976, 128) + dense(128, 64) + dense(64, 10) | 7090.1 | 7.52 x 10^7 | 96.20% | 891.02 |
| HSFL | cov2d(32, (5,5)) + cov2d(64, (3,3)) + dense(30976, 128) + dense(128, 64) + dense(64, 10) | N/A | 30.47 | 1.07 x 10^8 | 96.92% | 49.91 |
| HFSL | cov2d(32, (5,5)) + cov2d(64, (3,3)) | dense(30976, 128) + dense(128, 64) + dense(64, 10) | 7090.4 | 7.52 x 10^7 | 96.33% | 222.75 |

### Fashion-MNIST

| Architectures | Client network | Server network | Total comm. cost (MB) | Total comp. cost (FLOPs) | Test accuracy | Training time (Second) |
| --- | --- | --- | --- | --- | --- | --- |
| CL | N/A | ResNet(32) | N/A | N/A | 91.73% | 2.03 |
| FL | cov2d(32, (5,5)) + cov2d(64, (3,3)) + dense(30976, 128) + dense(128, 64) + dense(64, 10) | N/A | 60.94 | 1.07 x 10^8 | 80.21% | 52.77 |
| SL | cov2d(32, (5,5)) + cov2d(64, (3,3)) | dense(30976, 128) + dense(128, 64) + dense(64, 10) | 7090.1 | 7.52 x 10^7 | 68.51% | 891.02 |
| HSFL | cov2d(32, (5,5)) + cov2d(64, (3,3)) + dense(30976, 128) + dense(128, 64) + dense(64, 10) | N/A | 30.47 | 1.07 x 10^8 | 78.26% | 49.91 |
| HFSL | cov2d(32, (5,5)) + cov2d(64, (3,3)) | dense(30976, 128) + dense(128, 64) + dense(64, 10) | 7090.4 | 7.52 x 10^7 | 81.32% | 222.75 |

### MedMNIST

| Architectures | Client network | Server network | Total comm. cost (MB) | Total comp. cost (FLOPs) | Test accuracy | Training time (Second) |
| --- | --- | --- | --- | --- | --- | --- |
| CL | N/A | ResNet(32) | N/A | N/A | 91.73% | 2.03 |
| FL | ResNet(32) | N/A | 7.18 | 4.27 x 10^6 | 80.21% | 52.77 |
| SL | ResNet(2) | ResNet(30) | 1400.02 | 3.2 x 10^7 | 78.21% | 180.18 |
| HSFL | ResNet(32) | N/A | 3.59 | 4.27 x 10^6 | 82.41% | 52.66 |
| HFSL | ResNet(2) | ResNet(30) | 1400.18 | 3.2 x 10^7 | 81.32% | 45.04 |
between privacy disclosure and the amount of shared data, establishing a reputation/credit-based evaluation system.

V. PRIMARY SIMULATION

This section evaluates the performance of our proposed hybrid architectures in comparison with centralized learning (CL), FL, and SL on three datasets, namely, MNIST, Fashion-MNIST, and MedMNIST. Each dataset contains multiple classes of different objects, and can thus be utilized to train classification models. Specifically, MNIST includes grayscale images of handwritten digits from ‘0’ to ‘9’; Fashion-MNIST includes grayscale images of ten different clothing items; MedMNIST includes grayscale images of eight blood cell microscopes. Besides, four clients are supposed to participate in each architecture. To better evaluate the feasibility and stability of the proposed architectures, we adopt a highly non-IID dataset setting \[15\] for the clients and datasets. For example, we partition MNIST into four groups according to label spaces, while ensuring that any two groups have different label sets. For example, we assume client-1 has all the training data of class ‘0’ and ‘1’; client-2 has all the training data of class ‘2’ and ‘3’; client-3 has all the training data of class ‘4’, ‘5’ and ‘6’; client-4 has all the training data of class ‘7’, ‘8’ and ‘9’. A similar dataset setting is applied for Fashion-MNIST and MedMNIST. Besides, Table I demonstrates the model setting for different datasets and architectures. Note that a ResNet(32) model is applied for MedMNIST, where ResNet(2) and ResNet(30) mean that the first two hidden layers and the remaining 30 layers are deployed at the client-side and the server-side, respectively.

We run simulations with AMD Ryzen 7-5800H@3201MHz as clients and with NVIDIA GeForce RTX3070-8G as an edge server. To better measure the training time, the average uplink/downlink data rate between the edge server and any client is set as 10/50 MB/s, and the average D2D data rate between any two clients is 5 MB/s. In addition, all the clients conduct one local training epoch for each global training round.

Fig. 3 demonstrates the test accuracy of different architectures over training rounds, with four clients, upon considering three datasets. In general, CL converges rapidly and achieves the highest test accuracy, which embodies the advantages of CL. In contrast, SL converges the slowest, while FL, HSFL, and HSFL achieve relatively close performance on convergence, which proves the feasibility of our proposed architectures. Obviously, there exists a performance gap between distributed ML and CL, which grows with the complexity of dataset and model, mainly affected by the distribution of non-IID data. Besides, Table I illustrates the detailed performance comparison of different learning architectures on three datasets and models. Notably, MNIST and Fashion-MNIST reach the same performance except for test accuracy, owing to that they share the same data format, data size, and network model. Specifically, compared with FL, HSFL significantly reduces the communication cost (by 50%) and slightly reduces the training time, while raising the accuracy (e.g., by around 2.2% on MedMNIST). Similarly, compared with SL, HSFL significantly reduces the training time (by around 75%) and improves the accuracy (e.g., about 10% on Fashion-MNIST), while the communication cost of HSFL/HFSL is slightly higher than that of SL. The above discussed results demonstrate that our proposed HSFL/HFSL can significantly reduce communication cost/training time without loss of accuracy, in comparison with conventional FL/SL. Besides, additional comparison between HSFL and HSFL shows that HSFL generally gets lower communication cost and training time, while HSFL obtains lower computation cost, and they can achieve similar test accuracy. Therefore, the implementation of HSFL and HFSL based on resources availability of clients and performance requirements of ML services call for further attentions.

VI. CONCLUSION

In this article, we propose two hybrid architectures for distributed ML in heterogeneous wireless networks, namely, HSFL, and HFSL, based on integrating federated and split architectures. We first present basic architectures and analyze the advantages as well as performance comparisons of HSFL and HFSL. Then, interesting research directions are discussed to point out the potential challenges and opportunities for the future implementations of our proposed architectures. Finally, we conduct primary simulations to verify the feasibility of our proposed architectures on three datasets via considering highly non-IID data settings.

REFERENCES

[1] Z. Cheng, Z. Gao, M. Liwang, L. Huang, X. Du and M. Guizani, “Intelligent Task Offloading and Energy Allocation in the UAV-Aided Mobile Edge-Cloud Continuum,” IEEE Netw., vol. 35, no. 5, pp. 42-49, September/October 2021.
[2] P. Vepakomma, O. Gupta, T. Swedish, and R. Raskar, “Split Learning for Health: Distributed Deep Learning Without Sharing Raw Patient Data,” 2018, arXiv: 1812.00564. [Online]. Available: http://arxiv.org/abs/1812.00564
[3] S. Hosseinipour, C. G. Brinton, V. Aggarwal, H. Dai and M. Chiang, “From Federated to Fog Learning: Distributed Machine Learning over Heterogeneous Wireless Networks,” IEEE Commun. Mag., vol. 58, no. 12, pp. 41-47, Dec. 2020.
[4] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Y. Arcas, “Communication-Efficient Learning of Deep Networks from Decentralized Data,” in Proc. Int. Conf. Artif. Intell. Statist. (AISTATS), Apr. 2017.
[5] O. Gupta and R. Raskar, “Distributed Learning of Deep Neural Network Over Multiple Agents,” J. Netw. Comput. Appl., vol. 116, pp. 1–8, Aug. 2018.
[6] J. Jiang, L. Hu, C. Hu, J. Liu, and Z. Wang, “Baconmo—Bandwidth-Aware Decentralized Federated Learning,” Electronics, vol. 9, no. 3, p.440, 2020.
[7] M. N. H. Nguyen, N. H. Tran, Y. K. Tun, Z. Han and C. S. Hong, “Toward Multiple Federated Learning Services Resource Sharing in Mobile Edge Networks,” IEEE Trans. Mobile Comput., in press, doi: 10.1109/TMC.2021.3085979.
[8] J. Jeon and J. Kim, “Privacy-Sensitive Parallel Split Learning,” in Proc. 2020 International Conference on Information Networking (ICOIN), Barcelona, Spain, Jan. 2020.
[9] C. Thapa, M. A. P. Chamikara, and S. Camtepe, “Splifed-: When Federated Learning Meets Split Learning,” 2020, arXiv: 2004.12088. [Online]. Available: http://arxiv.org/abs/2004.12088
[10] V. Turina, Z. Zhang, F. Esposito and I. Matta, “Federated or Split? A Performance and Privacy Analysis of Hybrid Split and Federated Learning Architectures,” in Proc. 2021 IEEE 14th International Conference on Cloud Computing (CLOUD), Chicago, IL, USA, Sept. 2021.
[11] Y. Gao et al., “Evaluation and Optimization of Distributed Machine Learning Techniques for Internet of Things,” IEEE Trans Comput., in press, doi: 10.1109/TC.2021.3135752.
[12] A. Singh, P. Vepakomma, O. Gupta, and R. Raskar, “Detailed Comparison of Communication Efficiency of Split Learning and Federated Learning,” 2019, arXiv:1909.09145 [Online] Available: http://arxiv.org/abs/1909.09145

[13] M. LiWang, S. Hosseinalipour, Z. Gao, Y. Tang, L. Huang and H. Dai, “Allocation of Computation-Intensive Graph Jobs Over Vehicular Clouds in IoV,” IEEE Internet Things J., vol. 7, no. 1, pp. 311-324, Jan. 2020.

[14] M.H. ur Rehman, M.M. Gaber (Eds.), “Federated learning systems–Towards next-generation AI”, Springer International Publishing, 2021.

[15] Y. Zhao et al., "Federated Learning with Non-IID Data," 2018, arXiv:1806.00582 [Online] Available: https://arxiv.org/abs/1806.00582.