End-to-End Evaluation of Federated Learning and Split Learning for Internet of Things

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Abstract—Federated learning (FL) and split neural networks (SplitNN) enable machine learning without directly accessing raw data, which can often be personal and sensitive, from clients or end devices such as the Internet of Things (IoT). Such distributed machine learning techniques have great potential in distributed system applications in the context of IoT-Edge-Cloud scenario. In such a scenario, data are generated/collected by IoT devices at the client side; the application deployed in the edge/cloud is required to process the data without aggregating them when the client’s privacy should be preserved. However, there is a significant gap in the literature on the empirical end-to-end evaluations of these techniques in IoT-enabled distributed systems to gain insights and provide a deeper understanding of their practicality.

This work is the first attempt to evaluate and compare FL and SplitNN in real-world IoT settings in terms of learning performance and device implementation overhead. We consider a variety of datasets, different model architectures, multiple clients, and various performance metrics. For learning performance, which is specified by the model accuracy and convergence speed metrics, we empirically evaluate both FL and SplitNN under different types of data distributions such as imbalanced and non-independent and identically distributed (non-IID) data. We show that the learning performance of SplitNN is better than FL under an imbalanced data distribution, but worse than FL under an extreme non-IID data distribution. For implementation overhead, we end-to-end mount both FL and SplitNN on Raspberry Pis, and comprehensively evaluate overheads including training time, communication overhead under the real LAN setting, power consumption and memory usage. Our key observations are that under IoT scenario where the communication traffic is the main concern, the FL appears to perform better over SplitNN because FL has the significantly lower communication overhead compared with SplitNN, which empirically corroborate previous statistical analysis. In addition, we reveal several unrecognized limitations about SplitNN, forming the basis for future research.

Index Terms—Split learning, federated learning, distributed machine learning, IoT

I. INTRODUCTION

In recent years, a rapid proliferation of deep learning has led to stunning transformations in a wide variety of applications including computer vision, disease diagnosis, financial fraud detection, malware detection, access control, surveillance and so on [1]–[3]. In general, deep learning models learn high-level invariant features by training on rich data and use those features to solve the problems.

However, data can often be highly privacy-sensitive; for example, data collected from medical sensors [4] and microphones [5]. Consequently, users may resist sharing their data with service/cloud providers who are trying to build a deep learning model. On the other hand, the centralized data could be mishandled or incorrectly managed by service providers—e.g., incidentally accessed by unauthorized parties [6], or used for unsolicited analytics, or compromised through network and system security vulnerability—resulting in the data breach [7], [8]. Therefore, there is a demand for training a deep learning model without aggregating and accessing raw sensitive data at the client side.

In this context, distributed learning techniques are being developed to tackle the above issue by training a joint model without accessing decentralized raw data held by clients in a distributed manner. Such techniques offer a great potential for distributed system applications to reap the benefits from rich data generated/collected by IoT devices in the context of IoT-Edge-Cloud scenario. This is possible because distributed learning techniques keep the data locally, and utilize private data (e.g., medical records, voice records and text inputs) during the learning process to reduce privacy leakage risks.

In this paper, we consider two distributed learning techniques, namely federated learning (FL) and split neural network (SplitNN) (also referred to as split learning). FL is a well-known distributed learning technique [9], [10]. In FL, a joint model is built through aggregating (e.g., averaging) models trained on each client’s local data. SplitNN is a recently introduced distributed learning technique [11], [12]. In general, a neural network is split into two parts—vertically to the conventional neural network to client (e.g., IoT device) and server (e.g., cloud), who both collaboratively train the whole network. The first few layers belong to the client and the remaining layers belong to the server.

While there have been several theoretical and empirical evaluations on the FL, such evaluations on the SplitNN remain rare. In addition, apple-to-apple evaluations on both FL and SplitNN are quite limited. A very recent study [13] compare both models in terms of communication efficiency. However, they do not consider learning performance such as model accuracy and convergence speed especially when the data are imbalanced or non-IID (non-independent and identically distributed). We note that such imbalanced data situations would happen frequently in practice—e.g., IoT devices generate different types of and amounts of data. Furthermore, there is no study on the end-to-end evaluation of FL and SplitNN.
for real-world IoT settings in terms of their implementation overheads such as communication cost, power consumption, and training time. Indeed, as highlighted in [14], there is a demand to understand the deep learning performances on simple IoT/edge device hardware like Raspberry Pi [15]. Experimental results with real-world IoT devices would be used as a benchmark or guideline for the deployment of FL and/or SplitNN.

Thereby, this paper aims to take the first step of contributing benchmark studies of FL and SplitNN in the context of IoT applications. We investigate the practicality of both FL and SplitNN, specifically, through the comparative evaluation of both approaches in terms of learning performance and end-to-end device implementation overhead with various configurations and settings. Our key contributions in this paper are summarized as follows:

1) We are the first to evaluate SplitNN learning performance in terms of model accuracy and convergence under non-IID and imbalanced data distributions, and then compare it with FL under the same settings. Our extensive empirical results—up to simulated 100 clients—demonstrate that SplitNN exhibits better learning performance than FL under imbalanced data, but worse than FL under non-IID data. Our results reveal that the SplitNN model accuracy deteriorates with a large number of participants. Also, the accuracy of SplitNN can be greatly affected by the characteristics of the distributed data, for example, it could significantly decrease under non-IID distributed data.

2) We successfully apply SplitNN to deal with sequential data, one of the major data sources generated/colllected by IoT devices, via an 1D CNN model. We observed that SplitNN does not work with IoT devices for 2D CNN models that previous works on image data [11]—validated by our experiments.

3) We are the first to empirically extend SplitNN for ensemble learning by exploiting the sequential learning process of SplitNN and a high computational power of cloud to gain multiple models during the learning process of SplitNN while reducing the training expense.

4) We take the first step toward establishing benchmark comparisons between FL and SplitNN by implementing both techniques on real IoT/edge devices. We provide detailed performance overhead evaluations of training time, used memory, power consumption, communication overheads as well as peak power and temperature to serve as reference for practitioners. Under the IoT scenario, FL appears to be preferred due to significantly lower communication overhead since the communication traffic tends to be the main concern—noting that communication overhead reduction can benefit the training time, and energy consumption. An experimental video demo$^{1}$ is available from https://www.youtube.com/watch?v=x5mD1_EA2ps.

The remainder of this paper is organized as follows: Section II provides a brief background on learning techniques. Section III explains the details of dataset, models and the process specifications for experiments. We then comprehensively evaluate the learning performance of both FL and SplitNN under both imbalanced and non-IID data distributions in Section IV. Section V presents our implementations of both FL and SplitNN on real IoT devices to extensively evaluate the device implementation overheads. We discuss the insight gained and provide future works in Section VI, followed by conclusion.

II. BACKGROUND

In this section, we briefly explain FL, SplitNN, and ensemble learning techniques.

A. Federated Learning

Federated learning (FL) [9], [10] is a distributed machine learning technique that enables training over data distributed among different participants/clients. FL has a clear privacy advantage compared to conventional neural networks trained on a centralized server because FL is trained across distributed data without requiring the direct access to raw data for training. In general, as exemplified in Fig. 1a and detailed in Algorithm 1, during the training process, the server first initializes the global model $w_t$ and sends it to all participating clients. After receiving the model $w_t$, each client $k$ trains the global model on its local data—$s_k$ is the number of training

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$^{1}$We will release all source codes upon the publication of this work.

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Figure 1: Illustrated examples of FL and SplitNN.
samples held by client $k$ while $s$ is the total number of training samples across all clients—for some epochs, e.g., simply just one epoch. Afterward, each client returns the updated model $w^t_k$ to the server. The server then aggregates all these models to update the global model to get $w^t_{t+1}$. The above process/round continues repeatedly until the model converges.

### Algorithm 1: Federated Learning [9]

**Server executes:**

1. Initialize $w_0$

   - for each round $t = 1, 2, \ldots$ do
     - Select $C.K$ clients (at least one client) forming a set $S_t$ to update the global model.
     - for each client $k \in S_t$ in parallel do
       - $w^t_k \leftarrow$ ClientUpdate($k, w_t$)
       - $w^t_{t+1} \leftarrow \sum_{k=1}^{K} \frac{1}{s} w^t_k$
     - end
   - end

2. // Run on client $k$

   **ClientUpdate**($k, w_t$):

   - $B \leftarrow$ (split the local datasets in to the local batches)
   - for each local epoch $i$ from 1 to $E$ do
     - for batch $b \in B$ do
       - Calculate $w^t_k \leftarrow w_t - \eta \nabla \ell(w_t; b)$
     - end
   - end

   - Send local updates $w^t_k$ to the server.

### Algorithm 2: Split Learning [11]

**(Main) Server executes:**

- for a request from a client $k \in S_t$ with new data do
  - $A^t_k \leftarrow$ ClientUpdate($k, t$)
  - Compute $f_a(A^t_k, w_t)$ and calculate loss $L$
  - Compute $f_a(L)$ yielding $\nabla L(w_t; A^t_k)$
  - Update $w^t_{t+1} \leftarrow w_t - \eta \nabla L(w_t; A^t_k)$
  - Send the gradient $\nabla L(A^t_k; w_t)$ of the cut layer to client $k$ for ClientBackprop($k, t, \nabla L(A^t_k; w_t)$)
- end

2. // Run on client $k$

   **ClientBackprop**($k, t$):

   - $h^t_k \leftarrow$ ClientBackprop($k - 1, t - 1$) // $k-1$ is the last trained client with the server
   - $B \leftarrow$ (split the local datasets into the local batches)
   - for each local epoch $i$ from 1 to $E$ do
     - for batch $b \in B$ do
       - Concatenate $f_a(b, h^t_k)$ to $A^t_k$
     - end
   - end

   - return $A^t_k$ to server

3. // Run on client $k$

   **ClientBackprop**($k, t, \nabla L(A^t_k; w_t)$):

   - for batch $b \in B$ do
     - Compute $f_b(\nabla L(A^t_k; w_t; b))$ yielding $\nabla L(h^t_k; b)$
     - Update $h^t_{k+1} \leftarrow h^t_k - \eta \nabla L(h^t_k; b)$
   - end

   - Send $h^t_{k+1}$ to the next available client or weight server

### B. Split Learning

Split neural network (SplitNN) or split learning is a distributed machine learning technique introduced recently to learn a joint model by keeping data decentralized [11], [12]. Unlike FL in which each client trains the full neural network, SplitNN divides a neural network model into at least two sub-networks, and then trains the sub-networks, separately, on distributed parties (e.g., client and server). During the training period, the server has no access to clients’ sub-networks and data. Besides privacy benefit, each client only trains a sub-network consisting of a few layers while most layers are trained on the server. Therefore the client’s computation load can be reduced compared with training the full neural network as in FL.

To ease the understanding of SplitNN, an exemplified neural network is illustrated in Fig 1b and detailed in Algorithm 2. The network consists of seven layers excluding input data. The network layers can be convolutional, sub-sampling, and fully connected layers. When a network is split at the $i_{th}$ layer for SplitNN, we call the $i_{th}$ layer cut layer. In Fig. 1b, $C_3$ is the cut layer. Now the network is divided into two sub-networks. The first sub-network $h_t$ is trained and accessed by the client, and the second sub-network $w_t$ is trained and accessed by the server. Let $f_a$, $f'_a$, $f_b$ and $f'_b$ be the functions representing the forward and backward propagation functions carried out by the client and server, respectively. In SplitNN with a local input $X$, a client $k$ performs $f_a(X, h^t_k)$ and forwards the smashed data $A^t_k$ to the server. After receiving $A^t_k$, the server carries its forward propagation on $A^t_k$, i.e., $f_b(A^t_k, w_t)$ and calculates the error $L$ based on the ground-truth labels $y$ and predicted labels $y'$. To minimize the error, the server calculates the correction in the form of gradients through backward propagation (i.e., $f'_b(L)$), and updates its model to get $w_{t+1}$. The gradient $\nabla L(A^t_k; w_t)$ at the cut layer is passed to the client for local backward propagation. After receiving the gradient, the client carries its backward propagation, i.e., $f'_a(\nabla L(A^t_k; w_t; X))$, and updates its model to get $h^t_{k+1}$. The steps of forward and backward propagation continues until the model converges.

### C. Ensemble Learning

Deep learning models are nonlinear methods that learn via a stochastic training algorithm, which will result in models suffering high variance. To address this, multiple models can be trained for the same problem and their predictions are combined to make the final decision. This approach is called model averaging and belongs to a family of techniques called ensemble learning. In this paper, we show how the SplitNN can naturally enable ensemble learning to gain multiple different models during its training across multiple clients to reduce time overhead. Such learning exploits the resource-rich feature of the server and considers the fact that clients interact with the server in a round-robin fashion. In other words, we are able to train multiple models that are compatible with the SplitNN training process.
III. EXPERIMENT SPECIFICATIONS

In this section, we first describe the datasets and models used for our evaluations and then specify the process followed when performing FL, SplitNN, and ensemble learning enabled by SplitNN.

A. Datasets and Models

Sequential data or time-series data is pervasively collected and processed by IoMT devices. For examples, people can order and purchase goods using speech commands at their voice assistant. Wearable medical sensors are used to monitor users’ health status in real time. Consequently, we choose two such popular datasets: speech command (SC) and ECG for experimental evaluations. The SC is a personalized dataset, and The ECG is a medical dataset. Both datasets would be privacy-sensitive where users are unwilling to share.

1) Speech Commands (SC): This task is for speech command recognition. The SC contains many one-second .wav audio files: each sample has a single spoken English word [16]. These words are from a small set of commands and are spoken by a variety of different speakers. In our experiments, we use 10 classes: ‘zero’, ‘one’, ‘two’, ‘three’, ‘four’, ‘five’, ‘six’, ‘seven’, ‘eight’, and ‘nine’. There are 20,827 samples where 11,360 samples are used for training and the remaining samples are used for testing.

2) Electrocardiogram (ECG): MIT-BIH arrhythmia [17] is a popular dataset for ECG signal classification or arrhythmia diagnosis detection models. Following [18], [19], we collect 26,490 samples in total which represent 5 heartbeat types as classification targets: N (normal beat), L (left bundle branch block), R (right bundle branch block), A (atrial premature contraction), and V (ventricular premature contraction). A half of them are for training while the rest samples are for testing.

B. Specifications: FL and SplitNN

1) Federated Learning: According to [20], instead of training the model with local data only one epoch, each client trains the local model for a number of epochs before sending it to the server in one communication round, which is referred to as FedAvg that is one commonly used method for FL optimization. Although FedAvg usually works well, specifically for non-convex problems, there are no convergence guarantees. FL may diverge in practical settings, especially if data are non-IID and imbalanced distributed across clients [21].

2) SplitNN: We note that the learning performance (e.g., model accuracy and convergence) of SplitNN is the same as that of the model trained in the centralized manner [11] only when the data is balanced among clients and IID distributed. The learning performance of SplitNN is not investigated yet when the dataset is non-IID or distributed in an imbalanced manner. Therefore, in this work, we focus on evaluating the learning performance of SplitNN under imbalanced or non-IID distributed data.

Ensemble Learning: According to Algorithm 2, for SplitNN, the server interacts with each client in a sequential manner. On the one hand, at a time, there is only one active client while the rest are waiting to be called. On the other hand, the server is computationally powerful with a cluster of GPUs. In this context, we can utilize the resourceful server to obtain multiple models by taking advantage of idle clients during SplitNN training. Ensemble classifiers taking advantage of predictions from multiple models are beneficial for critical applications; for example, they have shown to be more secure against network copy attacks in addition to better prediction performance [22].

To ease understanding, we exemplify an ensemble learning process with two clients and two model architectures M1 and M2. By processing in parallel, at the first instant, the server trains M1 with client1 on D1 (data held by client1) and trains M2 with client2 on D2 (data held by client2). Afterward, the server continues to train M1 with client2 on D2 and trains M2 with client1 on D1 in parallel. Once D1 and D2 are trained for both M1 and M2, one round is completed—equal to one global epoch for all the data across clients. In this manner, the server can train and consequentially gain two models compatible with the SplitNN training process. This assembling training can reduce computational overheads (e.g., time) to gain multiple models in comparison with training each model individually in a sequence.

IV. LEARNING PERFORMANCE EVALUATION

In practice, data is often distributed among clients in an imbalanced manner, e.g., some sensors are more active than others—with more data, and non-IID distributed, e.g., personal medical sensor collects only one person’s data [21]. This corresponds to imbalanced data and non-IID data settings. We note that these cases were not intensively investigated yet in the view of SplitNN. Therefore, we specifically focus on empirical evaluations and then comparisons of model accuracy and convergence performance of both SplitNN and FL when the data is imbalanced and non-IID decentralized. Our results of SplitNN pose new research questions (RQ).

For all the tests in this section, the 4conv+2dense 1D CNN model architecture is used. Learning rate is set to be 0.001.

A. IID and Balanced Dataset

Starting with ideal IID and balanced data distribution, we evaluate FL and SplitNN using both SC and ECG dataset. Fig. 2 and 3 detail the testing accuracy with the number of rounds when FL and SplitNN are trained by a different number of clients—2, 5, 50, and 100 clients. Results indicate that SplitNN can always converge relatively faster than FL.

| Dataset       | # of labels | # of samples | Model Architecture | Total Parameters | Total Model Accuracy (Centralized data) |
|---------------|-------------|--------------|--------------------|-----------------|----------------------------------------|
| ECG           | 5           | 26,490       | 4conv + 2dense 1D CNN | 68,901          | 97.78%                                 |
| Speech Command| 10          | 32,187       | 4conv + 2dense 1D CNN | 522,586         | 85.29%                                 |

To the best of our knowledge, there is no explicit work on performing SplitNN among clients in a parallel manner. Designing an implementation of efficient SplitNN in a parallel manner is left as future work.
B. Imbalanced Data Distribution

We assume the data are distributed among clients following the normal distribution. Larger the sigma/variance, more imbalance the data distribution. For example, when the number of clients is 10 and total number of SC training dataset is 11360, the minimum number of training samples held by one client could be as few as 48 while the maximum number of training samples held by a client could be 3855—this is the setting for Fig. 4 (e). We have simulated clients up to 100. Given the same number of clients, same data distribution is applied to both FL and SplitNN.

According to Fig. 4, FL is hard to achieve the baseline accuracy of the centralized model even when multiple local epochs per round is adopted for a large number of clients. For the SplitNN, its model accuracy deteriorates when the number of clients is large, e.g., Fig. 4 (e) and (f).

For the convergence, according to Fig. 4, we can see that FL converges slower, especially when the number of clients goes up, e.g., 50 and 100 cases. Usage of more local epochs per round can expedite the convergence issue—but cannot completely prevent—*given the similar communication overhead.* However, we note more local epochs proportionally prolongs training time on the client side although it can reduce the communication overhead. SplitNN is less sensitive to imbalance data distribution since it can always quickly converge. In Fig. 4 (f), we can see that the training of SplitNN does not learn for the first 50 rounds/epochs. Once it starts learning, it indeed finds converge quickly. Eventually, this empirically found SplitNN convergence difficulty poses the third research question:

**RQ3:** How does SplitNN converge under factors of e.g., number of clients and imbalance data distribution?

C. Non-IID Dataset

Due to weight divergence from each local model, Zhao *et al.* [23] have shown that FL suffers a substantial accuracy drop, up to 51% on CIFAR10 using FedAvg algorithm [20], for highly skewed non-IID data when each client trains only on a single class of data. As for the SplitNN, the accuracy under non-IID setting remains unclear.

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**Figure 2:** Testing accuracy of FL (1 and 5 local epochs for 1 round) and SplitNN over rounds for the ECG data, which is IID and distributed in a balanced manner across 2, 5, 50, and 100 clients, respectively.

**Figure 3:** Testing accuracy of FL (1 and 5 local epochs for 1 round) and SplitNN over rounds for the SC data, which is IID and distributed in a balanced manner across 2, 5, 50, and 100 clients, respectively.

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with 1 local epoch—notably for SplitNN, the local epoch is always 1. FL struggles with converging, especially when the number of clients becomes larger.

One interesting phenomenon not reported in previous studies is that SplitNN testing accuracy starts dropping after it reaches an optimum point. This suggests that an increasing number of rounds will not help improve the accuracy. Stopping at the optimal point saves training time. In addition, SplitNN always exhibits an unstable learning curve with a high number of spikes.

The other interesting finding is that the model accuracy of SplitNN cannot reach the baseline accuracy of centralized model—85.29% for the SC and 97.78% for the ECG as detailed in Table I. This is obvious as shown in Fig. 3 when the number of clients is 50 and 100. These results indicate that the SplitNN model accuracy and convergence performance are not always the same as that of training a model through centralized data. Note that in the previous conclusions made in [11], the above result was shown to be the same but with the special assumption that the data arriving at multiple clients preserve the order and random weights use the same initialization. In this context, we pose the first two research questions (RQs):

**RQ1:** What are the factors (e.g., number of clients) that affect the SplitNN to achieve the baseline accuracy of the centralized model?

**RQ2:** How close the accuracy of SplitNN to the baseline accuracy of the centralized model?
For non-IID setting, the SC and ECG datasets are first sorted by class. Each client then receives data partition from only one single class, two classes, three classes, four classes and five classes, respectively.

**FL.** When each client has only one class data, the FL convergence is significantly fluctuated and slow as seen from Fig. 5 (a) and (c). It is clear from the figures that more skewness in the distributed data yields slower convergence and higher model accuracy drop. Nonetheless, it can still converge in most cases, except 1 client with 1 class data.

**SplitNN.** We can see from Fig 5 (b) and (d) that, unlike FL which learns slowly under extreme non-IID distributed data, SplitNN does not learn at all in our setup. To be precise, as for the ECG with 5 total number of classes, the SplitNN model does not learn when one client holds 1, 2 or 3 classes. Since the testing accuracy is always around 22.65%, which is similar to guess (5 classes in total). As for the SC with 10 total number of classes, the SplitNN model does not learn on the condition when the client holds 1, 2, 3 or 4 classes. Therefore, in contrast to FL, SplitNN fails often to learn in non-IID settings. In this context, our empirical results lead to the fourth following research question:

**RQ4:** What is the least number of classes required to be held by one client before SplitNN can learn under non-IID data distribution?

**D. SplitNN enabled Ensemble Learning**

Here, we simply intend to validate the practicality of extending SplitNN to perform an ensemble learning that obtains multiple models using less time compared with training each model individually. Therefore, we employ two different model architectures and only train across two clients. To be precise, model $M_1$ is with 4 1D CNN layers and two dense layers while $M_2$ is with 5 1D CNN layers and two dense layers. For both models, the client runs first two CNN layers while the server runs the remaining layers of the model.

Firstly, both server and clients are simulated in the same desktop with one GTX1050 GPU and one i7-7700HQ CPU. Only the server uses the GPU and the clients use CPU since we assume the clients have less computational resources. Under this setting, the ensemble learning—following steps detailed in Section III-B2—takes 5178s in total to build two models. We further use SplitNN to train $M_1$ and $M_2$ across two clients individually—without ensemble. $M_1$ takes 3456s and $M_2$ takes 3625s. Therefore, the ensemble is faster to obtain two models—5178s versus 7081s (3456s + 3625s), which reduces the time overhead by 26.8%. In terms of learning accuracy and convergence performance, there is no apparent difference when using ensemble learning to obtain two models and training them separately, as depicted in Fig. 6.

By taking advantage of parallel computation capability of the server, multiple models can be obtained via SplitNN enabled ensemble learning. Notably, the server can further use distillation to obtain a single model from multiple models to achieve improved prediction accuracy and less variance [24].
We have considered the following test settings:

1) ensemble learning to train model $M_1$ and $M_2$ concurrently across 2 clients, as well as training $M_1$ and $M_2$ individually across two clients via SplitNN (Section V-D);
2) evaluating FL and SplitNN across a range of clients from two to five with the same model architecture (Section V-E);
3) evaluating FL and SplitNN across five clients with different model architectures. For the SplitNN, two split layers run on clients regardless of model architectures (Section V-F);
4) evaluating SplitNN when a different number of layers is split and running on the client given the same model architecture. Specifically, one, two, three layers are split and running on the client (Section V-G).

Before providing detail results, we first describe the experimental setup, overhead metrics and how they are measured in our experiments. We have also briefly summarized the engineering challenges faced and the solutions we considered.

A. Experimental Setup

We use Raspberry Pi, in particular Raspberry Pi 3 model BV1.2 (Fig. 8) with the following settings: PyTorch version 1.0.0, OS Raspbian GNU/Linux 10 (buster), and Python version 3.7.3. We do not use CUDA as it is not available.

The server (laptop) has the following settings: CPU i7-7700HQ, GPU GTX 1050, Pytorch version 1.0.0, OS windows 10, Python version 3.6.8 using Anaconda, and the CUDA version 10.1.

B. Performance Metrics and Measurement Methods

a) Training Time: We use python time library to measure the training time. We set the time as $T_{\text{start}}$ when the model starts training. Once the training is finished, we set the time as $T_{\text{end}}$. As a result, training time is $T_{\text{end}} - T_{\text{start}}$. Please note that the training time is influenced by the network traffic in practice, because both FL and SplitNN require upstream and downstream communications.

b) Memory Usage: We use Linux `free -h` command for measuring the memory usage. This command provides the memory information of total, used, free, cached and available. Here the available is an estimation of available memory to start new applications, without swapping. It is roughly the sum of free and cached. total is the sum of used and available. The total memory of Raspberry Pi used in this work is 926 MB. Note that our focus here is to record and report the used memory during training.

c) Power Consumption: We use a plug-in powermeter, as shown in Fig. 8, to measure the power consumption. With this powermeter, the power consumption is measured in kilowatt-hour (kWh).

d) Temperature: We use python `CPUTemperature()` function from `CPUTemperature` library to monitor the temperature of the Raspberry Pi CPU.

e) Communication Overhead: We measure the sent and received data size from each client as well as the server. Specifically, we use the `pickle` library to monitor the size of the data whenever the data is sent and received. We record the length of the pickled data. We use the router DGN2200 v4 (N300 Wireless ADSL2+ Modem Router) for wireless communication between Raspberry Pi and the server.

C. Engineering Considerations

1) Low Performance: Though Raspberry Pi is considered as a high-end IoT device [26], its computation resource is still quite limited in comparison with even personal laptop. We firstly run MobileNet [27]. When we train CIFAR10 dataset with MobileNetv1\(^3\) (20 conv2D layers with model 3,228,170 parameters in total), it takes 8 hours 41 minutes for FL per round with 1 local epoch. For SplitNN, it takes about 2.5 hours for one epoch across five Raspberry Pis\(^4\) when only the first two layers are running on the Raspberry Pi. Secondly, we run ResNet20\(^5\) (with 20 conv2D layers and 269,722 parameters).

\(^3\)Source code is adopted from https://github.com/Tshzzz/cifar10.classifer/blob/master/models/mobilenet.py.

\(^4\)Source code is adopted from https://github.com/akamaster/pytorch_resnet_cifar10/blob/master/models/resnet.py.

\(^5\)Since the training sample for CIFAR10 is 50,000, we use 5 clients. Therefore, each client holds 10,000 images for both FL and SplitNN.
When we evaluate SplitNN across 5 Raspberry Pis, it takes 1 hour to finish one round across when the first two layers are running on the Pi. When we evaluate FL across 5 Raspberry Pis, it takes 37 minutes for one round with one local epoch.

In this context, it appears that it is hard to run models such as ResNet20 and MobileNet V1 on Raspberry Pi. Because they are still computationally heavy for simple IoT device even these 2D CNN models are lightweight for GPU platform. Therefore, for fully end-to-end tests, we opt for evaluating relatively simple model, in particular 1D CNN model, on sequential time series data. Sequential time series data are pervasive data source generated or/and collected by various IoT devices, e.g., sensor.

2) Install Pytorch on Raspberry Pi: We have made a unified manual guide of installing Pytorch v1.0.0 on Raspberry Pi\(^6\). This will help the research community as we faced a number of errors during installation that are hard to resolve and there are no resolutions online.

3) Temperature of Raspberry Pi: When training on the Raspberry Pi, especially FL that runs the entire model on the device, the temperature goes high—usually more than 80°C. Therefore, it is necessary to cool down the device. A cooling fan can be attached on the Raspberry Pi (Fig. 8). This can efficiently cool it down from 83°C to 54°C.

Next, we evaluate FL and SplitNN performance on Raspberry Pi according to the above considered test settings.

D. Ensemble Learning

If individually training \(M_1\) takes \(T_1\) and \(M_1\) takes \(T_2\), the SplitNN enabled ensemble training should roughly take \(\max(T_1, T_2)\) on the condition that the server has unlimited computation power. Because now the server can train the rest layers of \(M_1\) and \(M_2\) in ideal parallel.

As we treat the laptop equipped with only a low-end GPU as server, this ideal case is not met. Because the laptop is unable to ideally parallel train the remaining layers of \(M_1\) and \(M_2\). But, as we can see from Fig. 9 (a), the time for ensemble training, \(T_{\text{ensem}}\) is indeed always smaller than sequentially train each model, \(T_1 + T_2\). Specifically, \(T_{\text{ensem}}\) takes 11704 s to concurrently obtain both \(M_1\) and \(M_2\). Training \(M_1\) and \(M_2\) individually costs 8267 s and 6908 s, respectively. Therefore, ensemble learning reduces time overhead by 22.87%.

For the communication overhead, ensemble learning is same to individually training each model (Fig. 9 (b)). For the memory usage, we rely on the used memory for comparison\(^7\). Used memories of individually training \(M_1\) and \(M_2\) are 185MB and 186MB. In contrast, the used memory of ensemble training is 222MB. For power consumption, sequentially training \(M_1\) and \(M_2\) consumes 4 and 3 Wh (watt per hour) energy, while ensemble training consumes 6 Wh energy. Therefore, ensemble learning reduces power consumption as well, e.g., by 14.2%.

In summary, ensemble learning does not reduce communication overhead. However, it helps to reduce training time, used memory and power consumption overhead.

E. Same Model Across Different Number of Clients

Here, we evaluate both FL and SplitNN when the number of Raspberry Pis (clients) varies from two to five. The model architecture is with four 1D CNN layers and two dense layers. For the SplitNN, the first two 1D CNN layers run on Raspberry Pis.

Results are detailed in Fig. 10. Please note the overhead result is for one single individual Raspberry Pi as we evaluate the overhead from the client perspective rather than the server perspective—assuming the server is always resource-rich.

As for the time overhead in Fig. 10 (a), FL reduces as the number of Pis increases. This is due to the decrease in the local data size. The SplitNN slightly increases since each Pi runs the training sequentially. Overall, SplitNN usually takes several times longer than the FL given the same number of rounds.

The communication overhead is in Fig. 10 (b)\(^8\). The FL stays relatively constantly around 28,552,161 Bytes. The reason is that communication overhead is determined by the model parameters in FL rather than the local data size, and communication overhead stays same for the same model. SplitNN communication overhead decreases as is highly related to the local data size. It is worth to mention that, here, we are observing on one client and data samples held by each client decreases with the increasing number of clients for the same total data size. This agrees with recent work [13], where communication overhead of SplitNN is shown significantly higher than that of FL per round for low model complexity and fewer clients.

For the used memory, as shown in Fig. 10 (c), the FL is always higher than that of SplitNN, because the FL needs to train the entire model in the Raspberry Pi, while the SplitNN only needs to train a small part—few split layers. This also leads to the high power peak, as shown in Fig. 10 (e), and high temperature during training, as shown in Fig. 10 (f), in the FL case. Without cooling, the Raspberry Pi’s temperature can be up to 83°C during the FL learning.

However, although FL has a high power peak, the energy is lesser than that of SplitNN for the same number of rounds, as shown in Fig. 10 (d). This is because, in FL, each client trains local model in parallel, and consequently, the total time (accumulated computation and communication) for running a given number of rounds is lesser than that of SplitNN.

F. Same Model with Varying Split Layers of SplitNN

We perform our experiments on five Raspberry Pis to observe the effect of the varying split layers (running on it) to the overhead for the same model. This experiment is solely for SplitNN.

6This manual is now available via https://github.com/Minki-Kim95/RaspberryPi
7This includes 119MB memory used by the OS by default as it tends to be fair to include the memory occupied by the OS.
8Communication overhead of FL is invisible because it is orders of magnitudes smaller than that of SplitNN, e.g., megabytes vs. gigabytes.
In Fig. 12 (b), we observe that the communication overhead remains the same with the number of layers at the client-side. This is expected as the communication overhead in SplitNN depends on the number of parameters in the cut layer, which does not change in our case. Now for the memory usage in Fig. 12 (c), we observe only a slight increase with the split layers. Most noticeably, time overhead (depicted in Fig. 12 (a)) and energy overhead (depicted in Fig. 12 (d)) increase with the increase in the number of split layers. This is because an increase in the number of layers increases the number of parameters to be trained on the client-side, i.e., Raspberry Pi.

Therefore, in practice, from the overhead reduction perspective, it is important to run as few layers as possible on the client side for the SplitNN.

G. Different Models

To observe the effect of the different models brought to the IoT device overhead in SplitNN and FL, we perform an experiment using five Raspberry Pis. The entire models have varying number of convolutional layers ranging from four to eight. For SplitNN, we consider the same number of split layers running on the Raspberry Pi regardless of change of models.

According to results depicted in Fig. 13, the device implementation overhead including time, communication, used memory and energy, (linearly) increases with the increase in model complexity (defined by the number of layers in the model) for FL. In contrast, the overhead remains consistent for SplitNN because the number of layers running on Raspberry Pis is fixed. Altogether, SplitNN becomes advantageous given a complicated model.

VI. DISCUSSION AND FUTURE WORK

A. Results Summary

Firstly, for both FL and SplitNN, we have evaluated the learning performance specified by model accuracy and converge speed. Our empirical results show the following findings in our experimental setups:
Figure 12: SplitNN performance when a different number of split layers—1 to 3 conv layers—run on the Raspberry Pi. All tests run across 5 Raspberry Pis and in the lab environment. The model is with 4 conv layers and 2 dense layers.

Figure 13: Overhead performance of FL and SplitNN when the number of layers of the model vary from 4 conv to 8 conv. All tests run at the lab. For SplitNN, the number of layers is split to Raspberry Pi is the same—the first 2 conv layers. For communication overhead, we only show FL while SplitNN communication overhead, 1054 Mbytes, does not change since showing it makes the FL invisible as in Fig. 10.

1) SplitNN always achieves better model accuracy than that of FL when data is IID distributed, regardless of the number of clients.
2) SplitNN always converges much faster than FL once it learns.
3) However, SplitNN is more sensitive to non-IID data than FL. Under extreme non-IID cases, for example, one client 2 classes and one client 3 classes, SplitNN does not learn in our setup.

Next, we have fully implemented both FL and SplitNN on Raspberry Pis using 1D CNN models. This setup reflects a practical scenario for edge distributed learning since the number of parameters of 1D CNN model is usually small, which can be efficiently running on simple IoT devices. Our experimental results on Raspberry Pi suggest the following findings:

1) IoT application scenarios usually have communication as a major concern and simple models are trained due to limited resources. In this case, FL is preferred over SplitNN because FL has relatively lower communication overhead, especially with simple models. Note that reducing communication overhead can benefit training time, and energy consumption.
2) For applications where the communication is not a major concern (e.g., Ethernet or 5G are available), SplitNN is recommended to ensure better model accuracy and guarantee (fast) convergence.
3) For extreme non-IID data distribution, FL is preferable over SplitNN.

B. Implementing Optimization

This work follows typical setting of FL and SplitNN, and optimization is out of scope, especially when we mount them on the IoT devices. We have empirically shown that training 2D CNN, e.g., ResNet and MobileNet, is difficult on Raspberry Pi (Section V-C). To be more memory and computation efficient, one possible optimization is using XNOR-NET [28], [29] if the model accuracy through XNOR-NET can be retained.

C. Splitting Sequential Models

To process sequential time-series data, we have used the 1D CNN. This is because CNN can be split vertically, which is easy to be split to eschew data access requirement for SplitNN. Actually, before choosing 1D CNN to deal with sequential data, we have attempted to apply split learning on a sequential model such as LSTM and RNN that are common machine learning models to deal with sequential data.
However, we found that the sequential model is hard to be applied to SplitNN\(^9\). Applicability of SplitNN for sequential models leaves future work.

D. Future Work

Based on empirical results in our experimental setup, we pose four research questions—see highlights through bold fonts in Section IV-A (QR1, QR2), Section IV-B (QR3) and Section IV-C (QR4)—on SplitNN for future investigations. It appears that inapplicable data shuffling among clients is the only difference between SplitNN and centralized data training, which could be the main reason of above RQs. However, formal analyses like [30] are demanded for the SplitNN.

VII. Conclusion

As the first attempt to contribute to the benchmark of FL and SplitNN in the IoT scenario, firstly, we have comprehensively evaluated the learning performance in terms of model accuracy and convergence speed of FL and SplitNN. For our experiments, we have considered the realistic IoT data distribution, in particular, imbalanced and non-IID distributions. We validate that SplitNN performs better in the imbalance data distribution than FL, but worse in the non-IID data distribution. Our empirical results of SplitNN learning performance pose four research questions for future investigations. Secondly, we have extensively evaluated the practicality of mounting FL and SplitNN on Raspberry Pis to deal with pervasive sequential time-series data and provided useful comprehensive results—various implementation overheads—to the community. Overall, under the IoT scenario, the FL appears to require less overall communication, time, and power consumption overhead given practicality of mounting simple model—training complex model is hard to be mounted.

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