FLaaS: Federated Learning as a Service

Nicolas Kourtellis
Telefonica Research
Barcelona, Spain
nicolas.kourtellis@telefonica.com

Kleomenis Katevas
Telefonica Research
Barcelona, Spain
kleomenis.katevas@telefonica.com

Diego Perino
Telefonica Research
Barcelona, Spain
diego.perino@telefonica.com

ABSTRACT

Federated Learning (FL) is emerging as a promising technology to build machine learning models in a decentralized, privacy-preserving fashion. Indeed, FL enables local training on user devices, avoiding user data to be transferred to centralized servers, and can be enhanced with differential privacy mechanisms. Although FL has been recently deployed in real systems, the possibility of collaborative modeling across different 3rd-party applications has not yet been explored. In this paper, we tackle this problem and present Federated Learning as a Service (FLaaS), a system enabling different scenarios of 3rd-party application collaborative model building and addressing the consequent challenges of permission and privacy management, usability, and hierarchical model training. FLaaS can be deployed in different operational environments. As a proof of concept, we implement it on a mobile phone setting and discuss practical implications of results on simulated and real devices with respect to on-device training CPU cost, memory footprint and power consumed per FL model round. Therefore, we demonstrate FLaaS’s feasibility in building unique or joint FL models across applications for image object detection in a few hours, across 100 devices.

ACM Reference Format:
Nicolas Kourtellis, Kleomenis Katevas, and Diego Perino. 2020. FLaaS: Federated Learning as a Service. In 1st Workshop on Distributed Machine Learning (DistributedML’20), Dec. 1, 2020, Barcelona, Spain. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3426745.3431337

1 INTRODUCTION

Machine Learning as a Service (MLaaS) has been on the rise in the last years due to increased collection and processing of big data from different companies, availability of public APIs, novel advanced machine learning (ML) methods, open-sourced libraries, tools for large-scale ML analytics and cloud-based computation. Such MLaaS systems have been predominantly centralized: all data of users/clients/devices need to be uploaded to the cloud service provider (e.g., Amazon Web Services [1], Google Cloud [14] or Microsoft Azure [21]), before ML model data can be done.

Federated Learning (FL) [17] is a natural evolution of centralized ML methods, as it allows companies employing FL to build ML models in a decentralized fashion close to users’ data, without the need to collect and process them centrally. In fact, FL has been extended and applied in different settings, and recently deployed in real systems (e.g., Google Keyboard [5]). Also, privacy guarantees can be provided by applying methods such as Differential Privacy (DP) [13], or by computing models within a P2P network [4, 16]. In addition, recent start-up efforts in FL space (e.g., [9, 11, 22]) aim to provide FL support and tools to 3rd-party customers or end-users. However, these solutions have two shortcomings. First, they do not allow independent 3rd-parties to collaborate and build common ML models while protecting users’ privacy. This feature would enable different applications to collaborate to build better models thanks to larger and richer datasets, while preserving users’ privacy. Second, they do not provide an “as a service model” like existing MLaaS platforms. This feature is critical to enable developers and data scientists to deploy quickly and easily FL solutions, also fostering large adoption of the FL paradigm.

To enable these two features, there are a few fundamental challenges in FL space to be addressed first:

- How do we enable collaborative modeling across different 3rd-party applications, to solve existing or new ML problems?
- How do we perform effective permission and privacy management of data and models shared across collaborating parties?
- How do we take advantage of topological properties of communication networks, for better FL modeling convergence, without compromising user and data privacy?
- How do we provide collaborative FL models in an “as a Service” fashion?

In this paper, we propose the Federated Learning as a Service (FLaaS), to address such challenges and facilitate a wave of new applications and services based on FL. In particular, FLaaS makes the following contributions in FL space:

1. Provides high-level and extensible APIs, and an SDK for service usage and privacy/permissions management;
2. Enables the collaborative training of ML models across its customers on the same device using said APIs, in a federated, secured, and privacy-preserving fashion;
3. Enables the hierarchical construction and exchange of ML models across the network;
4. Can be instantiated in different types of devices and operational environments: mobile phones, home devices, edge nodes, etc. (cf. Figure 1);
5. Provides the first, to our knowledge, experimental investigation of on-device training costs of FL modeling on actual mobile devices.

Independently from the operational environment, in Section 3, we present different ways that FLaaS supports the building of collaborative models across 3rd-party applications in its FL environment, along with the challenges FLaaS must address. Then, we detail the FLaaS system design, APIs and software libraries and how FLaaS...
supports collaborative modeling, in Section 4. As a proof of concept, in Section 5, we deploy FLaaS on a mobile phone setting to assess the practical overheads of running such a service on mobiles. We demonstrate FLaaS capabilities in building unique or joint FL models for image object detection, for independent or collaborative mobile apps using shared data, respectively. We measure data sharing, ML training and evaluation costs of FLaaS with respect to CPU utilization, memory, execution time and power consumption, for on-device FL modeling in the above scenarios. We show that FLaaS can build FL models on mobile phones over 10s of rounds in a few hours, across 100 devices, with 10-20% CPU utilization, 10s of MBs average memory footprint and 3-5% battery consumption, per FL round and ML model trained.

2 BACKGROUND AND RELATED WORK

Here, we first cover fundamental assumptions on FL and the federated optimization problem, and then academic or industrial efforts on the topic of distributed ML and FL.

2.1 Preliminaries on Federated Learning

Assumptions. The FL optimization problem has the following typical assumptions [17, 20]:

- **Massively distributed:** Number of examples (data) available per client (device) is expected to be much smaller than the number of clients participating in an optimization.
- **Limited Communication:** Devices can be typically offline or with intermittent or slow connectivity; their bandwidth can be considered expensive commodity (especially if no WiFi connection is available).
- **Unbalanced:** Data available on each client is typically of different sizes, since users can have different usage profiles (some can be heavy hitters, others on the tail [34]).
- **Highly Non-IID:** Data available on each client is typically non-representative of the population distribution, as they only reflect the given client’s usage of the device.
- **Unreliable Compute Nodes:** Devices can go offline unexpectedly; there is expectation of faults and adversaries.
- **Dynamic Data Availability:** The subset of data available is non-static, e.g., due to differences in hour, day, country.

Notations. The next analytical formulations use these notations:

- Set of devices $\mathcal{K}$; total number of devices $K = |\mathcal{K}|$;
- A given client is identified as $k \in \mathcal{K}$;
- Total number of rounds $R$;
- A given round is identified as $r \in [0, R]$;
- Fraction of devices used per round: $\mathcal{C} \in [0, 1]$;
- Number of data samples across all clients: $n$;
- Set of indices of data samples on $k$: $P_k$;
- Number of data samples available at $k$: $n_k = |P_k|$;
- Batch size of data samples used per client: $B$;
- Number of iterations of device $k$ on local data: $t \in E$;

**Federated Aggregation:** We consider FL-based algorithms with finite-sum objectives of the form:

$$\min_{w \in \mathbb{R}^d} f(w), \text{ where } f(w) = \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

$f_i(w)$ is defined as loss of prediction on seen examples, i.e., $l(x_i; y_i; w)$, using the trained model with parameters $w$. All data available in the system ($n$) are partitioned over $K$ clients, each with a subset of indices $P_k$. Then, the problem objective can be rewritten as:

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w), \text{ where } F_k(w) = \frac{1}{n_k} \sum_{i \in P_k} f_i(w)$$

Given the assumption of non-IID data, $F_k$ could be an arbitrarily good or bad approximation to $f$.

The model optimization under FL assumes a decentralized architecture, which performs a Federated Aggregation algorithm with the clients and a central server. Each client $k$ executes a stochastic gradient decent (SGD) step (iteration $t$) on the local data available, $g_k = \nabla F_k(w_t)$. Assuming $C=1$, at iteration $t$, the server aggregates all gradients and applies the update on the global model: $w_{t+1} \leftarrow w_t - \eta \sum_{k=1}^{K} \frac{n_k}{n} g_k$, since $\sum_{k=1}^{K} \frac{n_k}{n} g_k = \nabla f(w_t)$, where $\eta$ is a fixed learning rate. Equivalently, every client can perform the update as: $w_{t+1} \leftarrow w_t - \eta g_k$, and the global model is $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$.

In fact, this process can be repeated for $t \in E$ iterations locally per client, before sharing models with the server in $R$ rounds. Therefore, the client can iterate the local update $w^k \leftarrow w^k - \eta \nabla F_k(w^k)$ for $E$ times, before the aggregation and averaging at the central server, per round $r$: $w_{r+1} \leftarrow w_r - \eta \sum_{k=1}^{K} \frac{n_k}{n} g_k$.

It becomes apparent that factors such as $E$ iterations per client, $C$ clients participating in each round, and $R$ rounds executed can have high impact on model performance, and communication cost incurred in the infrastructure to reach it. We note that $C$ is usually selected in such a way [5] to account for device unreliability (intermittent connectivity, failed computation, etc.).

2.2 Related Work

Several initiatives from startups and online communities have been recently proposed in the space of decentralized ML. For example, Decentralized Machine Learning (DML) [11] is a (now abandoned) blockchain (BC)-based project, enabling its participants to build models in a distributed fashion, while growing its BC network.
Open-source community efforts propose libraries and platforms that will allow users to train ML models in a decentralized, secured and privacy-preserving (PP) fashion. For example, OpenMined [22] proposes the libraries PySyft and PyGrid, by employing multiparty computation (MPC), homomorphic encryption, DP and FL for secured and PP-ML modeling in a decentralized fashion, in both mobile or desktop environments. In addition, Datakites [9] utilizes DP, secure MPC and role-based access control to build models inside or across enterprises, and on edge computing nodes. With similar technologies, FATE (Federated AI Technology Enabler) [12] focuses on desktop deployments.

Building on the popular TensorFlow (TF) framework, TensorFlow Federated (TFF) is an open-source framework for ML and other computations on decentralized data [27]. coMind [8] proposes a custom optimizer for TF to easily train neural networks via FL. There have also been benchmark frameworks proposed like LEAF [7], for learning in FL settings, with applications including FL, multi-task learning, meta-learning, and on-device learning.

In contrast to all these efforts, FLaaS follows a FL-as-a-Service model, with high-level APIs, enabling: a) independent 3rd-party applications (i.e., external to FLaaS operator) to collaborate and combine their common-type data and models for building joint meta-models for better accuracy; b) collaborative 3rd-party applications to combine their partial models into meta-models, in order to solve new joint problems, never before possible due to data siloing and applications’ isolation; c) 3rd-party applications to build the aforementioned FLaaS models on edge nodes, desktops, mobile phones or other low-resource (IoT) devices (cf. Figure 1).

3 FLaaS MOTIVATION & CHALLENGES
FLaaS aims at providing to single applications an easy way to use FL, without the costly process of developing and tuning the algorithms, as well as to enable multiple applications to collaboratively build models with minimal efforts. Specifically, FLaaS is designed to support the following use cases (some examples in Figure 1):

1. Unique FL modeling per individual application for an existing ML problem without the need of developing the algorithms. Traditionally, ML modeling is requested uniquely per application aiming to solve a specific, existing ML problem: e.g., a streaming music application (e.g., Spotify) that wants to model its users’ music preferences to provide better recommendations.

2. Unique FL model trained in a joint fashion between two or more collaborative applications for an existing ML problem. That is, a group $G$ of applications interested in collaborating to build a shared ML model that solves an existing problem, identical and useful for each application, but on more, shared and homogeneous data. For example, Instagram, Messenger and Facebook (owned by the same company) may want to build a joint ML model for better image recognition, on images of similar quality and scope, but coming from each application’s local repository.

3. Unique FL model trained in a joint fashion between two or more collaborative applications, as in case (2), but for a novel, never explored ML problem. For example, an application for planning your transportation (e.g., Uber, GMaps, or Citymapper) may want to model your music preference while on a specific transportation type (e.g., bicycle, bus, car, etc.).

Several challenges arise while supporting these use cases under a Federated Machine Learning setting, which we elaborate next.

**Permission management across applications and services:** Mobile and IoT systems provide mechanisms to grant application and services access to data such as mobile sensors, location, contacts or calendar. Such access is typically given at a very coarse granularity (e.g., all-or-nothing), and can be unrestricted or, more recently, granted per application. On top of these traditional permissions, FLaaS has to provide mechanisms to specify permissions across applications and services to share data and models among them. Further, it has to provide security mechanisms to guarantee these permissions are respected.

**Privacy-preserving schemes:** In FLaaS deployment scenarios and use cases, multiple applications and services can be involved in the FL execution. In order to guarantee the privacy of customers’ data, it is critical to leverage privacy-preserving mechanisms in the construction of FL models. In FLaaS, we plan to leverage Differential Privacy (DP) to provide further privacy guarantees to participating clients. DP noise can be introduced at different stages of the FL system: in the data source at the client side, also known as local-DP [25, 29, 30, 33], at the central server side [13] while building the global model, or at an intermediate stage such as edge computing nodes [19] or base stations [23], or with hybrid methods and hierarchical methods [6, 28, 31]. However, introducing DP noise in the ML pipeline reduces model utility [32] as it affects convergence rate of the FL-trained model. Note that, while FLaaS plans to build on existing DP solutions, finding an optimal way to add DP noise in FL is an open research problem, and beyond the scope of this work.

**Exchange model across a (hierarchical) network with FL:** As depicted in Figure 1, FLaaS can build models in a hierarchical fashion across different network layers: end-user device, ISP edge nodes, or the central server. Recent works considered the hierarchical FL case, where multiple network stages are involved in the training process [6, 19, 23]. Such efforts showed convergence and accuracy can be improved with proper design under such settings. FLaaS will build on these works to realize its hierarchical use cases. However, the design of optimal hierarchical FL methods is an open research problem beyond the scope of this work.

**Training convergence and performance:** As mentioned earlier, the usage of DP in multi-stage training and the hierarchical FL approach impact the convergence and performance of FL models. However, in FLaaS, the possibility of building cross-application models introduces another dimension, potentially impacting model convergence and performance. This is a relevant research problem that FLaaS will need to address in the near future.

**Platform usability:** Every service platform should enable a customer to use its services with limited overhead and knowledge of the underlying technology. On the one hand, existing commercial MLaaS platforms (e.g., AWS [1], Google Cloud [14] or Azure [21]) provide users with APIs and graphical user interfaces (GUI) to configure and use ML services in cloud environments. However, these APIs are not designed to deal with cross-application model building, nor tailored for FL services. On the other hand, existing FL libraries (e.g., TFF [27] or OpenMined [22]) are still in prototype phase and cannot support a service model, and do not provide GUIs, or high-level service APIs. They also do not support cross-application ML modeling as FLaaS does. FLaaS builds on these existing works...
and provides high-level APIs to support model building across applications on the same device and across the network, and software libraries or Software Development Kits (SDKs) for application developers to include the service in their apps and devices (cf. Sec. 4.2).

4 FLaaS SYSTEM DESIGN

4.1 Service Main Components

The FLaaS design comprises three main system components: 

**Front-End:** Main interface for customers (e.g., app or service developers), to bootstrap, configure, and terminate the service. It runs a GUI, processes front-end API calls from customers (or the GUI), and calls functions on the Controller to execute customer requests.

**Controller:** Takes as input commands received from Front-End, executes the required steps to configure the service, e.g., initialize the model, set appropriate permissions, etc. Once the service starts, the Controller is in charge of monitoring service health, budget, and terminating execution of ML modeling when requested.

**Central Server** and **Clients** (e.g., mobile or home devices, edge nodes): are the elements actually in charge of executing the FL algorithms and protocol (cf. Sec. 2.1). The Central Server, hosting the Controller and Front-End, is under the administrative domain of FLaaS, while the Clients are typically in another domain, e.g., at user side. The Server also runs a FLaaS Global module responsible for the federated aggregation of received models. Each Client runs a FLaaS Local module directly provided by the FLaaS provider. In addition, every application on the FLaaS Clients needs to embed a software library, providing the required functions that can be accessed via client APIs.

4.2 APIs and Software Libraries

**Front-End APIs:** FLaaS can be configured via front-end APIs, or a GUI that uses the front-end APIs under the hood. These APIs can be classified in three types, as follows:

- **DATA APIs** allow customers to describe data types the model takes as input for training or produces as output after inference. This is specified via JSON format and includes name and type of each input feature or output data column.

- **MODEL APIs** enable customers to create an ML model, define model type and parameters, or choose the option of parameter self-tuning. Also, these APIs allow customers to specify properties in the ML modeling, in case the model is built across (partially) different data from multiple customers, or as an average/ensemble across models.

- **PERMISSION APIs** enable customers to specify if and which other customers (e.g., apps) can access said data, or how other customers can access the model for inference, or to build models to solve new ML problems.

**Client APIs:** A set of functions need to be embedded in the application code to realize FLaaS functionality. To this goal, we design a software library (currently implemented as an Android SDK, cf. Sec 5) providing the implementation of such functions that are then exposed via a set of APIs. The library includes main functions such as: (i) Authenticate API to the Central Server. (ii) Support on-device training for ML applications, including: load a model (either pre-trained or with initial parameters), add training samples, conduct model training, predict from test samples, and save or load model parameters to device memory. (iii) Exchange/share data between FLaaS-enabled apps on-device, before local FL training takes place.

While training on-device a new model is possible, it requires a significant amount of processing power and many communication rounds, making it impractical in user devices with limited resources. Transfer Learning (TL) [26] is an ML technique that takes a model built for a basic task T (e.g., image recognition) and reuses it as the starting point for a new task, but related to T, to speed up training and improve model performance. FLaaS employs TL for various scenarios (e.g., image object recognition, text classification, item recommendations, etc.) as it is suitable for currently resource-constrained mobile devices and networks.

4.3 FLaaS Algorithmic Design

We now provide algorithmic details of how the main use cases outlined in Sec. 3 are supported by FLaaS design.

**FL modeling per application for existing ML problems:** We assume a set of apps, \( i \in A, \) installed on device \( k \in \mathbb{K} \), are interested in building FL models with FLaaS. In this case, each app wants its own model built on its local data.

Figure 2 outlines the general interactions of two apps \( i \) and \( j \) with the FLaaS Local module running on user devices \( k \) and \( m \). The apps communicate to the FLaaS Local their FL models built. Thus, for app \( i \) and device \( k \), in Fig. 2 we define \( \{.\}_k^i = f_k^i(w) \).

FLaaS Local collects all such models from individual apps, and transmits them in a compressed format to FLaaS Global:

\[
\{.\}_k^g = \{f_k^i(w)\}, \forall i \in A, \forall k \in \mathbb{K}
\]

Subsequently, FLaaS Global performs Federated Aggregation across all reported local models and builds one global weighted average model per app, which it then communicates back to the participating devices per app, i.e., in Fig. 2:

\[
\{.\}_k^g = f_k^g(w), \forall i \in A, \forall k \in \mathbb{K}
\]

Finally, the FLaaS Local module distributes the global model to each app, i.e., in Fig. 2:

\[
f_i^g(.) = f_i^g(w), \forall i \in A
\]

**Jointly-trained FL modeling between group of apps for existing ML problem:** In the following scenario, we assume a group of two or more apps, \( i \in A, \) installed on device \( k \in \mathbb{K} \), are interested in collaborating and building a common FL model with FLaaS. This model will be shared among all apps but will be built jointly on each application’s local data.

![Figure 2: Overview of FLaaS ML modeling architecture.](image-url)
Thus, in Figure 2, we can redefine the general interactions of a group $G$ of apps $i$ and $j$ (i.e., $G = \{(i,j)\}$) with FLaaS Local running on devices $k$ and $m$, in order to build such a joint model among them. In fact, we point out at least three different ways that such joint model can be built, by sharing different elements with FLaaS Local (Fig. 2):

1. **Sharing local data:** $\{x^j_k, y^j_k\}_k$
   Apps in $G$ share with FLaaS Local data they are willing to provide in the collaboration. FLaaS Local collects all shared data, which should have the same format, and performs SGD on them. For this way to be possible, participating applications must be willing, and permitted to share user data across applications.

2. **Sharing personalized gradients:** $\{x^j_k, y^j_k\}_k = \{\nabla F^j_k(w_i), \epsilon\}$
   Apps share with FLaaS Local their personalized gradient for iteration $t$ along with the error $\epsilon$, which was acquired after training their local model for the $t^{th}$ iteration. In this case, FLaaS Local uses the received gradients $g^j_k$ to incrementally correct the locally built joint model. Then, it releases back to apps the improved joint model, before receiving new updates in the next iteration.

3. **Sharing personalized model:** $\{x^j_k, y^j_k\}_k = F^j_k(w)$
   Apps share with FLaaS Local their complete personalized models built on their data, after they perform $E$ iterations. In this case, FLaaS Local performs Federated Aggregation on the received models, thus, building a joint model that covers all apps in $G$, with a generalized, albeit, local model. In the second and third ways, the apps do not need to worry about permissions for sharing data, as they only share gradients or models. Note that the user data never leave the device, in any of the aforementioned cases.

Then, for any of these ways, FLaaS Local reports to FLaaS Global the model jointly built on data or model updates, i.e., $\{x^j_k, y^j_k\}_k = F^j_k(w)$ for each primary app $i$, in order to build such a joint model among $G$.

Subsequently, FLaaS Global performs Federated Aggregation across all collected local models and builds a global weighted averaged model for each primary app, i.e., $\{x^j_k, y^j_k\}_k = F^j_k(w)$ for each primary app $i$, in order to build such a joint model among $G$. Then, it communicates each such global model back to participating devices, i.e., in Fig. 2:

$$\{x^j_k, y^j_k\}_k = F^j_k(w), \forall G \in \mathcal{G}, \forall k \in \mathbb{K}$$

Finally, FLaaS Local distributes the global model to each application of the collaborating group $G$, i.e., in Fig. 2:

$$f^j(\cdot) = f^G(\cdot), \forall i \in G$$

**Jointly-trained FL modeling between group of apps for a new ML problem:** In this scenario, we assume a primary app $i$ is interested in solving a new ML problem but does not have all data required to solve it. Therefore, it comes to an agreement with other, secondary apps ($j$) to receive such needed data ($x^j$) to build the new model, using FLaaS. Notice that these additional data are a subset of the full data that secondary apps produce, i.e., $x^j \subseteq x^i$. In a similar fashion as before, the collaborating apps must share data or models, in order to enable joint model building (Figure 2). In fact, we point out at least two ways that such joint model can be built, by sharing different elements with FLaaS Local:

1. **Sharing local data:**
   - 1a. Primary application $i$: $\{x^j_k, y^j_k\}_k$
   - 1b. Secondary applications $j$: $\{x^j_k, y^j_k\}_k$

   Apps share with FLaaS Local the data they are willing to provide. FLaaS Local collects all shared data and performs SGD in an iterative fashion, to build the final local model.

2. **Sharing personalized model:**
   - 2a. Primary application $i$: $\{x^j_k, y^j_k\}_k = F^j_k(w)$
   - 2b. Secondary applications $j$: $\{x^j_k, y^j_k\}_k = F^j_k(w)$

   Apps provide trained local models that solve portion of the overall new problem, after $E$ iterations.

Then, FLaaS Local builds a meta-model (e.g., based on hierarchical or ensemble modeling), to solve the new problem at hand. In either case, again, no data leave the device. Then, for either of the ways described, FLaaS Local reports to FLaaS Global the joint model jointly built, i.e., in Fig. 2:

$$\{x^j_k, y^j_k\}_k = F^j_k(w), \forall i' \in A', \forall k \in \mathbb{K}$$

Note: $A'$ is the set of primary apps building the novel models and does not include secondary apps helping. Subsequently, FLaaS Global performs Federated Aggregation across collected models and builds a global weighted averaged model for each primary app model requested, and communicates each such global model back to participating devices, i.e., in Fig. 2:

$$\{x^j_k, y^j_k\}_k = F^j_k(w), \forall i' \in A', \forall k \in \mathbb{K}$$

Finally, FLaaS Local distributes the global model to each primary application, i.e., in Fig. 2:

$$f^j(\cdot) = f^G(\cdot), \forall i' \in A'$$

5 **FLaaS PROOF OF CONCEPT**

We now present a proof-of-concept (PoC) FLaaS implementation in the mobile setting. We discuss early experimental results to showcase viability of two FLaaS use cases (Sec. 4.3): single app ML modeling and data sharing for ML modeling by two collaborative apps.

**PoC FLaaS Implementation.** On the client side, we focus on Android OS 10 (API 29). Specifically, we implement the FLaaS module as a standalone user level app and the library to be embedded in FLaaS-enabled apps as an SDK. Both FLaaS module and SDK leverage TensorFlow Lite 2.2.0 and Transfer API library from Google [15]. Exchange of data between FLaaS-enabled apps and the FLaaS Local module is performed using the OS’s BroadcastReceiver [2]. The Central Server is implemented using Django 3.07 with Python 3.7. Note that currently, Controller and Front-End are not implemented. Finally, the FLaaS-enabled apps used for the PoC are toy apps only performing the FLaaS functionality and storing a set of data. The current FLaaS version is implemented in 4.6k lines.
of Java code (for the FL-related modules), and 2k lines of Python for server modules.

**Experimental Setup.** We evaluated the performance of our implementation with respect to ML Performance, Execution Time, Memory Consumption, CPU Utilization and Power Consumption using three Android devices. D1: Google Pixel 4 (2.42 GHz octa-core processor with 6GB LPDDR4x RAM). D2: Google Pixel 3a (2.0 GHz octa-core processor with 4GB LPDDR4 RAM). D3: Google Nexus 5X (1.8 GHz hexa-core with 2GB LPDDR3 RAM). We updated all devices to the latest supported OS (D1 & D2: Android 10; D3: Android 8.1), and disabled automated software updates, battery saver and adaptive brightness features when applicable. We further set the device under Flight Mode, enabled WiFi access, connected to a stable WiFi 5GHz network, and set the brightness level to minimum.

As a base network, and to initialize the Transfer Learning process, we use MobileNetv2 [24], pre-trained with ImageNet [10] dataset with image size 224x224. As a head network (used for the model personalization), we use a single dense layer, followed by softmax activation (SGD optimizer with 0.003 learning rate). As a dataset for modeling for the two scenarios on the real devices.

In our experiments, we applied parameter values used in other FL works with CIFAR-10: 20 samples per batch, 50 epochs, 20 FL rounds, and 250 or 500 samples per user (S), corresponding to the two scenarios of individual app or joint FL modeling of two apps via data sharing. For measuring ML performance, we simulated the feasibility of our design and potential benefits of collaborative model building. Our long-term goal is to finalize FLaaS design and deployment for large scale evaluation. However, we argue that many of the challenges raised in the FLaaS design represent fundamental open research problems in the Federated Learning space.

**CONCLUSIONS AND DISCUSSION**

In this paper, we presented FLaaS, the first to our knowledge Federated Learning as a Service system enabling 3rd-party applications to build collaborative, decentralized, privacy-preserving ML models. We discussed challenges arising under these settings, and highlighted approaches that can be used to solve them. We also presented a FLaaS proof of concept under mobile phone settings, showing the feasibility of our design and potential benefits of collaborative model building. Our long-term goal is to finalize FLaaS design and deployment for large scale evaluation. However, we argue that many of the challenges raised in the FLaaS design represent fundamental open research problems in the Federated Learning space.

**ACKNOWLEDGEMENTS**

The research leading to these results has received funding from EU H2020 Programme, No 830927 (CONCORDIA), No 871793 (ACCORDION) and No 871370 (project PIMCITY). The paper reflects only the authors’ views and the Commission is not responsible for any use that may be made of the information it contains.
REFERENCES

[1] Amazon. 2020. Machine Learning on AWS. https://aws.amazon.com/machine-learning/. (2020).

[2] Android. 2020. Android BroadcastReceiver. https://developer.android.com/reference/android/content/BroadcastReceiver. (2020).

[3] Android. 2020. Android BroadcastReceiver. https://developer.android.com/topic/performance/power/setup-battery-historian. (2020).

[4] Aurelien Bellet, Rachid Guerraoui, Mahsa Tanski, and Marc Tommasi. 2018. Personalized and Private Peer-to-Peer Machine Learning. In 21st International Conference on Artificial Intelligence and Statistics (AISTATS).

[5] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konenecy, Stefano Mazzocchi, H. McMahan, Timon Overveldt, David Petrou, Daniel Ramage, and Jason Roselander. 2019. Towards Federated Learning at Scale: System Design. In 2nd SysML Conference.

[6] Christopher Briggs, Zhong Fan, and Peter Andras. 2020. Federated learning with hierarchical clustering of local updates to improve training on non-IID data. https://arxiv.org/pdf/2004.11791.pdf. (2020).

[7] Sebastian Caldas, Sai Meher Karthik Duddu, Peter Wu, Tian Li, Jakub Konenecy, H. Brendan McMahan, Virginia Smith, and Ameel Talwakar. 2019. LEAF: A Benchmark for Federated Settings. https://leaf.cmu.edu. (2019).

[8] CoMind. 2019. CoMind: Collaborative Machine Learning. https://comind.org. (2019).

[9] DataFleets. 2020. DataFleets: The Federated Intelligence Platform. https://www.datafleets.com. (2020).

[10] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. 2009. ImageNet: A Large-Scale Hierarchical Image Database. In CVPR09.

[11] DML. 2018. Decentralized Machine Learning. https://decentralizedml.com. (2018).

[12] FATE. 2020. Federated AI Technology Enabler. https://github.com/FederatedAI/FATE. (2020).

[13] Robin C Geyer, Tassilo Klein, and Moin Nabi. 2017. Differentially private federated learning: A client level perspective. In NIPS Workshop: Machine Learning on the Phone and other Consumer Devices.

[14] Google. 2020. AI Platform. https://cloud.google.com/ai-platform. (2020).

[15] Google. 2020. Google Transfer API library. https://github.com/tensorflow/examples/blob/master/lite/examples/model_personalization/. (2020).

[16] Abhijit Guha Roy, Tassilo Klein, and Moin Nabi. 2019. BrainTorrent: A Peer-to-Peer Environment for Decentralized Federated Learning. https://arxiv.org/pdf/1905.06731.pdf. (2019).

[17] Jakub Konenecy, H. Brendan McMahan, Felix Yu, Peter Richtarik, Ananda Theertha Suresh, and Dave Bacon. 2016. Federated Learning: Strategies for Improving Communication Efficiency. In 29th Conference on Neural Information Processing Systems (NIPS).

[18] Alex Krizhevsky, Geoffrey Hinton, et al. 2009. Learning multiple layers of features from tiny images. (2009).

[19] Lumin Liu, Jun Zhang, S.H. Song, and Khaled B. Letaief. 2020. Client-Edge-Cloud Hierarchical Federated Learning. In IEEE International Conference on Communications.

[20] H. Brendan McMahan, Eider Moore, Daniel Ramage, and Blaise Agiyea y Arcas. 2017. Communication-Efficient Learning of Deep Networks from Decentralized Data. In 30th International Conference on Artificial Intelligence and Statistics (AISTATS).

[21] Microsoft. 2020. Azure Machine Learning. https://azure.microsoft.com/en-us/services/machine-learning/. (2020).

[22] OpenMined. 2020. OpenMined. https://www.openmined.org. (2020).

[23] Mehdi Salehi Heydar Abad, Emre Ozfatura, Deniz Gunduz, and Ozgur Ercetin. 2020. Hierarchical Federated Learning Across Heterogeneous Cellular Networks. (2020).

[24] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. 2018. MobileNetV2: Inverted Residuals and Linear Bottlenecks. In IEEE/CVF Conference on Computer Vision and Pattern Recognition.

[25] Mohamed Seif, Ravi Tandon, and Ming Li. 2020. Wireless federated learning with local differential privacy. In IEEE International Symposium on Information Theory (ISIT).

[26] Chuansi Tan, Fuchun Sun, Tao Kong, Wenchang Zhang, Chao Yang, and Chunfang Liu. 2018. A Survey on Deep Transfer Learning. In Artificial Neural Networks and Machine Learning (ICANN), Véra Kůrková, Yannis Manolopoulos, Barbara Hammer, Lazaros Iliadis, and Ilias Maglogiannis (Eds.). Springer International Publishing, Cham, 270–279.

[27] TensorFlow. 2020. TensorFlow Federated: Machine Learning on Decentralized Data. https://www.tensorflow.org/federated. (2020).

[28] Stacey Truex, Nathalie Baracaldo, Ali Anwar, Thomas Steinke, Heiko Ludwig, Rui Zhang, and Yi Zhou. 2019. A hybrid approach to privacy-preserving federated learning. In Proceedings of the 12th ACM Workshop on Artificial Intelligence and Security.

[29] Stacey Truex, Ling Liu, Ka-Ho Chow, Mehmet Emre Gursoy, and Wenqi Wei. 2020. LDP-Fed: Federated Learning with Local Differential Privacy. In 3rd International Workshop on Edge Systems, Analytics and Networking (EdgeSys).

[30] Kang Wei, Jun Li, Ming Ding, Chuan Ma, Howard H Yang, Farhad Farokhi, Shi Jun, Tony QS Quek, and H Vincent Poor. 2020. Federated learning with differential privacy: Algorithms and performance analysis. IEEE Transactions on Information Forensics and Security (2020).

[31] Jiale Zhang, Junyu Wang, Yanchao Zhao, and Bing Chen. 2019. An Efficient Federated Learning Scheme with Differential Privacy in Mobile Edge Computing. In International Conference on Machine Learning and Intelligent Communications. Springer, 538–550.

[32] Benjamin Zi Hao Zhao, Mohamed Ali Kaafar, and Nicolas Kourtellis. 2020. Not one but many Tradeoffs: Privacy Vs. Utility in Differentially Private Machine Learning. In ACM Cloud Computing Security Workshop (CCSW).

[33] Yang Zhao, Jun Zhao, Mengmeng Yang, Teng Wang, Ning Wang, Lingjuan Lyu, Dusit Niyato, and Kwok-Yan Lam. 2020. Local Differential Privacy based Federated Learning for Internet of Things. IEEE Internet of Things Journal (2020).

[34] Wenhao Zhu, Peter Kairrrez, Brendan McMahan, Haicheng Sun, and Wei Li. 2020. Federated Heavy Hitters Discovery with Differential Privacy. In 23 International Conference on Artificial Intelligence and Statistics (AISTATS).