# Emulation Framework for AIoT Federated Learning

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# 1 Abstract

Federated Learning (FL) allows a fleet of devices to collaborate towards a globally trained machine learning model. Research has continued to produce novel algorithms to tackle different issues faced in FL such as data heterogeneity and network costs. The performance of these algorithms depend, in part, on the system parameters used such as the number of clients participating in each round as well as real world factors such as client drop off. However, measuring this performance through a realistic benchmark would require one to procure a large fleet of devices which is infeasible and costly. Therefore, the role of software simulation is to support researchers with the tools to do so. This work introduces a software emulation framework utilizing QEMU and the Zephyr OS to streamline the process of building a fleet of clients and allow validation testing of FL system parameters that is not hardware-agnostic.

# 2 Acknowledgements

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# 3 Introduction

Federated Learning (FL) emerged as a method for solving key issues with the standard centralized learning approach, namely, it achieves the following properties:

- Data Privacy: a centralized training approach involves the need for the centralized machine performing the computation to have full access to the entire data set. With FL, data never leaves each individual client's device. Instead, only the updated weights are shared to form the global model.
- Scalability: FL enables leveraging a network to perform computation in parallel.

These properties makes FL widely used in in the context of Artificial Intelligence of Things (AIoT) devices. By leveraging the vast amount of data generated by IoT devices, FL harnesses the collective intelligence of edge devices while respecting data sovereignty and privacy regulations.

While FL has been successful in these aspects, there are a few limitations to the approach which may not make FL practical in some applications. In particular, the distributed nature of FL poses a few key challenges:

- Limited computing resources: individual devices may face memory constraints, limiting the size of the local model it is able to train. Constraints on computing power also lead to longer training times. This is particularly so for low-powered IoT devices.
- Network limitations: communication speed can become the bottleneck for performance as IoT devices rely on unstable wireless communication networks. Furthermore, data constraints can exist such that the number of bytes sent may be a cost inducing factor.

Hence, the development of FL algorithms often seek to advance progress towards solving the aforementioned issues.

## 3.1 Problem

Prior to effectively deploying FL, different factors including the convergence rate and model accuracy needs to be well studied. This gives rise to the need for software simulation. However, the simulation of FL in the distributed setting involves

dealing with issues which do not arise in datacenter ML research. These include running on different simulated devices, each with potentially varying amounts of data. Furthermore, metrics such as the number of bytes transferred by the device, as well as the ability to simulate real-world issues such as client drop-out, can also be important for proposed FL algorithms to handle.

difference between pre-trained and on-device training

## 3.2 Literary Review

FLSim[1] aims to provide a simulation framework for FL by offering its users a set of software components – which can then be mixed and matched to create a simulator for their use case. Developers need only define the data, model and metrics reported, and FL system parameters can be altered in a JSON configuration file. FLUTE[2] adds additional features by allowing users to gain access to cloud based compute and data. However, these simulation solutions are consequently hardware-agnostic. Without taking into account the specific platforms which FL is performed on, these simulators cannot provide insight into whether the system will work in the production environment.

In contrast, FedML[3] is a research-oriented library which supports various algorithms and 3 platforms, on-device training for IoT and mobile devices, distributed computing and single-machine simulation. Simulation is offered through the FedML Parrot[4], which offers an accelerated simulation framework employing multiple optimizations to improve simulation speed. However, on-device training is supported only on Raspberry Pi 4 and NVIDIA Jetson Nano which limits hardware validation to these 2 devices.

One approach to acquiring hardware dependent results is to emulate the hardware environment. This can be achieved through software systems. One such system explored the combination of Quick Emulator (QEMU) and Zephyr, a real time operating system to emulate embedded devices in the FL contenxt[5]. However, this approach only emulated machine learning inference rather than on-device training.

Here, this work proposes a new emulation framework "zfl", which aims to achieve the following properties:

- Provide better insight into hardware specific support by running FL on emulated hardware through QEMU and Zephyr OS.

- Collect useful metrics during the FL lifecycle.
- Support simulation of real word issues such as variable data and client drop-off.

### 3.3 QEMU

QEMU[6] is an open source machine emulator and virtualizer. It enables system emulation, creating a virtual model of an entire machine (CPU, memory and emulated devices) to run a guest OS. In this mode, the CPU may be fully emulated, or it may work with a hypervisor to allow the guest to run directly on the host CPU. In zfl, QEMU with full CPU emulation is used without a hypervisor as part of its software architecture to emulate hardware. Note that by default, the framework is built for QEMU x86 32-bit, which entails the use of the qemu-i386 binary in section 4.

### 3.4 Zephyr OS

To emulate the issue of limited computing resources, it is important to make use of system runtimes used by those devices. Zephyr OS[7] is one such operating system. It is based on a small-footprint kernel designed for use on resource-constrained and embedded systems: from simple embedded environmental sensors and LED wearables to sophisticated embedded controllers, smart watches, and IoT wireless applications. Furthermore, Zephyr is highly configurable, allowing the user to choose only the specific kernel services required, and also delve into lower level memory mapping of the system SRAM and DRAM. Most importantly, Zephyr supports a wide range of CPU architectures including ARM, RISC-V and x86. Zephyr also provides built-in capabilities for building for the QEMU environment, and implements key features such as networking through the QEMU built-in Ethernet adapter. In zfl, client code will be written to work in the Zephyr OS environment.

## 4 Implementation

The framework implements the classical FedAvg algorithm[8] as part of its simulation, where each client sends its updated model weights to a central server, which then performs aggregation using simple averaging. Hence, the architecture of the framework is based on the assumption of multiple clients talking to a single server.

To run on Zephyr OS, the entire software stack is developed in the C programming language. Although Zephyr also supports applications written in C++, the C programming language would make the framework more suitable to run on embedded devices. Note that the framework is implemented for Linux and all tests are run on a Debian based machine.

## 4.1 Configuration

In order to run machine learning training on each client, some configuration is required to ensure that we have sufficient memory to allocate for the neural network model and training data. Depending on the architecture of the model and the size of the data, these options may need to be further tweaked to prevent any runtime memory allocation crashes. Listing 1 shows the options made to `prj.conf` to create a runtime capable of up to 10MB of heap memory. Listing 2 shows the configuration made to the QEMU board under `qemu_x86.dts` for a total DRAM size of 15MB. This is in excess of the heap memory size as additional memory is reserved for the kernel image and stack memory.

```
CONFIG_SRAM_SIZE=15360
CONFIG_MAIN_STACK_SIZE=8192
CONFIG_KERNEL_VM_SIZE=0
    x7000000
CONFIG_HEAP_MEM_POOL_SIZE
    =10485760
```

Listing 1: Zephyr prj.conf

```
#define DT_DRAM_SIZE
    DT_SIZE_K(15360)
```

Listing 2: QEMU board.dts

The main zfl binary is used to bootstrap either the client or server aspects of FL simulation. Listing 3 shows the different options available for configuring FL parameters and their meanings.

```
./zfl client -c num_clients -e epochs -b batch_size
# -c num_clients: Number of clients to boot up.
# -e epochs:      Number of epochs (training passes on the entire
    data set).
# -b batch_size:  Number of training labels used for a single
    update.

./zfl server -r num_rounds -c clients_per_round
# -r num_rounds:        Number of rounds of aggregation.
# -c clients_per_round: Number of clients that need to respond to
```

```
    start a round.
```

Listing 3: The main zfl binary

## 4.2 Bootstrapping Process

Next the framework needed a method for spawning an arbitrary number of QEMU instances, and allowing these instances to communicate back to the server. When called in client mode (Listing 5), zfl accomplishes this by making use of the "fork" and "exec" pattern with the desired number of clients.

However, each instance of QEMU persists in an isolated network different from the host PC, and is not able to communicate. We can bypass this limitation using a network bridge to act as a virtual network device forwarding packets between connected network devices. The network bridge is set up on the host under the name "zfl" with a set of network parameters using the `ip` command line utility as shown in Listing 4.

```
ip link add $INTERFACE type bridge
ip addr add $IPV4_ADDR_1 dev $INTERFACE
ip link set enp61s0 master $INTERFACE
ip route add $IPV4_ROUTE_1 dev $INTERFACE > /dev/null 2>&1
ip link set dev $INTERFACE up
```

Listing 4: Network bridge setup

To tell QEMU to use it, we pass the name of the bridge along with a randomly generated MAC address as arguments to the `-nic` flag:

```
-nic bridge,model=e1000,mac=%s,br=zfl
```

Although each QEMU client is now able to communicate with the host via the NIC adapter, we still needed a way to monitor the output of each instance. One method is to transmit output and logs over the network. However, this would not allow important crash logs and stacktrace information to be transmitted as the application software would have shutdown. To overcome this, the host creates a named or FIFO pipe for each client, which then is passed into QEMU through the `-serial` flag. Now, all standard output goes through the named pipe, ready to be read by the host. Another outcome of this is that the host is also able to send input to each instance, whose importance will be described in the next section. Listing 5 showcases how each feature is configured through the QEMU command line binary.

```
pid_t child = fork();
if (child < 0) {
    printf("ERROR: could not fork client %d: %s\n", i, strerror(
    errno));
    return 1;
}
...

// generate serial arguments
char serial_arg[80];
snprintf(serial_arg, 80, "pipe:%s", pipe_path);

// generate nic arguments
char nic_arg[100];
char *mac = generate_random_mac();
snprintf(nic_arg, sizeof(nic_arg), "bridge,model=e1000,mac=%s,br=
    zfl", mac);

// start client as new process
execlp("qemu-system-i386", "qemu-system-i386",

       "-m", "15", "-cpu", "qemu32,+nx,+pae", "-machine", "q35",
       "-device", "isa-debug-exit,iobase=0xf4,iosize=0x04",

       "-no-reboot", "-nographic", "-no-acpi",

       "-serial", serial_arg,

       "-nic", nic_arg,

       "-kernel", "./zflclient/out/zephyr/zephyr.elf",

       NULL);
```

Listing 5: Client forking process

In addition to the NIC adapter configuration, each client needed a unique Internet Protocol Version 4 (IPv4) address in order to establish TCP based connections with the central server. Samples provided by Zephyr OS describe a way to achieve this by setting a compile time configuration flag `CONFIG_NET_CONFIG_MY_IPV4_ADDR`. However, this is impractical to scale to a large number of clients, since each client would need a separately compiled binary. One solution to this problem is to assign the IPv4 address dynamically using the built-in Zephyr network function[9]:

`net_if_ipv4_addr_add`

To achieve this, each client starts off as a Zephyr shell instance and a user-defined command `run` is registered. This exposes a shell command that takes in a command line argument which defines the desired IP address of the instance (Listing 6). Finally, this command triggers the run function (Listing 7) as a way to start the main program.

Overall, the complete emulation architecture is illustrated in figure 1, describing the interactions between the host system and guest instances.

```
SHELL_CMD_ARG_REGISTER(run, NULL, "Run with IPv4 address", run,
    4, 0);
```

Listing 6: Registering user defined command "run" to the function pointer run

```
int run(const struct shell *sh, size_t argc, char **argv) {
    // ...
    char *addr_str = argv[1];
    LOG_INF("instance ipaddr is %s", addr_str);
    struct in_addr addr;
    zsock_inet_pton(AF_INET, addr_str, &addr);
    if (!net_if_ipv4_addr_add(net_if_get_default(), &addr,
    NET_ADDR_MANUAL, UINT32_MAX)) {
        LOG_ERR("failed to add %s to interface", addr_str);
        return -1;
    }
    // ...
}
```

Listing 7: The "run" function which performs IP address assignment at runtime

## 4.3 Client

The first step within the internal implementation of each client is to establish TCP socket connection to the central server and obtain their assigned ID. This is then used to obtain the training data from the server which corresponds to that ID. Thus, this process allows for training data to be dynamically assigned to different instances. Finally, each client starts a HTTP server and marks itself as ready to begin the training round. The complete initialization process is illustrated in Figure 2.

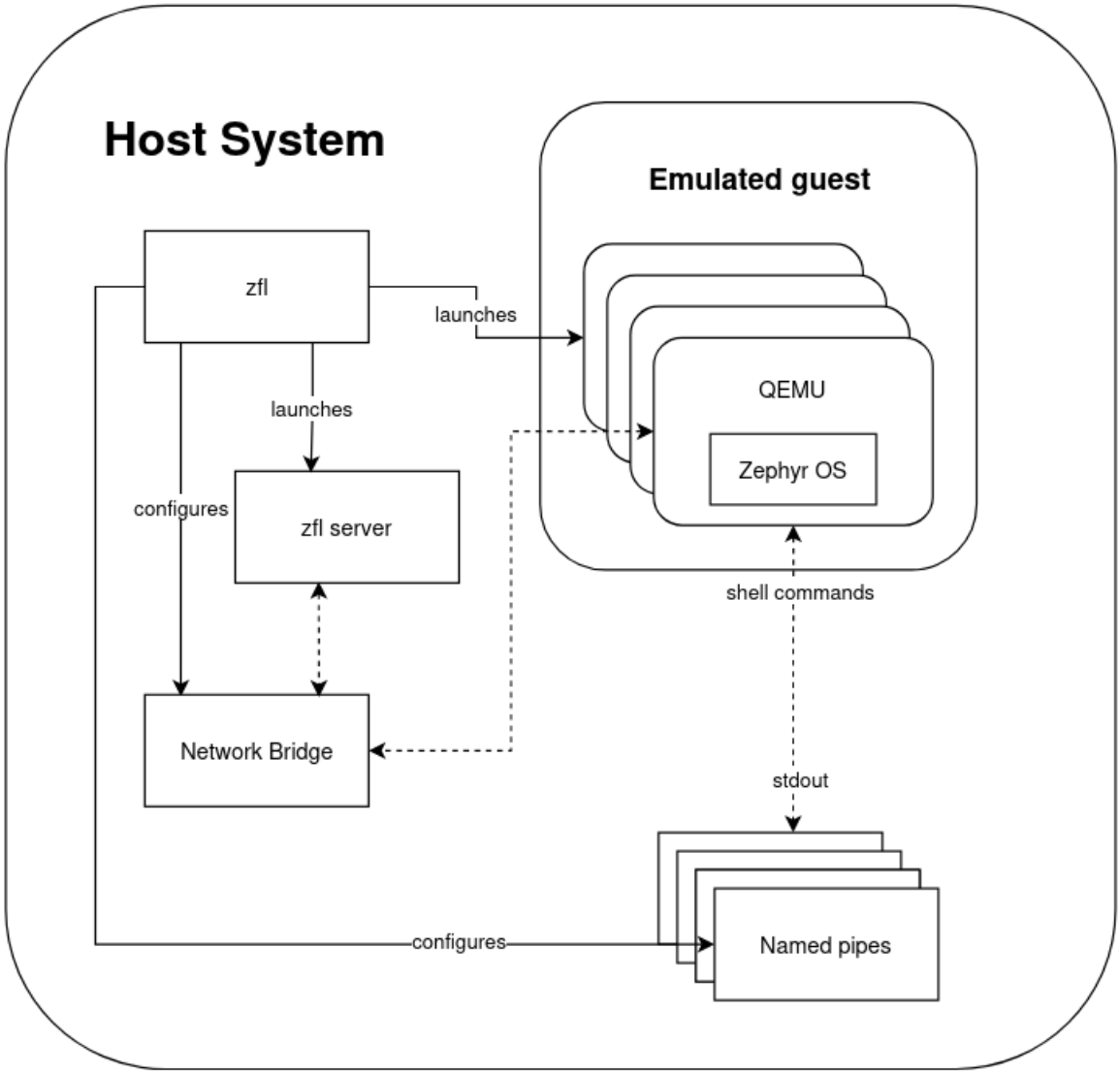



Figure 1: Host-guest emulation architecture

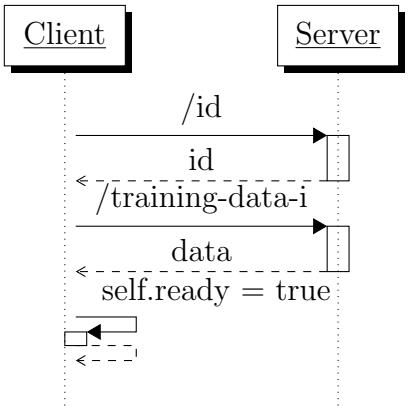



Figure 2: Client initialization sequence

### 4.3.1 Machine Learning

Once initialized, clients wait for a request to their `start` HTTP endpoint. This triggers the train function, which performs forwarding and backpropagation on the local data set. The underlying neural network implementation utilizes nn.h[10], an open source educational neural network C library. Porting the library for use included updating traditional POSIX syscalls to the Zephyr kernel syscalls. However, further modifications were made for specific use as described in section 5.

## 4.4 Server

The central server runs on the host machine without needing additional configuration. Its primary purpose is to aggregate individual client weights every round. Implemented HTTP endpoints are described in figure 4. After assigning each connecting client their ID and training data, it performs the function `start_round` at an interval of 10 seconds. Each time, the server pings all previously connected clients to check if they are ready to start the training round. When enough clients are ready, it sends a HTTP POST request to the `start` endpoint of the client, which then triggers the training function. Once the client has completed its training, it sends the resulting weights of the local model to the HTTP POST endpoint `results` of the server, which then performs the aggregation. The sequence of events for a single round is illustrated in Figure 3.

### 4.4.1 Metrics

As part of the framework's aim to track useful metrics, the server keeps track of the total number of bytes transferred between the clients and itself during the entire FL lifecycle. The total training time in seconds is also tallied. This

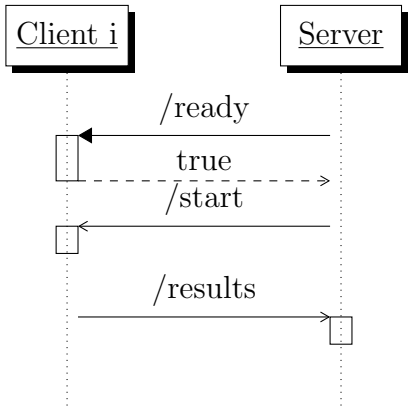



Figure 3: FL round

| Client | | |
|---|---|---|
| Endpoint | HTTP Method | Description |
| /start | POST | Initiates training round using updated weights with JSON body: {weights: int} |
| /ready | GET | Gets client ready status |
| Server | | |
| /results?id= | POST | Client id submits results with JSON body: {round: int, weights: string} |
| /id | GET | Obtain an id for round participation |
| /training-data?id= | GET | Obtain training data for id |
| /training-labels?id= | GET | Obtain training labels for id |

Figure 4: HTTP endpoints

is displayed along with additional details such as the current round, number of ready clients, as well as a graph of the validation set loss and accuracy on a simple graphical user interface shown in Figure 5.

# 5 Experiments

The framework is tested using FedAvg over the MNIST digit recognition data set of 60000 labels. Due to memory constraints, clients are configured with a neural network architecture with 1 hidden layer of 16 nodes. Additionally, implementations for the softmax activiation and cross entropy were made to ensure suitability for machine learning with MNIST categorical data.

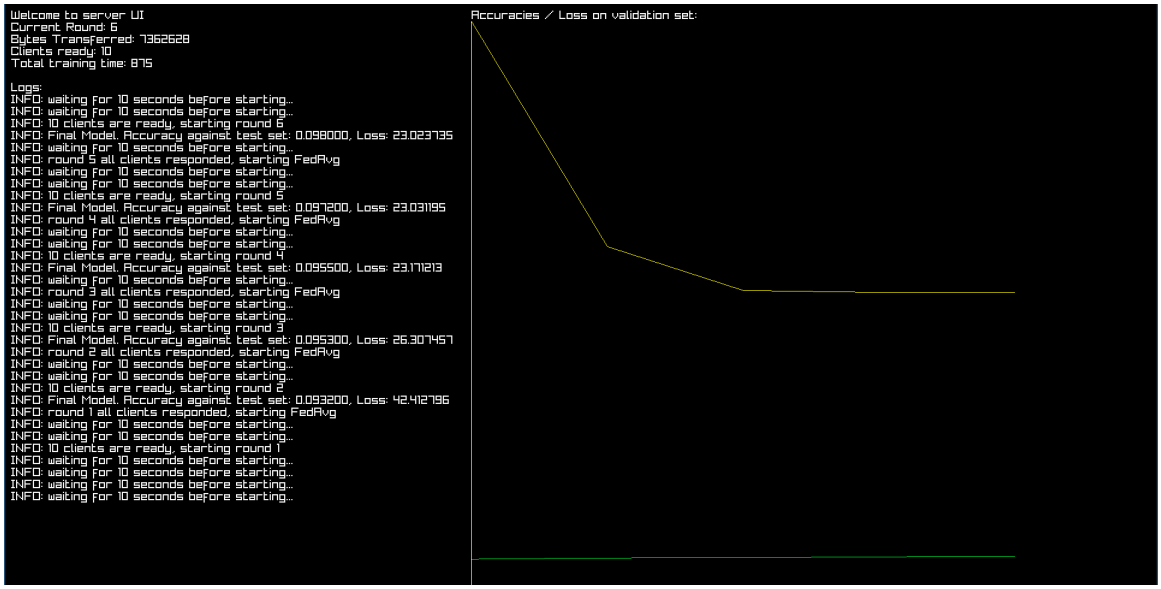


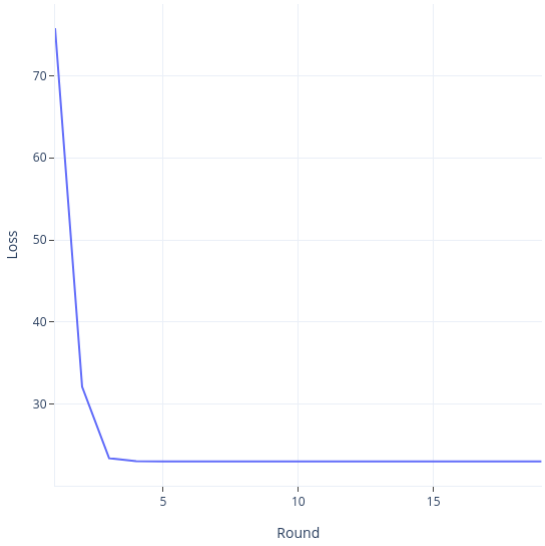

Figure 5: GUI Implementation

To test the sanity of the framework, the data is first shuffled and split equally into 100 sets of 6000 labels. The server is started for 20 rounds and 100 clients per round and clients were started with 5 epochs and a batch size of 600. Figure 6a shows the validation set loss and Figure 6b shows the validation set accuracy at the end of each round. There can be many reasons for the lack of accuracy gain. For one, the model architecture is very shallow, reducing each clients ability to make significant steps towards their local minima. Furthermore, traditional FedAvg also suffers from model inaccuracy caused by the loss of knowledge during model training[11]. Nevertheless, although the framework is unable to converge towards an acceptable target accuracy during the experiment, a steadily decreasing cross entropy loss helps to validate that the entire system is performing.

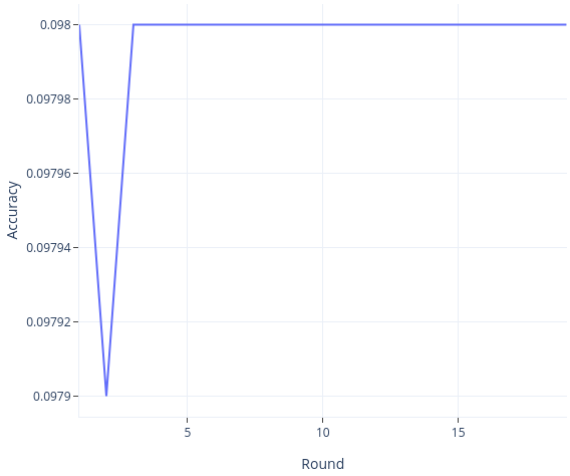
# 6 Limitations

## 6.1 Long training times

Unoptimized client training implementations has resulted in long training times required per FL round. This is because standard implementations for machine learning algorithms that can be easily ported and suitable for use in Zephyr OS could not be found. Traditional runtimes such as Tensorflow[12] rely on the availability of a Python interpreter on the device. Furthermore, these runtimes are usually not developed or optimized for resource constrained environments, incurring a large binary size and high memory usage. However, there is progress




(a) 20 round validation set loss




(b) 20 round validation set accuracy

towards integrating Tensorflow Lite Micro into Zephyr OS through external modules and has examples for running pre-trained neural network on their platform. However, on-device training is still not supported.

## 6.2 Limited algorithm support

The framework currently only implements training algorithms for FedAvg. The architecture of zfl also inherently assumes the use of a single server instance used for aggregation. However, this limitation can be bypassed by porting specific HTTP endpoints from the server to the client. For example, the implementation of the `results` endpoint, would effectively move aggregation into each client instance. This could potentially allow the framework to support hierarchical FL algorithms[13].

Furthermore, future work could also look into implementing other FL algorithms in a bid to improve the usability of the framework. These algorithms should aim to achieve higher model accuracy without compromising on the requirements needed to function in an embedded low-powered device environment. One example could be Distillation Based Federated Learning[14].

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