Federated Learning-Based Computation Offloading for Low-Bandwidth Edge Internet of Things

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***Abstract*—Internet of Things (IoT) devices generates massive amounts of data continuously, making it difficult to combine this data at the edge node or central edge server for AI techniques to be applied, especially on low-bandwidth networks. Traditional computation offloading involves extensive resource management, queuing, and high bandwidth usage to send data from an edge device to a server. To mitigate this challenge, federated learning is applied in this paper, to offload the computation of the edge server. Simulation results show the efficiency of the proposed method over the centralized method.**

***Index Terms*—Federated learning, task offloading, edge computing, internet of things.**

I. Introduction

Wide use of the internet of things (IoT) in smart cities, smart grids, smart medical systems, surveillance systems, intelligent transportation systems, smart factories, smart logistics and other fields transformed the way of living also social-economic conditions [1]. The diverse and massive number of IoT devices are going applied soon to fulfill the demand of future upcoming technology like metaverse, internet 3.0, Industry 5.0, unmanned aerial vehicles and autonomous vehicle operation [2], etc. For centralized machine learning, which gathers data from a big number of heterogeneous devices for training, this will result in a significant system delay. Edge computing deployment by facilitating computation offloading is one of the solutions to reducing the burden on the network. In edge computing, IoT devices offload the task to the edge nodes to save energy and computation efficiency. There are mainly two ways of task offloading partial offloading and full offloading [3]. In partial offloading, a portion of the task whereas the rest are processed on the local machine. And in full offloading total data are transferred to central server for processing. Game theory, convex optimization were used previously for task resource allocations and offloading. Hoa et al.[4] proposed data fragmentation concept based task offloading for fog computing system. Wang et al. [5] integrate federated learning with deep reinforcement learning for edge computing to computing and catching system. Paper [6], adopted federated learning based computation offloading to resolve the problem of limited resource, high data consumption in vehicular edge computing. Support vector machine based federated learning algorithm is proposed for mobile edge enabled high-altitude balloons (HABs) network in [7]. Earlier mentioned federated learning for specific application area. However, this article propose a edge enable federated learning framework for IoT. Here edge nodes consider as clients and do federated computation and send result parameters to the server.
The remainder of the paper is structured as: Section II describes the system model of federated learning empowered computation offloading. Section III demonstrates results and discussion of simulating work. And finally, Section IV concludes the paper.

II. System Model

Figure 1 illustration the proposed architecture of federated learning based computation offloading of edge IoT. There are three layers in the architecture. The upmost layer is the edge server, where clients learning output integrate using federated aggregation function, send local updates to the client edge nodes. The middle part is the edge nodes, here perform the federated computation part, based on the learning model send from edge server. And the lowest part is the IoT devices where data are generated. In this work, the energy to transmit and execute the task of the IoT devices is kept constant, which means devices are capable of energy harvesting. Take into account a federated learning situation where N denotes the number edge nodes or clients. Edge server is connected with a frequency bandwidth B Hz to a set of edge nodes as, N= 1, 2,..., N. Each edge node i has a local database Di which is formed Independent and Identically Distributed (I.I.D.) way from IoT devices data. Each edge nodes first upload a portion of data to the server for processing. The local model will be updated using the rest of the data in each client. In the meantime, the server will update its model using the aggregated data. One of two options is available when a task is selected from the task queue: it can either be carried out locally on the edge node or offloaded to the server for processing.

III. Performance Evaluation

In order to validate our proposed federated learning based task offloading for edge IoT system, CIFAR10 dataset is used since it is extensively used in academia. It is a image dataset with 60,000 samples of 32×32×3 color channel and

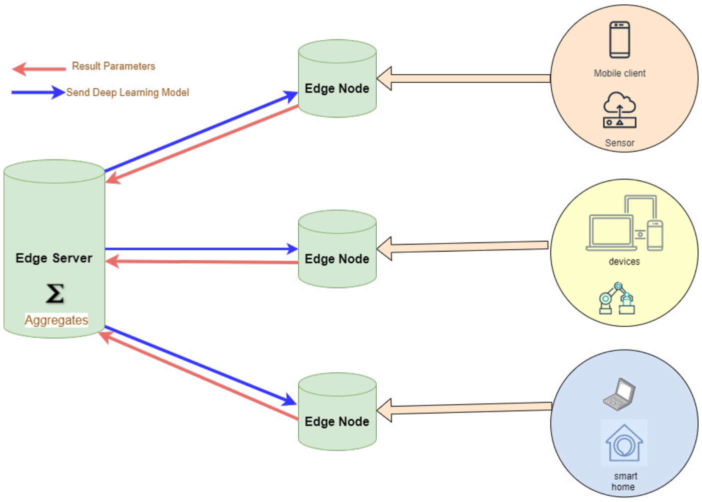

Fig. 1: Architecture of federated learning based offloading system

10 classes. Where learning model is a Convectional Neural Network (CNN) with two 3×3 convolutions layers, a fully connected layer with in features 128 ×16×16. The data is divided unbalanced partition IID among clients. Here total number of clients is considered 5 and each client receives 12,000 samples. Figure 2, shows the learning performance of centralized and federated learning. And in the case of accuracy, federated learning performed better, with 72.75 percent for centralized and 75.69 percent for federated learning, although the CNN model is the same. Figure 3 and 4 shows the bar

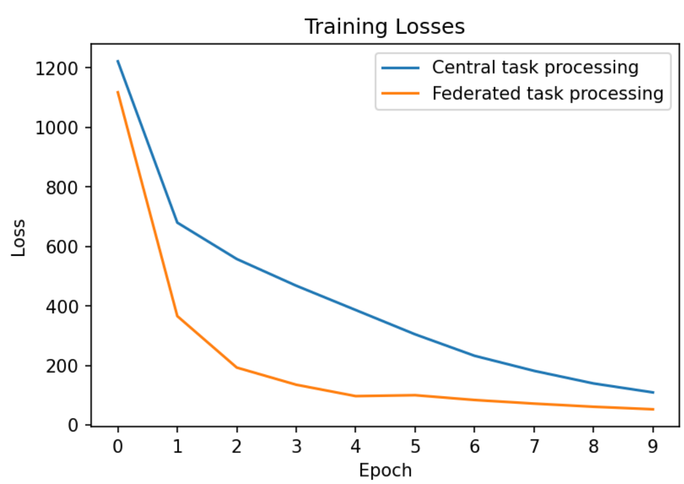

Fig. 2: Learning performance of centralized and federated learning

graph about number of training image and model parameters of centralized and federated learning based edge IoT. From the above we see that each client model was trained using 12000 images, with same training model. Since the amount of data is small compared to centralized edge server, time consumption in training process will also takes lower than centralized server.In federated process instead of sending all the data, here edge device only sends the learning parameters to edge server. Edge nodes send less communication resources during each aggregation step. The amount of data needed to train the global model at each epoch step drastically decreased by federated learning which is suitable for low bandwidth network.

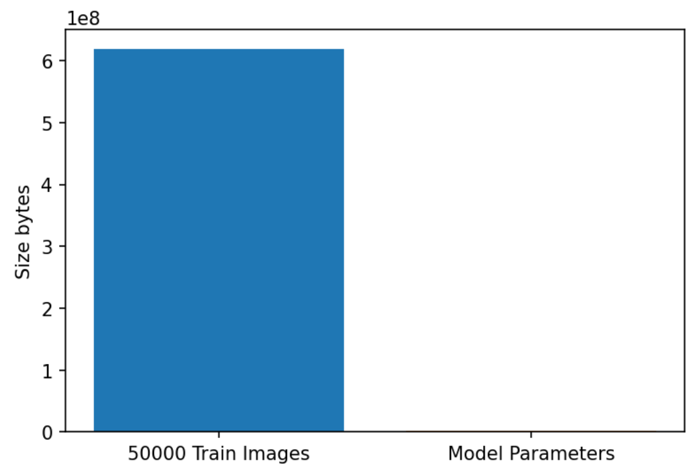

Fig. 3: Centralized training image vs model parameter

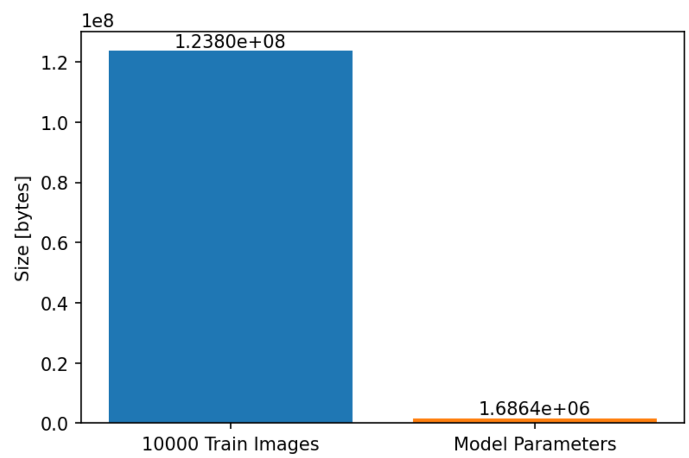

Fig. 4: Training image of each client vs model parameter

IV. Conclusion

This paper shows that the application of federated learning in edge IoT system is effective than centralized learning. The effectiveness is considered in case of computation task offloading, or data passing through the network. In future work, more details effect like network delay, power consumption, transmission time, dynamic client selection of federated learning in edge server will be considered.

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