Federated Learning for Multi-Institutional Medical Image Segmentation

Avo Elvis Theyo
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Under the supervision of:
Dr. W Wilfred Godfrey

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1 Background and Problem Statement

Deep Learning has been widely used for medical image segmentation and a large number of papers have been presented recording the success of Deep Learning in this field [1]. The performance of Deep Learning models strongly relies on the amount and diversity of data used for training. In the Medical Imaging field, acquiring large and diverse datasets is a significant challenge. Unlike photography images, labeling medical images require expert knowledge. Ideally, collaboration between institutions could address this challenge but sharing medical data to a centralized location faces various legal, privacy, technical, and data-ownership challenges. This is a significant barrier in pursuing scientific collaboration across transnational medical research institutions.

Traditionally, Artificial Intelligence techniques require centralized data collection and processing that may be infeasible in realistic healthcare scenarios due to the aforementioned challenges [2]. In recent years, Federated Learning [3] has emerged as a distributed collaborative AI paradigm that enables the collaborative training of Deep Learning models by coordinating with multiple clients (e.g., medical institutions) without the need of sharing raw data. Although Federated Learning was initially designed for mobile edge devices, it has attracted increasing attention in the healthcare domain because of its privacy preserving nature of the patient information.

In Federated Learning, each client trains its own model using local data, and only the model updates are sent to the central server. The server accumulates and aggregates the individual updates to yield a global model and then sends the new shared parameters to the clients for further training. In this way, the training data remains private to each client and is never shared during the learning process. Only the model's updates are shared, thus keeping patient data private and enabling multi-institutional collaboration.

Sheller *et al.* [4] proposed a federated learning approach for brain tumor segmentation to enable multi-institutional collaboration. The dataset from the Brain Tumor Segmentation (BraTS) Challenge 2018 [5] [6] [7] is used which contains data collected from 19 institutions, using various MRI scanners. The popular Convolutional Neural Network (CNN) architecture: U-Net [8] is used to train the data at each individual client.

Wang *et al.* [9] collaboratively generated and evaluated a Federated Learning model for Pancreas Segmentation without sharing the data. The data consisted of healthy and unhealthy pancreas collected at two institutions from different countries namely Taiwan and Japan. The model utilized was from coarse-to-fine network architecture search (C2FNAS) [10] with an additional variational auto-encoder (VAE) [11] branch to the encoder endpoint. It was demonstrated that Federated Learning dramatically improved the generalizability of models on server-side and client-side for both datasets.

Yang *et al.* [12] proposed a novel system based on federated and semi-supervised learning for COVID Region Segmentation in Chest CT using Multi-National Data from China, Italy, Japan. Federated Learning gives sufficient flexibility to different institutions to collaboratively train deep learning models without data sharing while semi-supervised learning ensures effective training even when some sites have only limited amount of annotated data but large amount of unannotated data. A 3D U-shape Fully Convolution Network (FCN) [13] was used to segment the ground glass-like opaque (GGO) regions (COVID-19 affected regions) of the lung from the 3D chest CT.

As witnessed from the survey of prior related works above, although several studies have dealt with the topic of Federated Learning for medical image segmentation, they either use a single variant of U-Net or another single model to train the data in a federated setting. The aforementioned works also evaluated the performance of federated learning models on only a single multi-institutional medical image segmentation dataset and hence it limits the possibility of generalisation to other medical image segmentation tasks.

In this work, various variants of the U-Net model architectures [14] will be trained to evaluate the performance of each variant in the federated setting. Furthermore, various medical image segmentation tasks will be explored using Federated Learning to evaluate the performance of federated learning models with standalone training models on segmentation datasets from multiple institutions.

2 Project Objectives

To the best of my knowledge, this work is the first to utilise the various variants of U-Net architecture in a federated setting for several multi-institutional medical image segmentation datasets. The main objectives of this project can be summarised as follows:

- Through this project, the effectiveness of Federated Learning for Multi-Institutional Medical Image Segmentation will be demonstrated by training various variants of the U-Net architecture such as U-Net++, Attention U-Net, etc. The performance of each variant will be evaluated to identify the best model for each medical image segmentation task.

- The models trained in a federated setting aims to achieve better or comparable segmentation performance to centrally trained models while ensuring preservation of sensitive patient information.

- As demonstrated in Sheller *et al.* [4], along with Brain Tumor Segmentation, this project will extend towards two additional multi-institutional medical image segmentation tasks i.e Liver Tumor Segmentation and Lung Segmentation. Through this, the generalizability of models on server-side and client-side will be evaluated for various medical image segmentation tasks.

3 Requirements

3.1 System Requirements

- A computer with RAM of size 4-8 GB.

- A computer with GPU (Alternative: Google Colab)

3.2 Software Requirements

- Python 3

- Keras 2.2.0 or TensorFlow 1.13

- keras-applications 1.0.8

- image-classifiers 1.0.0

- efficientnet 1.0.0

- Segmentation models

- Jupyter Notebook

- Visual Studio Code

4 System Overview

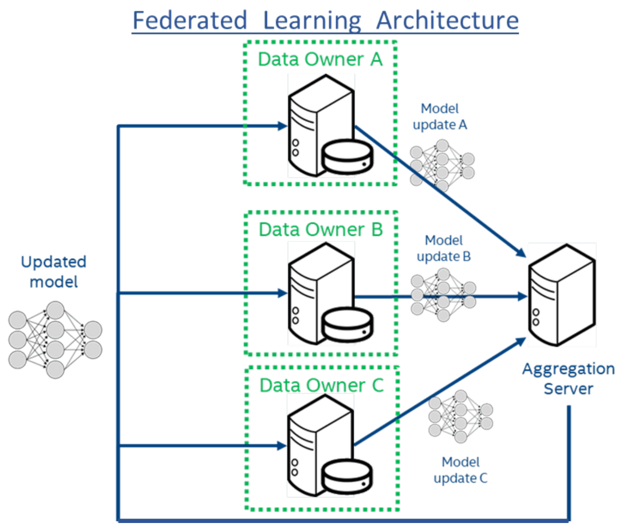

Fig. 1. System Architecture of Federated Learning.

5 Timeline

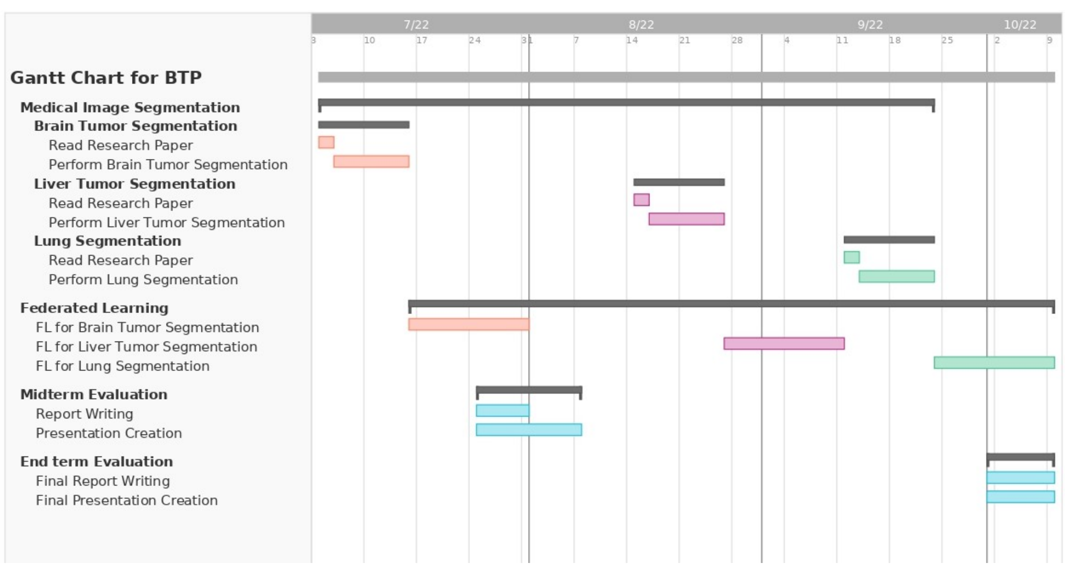

Fig. 2.: Gantt Chart.

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