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 Introduction

Medical image segmentation is one of the most important areas in medical image analysis and is necessary for diagnosis, monitoring, and treatment. The aim of medical image segmentation is to identify a region of interest (RoI) like tumor and lesion. Popular medical image segmentation tasks include liver and liver-tumor segmentation, brain and brain-tumor segmentation, optic disc segmentation, cell segmentation, lung segmentation, pulmonary nodule, cardiac image segmentation, etc. [1]

In this report, I present an approach to brain tumor segmentation using Federated Learning [2] in order to enable multi-institutional collaboration and protect sensitive patient data. The goal of brain tumor segmentation is to generate accurate delineation of brain tumor regions [3].

Research Insitutions often struggle to gain access to large-scale annotated medical imaging datasets for training and testing their algorithms since sharing medical data to a centralized location faces various legal, privacy, technical, and data-ownership challenges. In recent years, Federated Learning 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. 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.

2 Literature Survey

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.

Wenqi *et al.* [9] investigated the feasibility of applying differential-privacy techniques to protect the patient data in a federated learning setup for brain tumor segmentation using the BraTS dataset. The experimental results demonstrated that there is a tradeoff between model performance and privacy protection costs

Wang *et al.* [10] 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) [11] with an additional variational auto-encoder (VAE) [12] branch to the encoder endpoint. It was demonstrated that Federated Learning dramatically improved the generalizability of models on the server-side and client-side for both datasets.

Yang *et al.* [13] 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, and 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) [14] was used to segment the ground glass-like opaque (GGO) regions (COVID-19 affected regions) of the lung from the 3D chest CT.

3 Methodology

In order to simulate a federated setting, I implemeted the building blocks of Federated Learning using Python and TensorFlow. The collaborating institutions were represented by partitioning the dataset into the required number of data shards. This ensures that each institution will have its own local data to train on. Initially each local model receives the current global model's weights from the server. The local models then train on each of their local data which generates the updated parameters and are sent to the server for aggregation using the Federated Averaging (FedAvg) Algorithm. This cycle persists until a certain number of federated rounds.

3.1 BraTS Dataset

To evaluate Federated Learning for Brain Tumor Segmentation, I have used the BraTS 2020 Datset [5] [6] [7]. All BraTS multimodal scans are available as NIfTI files (.nii.gz) and describe a) native (T1) and b) post-contrast T1-weighted (T1Gd), c) T2-weighted (T2), and d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) volumes, and were acquired with different clinical protocols and various scanners from multiple (n=19) institutions. All the imaging datasets have been segmented manually, by one to four raters, following the same annotation protocol, and their annotations were approved by experienced neuro-radiologists. Annotations comprise the GD-enhancing tumor (ET — label 4), the peritumoral edema (ED — label 2), and the necrotic and non-enhancing tumor core (NCR/NET — label 1).

3.2 U-Net Architectures

To train the data, the following U-net architectures were implemented:

- **Basic U-Net**
  The U-Net architecture was designed primarily for medical image segmentation [8]. It consists of two paths: The first path is the contracting path, also known as the encoder or the analysis path, which is similar to a regular convolution network and provides classification information. The second is an expansion path, also known as the decoder or the synthesis path, consisting of up-convolutions and concatenations with features from the contracting path. This expansion allows the network to learn localized classification information. The resulting network is almost symmetrical which gives it a u-like shape.

- **U-Net++**
  U-Net++ [15] is inspired from DenseNet. It uses a dense network of skip connections as an intermediary grid between the contracting and expansive paths. This aids the network by propagating more semantic information between the two paths enabling it to segment images more accurately. In traditional U-net, the feature maps of the contracting path are directly concatenated onto the corresponding layers in the expansive path. However, U-net++ has a number of skip connection nodes between each corresponding layer.

- **Attention U-Net**
  Attention U-Net [16] has the ability to focus on specific objects that are of importance while ignoring unnecessary areas. This is achieved by making use of the attention gate, a unit which trims features that are not relevant to the ongoing task. Each layer in the expansive path has an attention gate through which the corresponding features from the contracting path must pass through before the features are concatenated with the upsampled features in the expansive path.

The various U-net architectures were implemented using the library:
keras unet collection [17].

4 Results

Table 1: Comparing U-Net variants performance after 5 federated rounds.

Metric	**U-Net**	**U-Net++**	**Attention U-Net**
Accuracy	96.71%	98.15%	98.32%
Loss	6.72	6.46	6.81
Dice Coefficient	0.032	0.057	0.018

5 Conclusion

The experiments demonstrate that clinical institutions around the globe can collaborate to train a model without sharing their data and thereby ensuring patient data privacy using Federated Learning. As seen from the quantitative results, for brain tumor segmentation in a federated setting, the U-Net Architecture, U-Net++ has given the best performance. In the future, I will be working on implementing both lung segmentation and liver tumor segmentation in a federated setting to evaluate the generalizability of models for various medical image segmentation tasks.

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