Sequential federated learning for decentralized brain glioma segmentation

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Introduction

Federated learning (FL) is a distributed deep learning paradigm in which models are transferred between institutions instead of data. FL can help radiology research by enabling medical institutions to collaboratively train deep learning models without sharing data. In this project, brain MRI samples of glioma patients are segmented using two different FL algorithms.

Keywords: Federated learning, Medical imaging, Privacy-preserving deep learning

Material and Methods

The FL algorithm keeps data locally, and the model is sequentially transferred between multiple clients. Clients are defined by assigning chunks of data to GPU workers. The FL experiment was also done using Varian Learning Portal (VLP), a cloud service that enables privacy-preserving communication between researchers and multiple data centers.

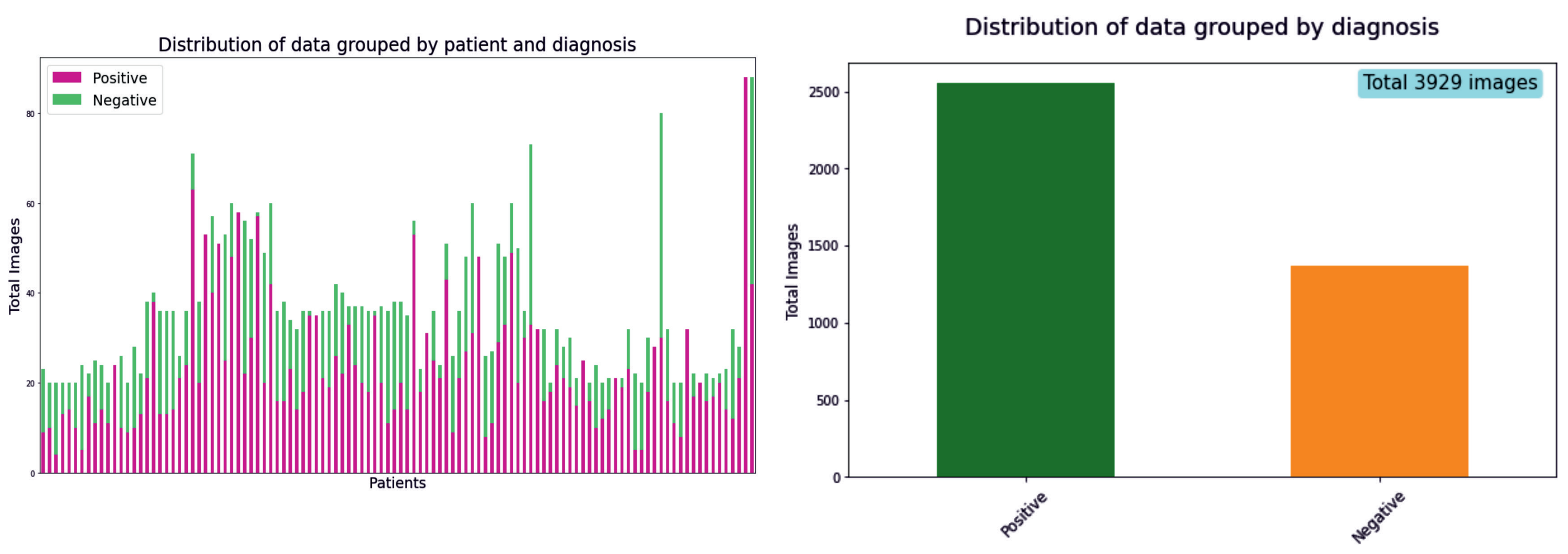

Figure 1. Communication between client and server, exchanging the model

Dataset consisted of 3929 samples gathered from 5 US hospitals, annotated and labeled by a board-certified radiologist. The deep learning model used for segmentation was U-Net with ResNext50[3] backbone. Two hundred samples were used for the local experiment, and 80 samples were used for the VLP experiment. The learning rate was 5×10^{-4}. The model was trained for 2 rounds and 2 epochs per round.

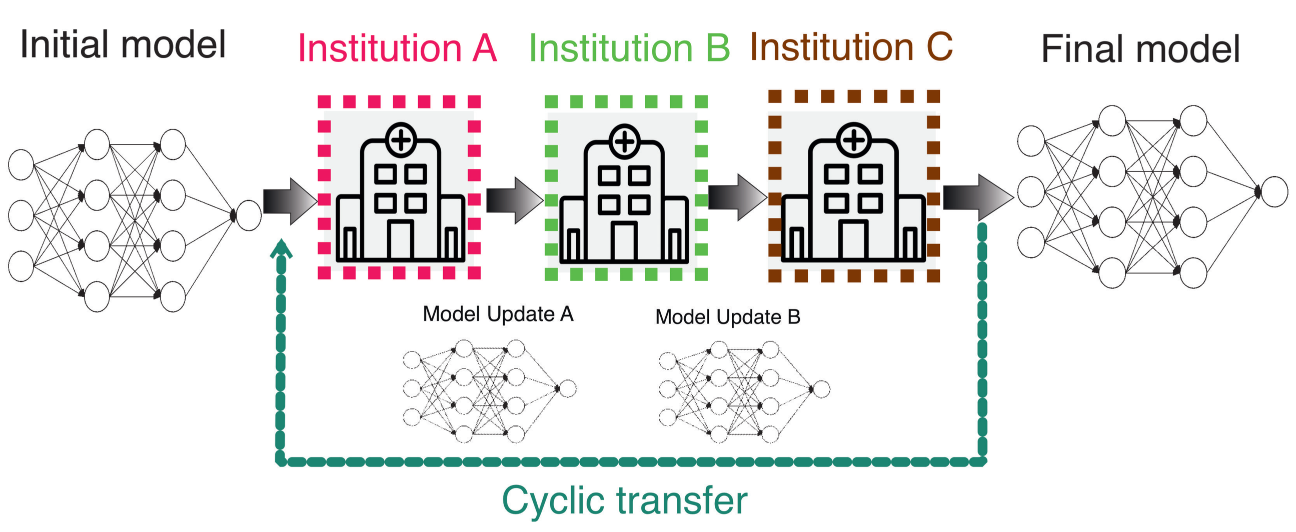

Figure 2. Cyclic weight transfer

This research examines two FL methods. For the local experiments, Cyclic Weight Transfer (CWT)[2] was used, in which the model meets each institution twice. For the experiments using VLP, Single weight transfer(SWT) was used, in which the model meets each institution only once. Schemas of these FL models are shown in Figures 2 and 3.

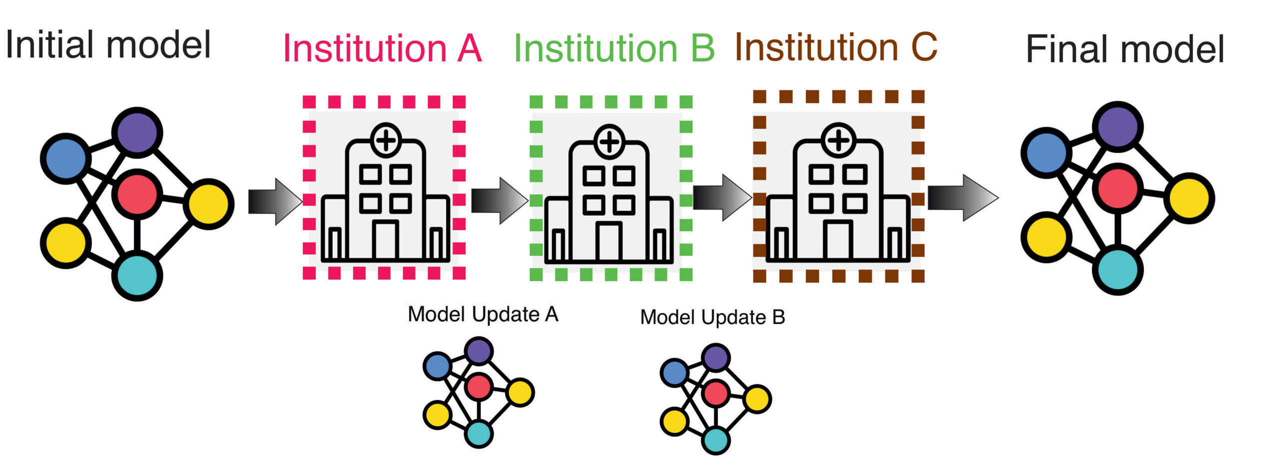

Figure 3. Single weight transfer

Results

The initial results of segmentation were promising. The DICE score for brain MRI segmentation was 0.844 on local servers and 0.650 on VLP. These results are on par with current segmentation models [1], with the advantage of keeping data private and decentralized training with an extremely low communication load.

Figures 4 & 5 show sample outputs of FL models.

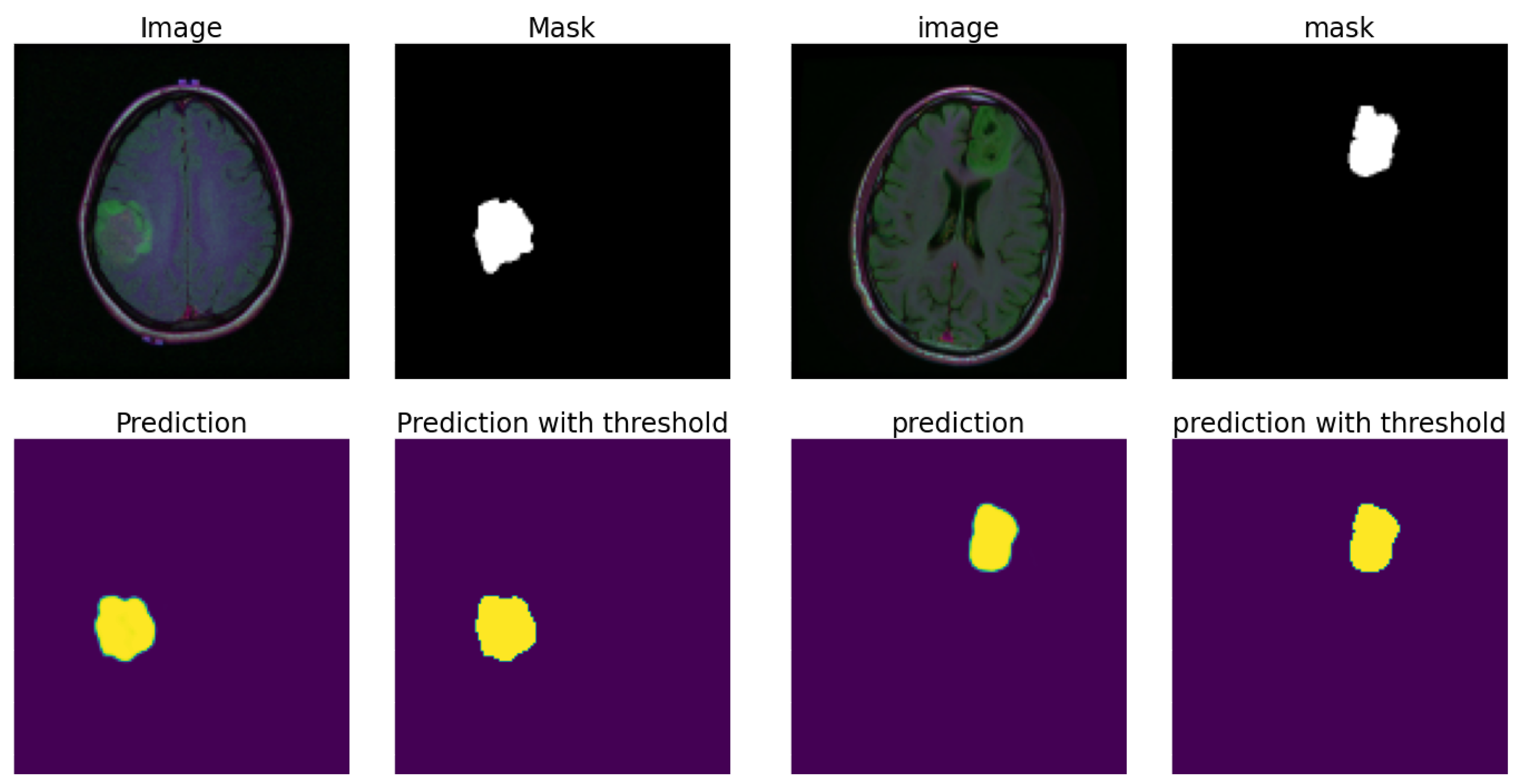

Figure 4. Brain MRI images of two patients with low-grade glioma. Sample output of CWT algorithm, and ground-truth segmentation masks.

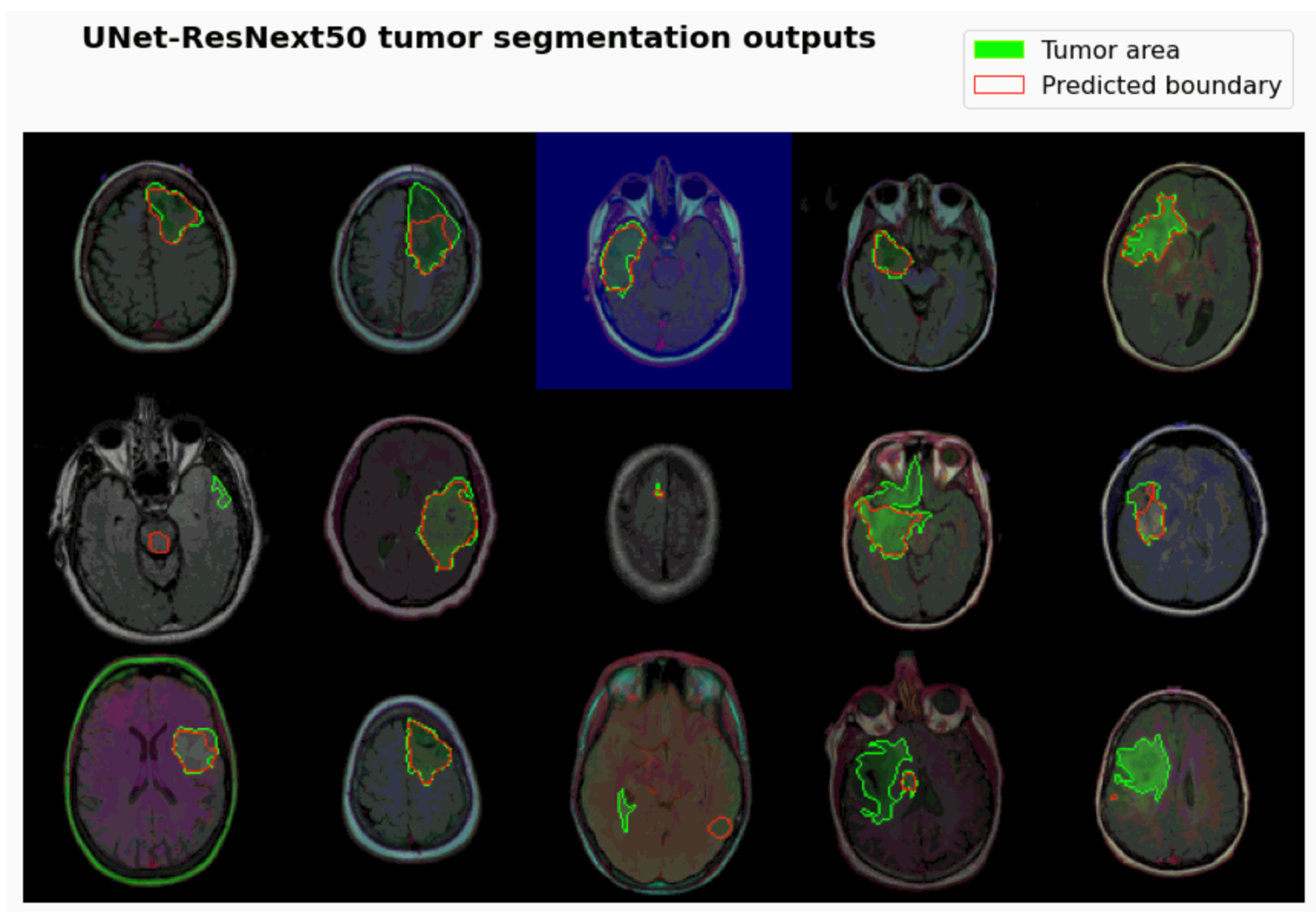

Figure 5. Sample outputs of CWT algorithm

Discussion and conclusion

A proof of concept of FL in segmentation was successfully done using VLP and local machines. For FL algorithms to be implemented in real-world practice, further improvements are required to address current issues in FL, such as domain shift, security/privacy, and bias.

References

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