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Whole-brain radiomics for clustered federated personalization in brain tumor segmentation

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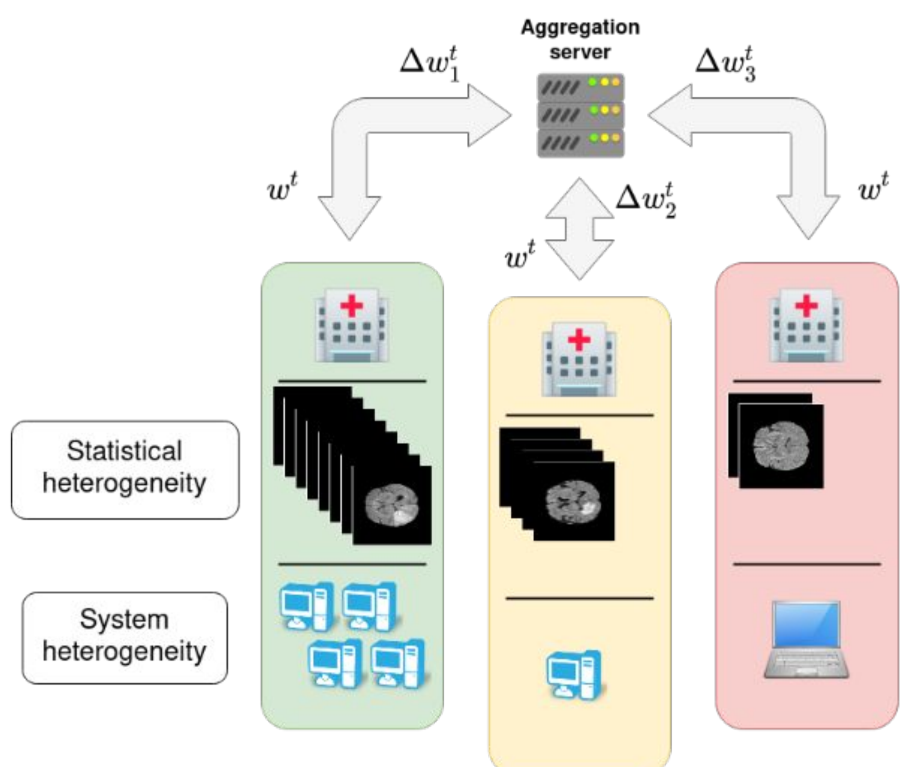
Motivation

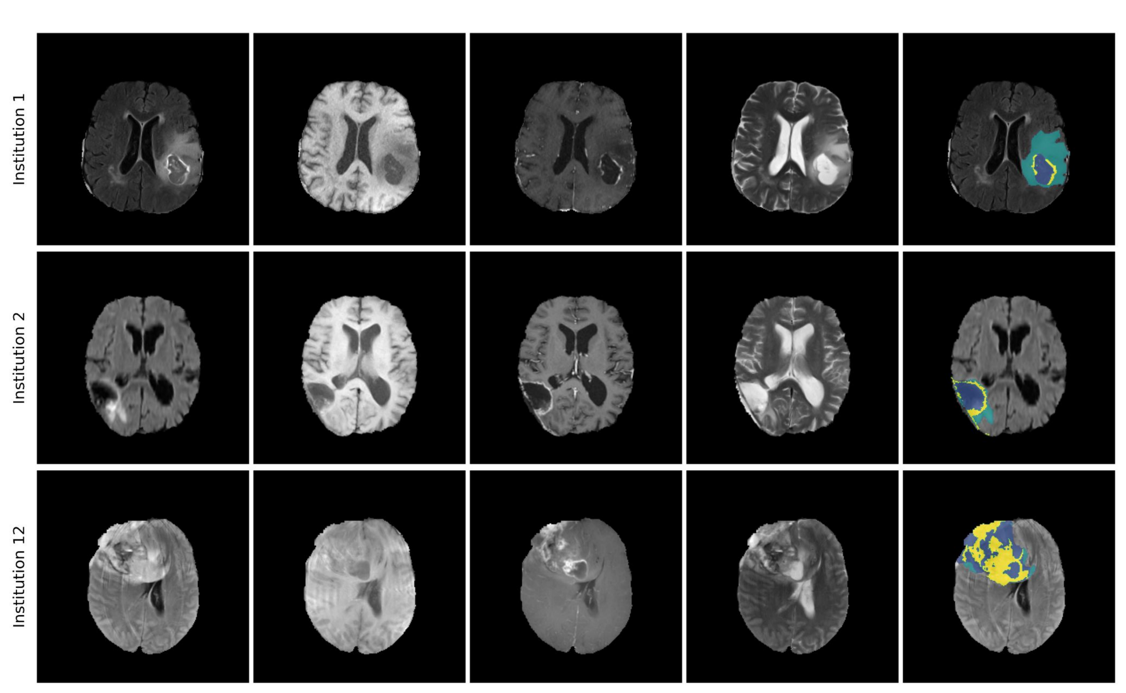
- Federated learning (FL) enables to efficiently train deep neural models on large decentralized datasets without sharing raw data between health institutions,



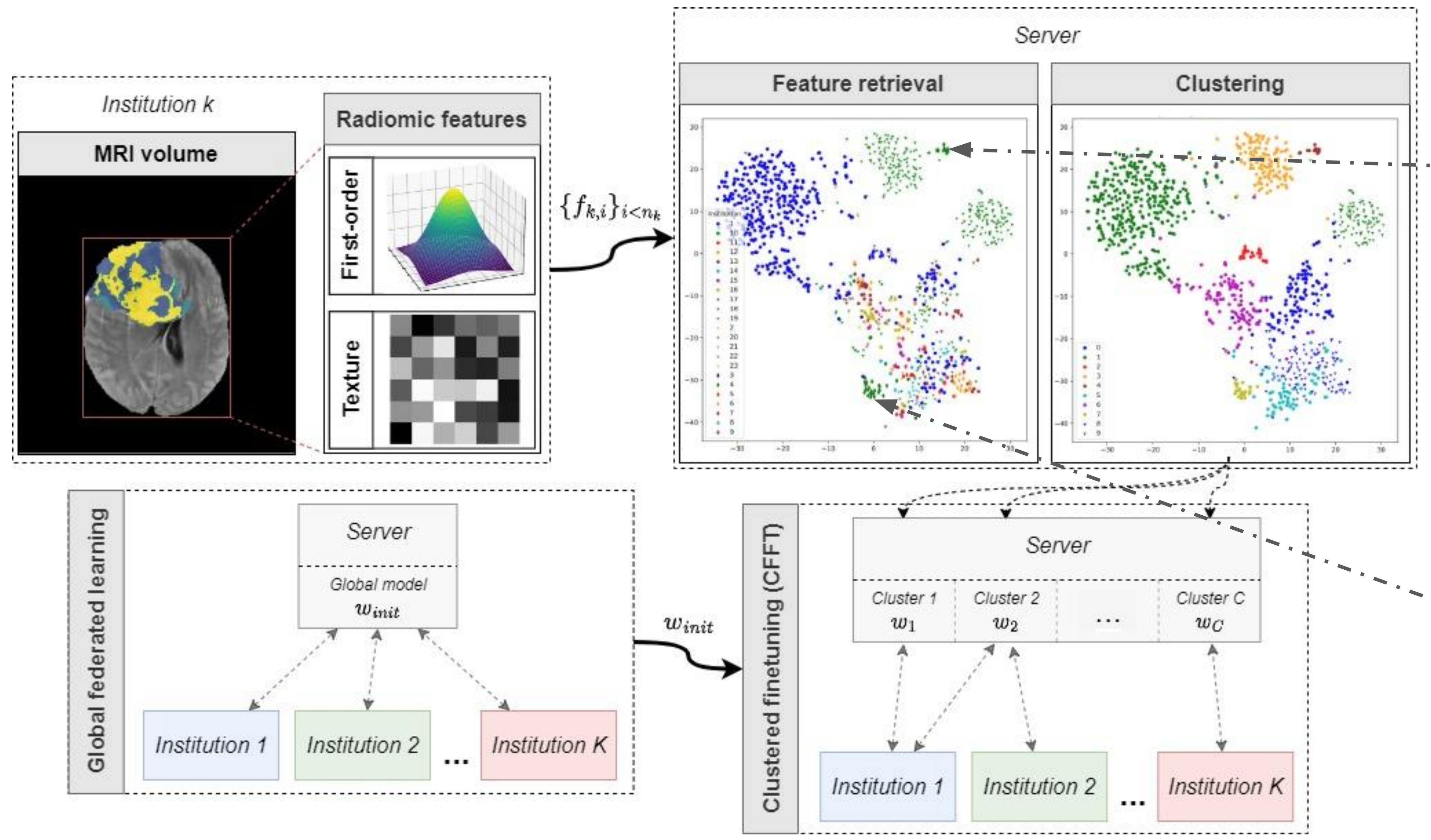
- It underperforms with statistically heterogeneous distributed data,
- Personalization methods mostly assume local datasets homogeneity, hardly true in realistic cases,
- Clustered FL is particularly interesting in case of limited amount of data per institution.

Brain tumor segmentation

- **Dataset :** Federated Brain Tumor Segmentation 2022 (**FeTS2022**[10]),
- **Input :** 1251 3D *T1*, *T1ce*, *T2*, *FLAIR* brain MRIs.
- **Task :** Multi-label brain tumor segmentation : Enhancing tumor (***ET***), Tumor core (***TC***) and Whole tumor (***WT***),
- **Partitioning :** original 23 clinical institutions (*~61% with less than 15 samples*),
- **Model :** 3D U-Net *(~1.4M parameters)*.



Clustered Federated Finetuning (CFFT)



- Each institution extracts ***intensity*** (median, energy, …) and ***texture*** (GLCM, GLRLM, …) metrics from each of its volumes : **93 features** per modality and volume.
- The server performs standard clustering on the features of every institution : **feature normalization ⇨ PCA ⇨ GMM**
- After several rounds of standard FL (such as FedAvg), the server performs federated trainings in parallel on the C clusters of decentralized data, based on the following **sample-level clustered federated objective with C clusters**

$$\{w_c^*\}_{c=1}^C = \underset{\{w_c\}_{c=1}^C \in \mathcal{W}^C}{argmin} \sum_{k=1}^K \sum_{i=1}^{n_k} l(w_{Cluster(\hat{f}_{k,i})}, x_{k,i}, y_{k,i})$$

Segmentation performance

Dice

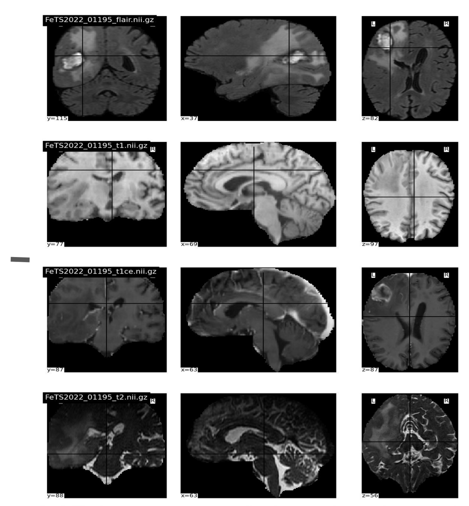
Training algorithm	Average	TC	WT	ET
Centralized	0.8912 ± 0.1201	0.8896 ± 0.1878	0.9188 ± 0.0859	0.8651 ± 0.1956
FedAvg	0.8803 ± 0.1414	0.8722 ± 0.2251	0.9099 ± 0.0906	0.8588 ± 0.2005
Local finetuning	0.8879 ± 0.1202	0.8876 ± 0.1863	0.9132 ± 0.0891	0.8629 ± 0.1960
CFFT_{ideal}	0.8887 ± 0.1239	0.8867 ± 0.1891	0.9139 ± 0.0892	0.8654 ± 0.1960
CFFT	0.8874 ± 0.1254	0.8799 ± 0.2056	0.9120 ± 0.0907	0.8704 ± 0.1852

95% Hausdorff distance

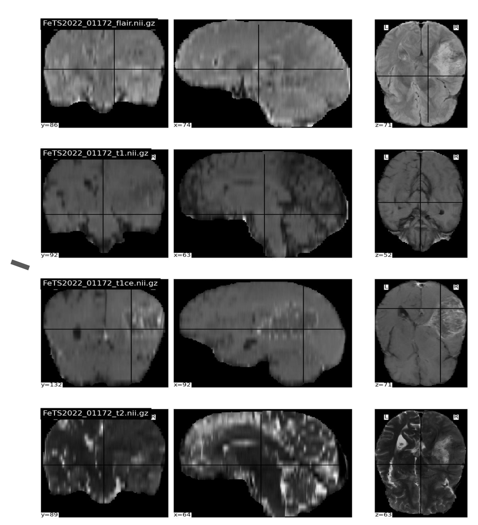
Training algorithm	Average	TC	WT	ET
Centralized	5.1348 ± 6.2212	4.4407 ± 7.2052	7.0318 ± 11.0671	3.7770 ± 8.5314
FedAvg	5.8854 ± 7.7368	4.7745 ± 8.0444	8.8814 ± 15.9499	3.7091 ± 7.6837
Local finetuning	5.9334 ± 7.9817	4.8587 ± 9.3901	8.9284 ± 16.3270	3.5861 ± 7.5650
CFFT_{ideal}	5.5915 ± 7.2588	4.6436 ± 7.3390	8.3688 ± 15.3738	3.5383 ± 7.5576
CFFT	5.8749 ± 7.6108	4.7359 ± 7.4458	8.8709 ± 16.4791	3.6520 ± 7.6291

CFFT matches the performance of other personalization methods while focusing only on the feature shift.

Clustering analysis

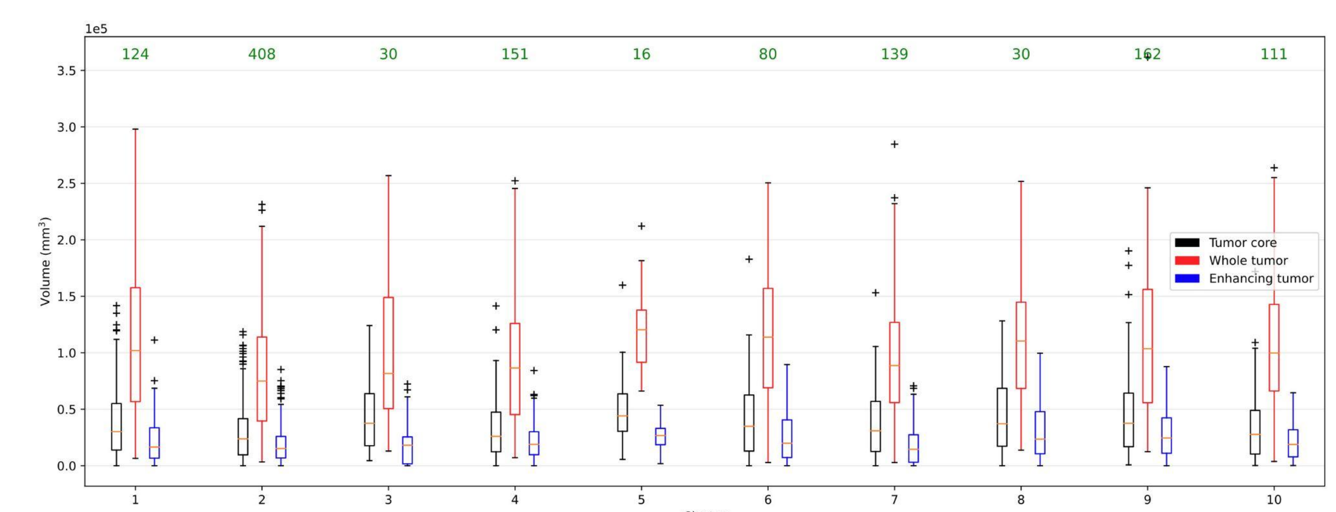


MRI exam of institution 4 assigned to cluster 4



MRI exam of institution 4 assigned to cluster 7

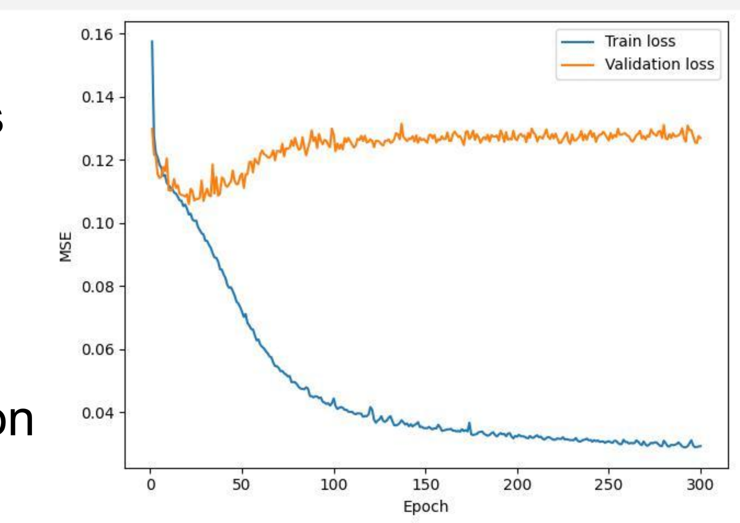
- Volumes from a single institution can have very different appearance.
- They are placed in different clusters, with volumes of other institutions of similar appearance,
- Label distributions are a lot more alike between clusters than between institutions.

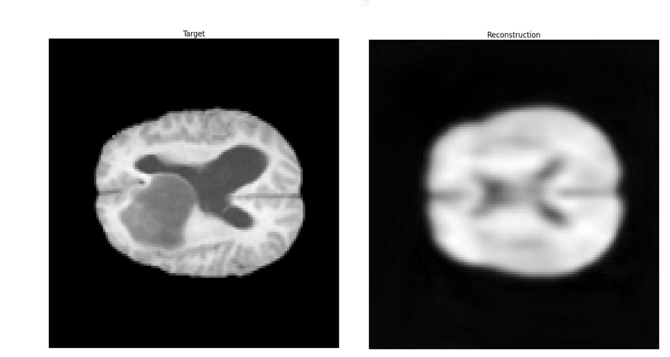


Label distribution per computed cluster

Basic privacy validation

- Sample-level federated clustering requires communicating features for each sample, risking sensitive information leakage.
- **Attack setup** : train a neural network to reconstruct a subsampled volume based on its radiomic features.
- **Results** : Quick overfitting, feature vectors contain only global textural information, tumorous parts are completely withdrawn from the reconstructions.





Conclusion and future work

- The standard personalized federated learning assumption of local datasets homogeneity is too idealistic,
- The isolation of the feature shift in radiomic embeddings and clustered federated finetuning do improve the segmentation performance compared to FedAvg,
- We will explore more complex and rich embeddings to further improve the convergence of federated algorithms on each cluster.

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