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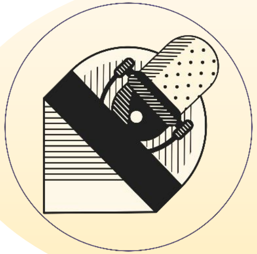
Topic: Enhancing Parallelism in Cross-silo Federated Learning for Brain Disease Classification



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Outline of Presentation

- Introduction
- Literature Review
- Methodology
  - Proposed Work
- Result and Discussion
- Conclusion
- Reference

Introduction

Major Problem of Centralized Learning

- Inability to protect subject's data confidential.
- Aggregate all the data in a place.

How to overcome this hurdle?

- Federated Learning

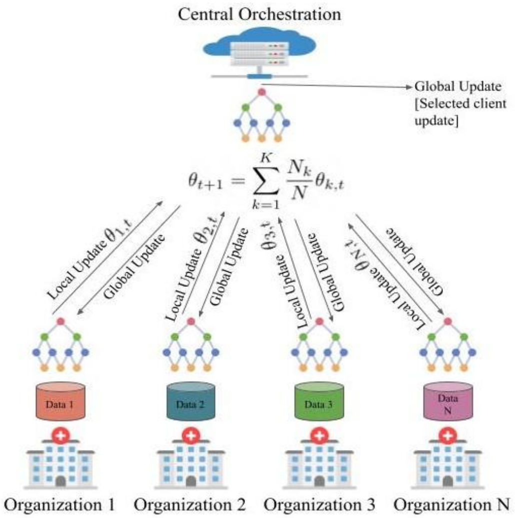

Figure 1: Mechanism of Federated Learning.

Introduction (Cont'd)

Alzheimer's disease

- Alzheimer's is caused by damage to nerve cells (neurons) in the brain.
- 55 million in 2019 – is expected to rise to 139 million in 2050 globally.
- According to Alzheimer's disease facts and figures 2023, In USA every 1 in 3 seniors die of Alzheimer's or another dementia.

Figure 2: Impact of Alzheimer's disease[1].

[1] Source: https://www.buoyhealth.com/learn/is-dementia-hereditary

Introduction (Cont'd)

Brain tumor

- Brain tumor is a caused by growth of abnormal cells in the brain.
- Example of source of cancerous or malignant tumor is olfactory neuroblastoma, chondrosarcoma and medulloblastoma.
- About 78% of cancerous primary brain tumors are gliomas[1].

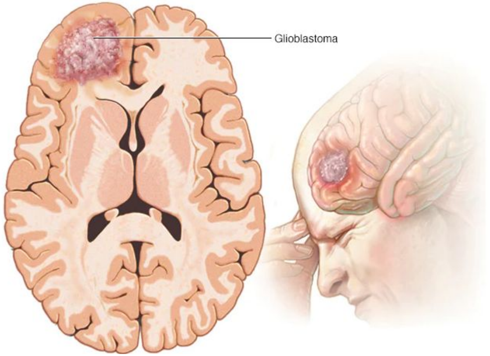

Figure 3: Glioblastoma Brain Tumor[1].

[1] Source: https://my.clevelandclinic.org/health/diseases

Introduction (Cont'd)

Objectives

- This paper mainly utilizes the increasing parallelism method of FL for the classification of brain diseases.
- We investigate the minimum number of client participants required to achieve a standard performance in cross-silo FL.
- We employ the simple but effective LeNet5 CNN model, and also focus on performance improvement by considering numerous metrics.

Literature Review

Summarization of prior Alzheimer’s disease classification papers

Type	Data	Ref.	Model	Performance	Year
Federated	MRI	[3]	CNN	Acc = 0.86, pre = 0.81, rec = 0.81, and f1=0.81	2022
Federated	MRI	[4]	CNN	Acc = 0.92, rec = 1.0, spec = 0.91	2021
Centralized	EEG	[5]	SVM, LR, KNN, DT	Sen = 0.99, spec = 1.0, f1 = 0.98 using 10-fold CV	2022
Centralized	EEG	[6]	ELM, SVM, KNN	Acc = 0.99, pre = 1.0, rec = 0.98, and f1 = 0.99 using ELM.	2020
Centralized	EEG	[7]	SVM, LR	Acc = 0.88, rec = 0.85, spe = 95	2019
Centralized	MRI	[8]	CNN	Acc = 1.0 for fMRI, and acc = 0.99 for MRI.	2016
Centralized	MRI	[9]	SVM	Acc = 0.88, sen = 0.9, spe = 0.87, and AUC = .89	2016

Table 1: Summarization of prior Alzheimer’s disease classification papers.

Literature Review (Cont'd)

Summarization of prior brain tumor classification papers

Type	Data	Ref.	Model	Performance	Year
Federated	MRI	[12]	CNN	Acc = 0.95, pre = 0.97, rec = 0.96, and f1=0.94	2022
Centralized	MRI	[13]	UNet, Markov M.	Acc train = 0.91, acc test = 0.92 using U-Net.	2020
Centralized	EEG	[14]	VGGNet, AlexNet,GoogleNet	Acc = 0.99 max by using VGGNet.	2020
Centralized	EEG	[15]	CNN	Acc train = 0.99 and acc valid = 0.84.	2019
Centralized	EEG	[16]	Caps-Net	Acc = 0.87	2019
Centralized	MRI	[17]	CNN	Acc = 0.91 and rec = 0.88, 0.81, 0.99 for the detection of Meningioma, glioma, and pituitary tumor respectively.	2016
Centralized	MRI	[18]	SVM	Acc = 1.0 using RBF and polynomial kernel.	2016

Table 2: Summarization of prior brain tumor classification papers.

Literature Review (Cont'd)

Research gaps

- Centralized approaches aggregate all the training data dynamics in a place that's indicates it is unable to provide data confidentiality.
- Empirical analysis of privacy-preserving federated learning in Alzheimer's and Brain tumor classification.
- Performance improvement by considering numerous metrics for federated settings.

Methodology

Proposed work

- Parallelism in federated learning for brain disease classification.
- Minimum client participation for moderate or better performance.

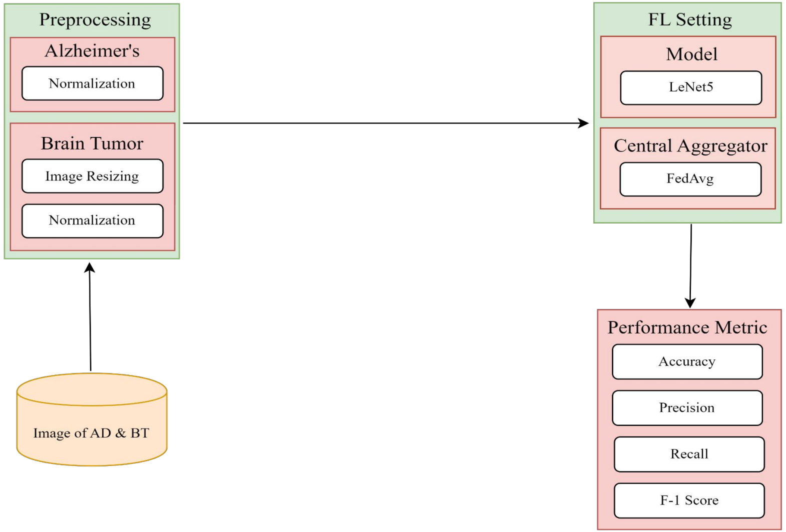

Figure 4: Overview diagram of this paper.

Methodology (Cont'd)

Datasets description

Type	Total	Trainset	Testset
Alzheimer's Disease	3200	2560	640
Healthy Control	3200	2560	640

Table 3: Description of Alzheimer's disease data.

Type	Total	Trainset	Testset
Glioma	1621	1297	324
Meningioma	1645	1316	329
Pituitary	1757	1406	351
Healthy Control	2000	1600	400

Table 4: Description of brain tumor data.

Methodology (Cont'd)

Dataset preprocessing

- Resizing
- Normalization

Classification model

- CNN (LeNet5)

Federated settings

- Cross-silo federated learning.
- 10 Clients.
- Central aggregator FedAvg algorithm.
  - Working mechanism: weighted mean.

Evaluation metrics

- Accuracy
- Precision
- Recall
- F1-score

Result and Discussion

Findings of Alzheimer's disease classification

Client	Optimizer	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
0.1	Adam	77.12%	82.19%	82%	82%	82%
0.2	Adam	79.81%	82.42%	83%	82%	82%
0.3	Adam	82.88%	83.36%	84%	83%	83%
0.7	Adam	89.81%	80.69%	85%	85%	85%
0.8	Adam	81.73%	80.94%	81%	81%	81%
0.9	Adam	78.46%	77.79%	78%	77%	77%
1.0	Adam	86.15%	85%	85%	85%	85%

Client	Optimizer	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
0.1	SGD	91.35%	90.94%	91.0%	91.0%	91.0%
0.2	SGD	95.0%	93.67%	94.0%	94.0%	94.0%
0.3	SGD	96.15%	93.52%	94.0%	94.0%	94.0%
0.7	SGD	88.08%	92.73%	93.0%	93.0%	93.0%
0.8	SGD	91.73%	93.98%	94.0%	94.0%	94.0%
0.9	SGD	95.96%	95.23%	95.0%	95.0%	95.0%
1.0	SGD	96.16%	95%	95%	95%	95%

Table 5: Findings of Alzheimer's disease classification.

Result and Discussion (Cont'd)

Visualization of Alzheimer's disease findings

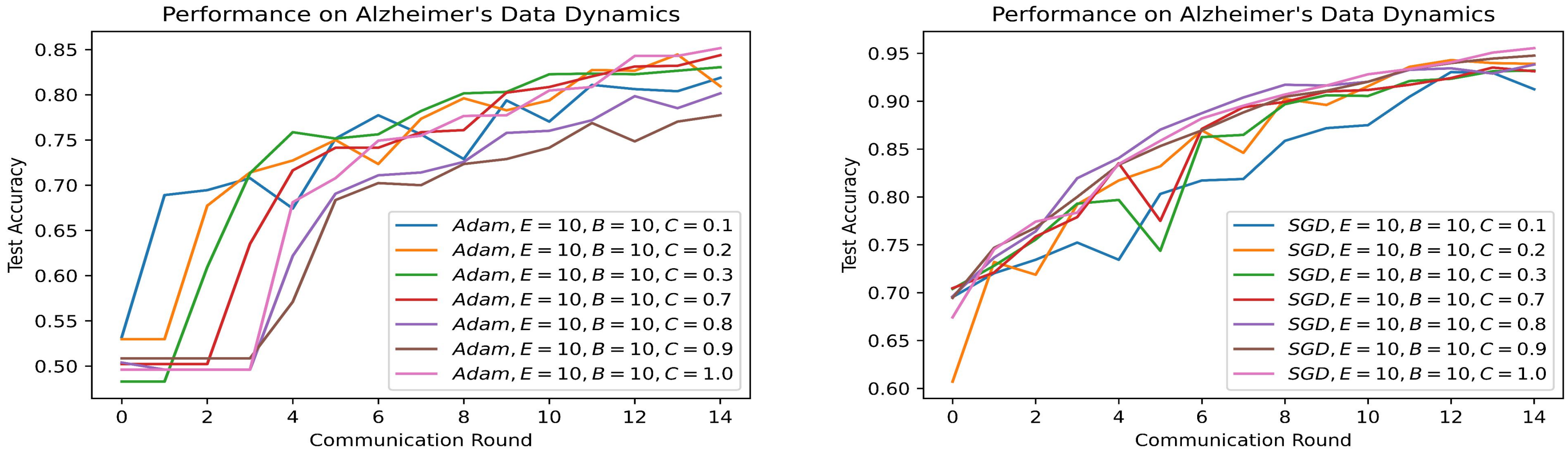

Figure 5:Visualization of Alzheimer's disease findings.

Result and Discussion (Cont'd)

Performance comparison for Alzheimer's disease classification

Type	Data	Ref.	Model	Performance	Year
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Our Proposed	MRI	-	LeNet5	Acc = 0.95, pre = 0.95, rec = 0.95, f1 = 0.95	2024
Centralized	EEG	[5]	SVM, LR, KNN, DT	Sen = 0.99, spec = 1.0, f1 = 0.98 using 10-fold CV	2022
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Table 6:Performance comparison for Alzheimer's disease classification.

Result and Discussion (Cont'd)

Findings of brain tumor classification

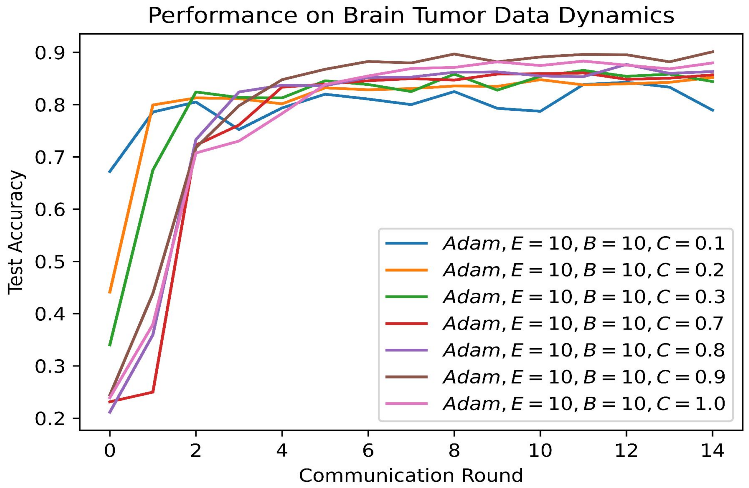
Client	Optimizer	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
0.1	Adam	69.47%	79.15%	79%	79%	78%
0.2	Adam	89.30%	84.27%	84%	84%	84%
0.3	Adam	85.79%	84.34%	85%	84%	84%
0.7	Adam	88.42%	85.62%	86%	86%	86%
0.8	Adam	87.72%	85.91%	86%	86%	86%
0.9	Adam	90.18%	89.68%	90%	90%	90%
1.0	Adam	87.89%	87.97%	88%	88%	88%

Client	Optimizer	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
0.1	SGD	91.93%	92.95%	93.0%	93.0%	93.0%
0.2	SGD	94.56%	93.67%	94.0%	94.0%	94.0%
0.3	SGD	91.93%	94.52%	95.0%	95.0%	95.0%
0.7	SGD	91.23%	93.45%	93.0%	93.0%	94.0%
0.8	SGD	96.67%	94.66%	95.0%	95.0%	95.0%
0.9	SGD	87.71%	94.38%	94.0%	94.0%	94.0%
1.0	SGD	88.42%	94.38%	95%	95%	95%

Table 7: Findings of brain tumor classification.

Result and Discussion (Cont'd)

Visualization of brain tumor findings



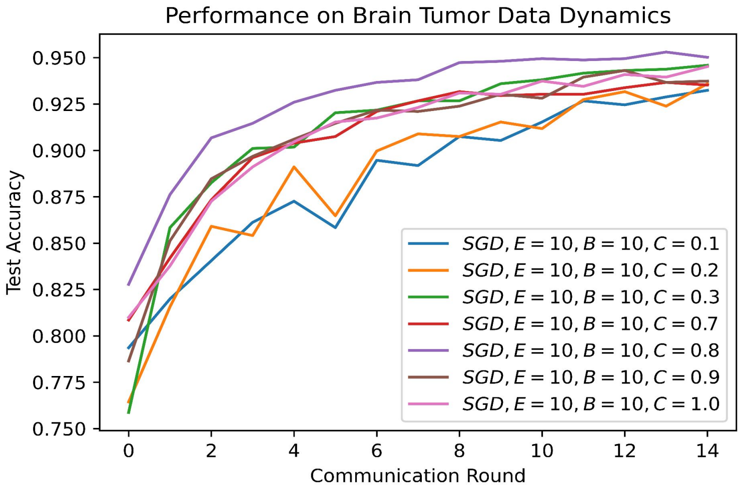


Figure 6:Visualization of brain tumor findings.

Result and Discussion (Cont'd)

Performance comparison for brain tumor classification

Type	Data	Ref.	Model	Performance	Year
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Our Proposed	MRI	-	LeNet5	Acc = 0.95, pre = 0.95, rec = 0.95, f1 = 0.95	2024
Centralized	MRI	[13]	UNet, Markov M.	Acc train = 0.91, acc test = 0.92 using U-Net.	2020
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Table 8: Performance comparison of brain tumor classification.

Conclusion

The key points to conclude are listed below:

- The LeNet5 model, with the Adam and SGD optimizers, achieves an average of 95% accuracy, precision, recall, and F1 score for Alzheimer's disease classification with 90% and 100% client participation.
- For brain tumor classification, a mean accuracy of 94.66%, and precision, recall, and F1 score of 95% are achieved using the LeNet5 with SGD optimizer.
- About a minimum of 20% of client participation is required to achieve a moderate or better result in case of balanced or mostly balanced dataset.

Conclusion (Cont'd)

The following are considered for future advancement:

- secure communication of model parameters.
- Communication round minimization.

References

1. Stripelis, D., Gupta, U., Saleem, H., Dhinagar, N., Ghai, T., Sanchez, R., Anastasiou, C., Asghar, A., Steeg, G.V., Ravi, S. and Naveed, M., 2022. Secure Federated Learning for Neuroimaging. *arXiv preprint arXiv:2205.05249*.
2. Huang, Y.L., Yang, H.C. and Lee, C.C., 2021, November. Federated Learning via Conditional Mutual Learning for Alzheimer's Disease Classification on T1w MRI. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 2427-2432). IEEE.
3. Movahed, R.A. and Rezaeian, M., 2022. Automatic Diagnosis of Mild Cognitive Impairment Based on Spectral, Functional Connectivity, and Nonlinear EEG-Based Features. *Computational and Mathematical Methods in Medicine*, *2022*.
4. Siuly, S., Alçin, Ö.F., Kabir, E., Şengür, A., Wang, H., Zhang, Y. and Whittaker, F., 2020. A new framework for automatic detection of patients with mild cognitive impairment using resting-state EEG signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *28*(9), pp.1966-1976.
5. Durongbhan, P., Zhao, Y., Chen, L., Zis, P., De Marco, M., Unwin, Z.C., Venneri, A., He, X., Li, S., Zhao, Y. and Blackburn, D.J., 2019. A dementia classification framework using frequency and time-frequency features based on EEG signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(5), pp.826-835.
6. Lee, B., Lee, T., Jeon, H., Lee, S., Kim, K., Cho, W., Hwang, J., Chae, Y.W., Jung, J.M., Kang, H.J. and Kim, N.H., 2022. Synergy through integration of wearable EEG and virtual reality for mild cognitive impairment and mild dementia screening. *IEEE Journal of Biomedical and Health Informatics*, *26*(7), pp.2909-2919.
7. Talo, M., Yildirim, O., Baloglu, U.B., Aydin, G. and Acharya, U.R., 2019. Convolutional neural networks for multi-class brain disease detection using MRI images. *Computerized Medical Imaging and Graphics*, *78*, p.101673.
8. Mahlool, D.H. and Abed, M.H., 2022. Distributed brain tumor diagnosis using a federated learning environment. *Bulletin of Electrical Engineering and Informatics*, *11*(6), pp.3313-3321.
9. Tairi, H., 2020, June. Segmentation of medical images for the extraction of brain tumors: A comparative study between the Hidden Markov and Deep Learning approaches. In *2020 International Conference on Intelligent Systems and Computer Vision (ISCV)* (pp. 1-5). IEEE.
10. Rehman, A., Naz, S., Razzak, M.I., Akram, F. and Imran, M., 2020. A deep learning-based framework for automatic brain tumors classification using transfer learning. *Circuits, Systems, and Signal Processing*, *39*, pp.757-775.
11. Abiwinanda, N., Hanif, M., Hesaputra, S.T., Handayani, A. and Mengko, T.R., 2019. Brain tumor classification using convolutional neural network. In *World Congress on Medical Physics and Biomedical Engineering 2018: June 3-8, 2018, Prague, Czech Republic (Vol. 1)* (pp. 183-189). Springer Singapore.
12. Afshar, P., Mohammadi, A. and Plataniotis, K.N., 2018, October. Brain tumor type classification via capsule networks. In *2018 25th IEEE international conference on image processing (ICIP)* (pp. 3129-3133). IEEE.
13. Milletari, F., Ahmadi, S.A., Kroll, C., Plate, A., Rozanski, V., Maiostre, J., Levin, J., Dietrich, O., Ertl-Wagner, B., Bötzel, K. and Navab, N., 2017. Hough-CNN: Deep learning for segmentation of deep brain regions in MRI and ultrasound. *Computer Vision and Image Understanding*, *164*, pp.92-102.
14. Hebli, A. and Gupta, S., 2017, December. Brain tumor prediction and classification using support vector machine. In *2017 international conference on advances in computing, communication and control (ICAC3)* (pp. 1-6). IEEE.

Thank You !

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