Cross-silo Federated Learning for Brain Disease Classification

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Presentation Outlines

1. Introduction
2. Literature Review
3. Analysis Design
4. Results and Discussions
5. Conclusion & Future Work
6. References

Introduction

Human Brain

- Brain operates as the body’s primary regulating center.
- About 86 billion neuron.

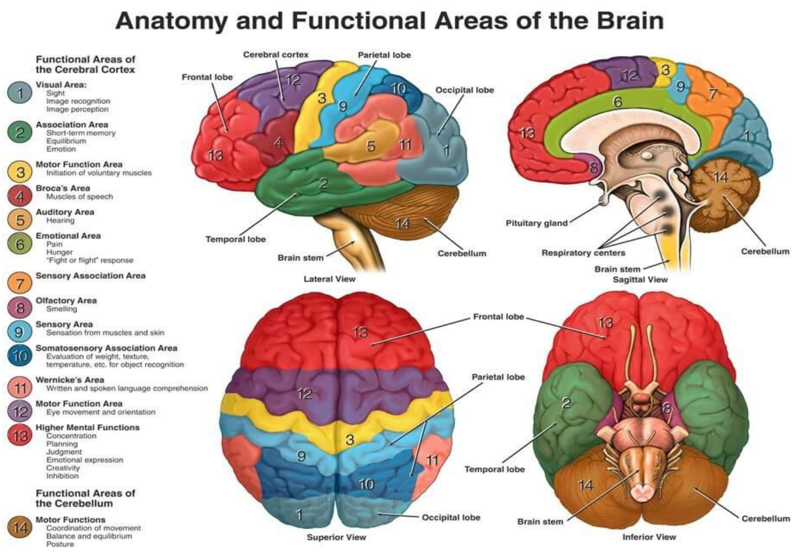


Figure-1.1: Functional areas of Brain

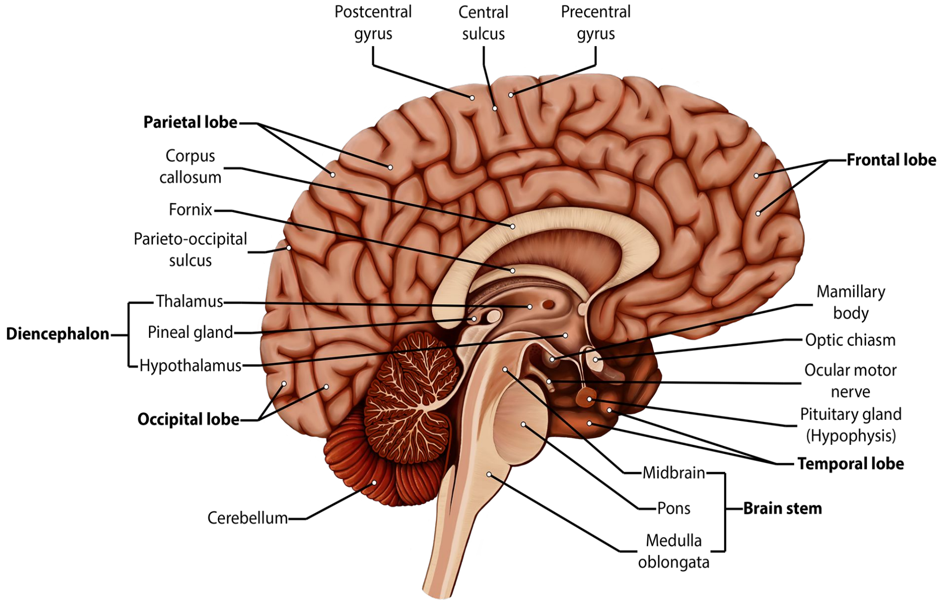


Figure-1.2: Structure of Brain

Image Courtesy: The Human Origin Project & Kind PNG.

Introduction Cont'd

Top 10 Leading Causes of Death:

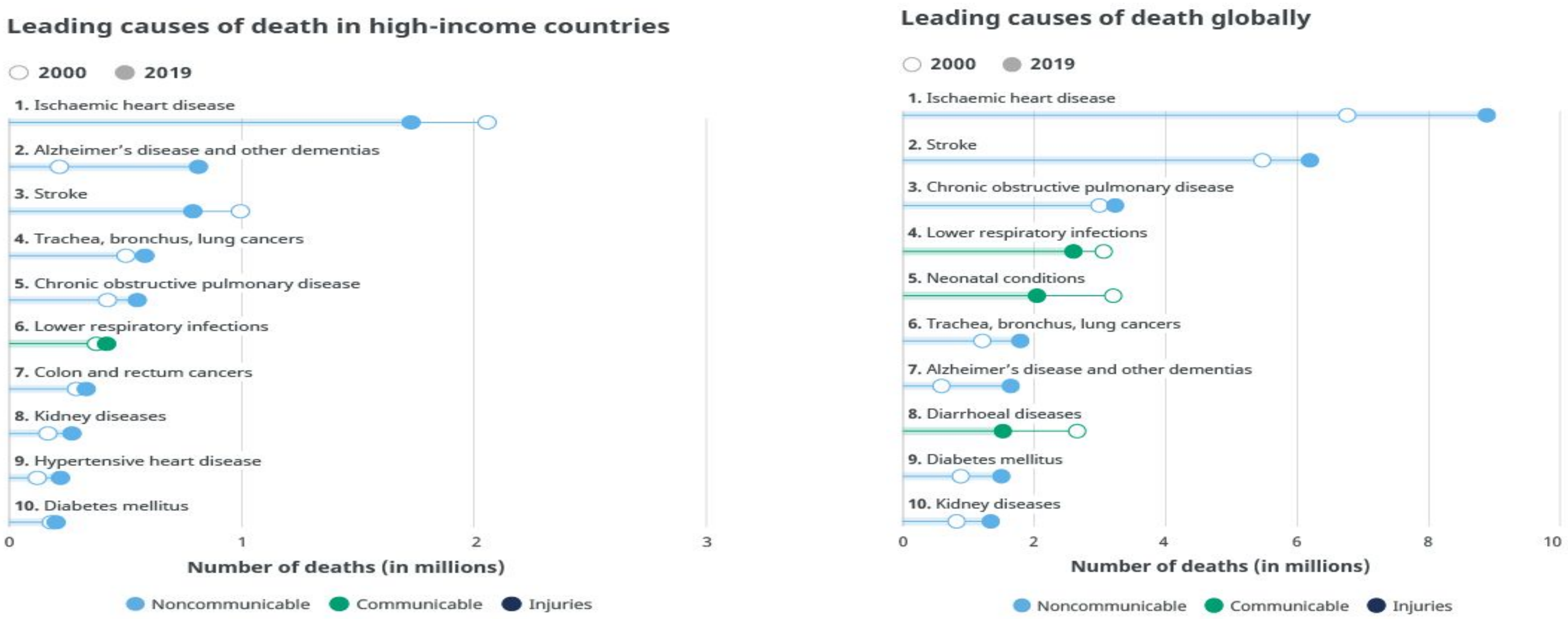


Figure-1.3: Leading cause of death (a) High-income country (b) Globally

Image Courtesy: WHO Global Health Estimates.

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.
- About 60-80% of all dementia are labeled as Alzheimer’s [1, 2].
- According to Alzheimer’s disease facts and figures 2023, In USA every 1 in 3 seniors die of Alzheimer’s or another dementia.

Figure-1.5: 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, chondrosar-coma and medulloblastoma.
- About 78% of cancerous primary brain tumors are gliomas[1].

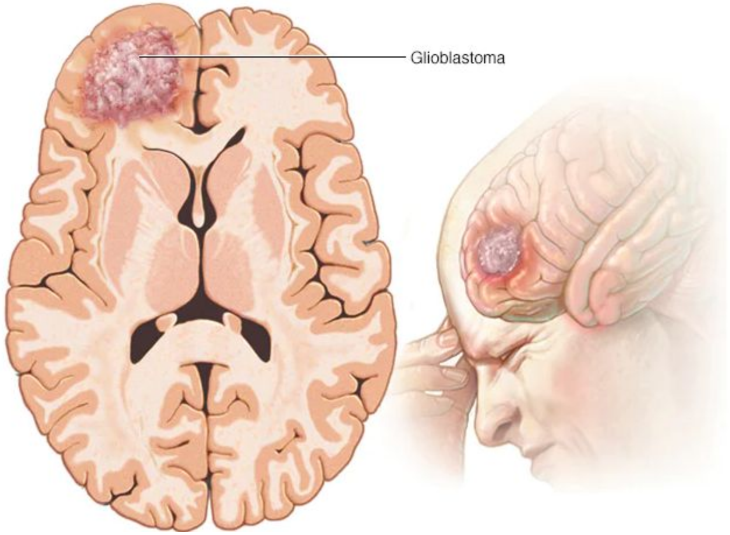


Figure-1.6: Glioblastoma Brain Tumor[1]

[1] Source: https://my.clevelandclinic.org/health/diseases/6149-brain-cancer-brain-tumor

Literature Review

Review findings of for Alzheimer’s disease classification

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
Centralized	EEG	[10]	SVM	Acc = 0.84 for EO, 0.97 for CT, and 0.72 for EC.	2014
Centralized	EEG	[11]	SVM	Acc = 0.84, rec = 0.75, and spe = 0.94	2013

Literature Review Cont'd

Review Findings for Brain Tumor classification

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

Literature Review Cont'd

Summary of the literature review

- Centralized approaches perform better for the detection and classification of both the diseases.

- Conducted Research based on privacy preserving federated learning is not well enough for the detection and classification of Alzheimer’s and Brain tumor.

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.
- Privacy preserving disease detection and classification is needed.
- Empirical analysis of privacy-preserving federated learning in Alzheimer’s and Brain tumor classification.
- Performance improvement by considering numerous metrics for federated settings.

Introduction Cont'd

Magnetic Resonance Imaging

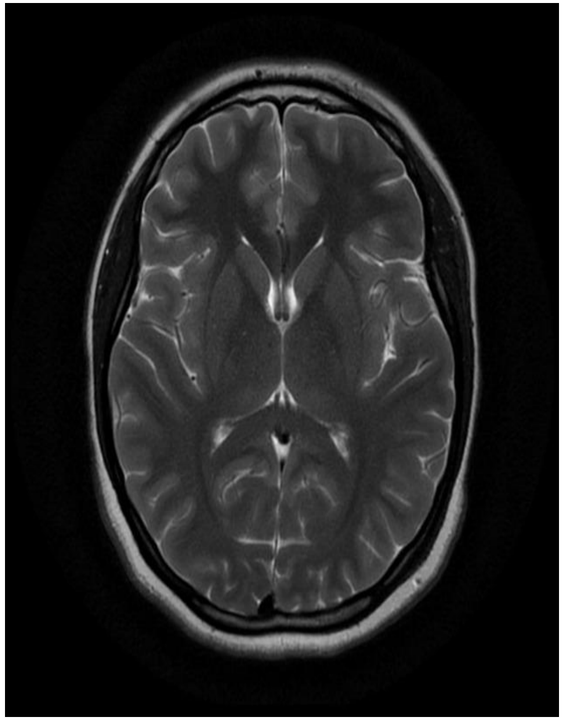


Figure-1.7: Healthy MRI

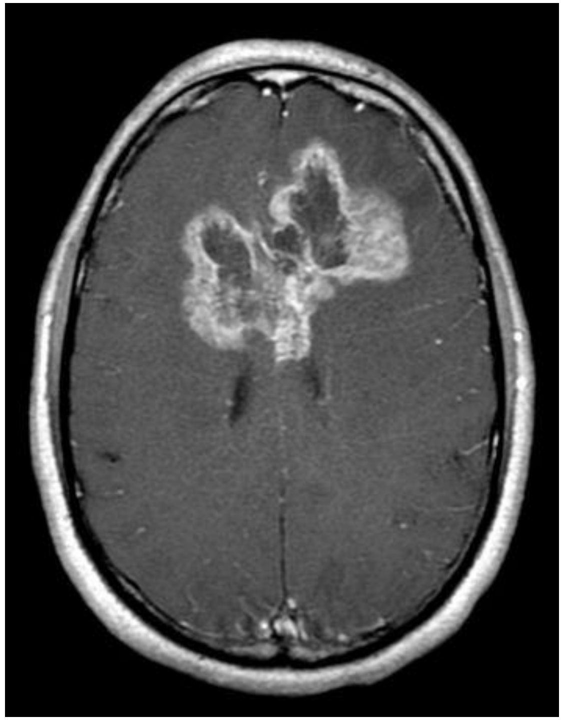


Figure-1.8: Glioblastoma MRI

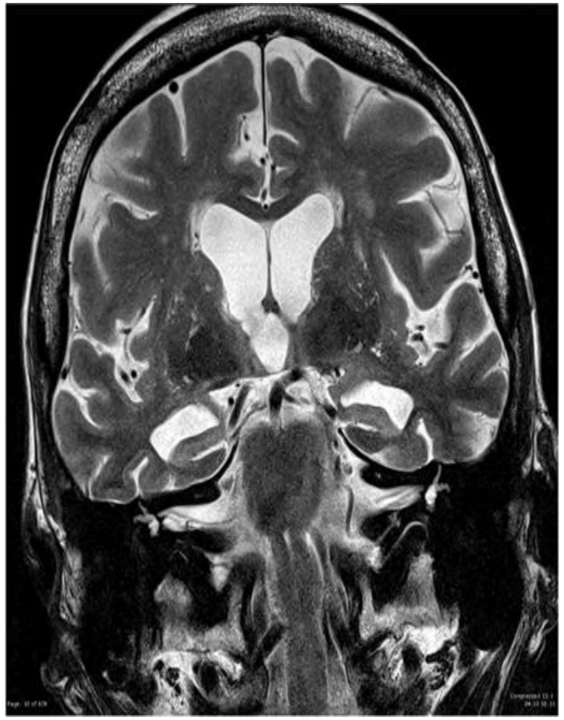


Figure-1.7: Alzheimer’s MRI

Image Courtesy: Google

Analysis Design

Aim and Objectives

- Federated learning based Alzheimer's and Brain tumor classification.
- Identify the participation of client's needed to achieve a better performance.

Analysis Design

- Cross-silo federated learning.
- Central aggregator FedAvg algorithm.
- LeNet5 as a classification model.
- Performance evaluation.

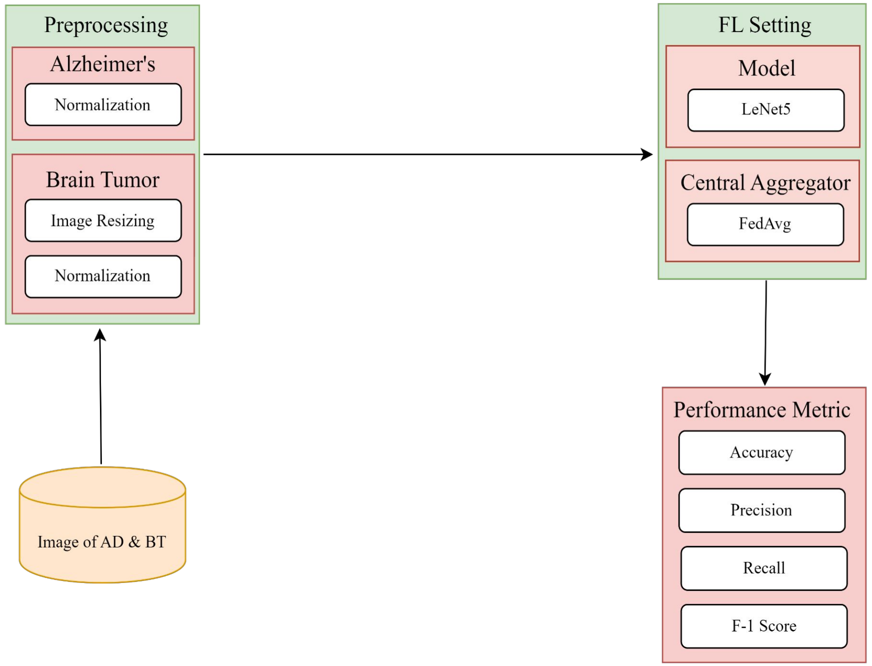


Figure-3.1: Overview Diagram

Analysis Design Cont'd

Dataset Description

- **Alzheimer's Dataset:** Binary classification.

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

- **Brain Tumor:** Multi-class classification.

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

Analysis Design Cont'd

Dataset Preprocessing

- Resizing.
- Normalization.

Results and Discussions

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%

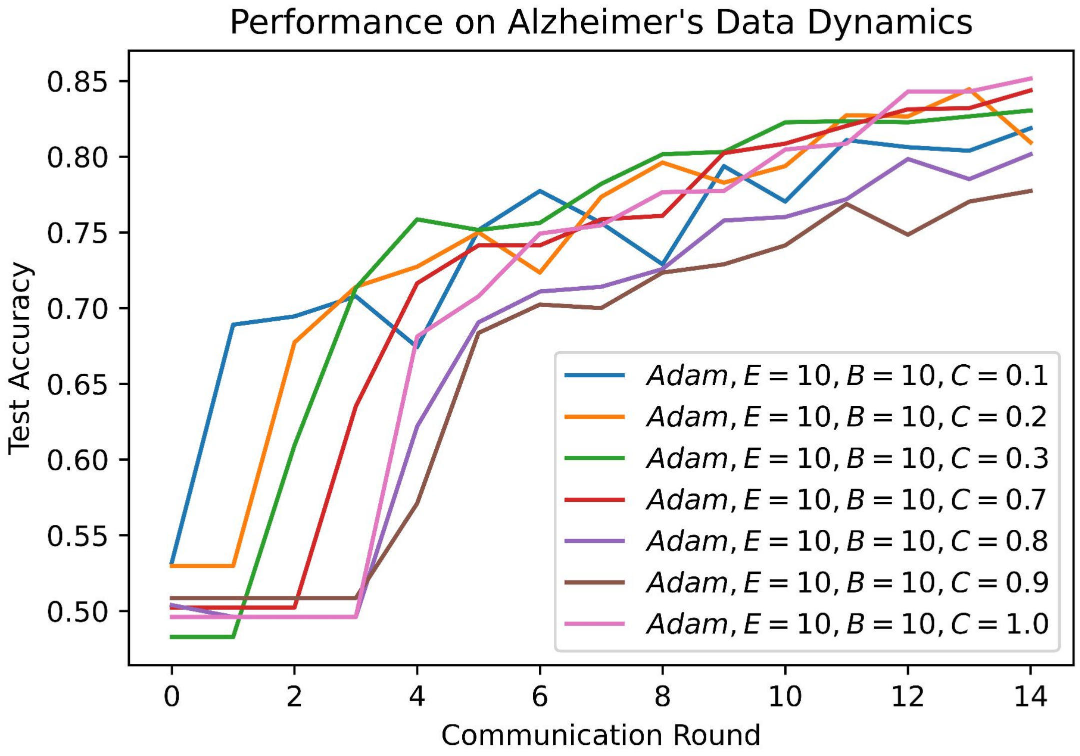
Results and Discussions Cont'd

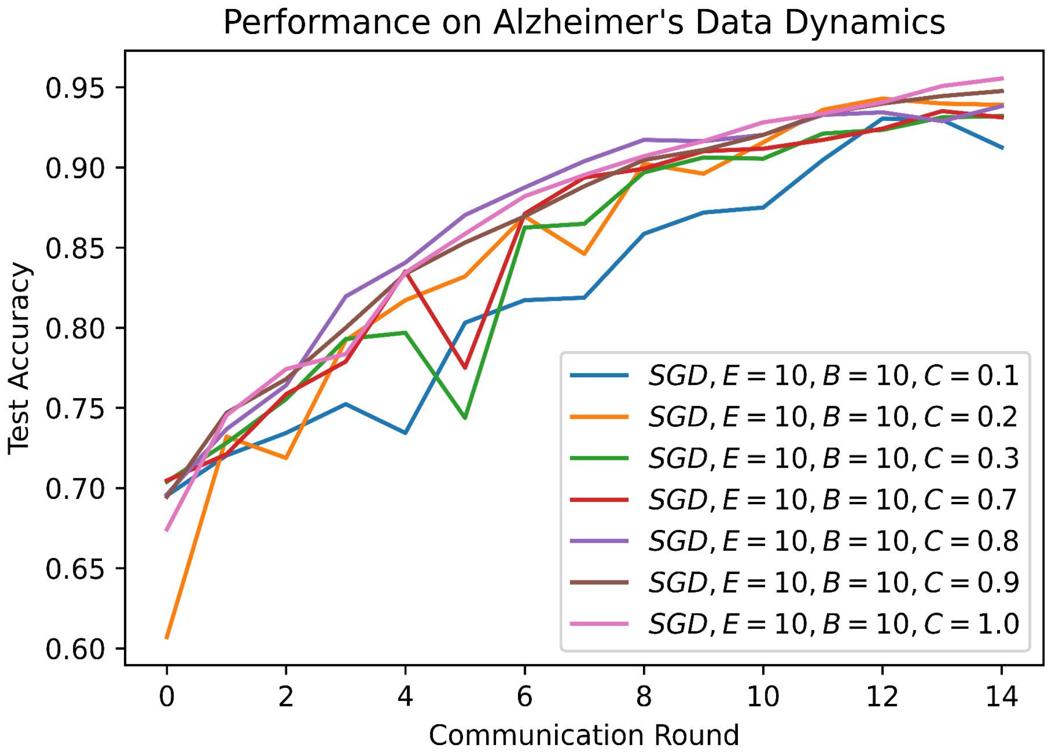
Findings of Alzheimer’s Disease Classification

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%

Results and Discussion Cont'd

Visualization of Alzheimer’s Disease Findings





Results 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%

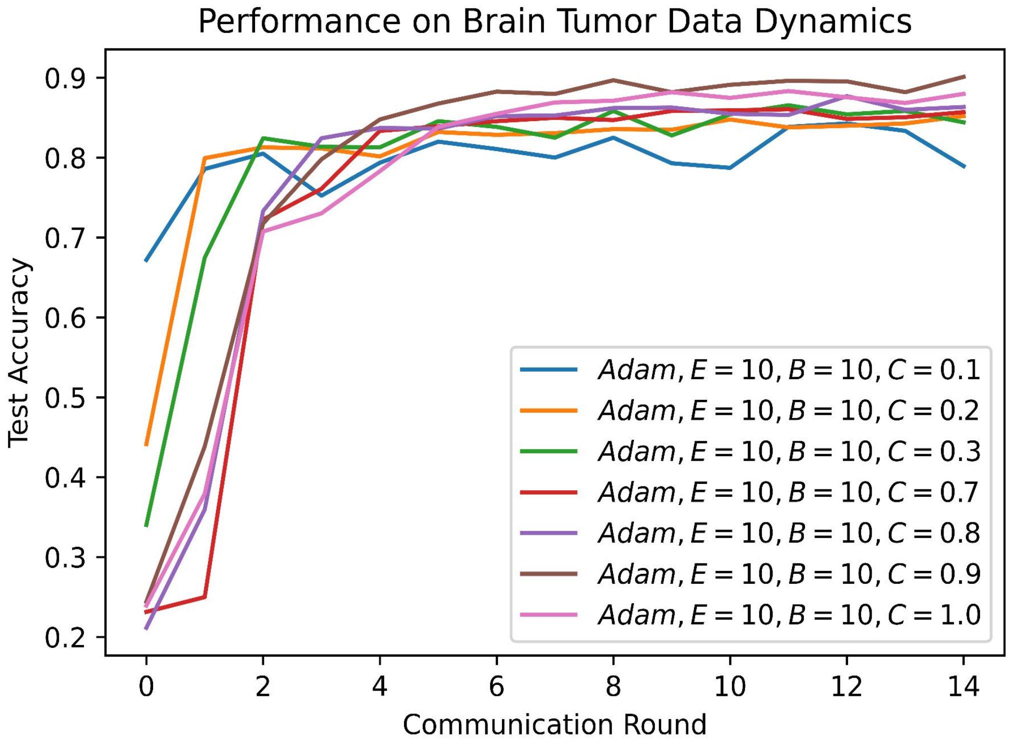
Results and Discussion Cont'd

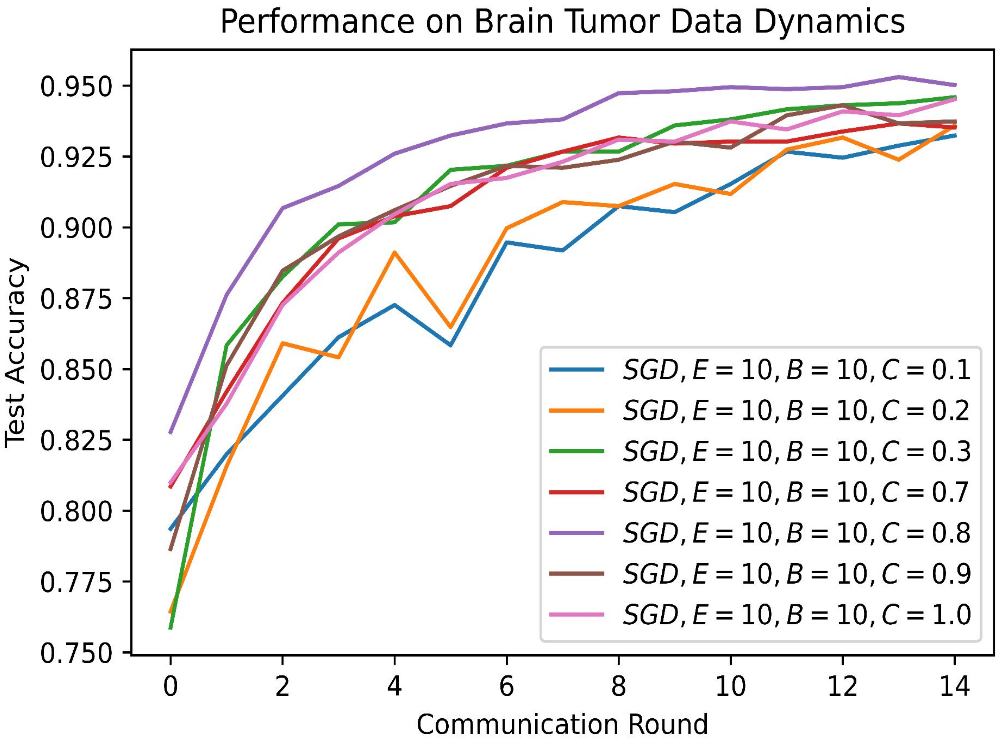
Findings of Brain Tumor Classification

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%

Results and Discussions Cont'd

Visualization of Brain Tumor Findings





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Our Prop.	MRI	-	LeNet5	Acc = 0.95, pre = 0.95, rec = 0.95, f1 = 0.95	2022
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Conclusion and Future Work

Conclusion

The key points to conclude is listed below:

- Better detection and classification performance.
- Percentage of client participation prediction to get optimal result is very hard.

Conclusion and Future Work Cont'd

Future Works

The following are considered for future advancement:

- Privacy-preserving communication of model parameters.
- Communication round minimization.

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Thank you
Warmly welcome any questions