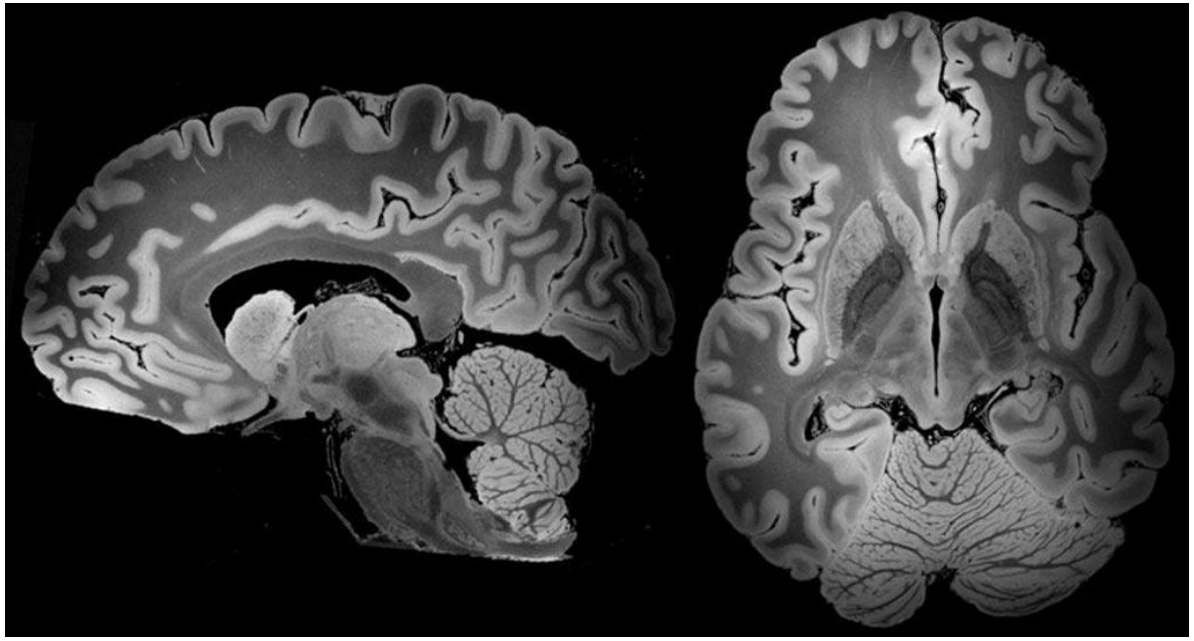
Image analysis

Problems we have faced

- Per each volume, we have ~8.7 million voxels
- GPU limits model size when using 3D models
- Even by leveraging on **pre-trained 3D** models, we face training limitations

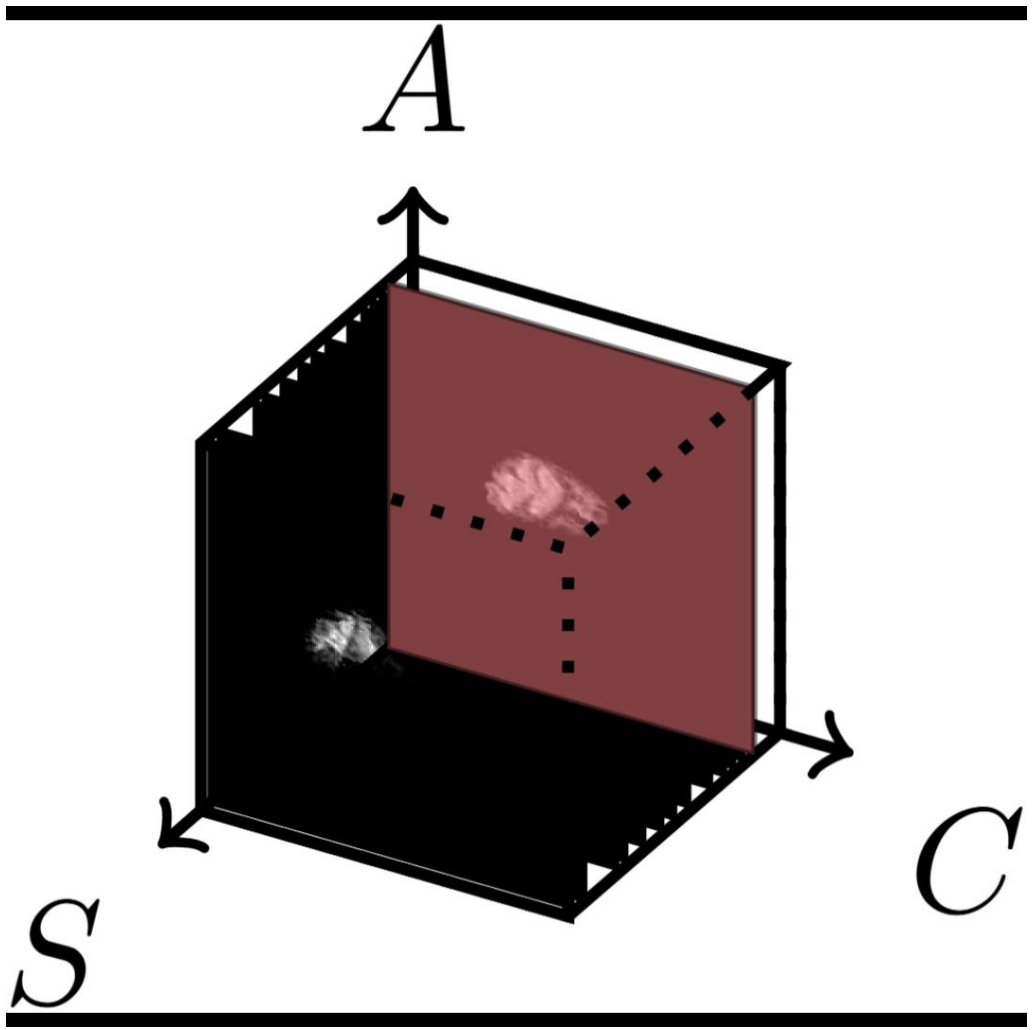
Objective

- Limit the size of our models using 2D variants
- By selecting **a subset of scans** that we call **slices**
- **But which slice to select?**



Which scans to select?

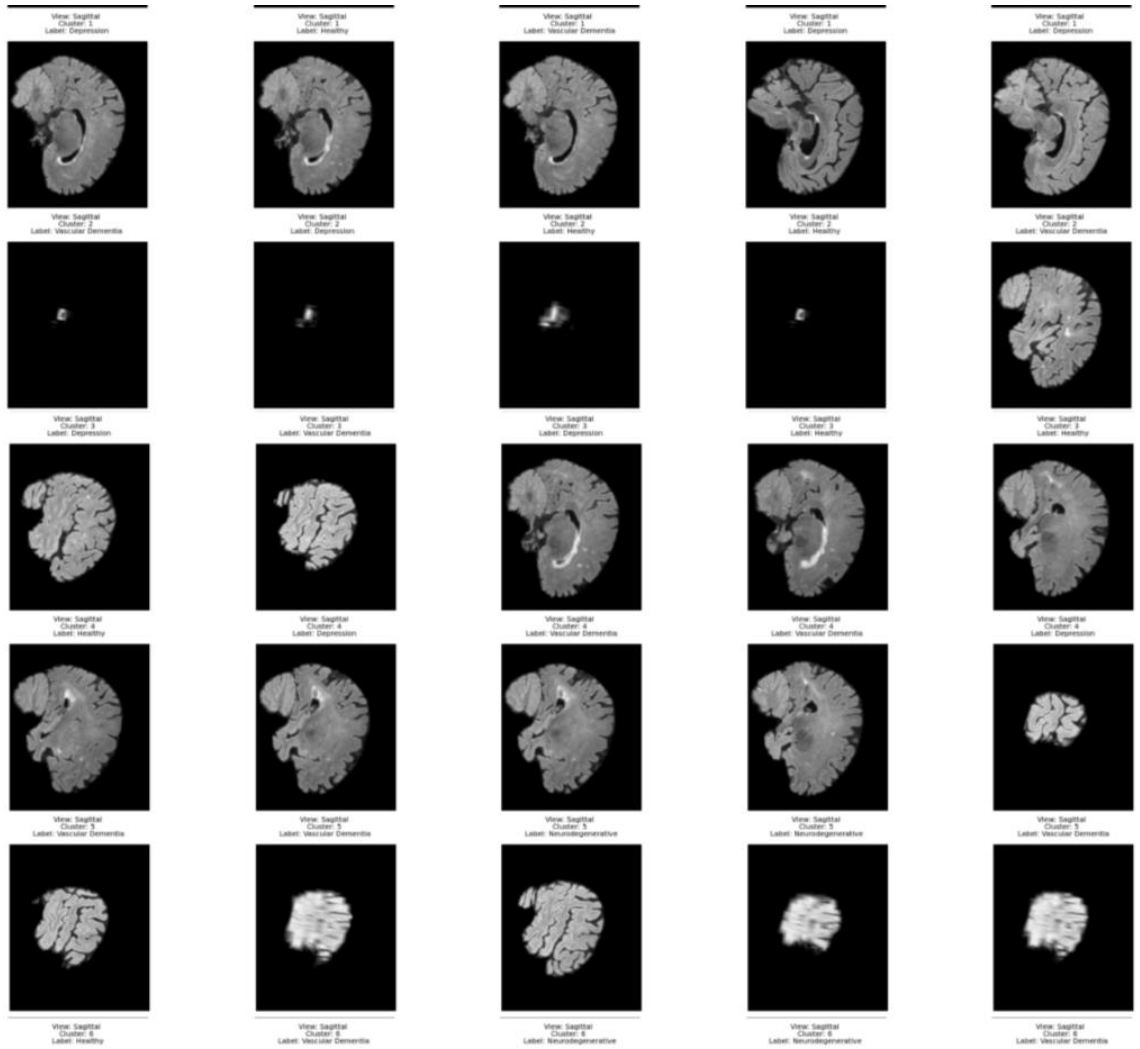
- Objective:
  Reduce the size of the MRI
  1. How?
  2. For each patient, for each view
     - Select some of the scans/slices
- What we tried:
  - Select the middle
  - Select some at random
  - Select some with a fixed “jump”



Sagittal view for an MRI

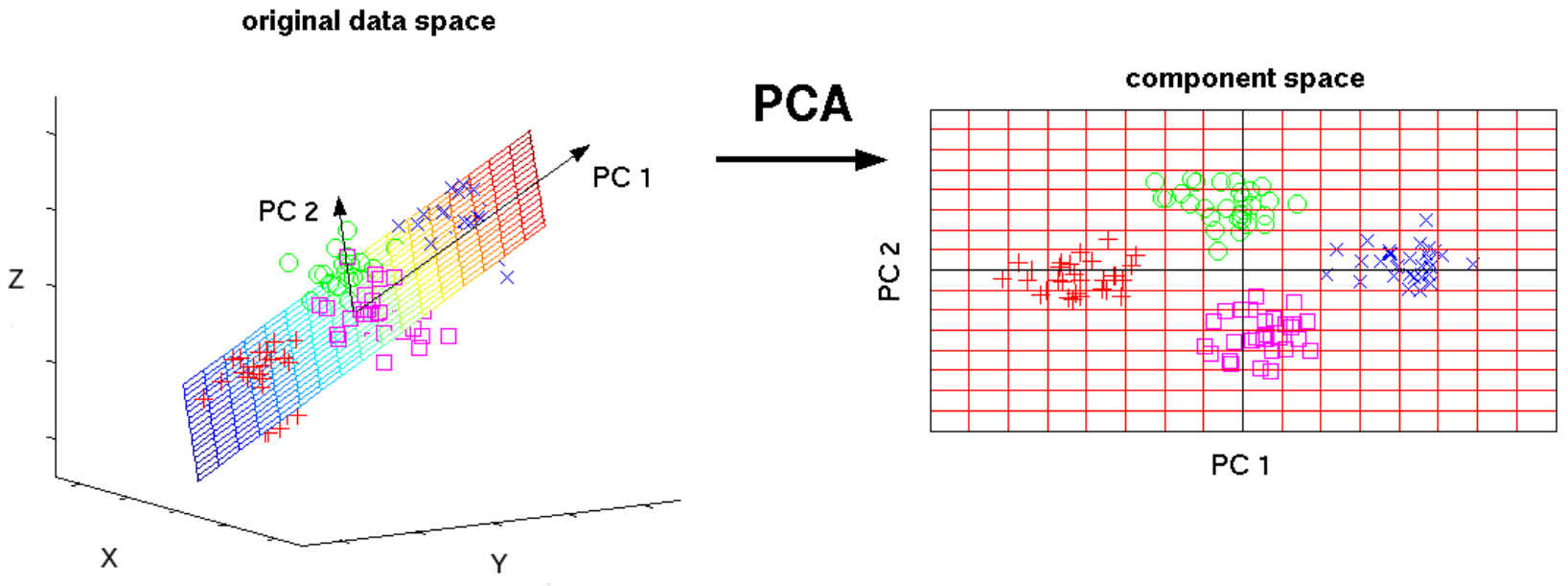
What we tried?

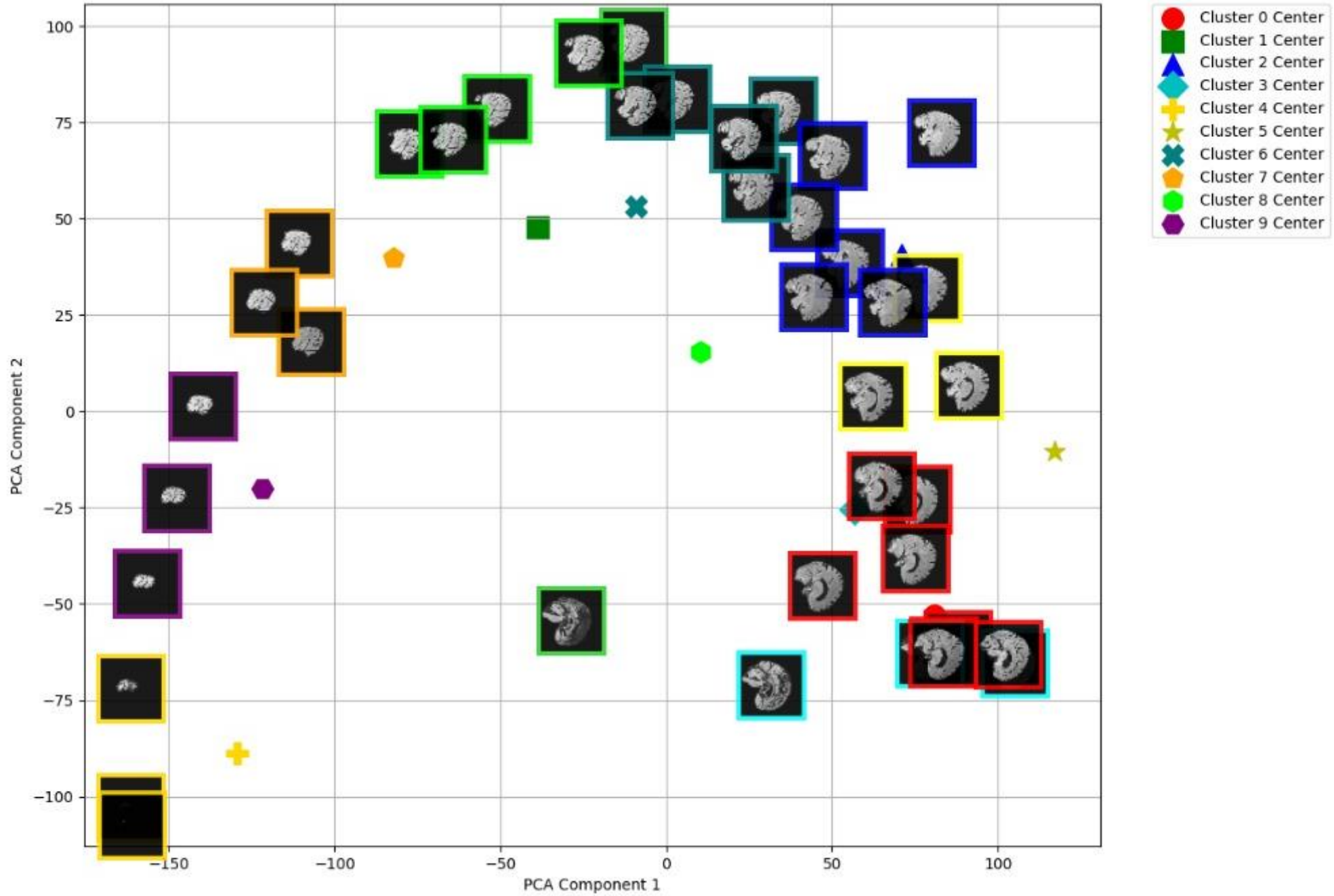
- Select the middle
- Select some at random
- Select some with a fixed “jump”



Dimensionality reduction + clustering

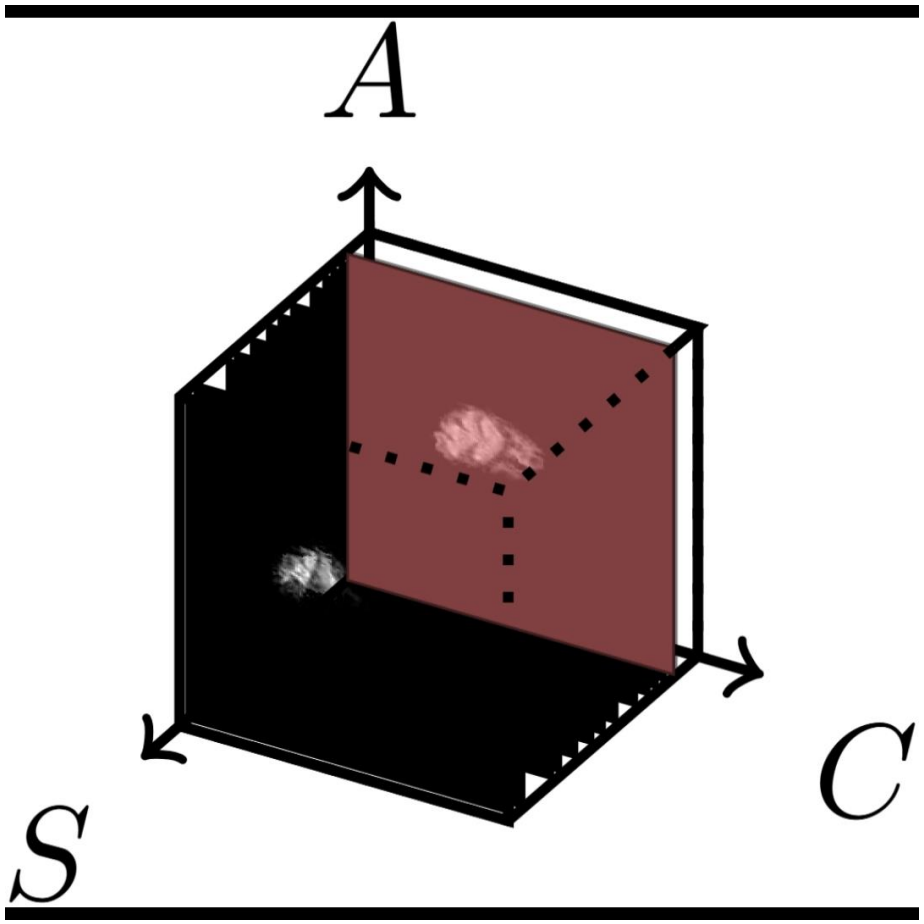
- We selected at random 15 patients per syndrome
- We create a “Dataset of slices” and try to learn “types” of slices we call **clusters** using a dimensionality reduction technique called **PCA**

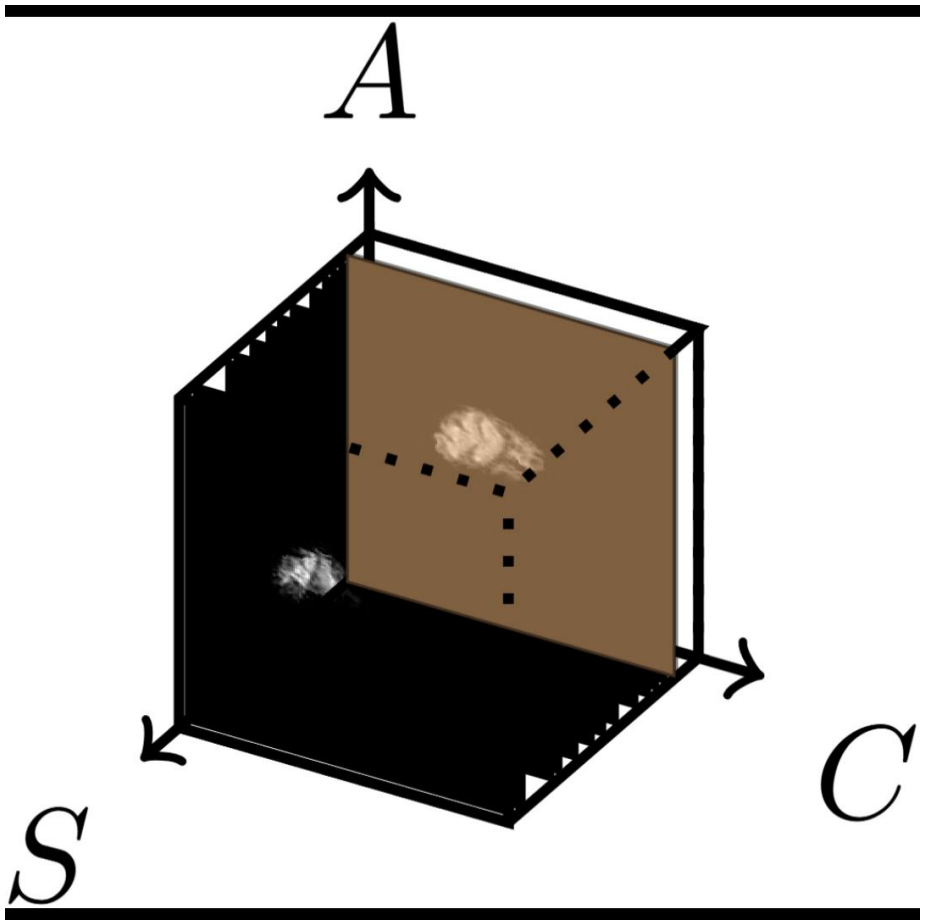



Cluster 0 Center
Cluster 1 Center
Cluster 2 Center
Cluster 3 Center
Cluster 4 Center
Cluster 5 Center
Cluster 6 Center
Cluster 7 Center
Cluster 8 Center
Cluster 9 Center
PCA Component 2
PCA Component 1
100
75
50
25
0
−25
−50
−75
−100
−150
−100
−50
0
50
100

Clustering view

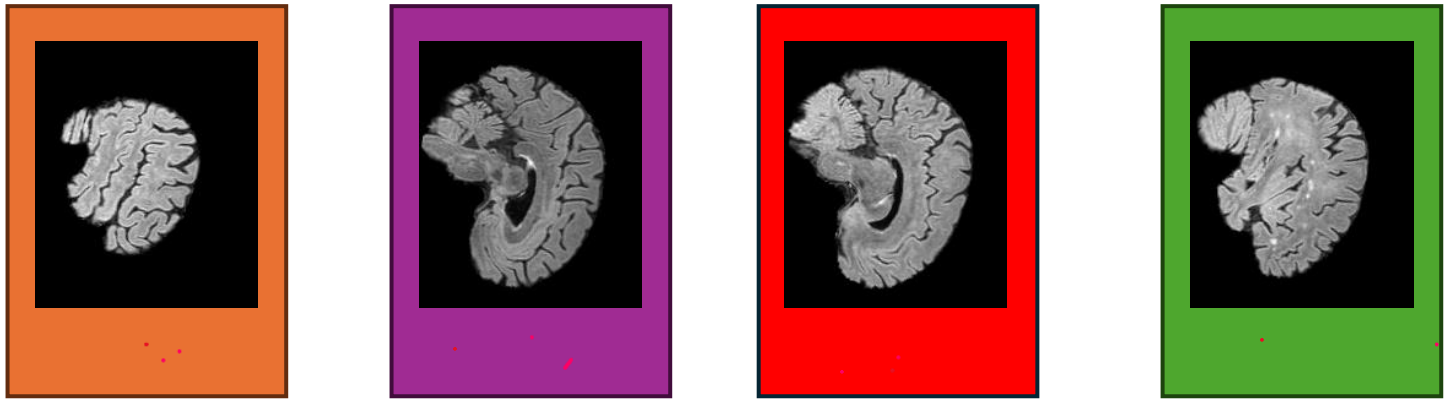
Sagittal example



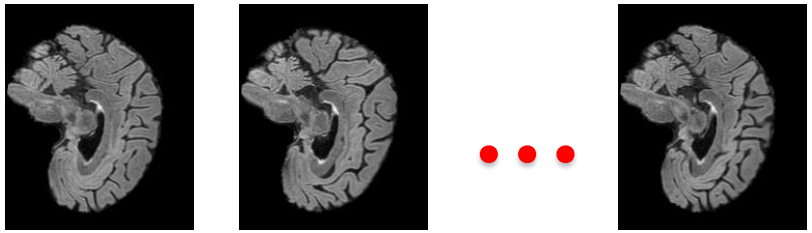


How to select the best scans?

- So, a patients is going to be processed
- We need at least one slice/scan per cluster

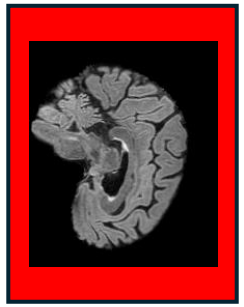


How to select the best scan?



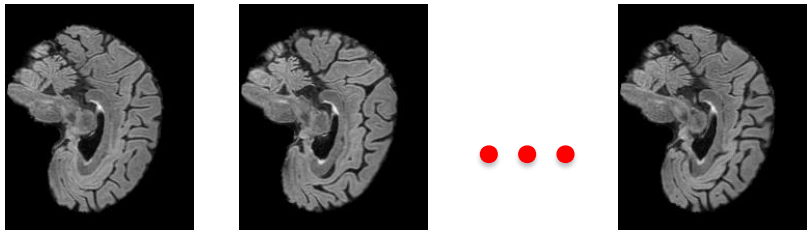
1 2 … N

?

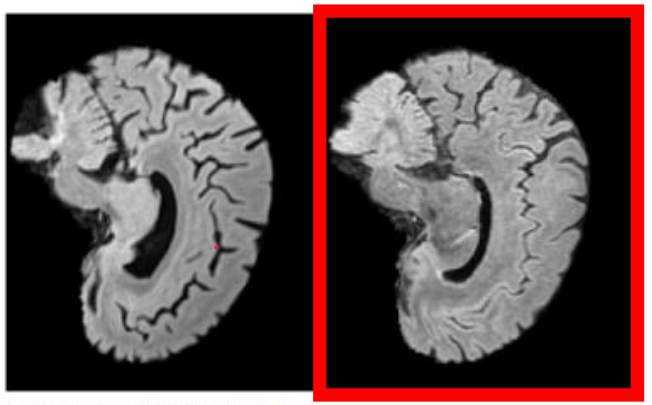


2

How to select the best scan?

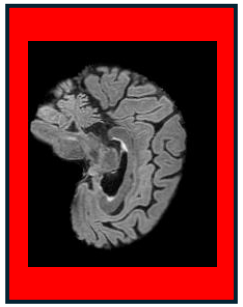


1 2 … N



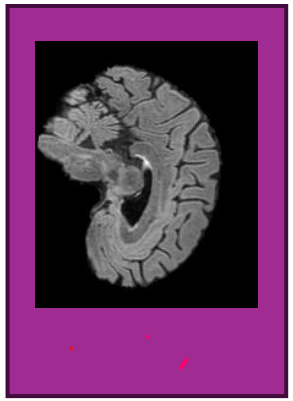
Correlation: 0.9985005423769021
Chi-Square: 0.02777257028366054
Intersection: 1.57421018416062
Bhattacharyya: 0.048095605327900186
Feature matches: 9/286 (0.03 ratio)
MSE: 2581.5331434620425

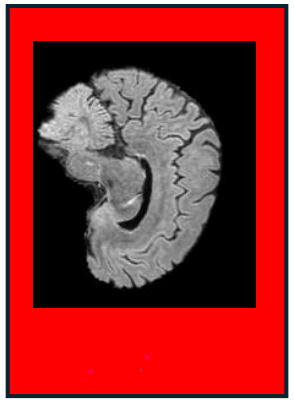
Reference image

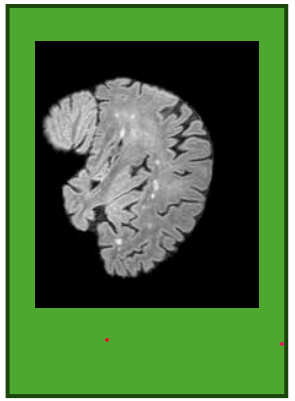


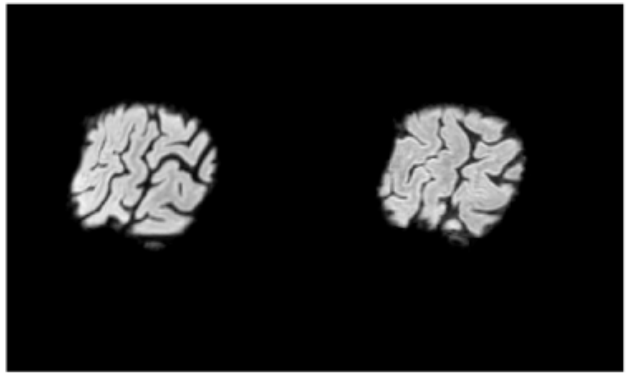
2

How to select the best scans?

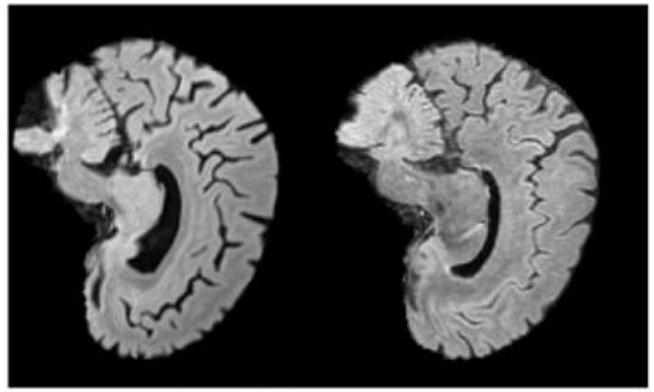




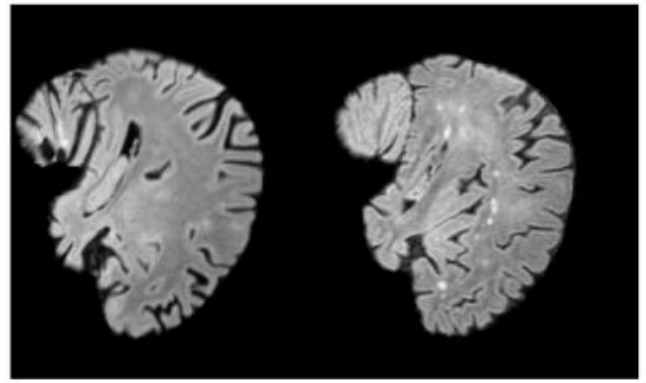




Correlation: 0.9997457178837879
Chi-Square: 0.012365181198860431
Intersection: 1.1092437747865915
Bhattacharyya: 0.03884879628757561
Feature matches: 8/145 (0.06 ratio)
MSE: 1032.5487700373021



Correlation: 0.9985005423769021
Chi-Square: 0.02777257028366054
Intersection: 1.57421018416062
Bhattacharyya: 0.048095605327900186
Feature matches: 9/286 (0.03 ratio)
MSE: 2581.5331434620425

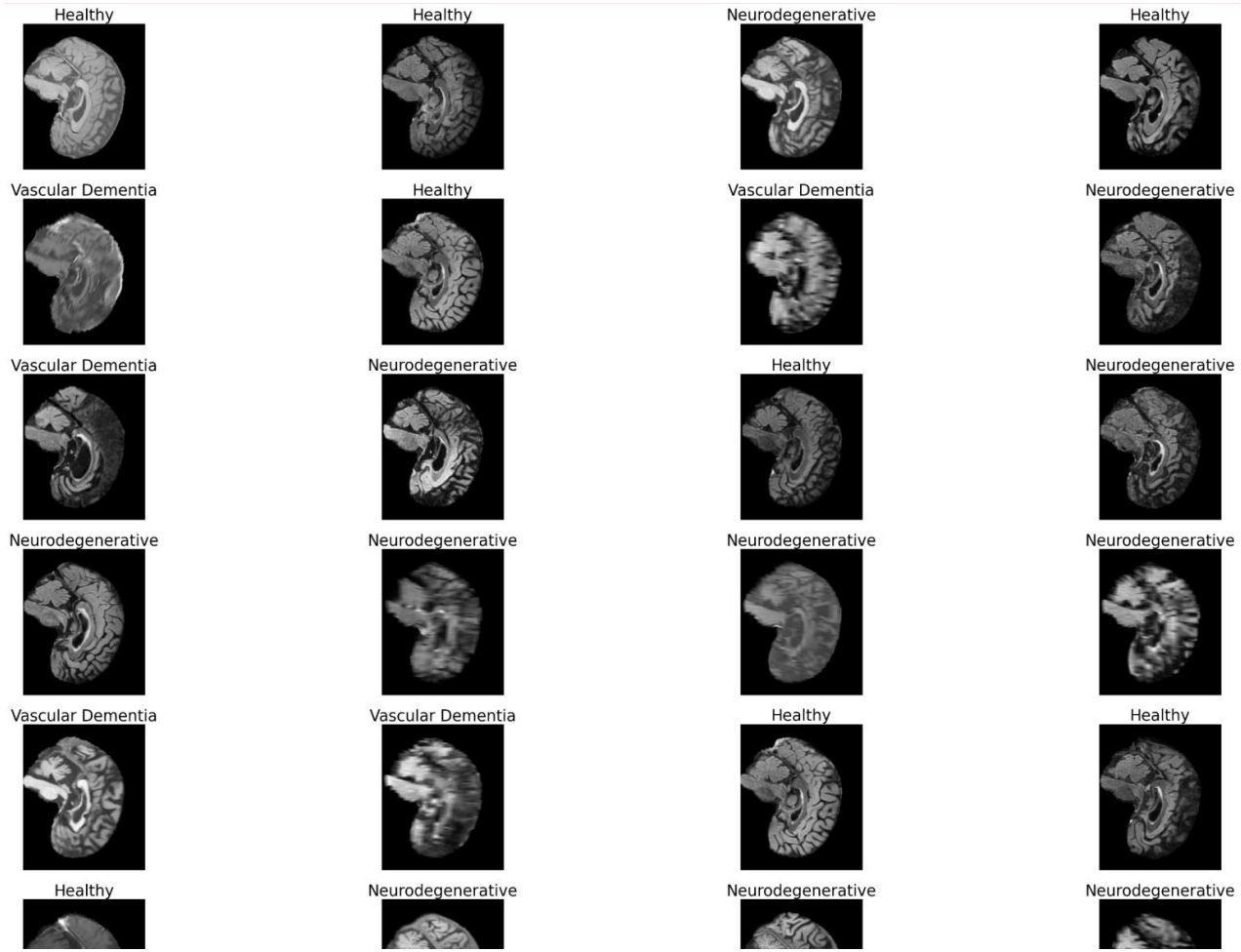


Correlation: 0.9990789523082004
Chi-Square: 0.021340032981119153
Intersection: 1.595264443079941
Bhattacharyya: 0.04418757851255386
Feature matches: 10/278 (0.04 ratio)
MSE: 1194.9995463252344

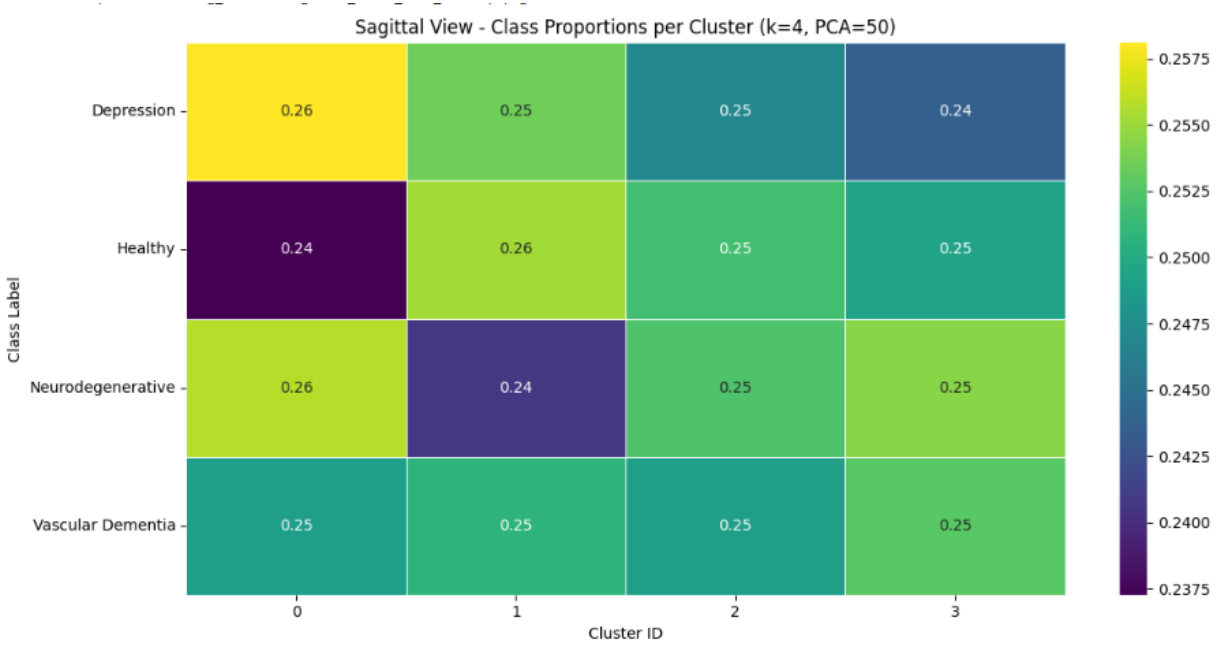
The centers

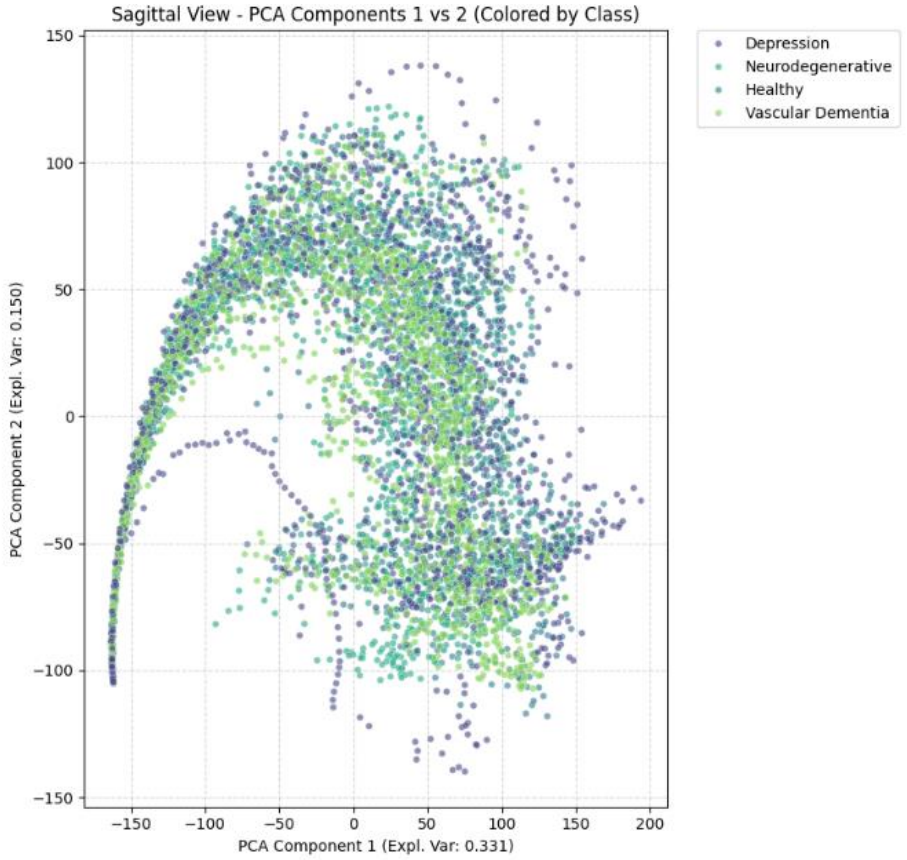

center_0_0
center_0_1
center_0_2
center_0_3
center_0_4
center_0_5
center_0_6
center_0_7
center_0_8
center_0_9
center_1_0
center_1_1
center_1_2
center_1_3
center_1_4
center_1_5
center_1_6
center_1_7
center_1_8
center_1_9
center_2_0
center_2_1
center_2_2
center_2_3
center_2_4
center_2_5
center_2_6
center_2_7
center_2_8
center_2_9
center_3_0
center_3_1
center_3_2
center_3_3
center_3_4
center_3_5
center_3_6
center_3_7
center_3_8
center_3_9

Uniform dataset

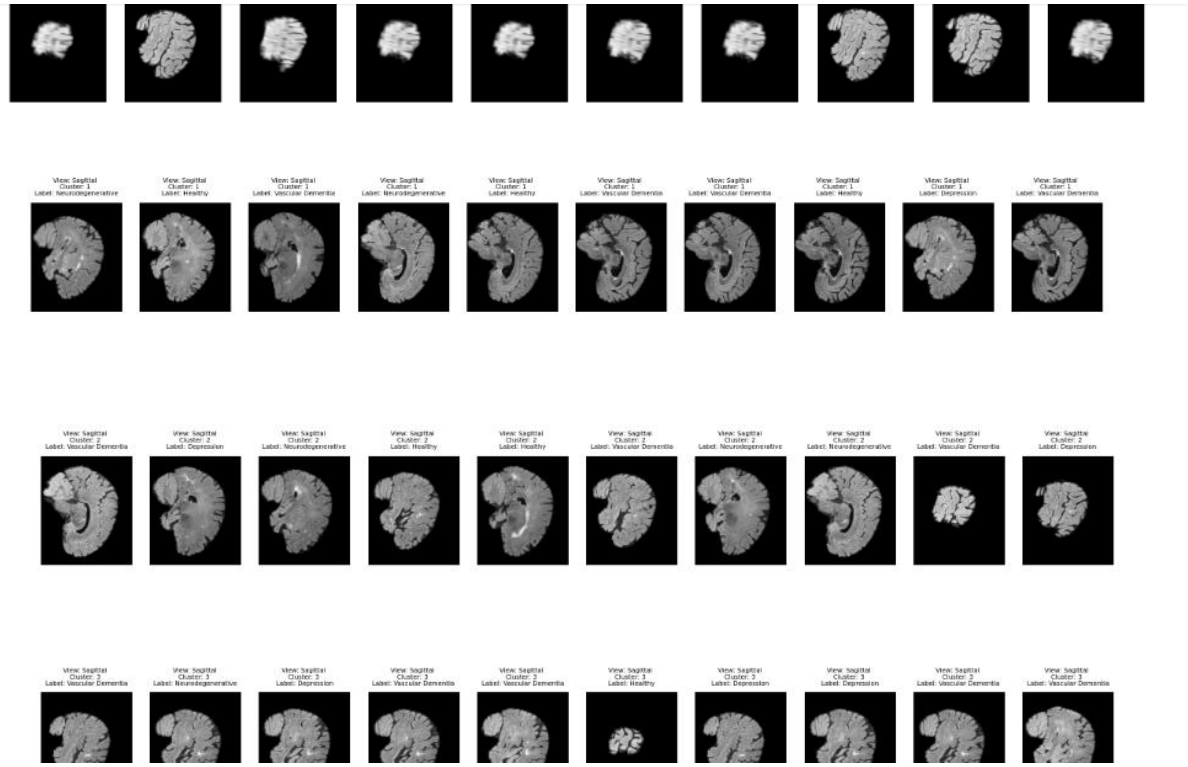


Sagittal


Sagittal View - Class Proportions per Cluster (k=4, PCA=50)
Depression
Healthy
Neurodegenerative
Vascular Dementia
Class Label
0.26
0.25
0.25
0.24
0.24
0.26
0.25
0.25
0.26
0.24
0.25
0.25
0.25
0.25
0.25
0.25
0
1
2
3
Cluster ID
0.2575
0.2550
0.2525
0.2500
0.2475
0.2450
0.2425
0.2400
0.2375


Sagittal View - PCA Components 1 vs 2 (Colored by Class)
Depression
Neurodegenerative
Healthy
Vascular Dementia
PCA Component 2 (Expl. Var: 0.150)
PCA Component 1 (Expl. Var: 0.331)
150
100
50
0
−50
−100
−150
−150
−100
−50
0
50
100
150
200

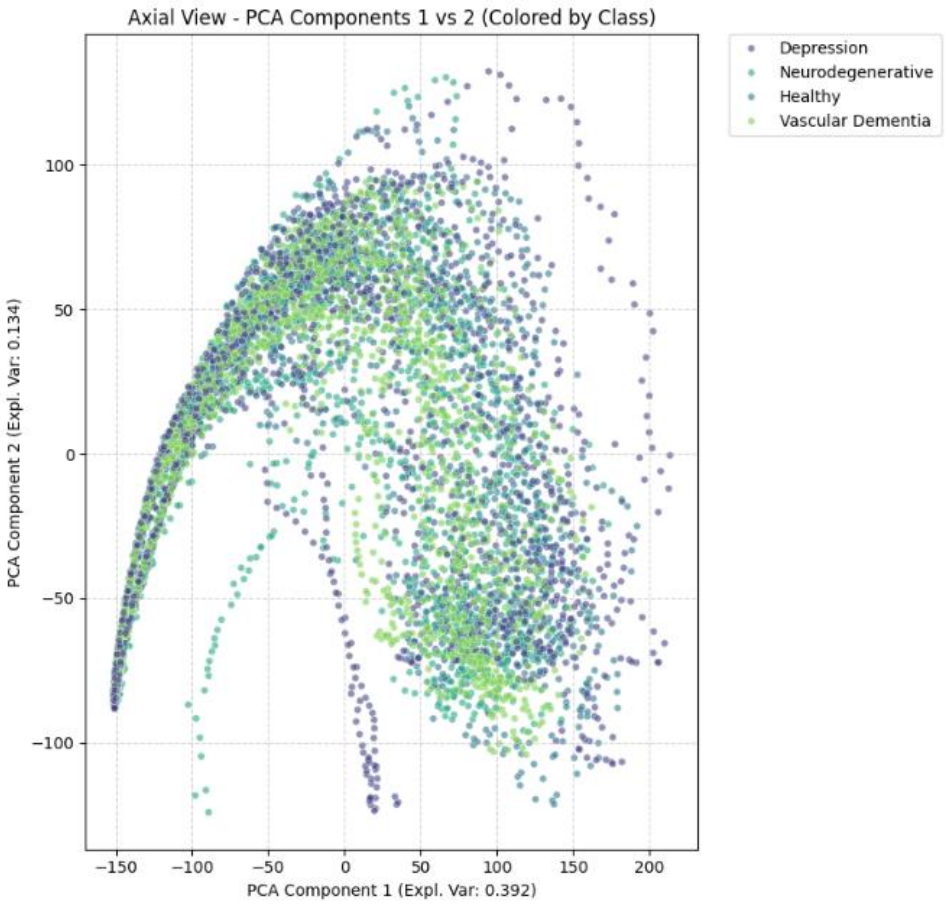
Clusters



Axial


Axial View - Class Proportions per Cluster (k=9, PCA=50)
Depression
Healthy
Neurodegenerative
Vascular Dementia
Class Label
0.24 0.26 0.25 0.25 0.25 0.25 0.25 0.25 0.25
0.24 0.25 0.24 0.25 0.25 0.27 0.25 0.26 0.25
0.27 0.24 0.26 0.25 0.25 0.23 0.25 0.24 0.24
0.24 0.25 0.25 0.25 0.26 0.25 0.25 0.25 0.26
0 1 2 3 4 5 6 7 8
Cluster ID
0.270
0.265
0.260
0.255
0.250
0.245
0.240
0.235

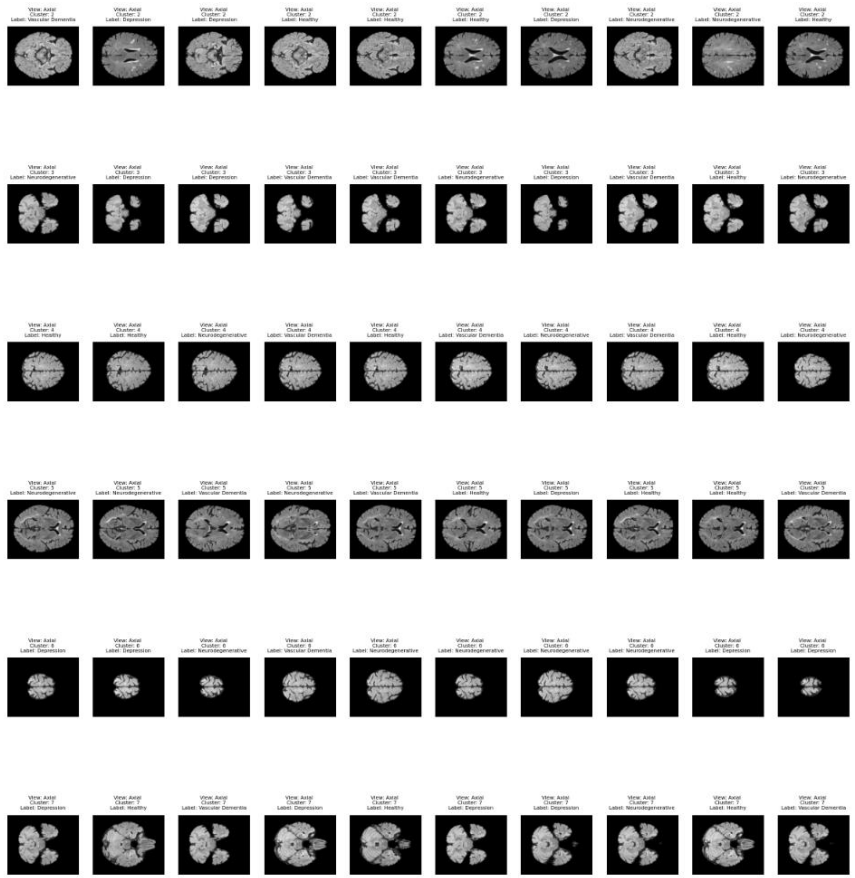
Axial – PCA


Axial View - PCA Components 1 vs 2 (Colored by Class)
Depression
Neurodegenerative
Healthy
Vascular Dementia
PCA Component 2 (Expl. Var: 0.134)
PCA Component 1 (Expl. Var: 0.392)
100
50
0
−50
−100
−150
−100
−50
0
50
100
150
200

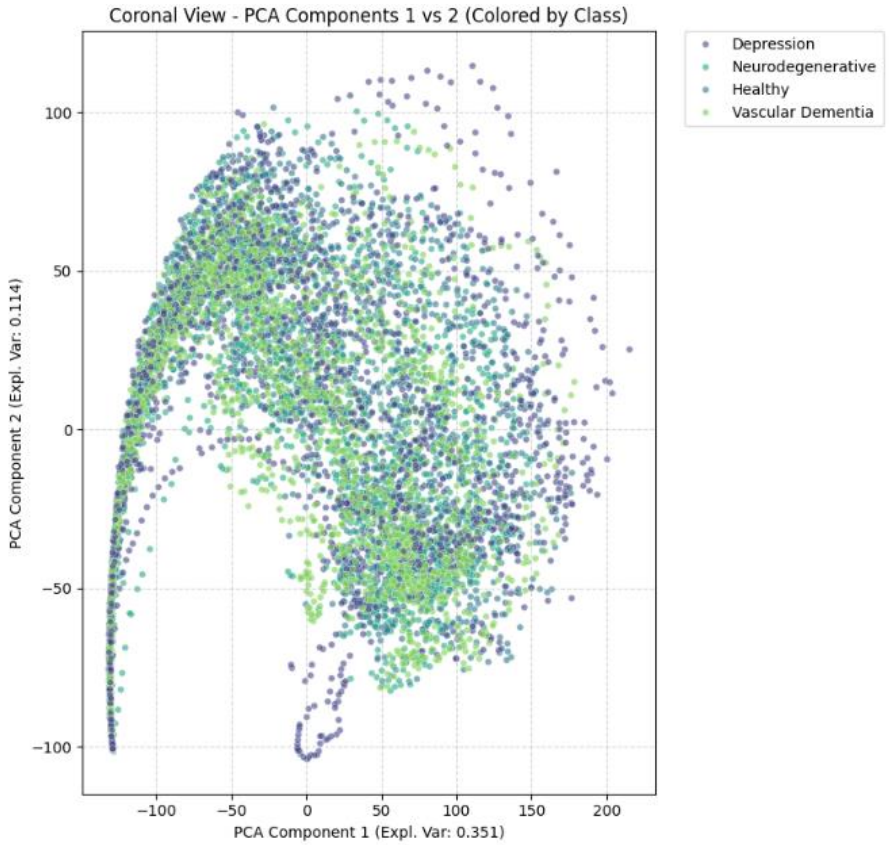
Coronal


Coronal View - Class Proportions per Cluster (k=6, PCA=50)
Depression
Healthy
Neurodegenerative
Vascular Dementia
Class Label
0.25 0.25 0.24 0.25 0.25 0.25
0.24 0.25 0.25 0.25 0.25 0.26
0.27 0.24 0.25 0.25 0.25 0.24
0.24 0.25 0.25 0.24 0.26 0.25
0
1
2
3
4
5
Cluster ID
0.265
0.260
0.255
0.250
0.245

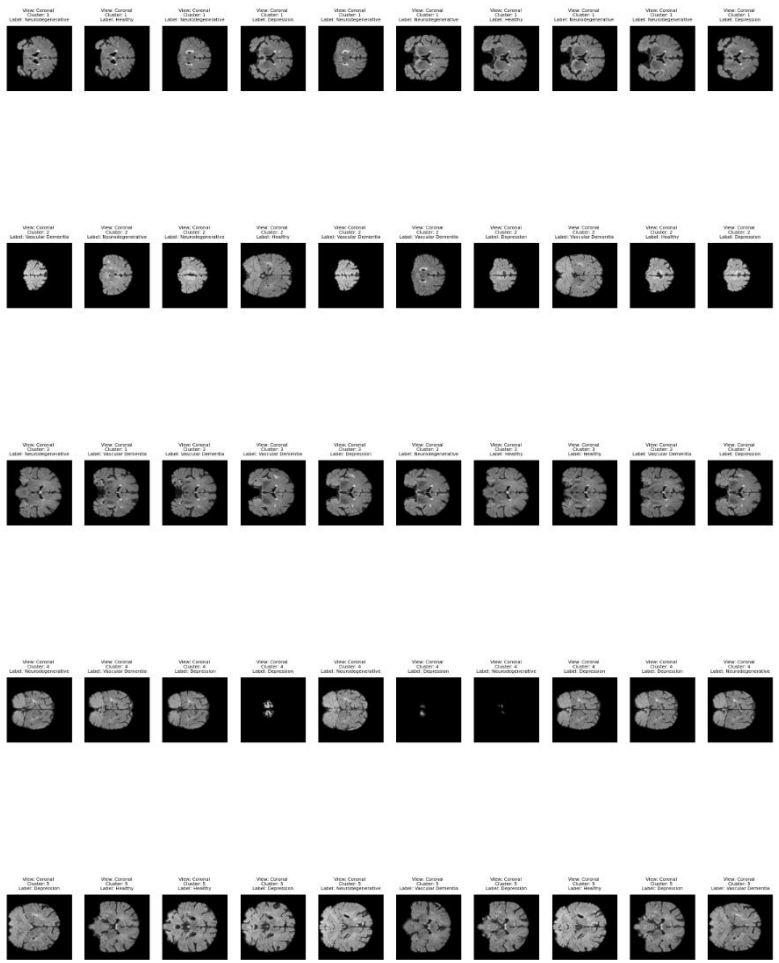
Axial - Clusters



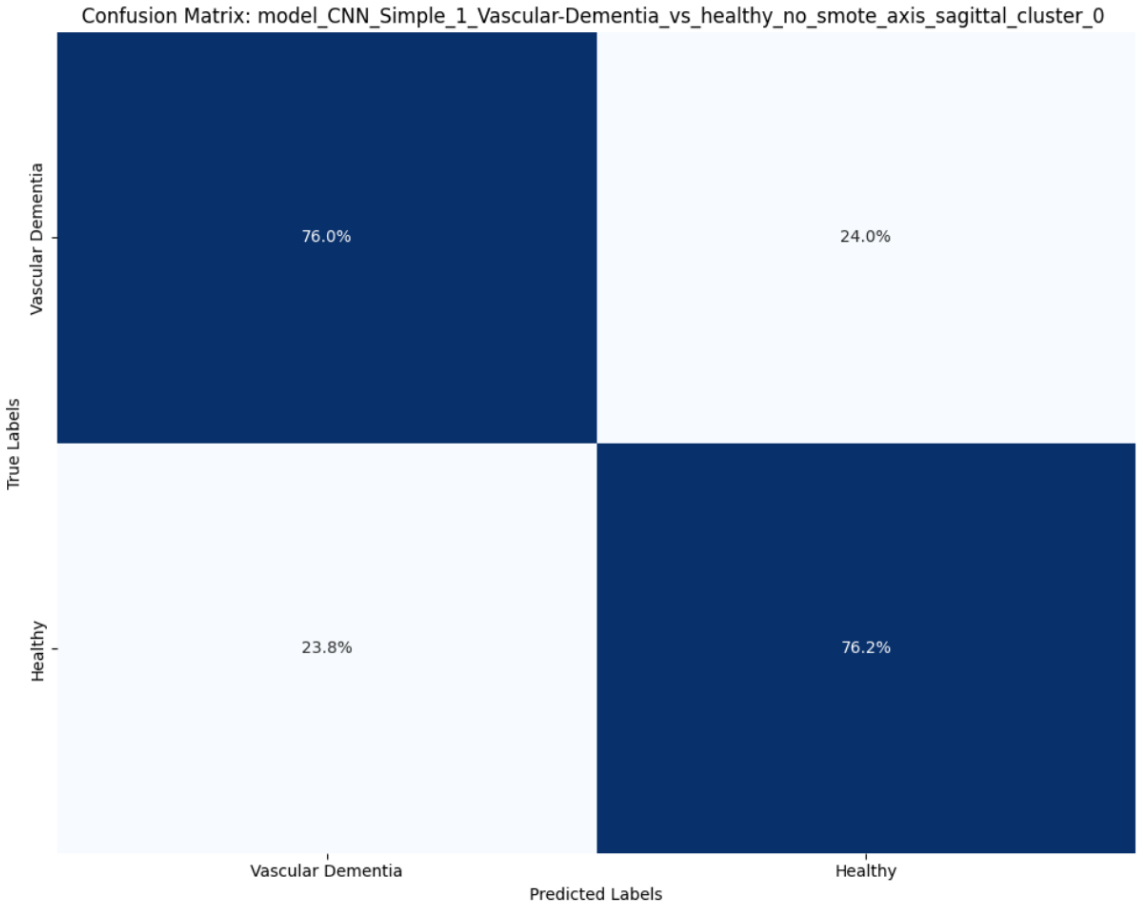
Coronal - PCA

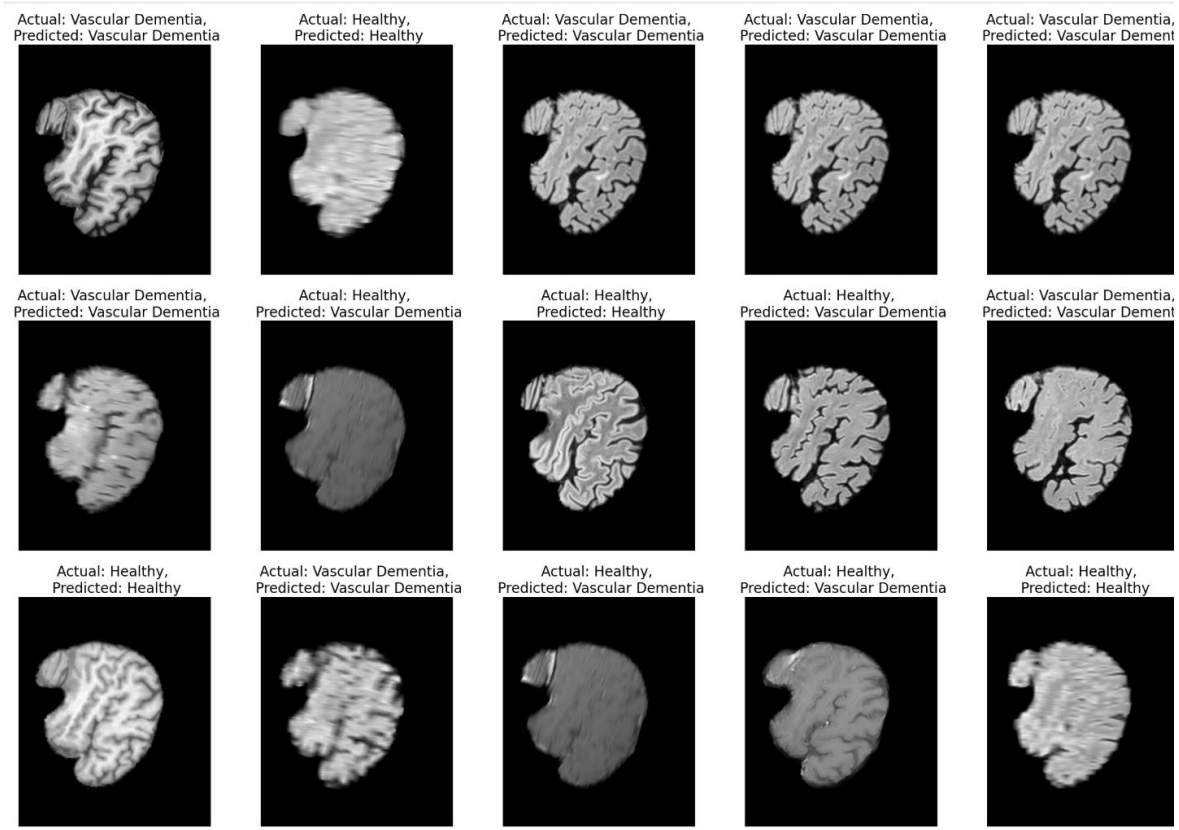

Coronal View - PCA Components 1 vs 2 (Colored by Class)
Depression
Neurodegenerative
Healthy
Vascular Dementia
PCA Component 2 (Expl. Var: 0.114)
PCA Component 1 (Expl. Var: 0.351)
100
50
0
−50
−100
−100
−50
0
50
100
150
200

Coronal - clusters



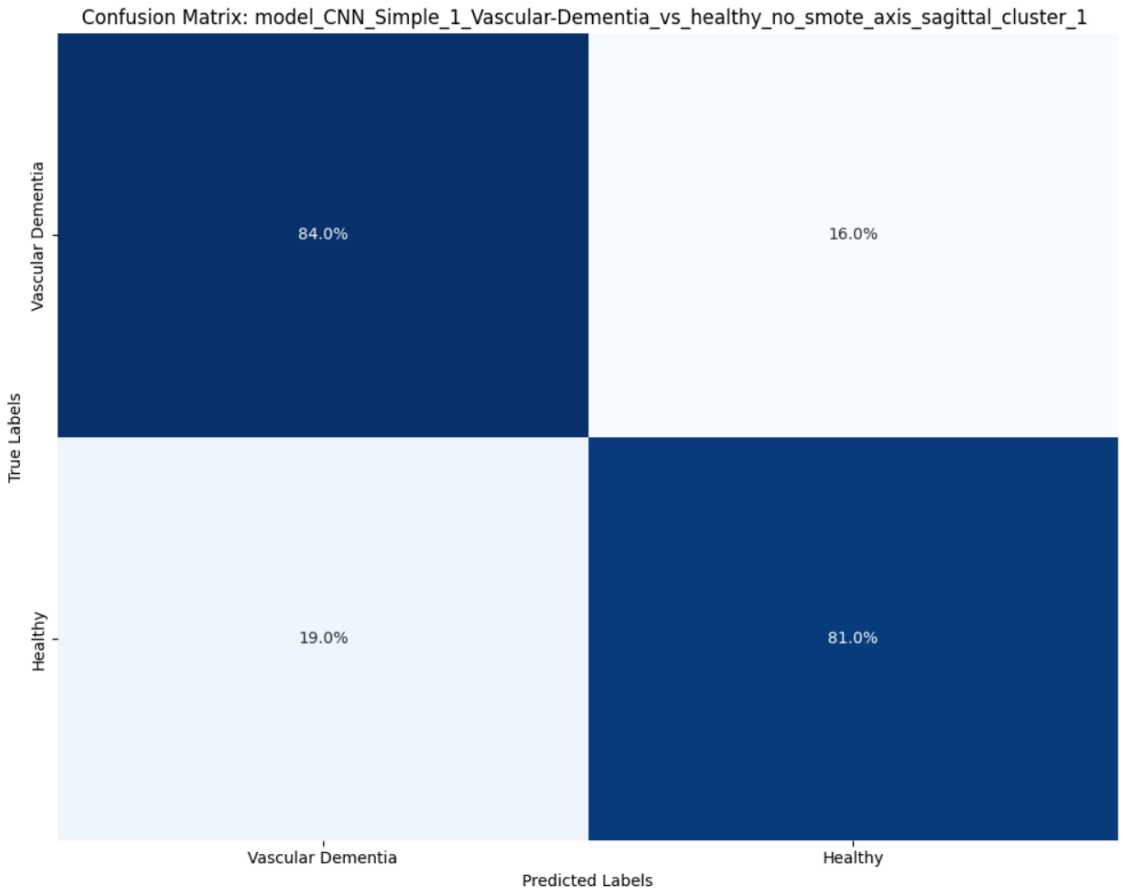
Sagittal 0

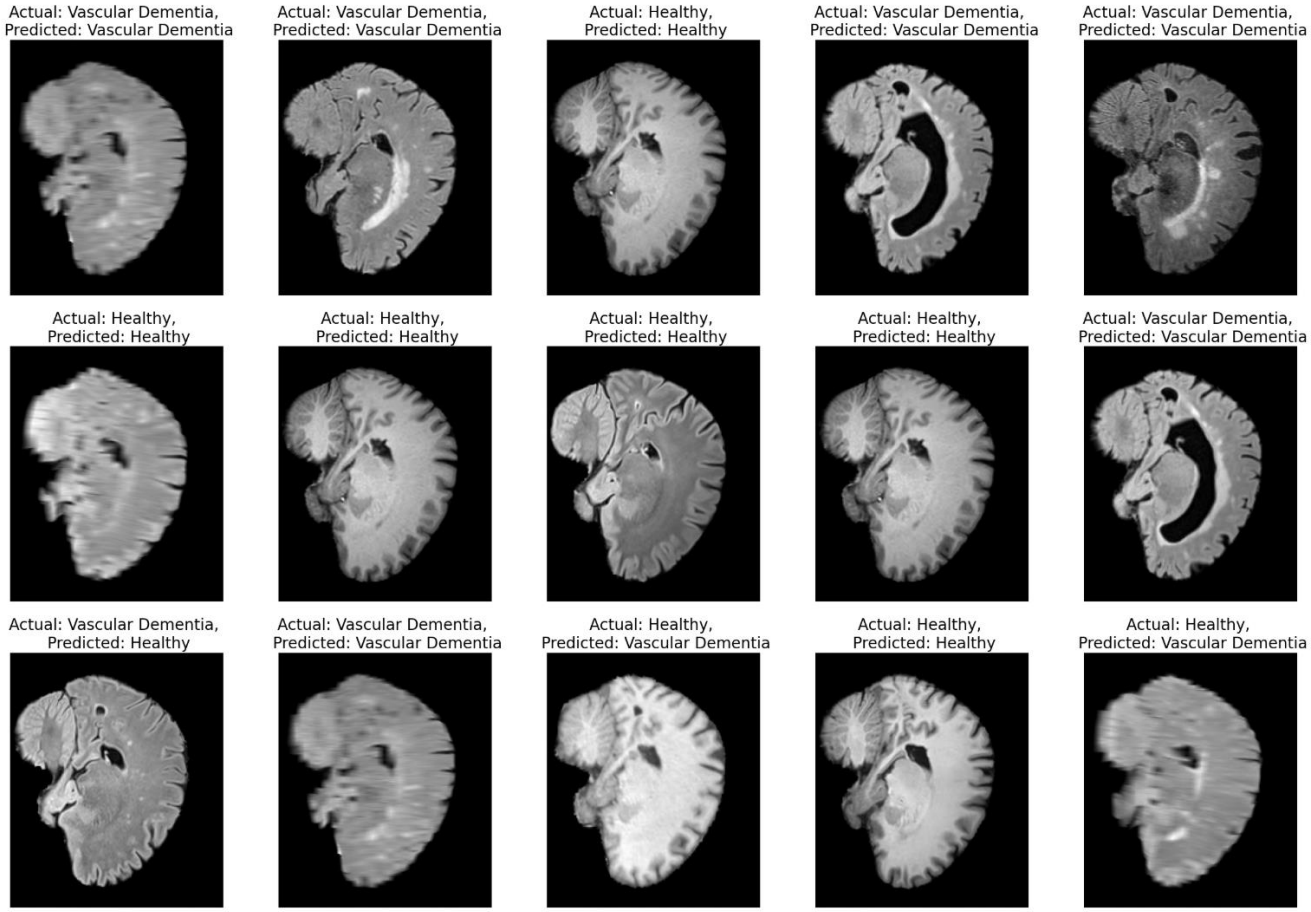




	precision	recall	f1-score	support
0	0.82	0.56	0.67	25
1	0.62	0.86	0.72	21
accuracy			0.70	46
macro avg	0.72	0.71	0.69	46
weighted avg	0.73	0.70	0.69	46

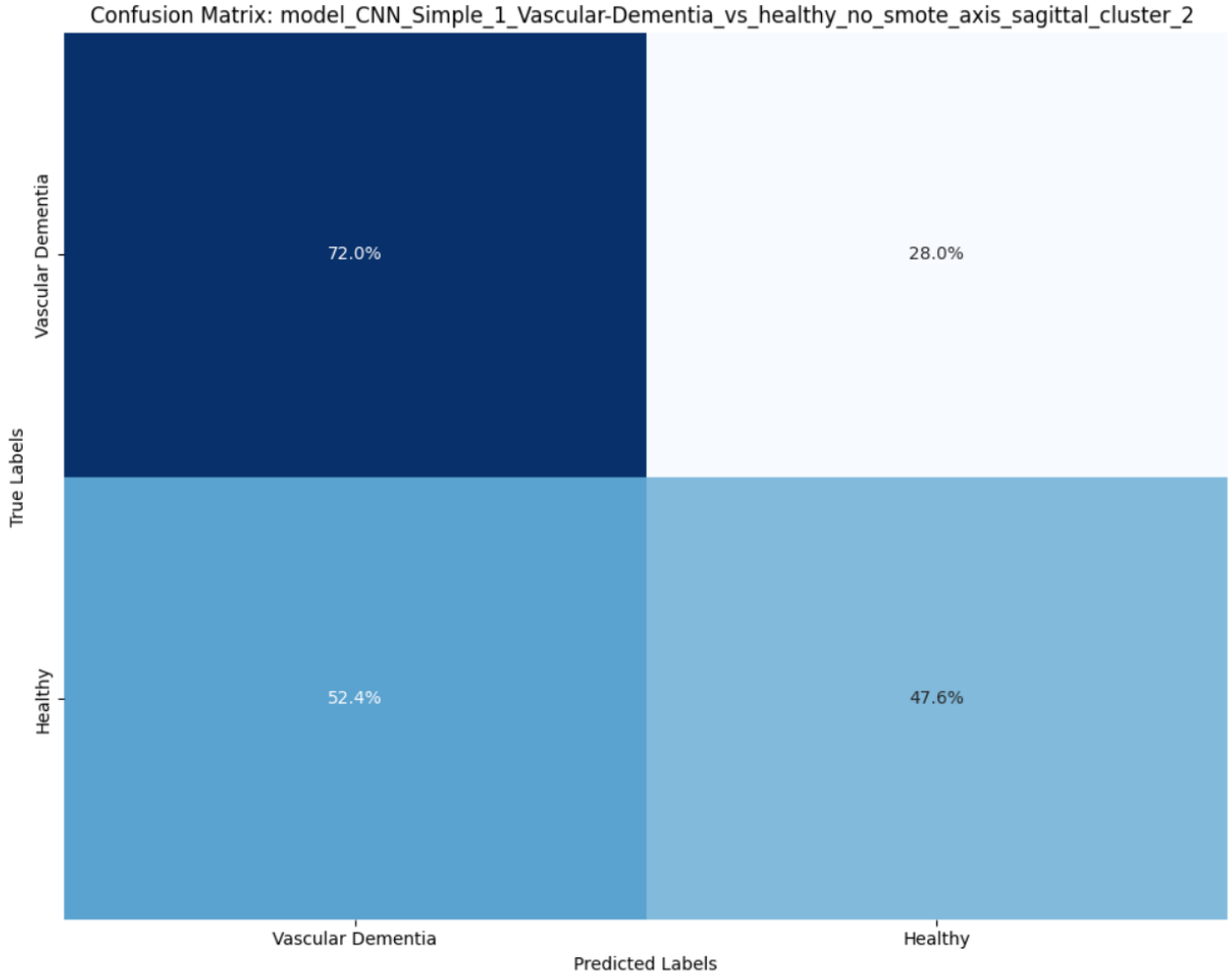
Sagittal 1

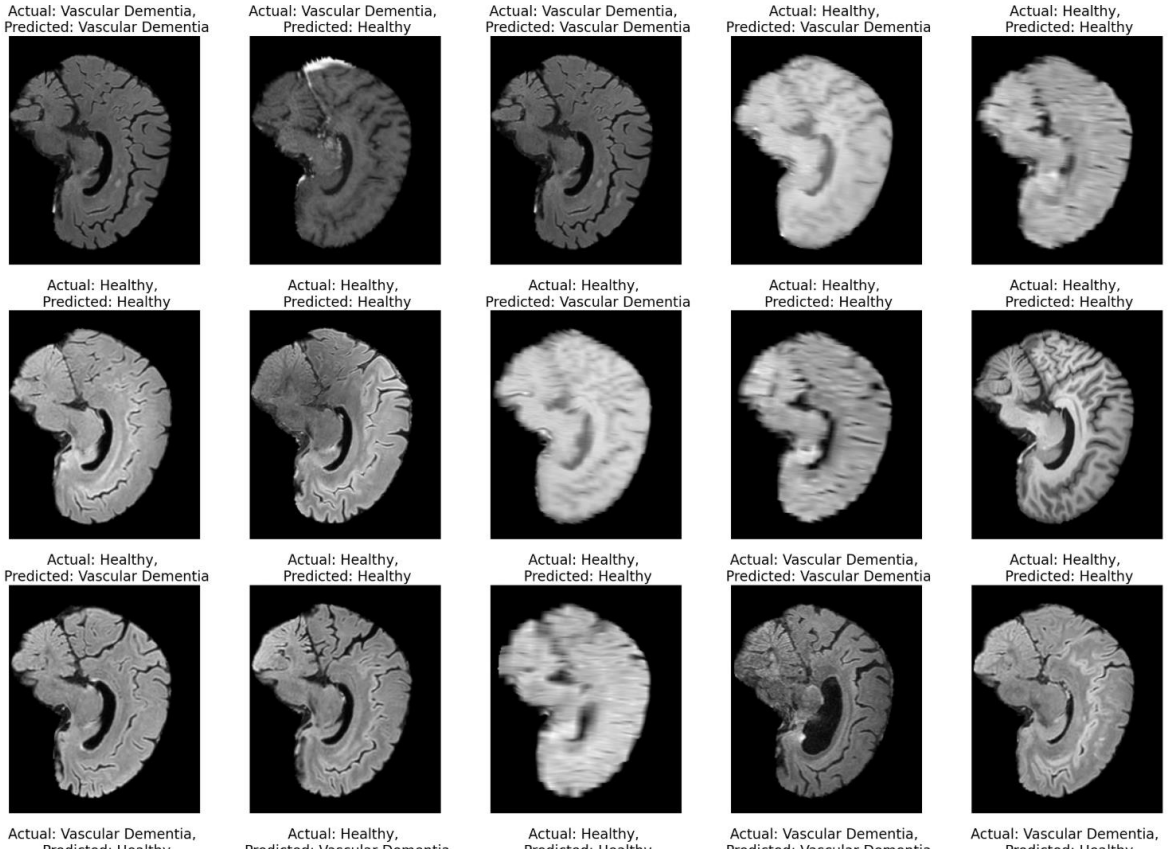




	precision	recall	f1-score	support
0	0.82	0.56	0.67	25
1	0.62	0.86	0.72	21
accuracy			0.70	46
macro avg	0.72	0.71	0.69	46
weighted avg	0.73	0.70	0.69	46

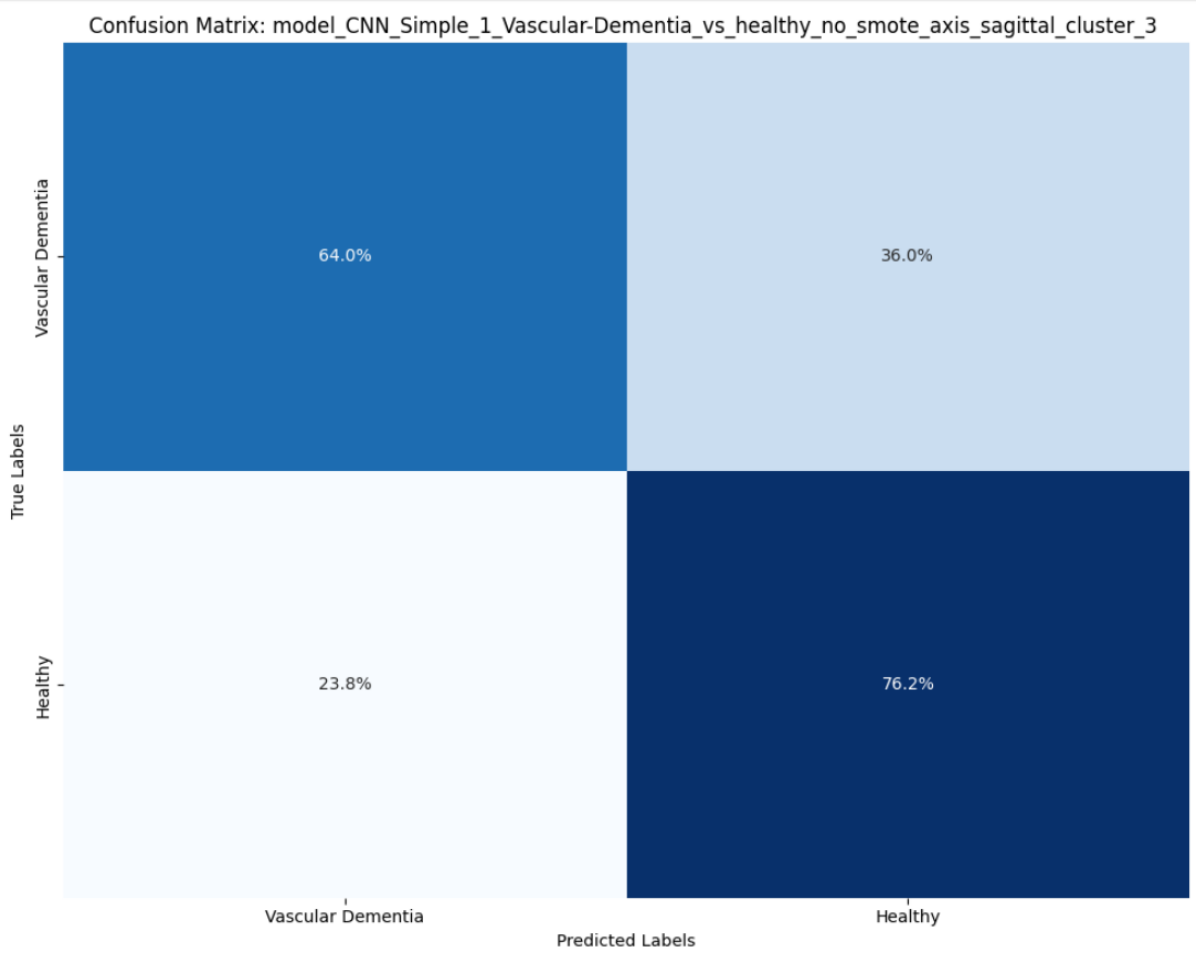
Sagittal 2

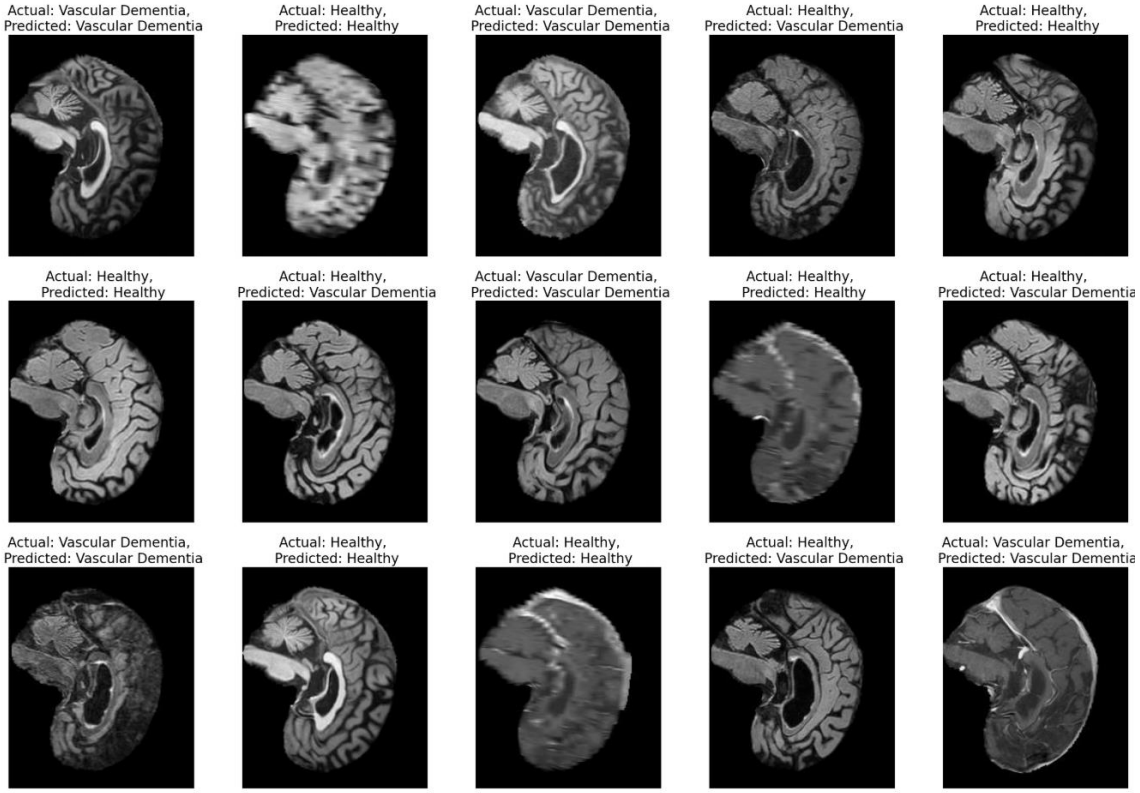




	precision	recall	f1-score	support
0	0.62	0.72	0.67	25
1	0.59	0.48	0.53	21
accuracy			0.61	46
macro avg	0.60	0.60	0.60	46
weighted avg	0.61	0.61	0.60	46

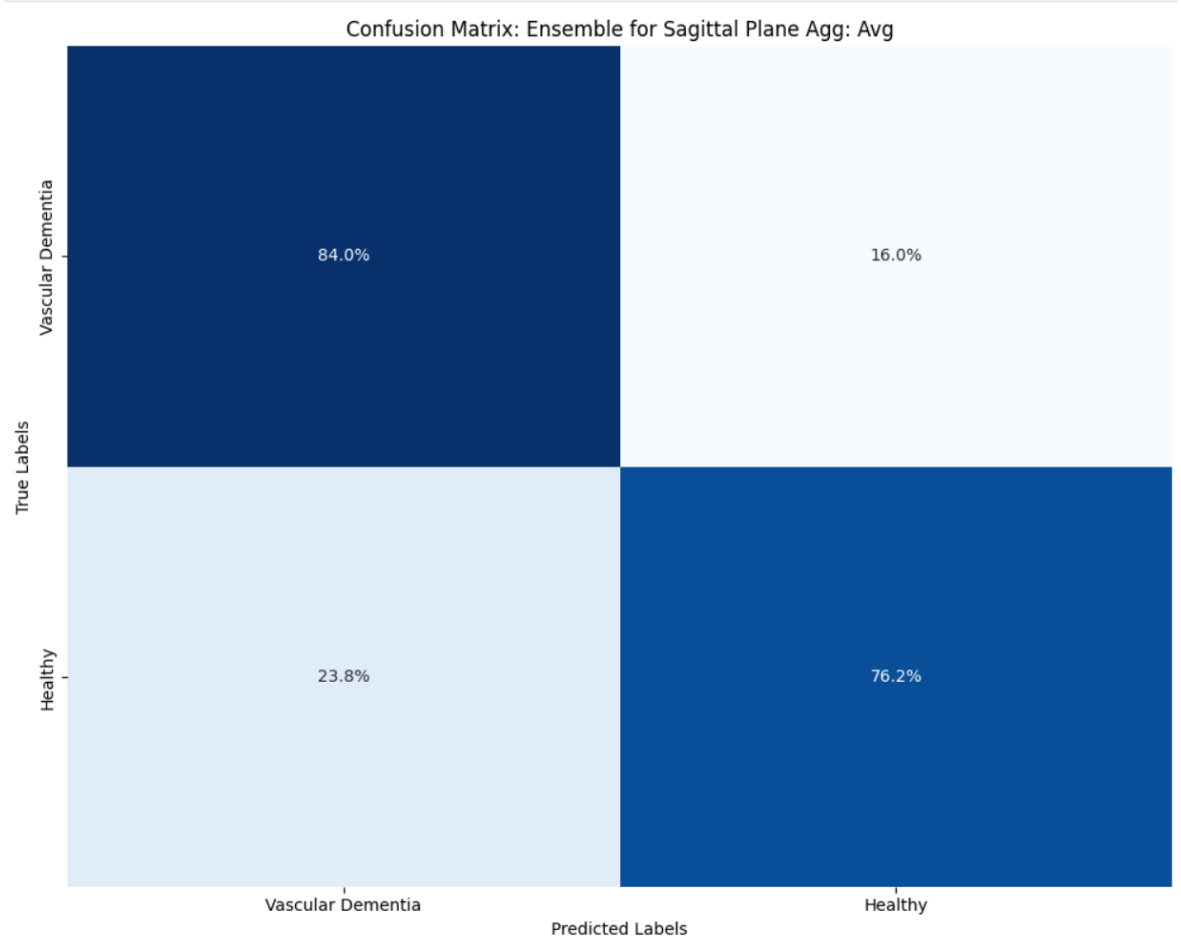
Sagittal 3





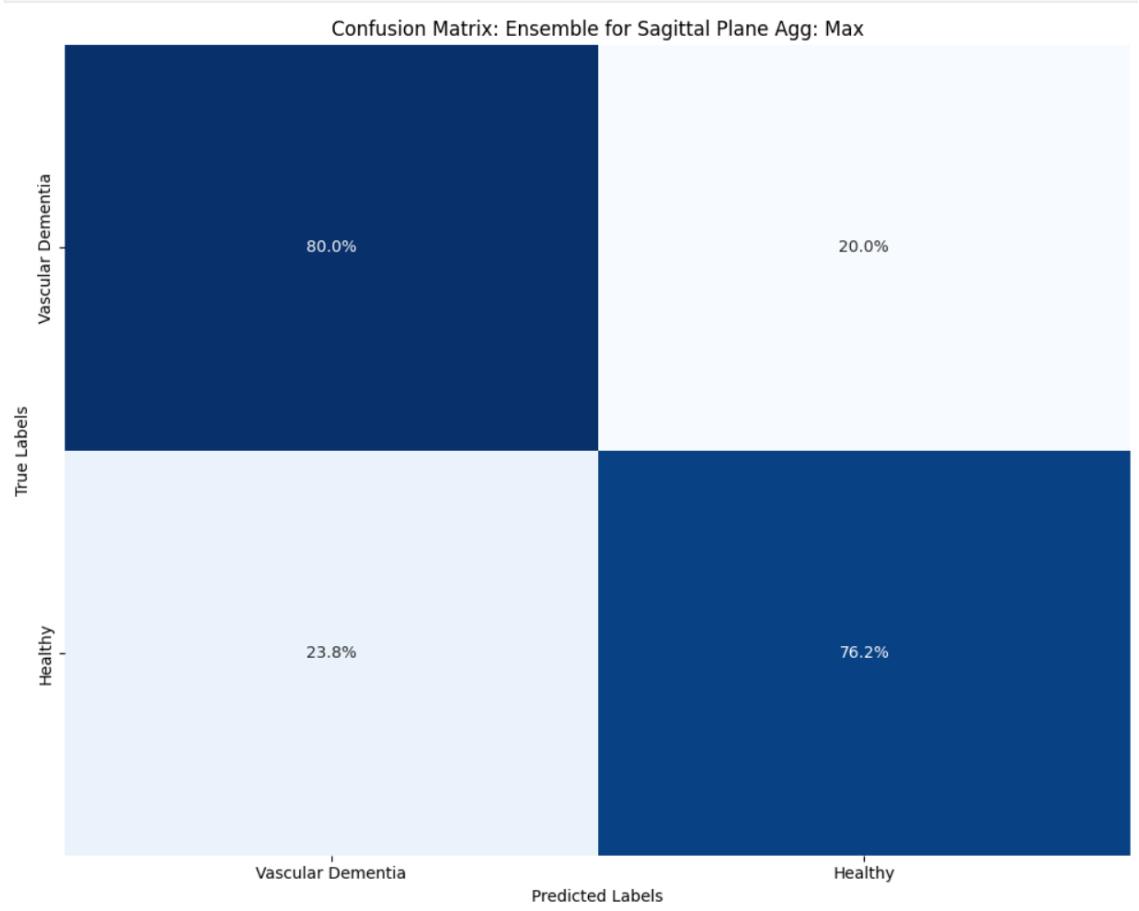
	precision	recall	f1-score	support
0	0.76	0.64	0.70	25
1	0.64	0.76	0.70	21
accuracy			0.70	46
macro avg	0.70	0.70	0.70	46
weighted avg	0.71	0.70	0.70	46

Ensemble: Aggregating by average



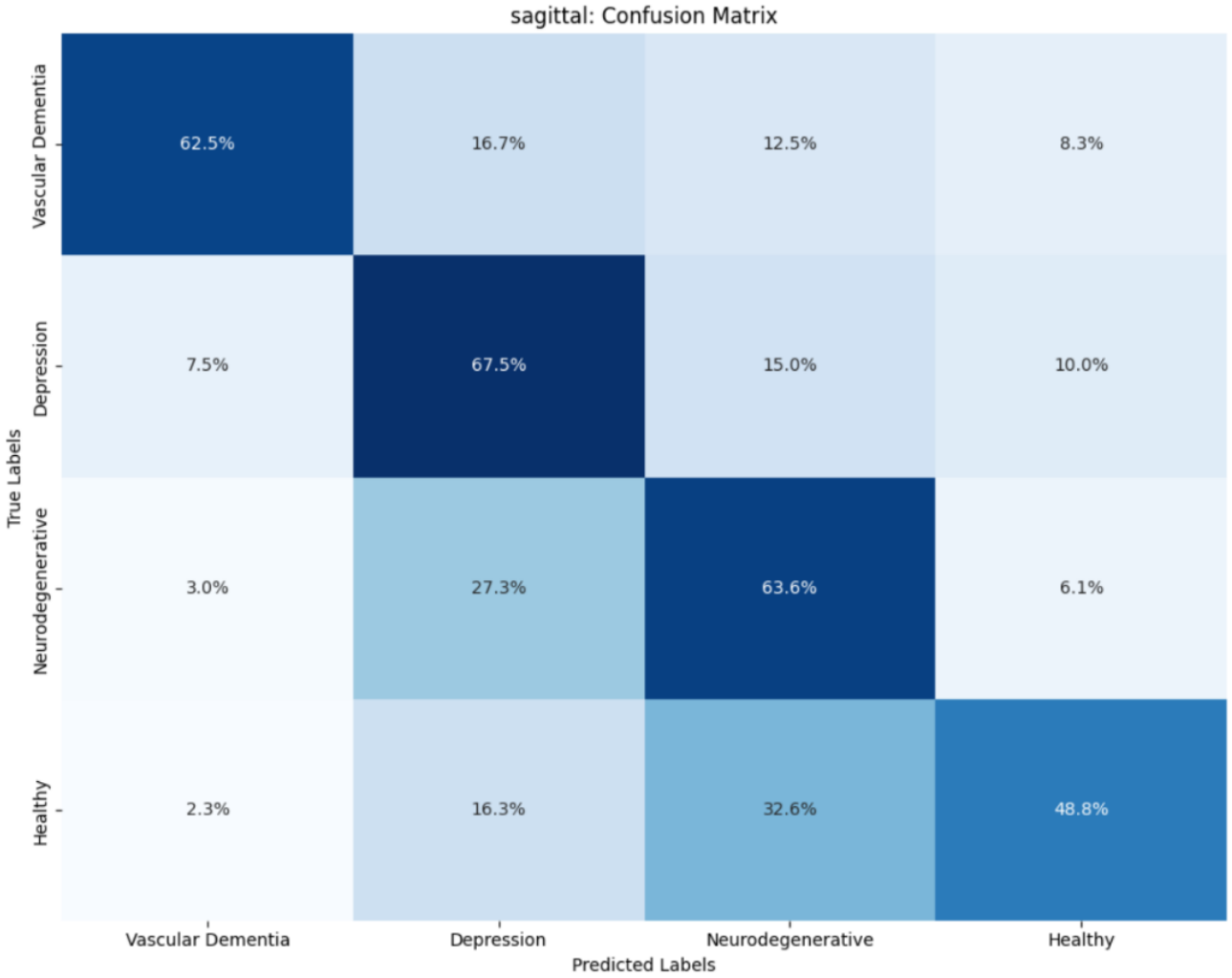
	precision	recall	f1-score	support
0	0.81	0.84	0.82	25
1	0.80	0.76	0.78	21
accuracy			0.80	46
macro avg	0.80	0.80	0.80	46
weighted avg	0.80	0.80	0.80	46

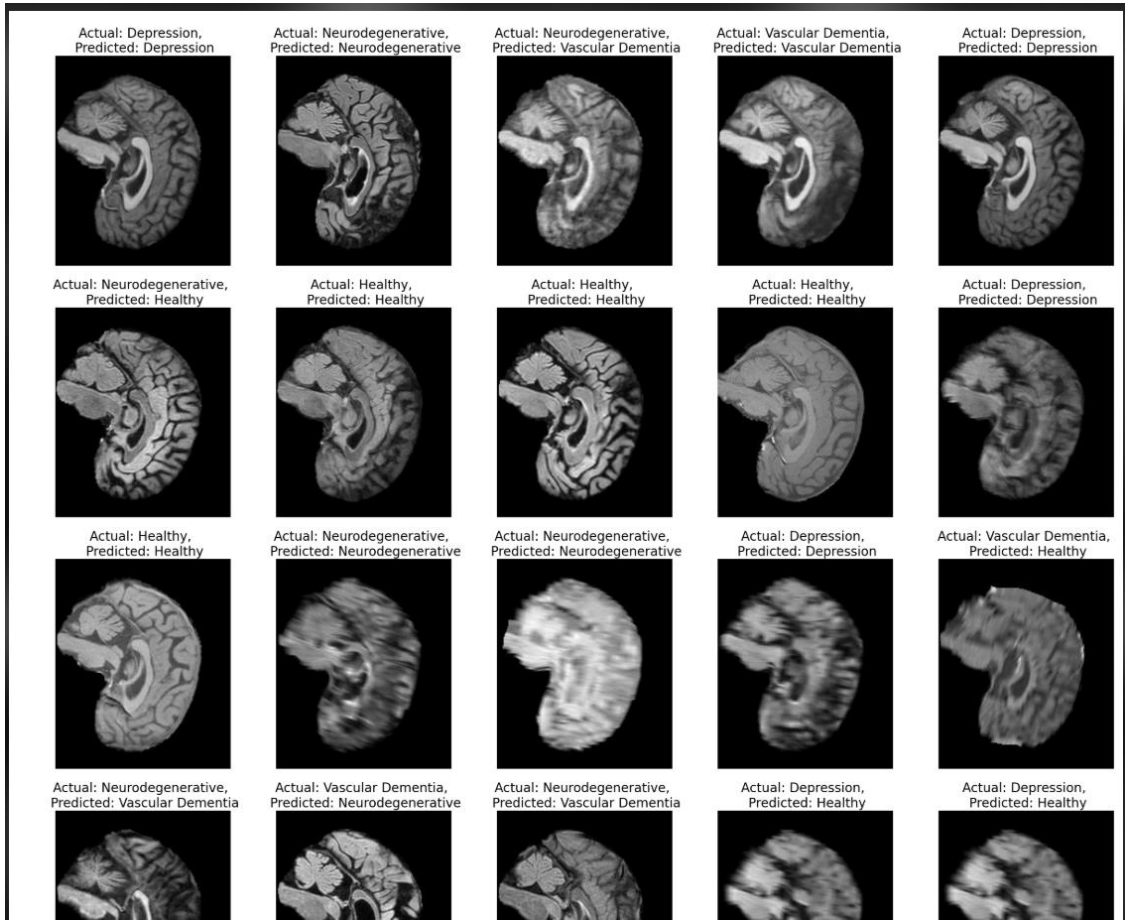
Ensemble: Aggregating by max

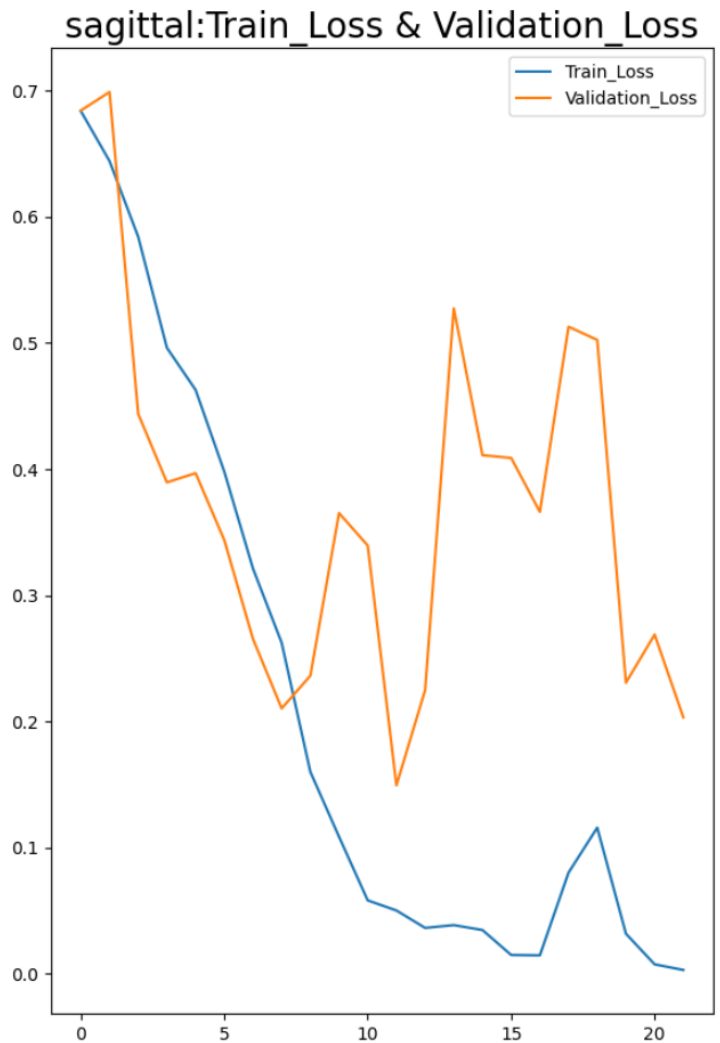


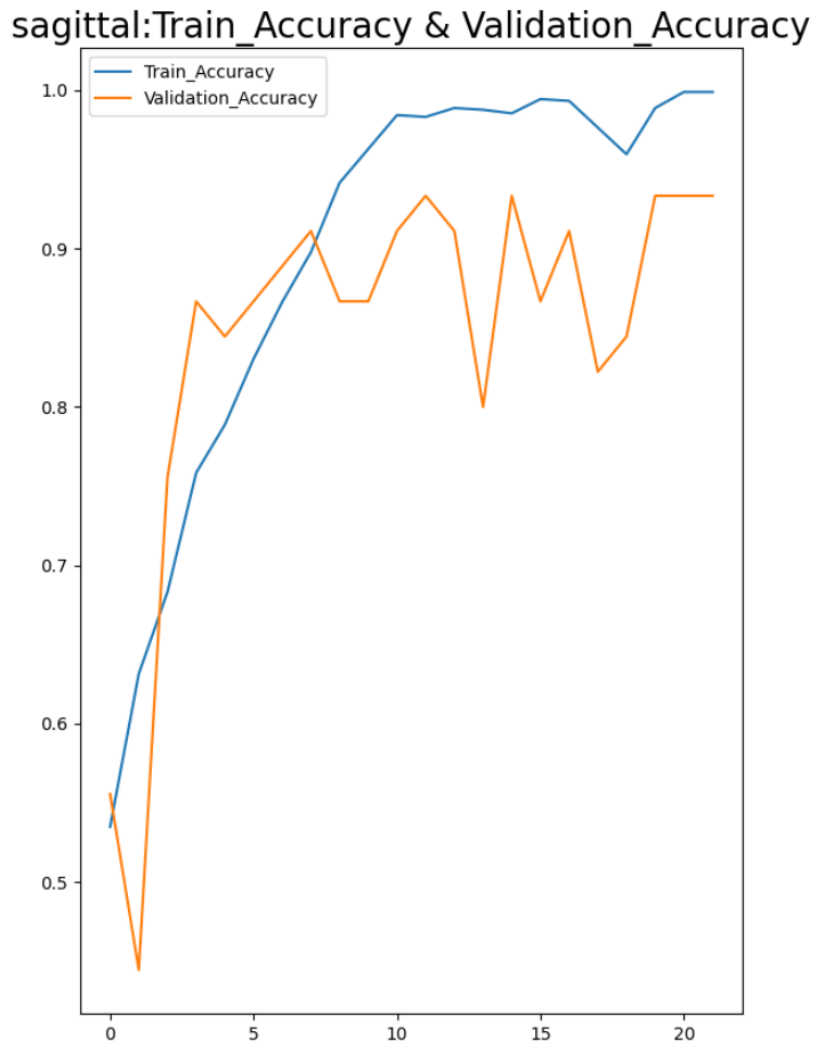
	precision	recall	f1-score	support
0	0.80	0.80	0.80	25
1	0.76	0.76	0.76	21
accuracy			0.78	46
macro avg	0.78	0.78	0.78	46
weighted avg	0.78	0.78	0.78	46

All classes, sagittal cluster 3






sagittal:Train_Loss & Validation_Loss
Train_Loss
Validation_Loss
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
5
10
15
20


sagittal:Train_Accuracy & Validation_Accuracy
Train_Accuracy
Validation_Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
0
5
10
15
20