

Comparative Evaluation of Neuroimaging Modalities for Distinguishing Cognitive Aging Classes: A UK Biobank Analysis



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INTRODUCTION

Cognitive decline is a growing concern in aging populations, and early detection is key to timely intervention. This study focuses on two aging trajectories: **Cognitive Decliners**, who exhibit measurable decline in cognitive performance over time, and **Positive Agers**, who maintain superior cognitive performance over time compared with their age-matched peers. Magnetic Resonance Imaging (MRI) offers a non-invasive approach to study brain, with each type capturing unique aspects of brain health: resting-state functional MRI (rsfMRI) assesses functional connectivity, diffusion MRI (dMRI) evaluates white matter integrity, and structural MRI (sMRI) captures structural changes. We compare these three MRI types to answer two key questions: **Can imaging reveal who is aging well versus who is not, and which MRI type is most effective in capturing brain changes linked to cognitive aging?** Using data from the UK Biobank and applying machine learning techniques, we aim to identify neuroimaging markers that can track and predict cognitive trajectories in older adults.

DATA

We included $n = 600$ participants aged at least 60 at t_3 .

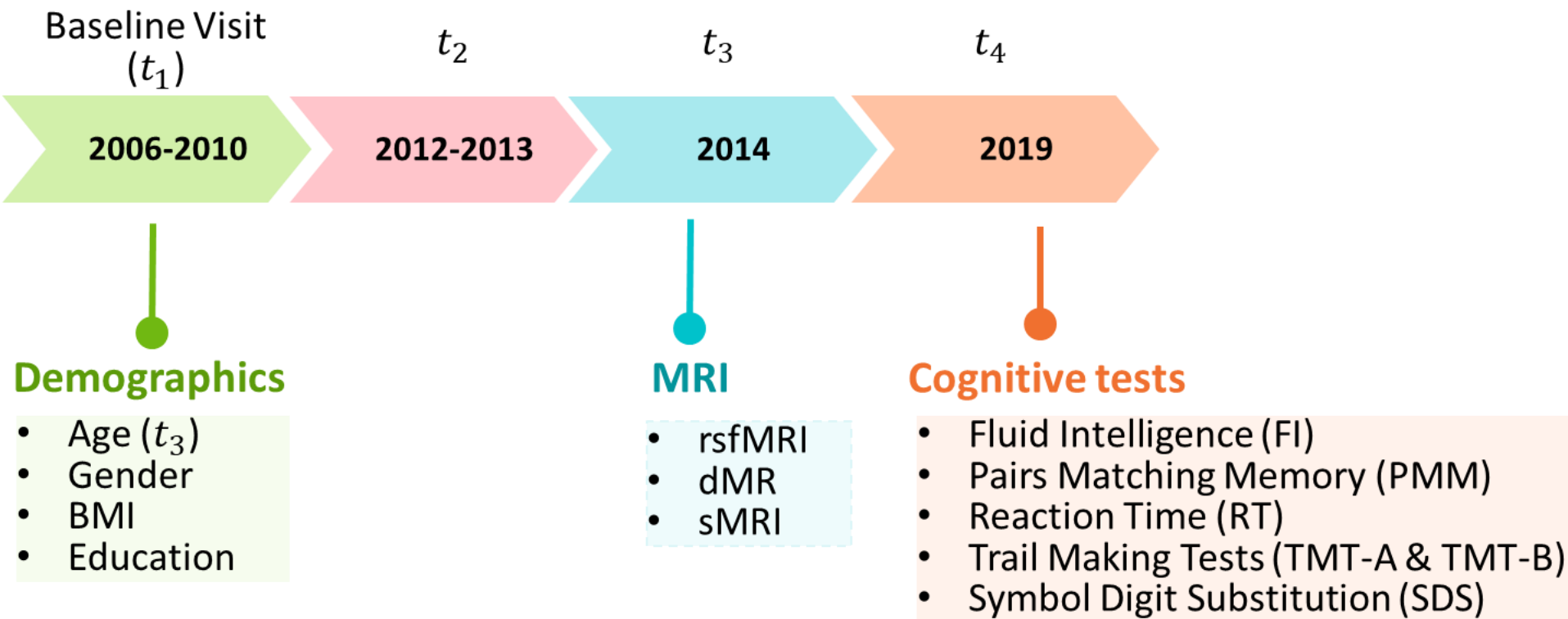


Figure 1. Data Collection Timeline of the UK Biobank.

METHOD

I. Labeling

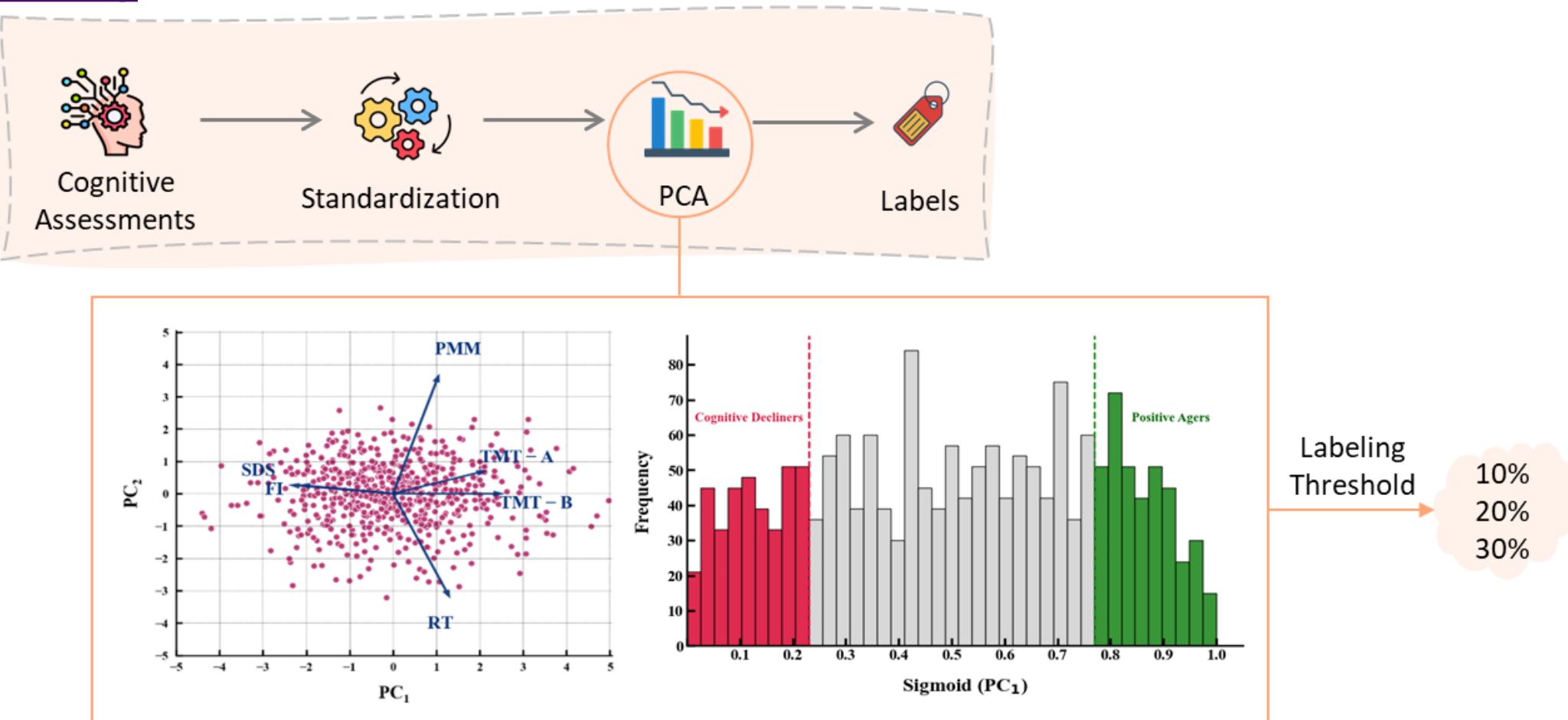


Figure 2. Labeling Flowchart.

METHOD

II. Feature Preparation

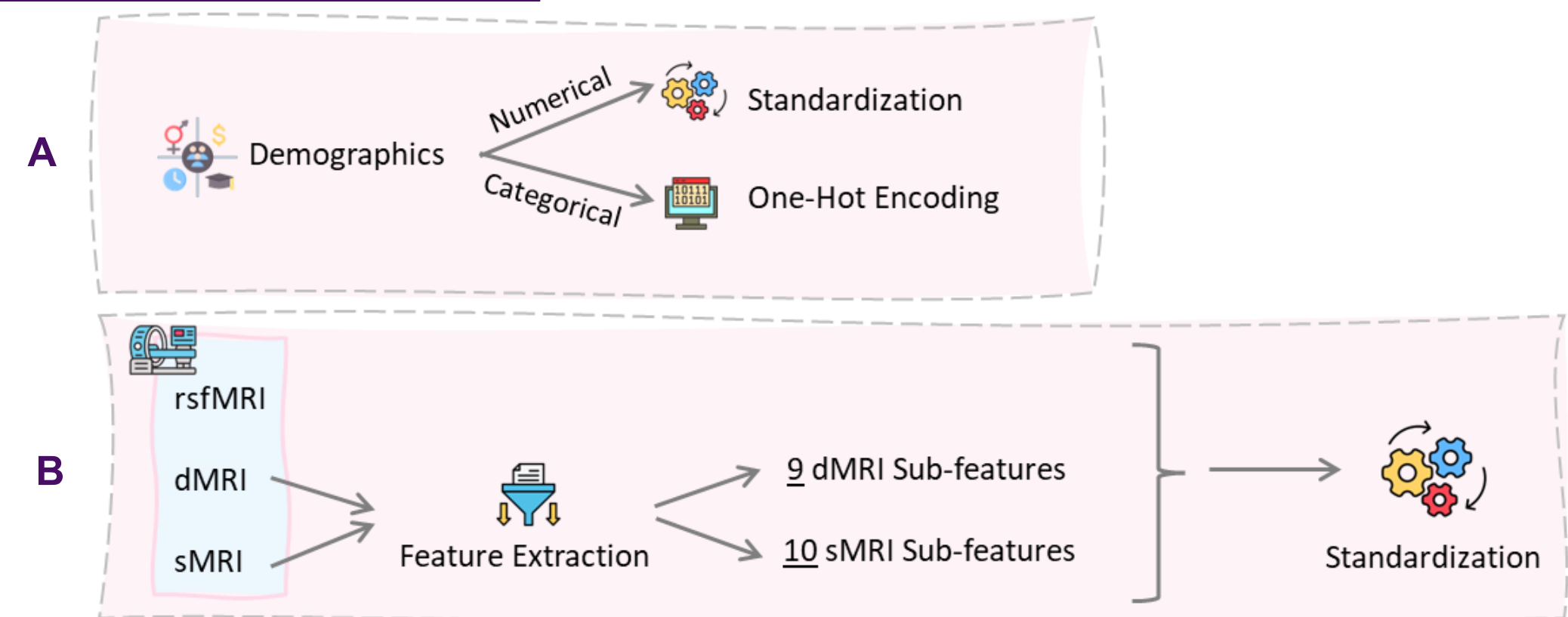


Figure 3. Feature Preparation Flowchart for (A) Demographics and (B) MRI Data.

III. Classification Model

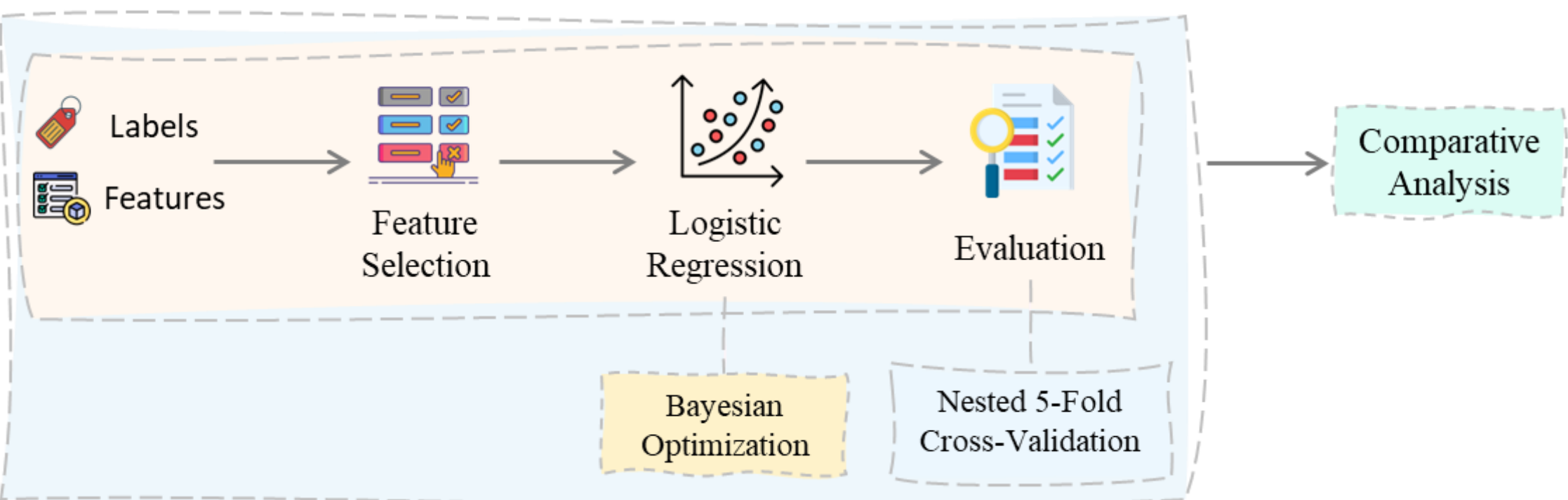


Figure 4. Classification Flowchart.

RESULTS

I. Classification Results

- All MRI types showed comparable performance across three labeling thresholds.
- Stricter thresholds improved classification, while broader thresholds increased group overlap and reduced performance.

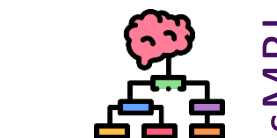
Table 1. Classification Results for 20% Labeling Threshold.

Dataset	Accuracy	Precision	Sensitivity	Specificity	F1	AUC
rsfMRI	0.71 ± 0.03	0.72 ± 0.09	0.70 ± 0.07	0.73 ± 0.08	0.71 ± 0.05	0.78 ± 0.05
FA	0.69 ± 0.06	0.69 ± 0.12	0.67 ± 0.06	0.71 ± 0.09	0.68 ± 0.08	0.77 ± 0.09
ICVF	0.74 ± 0.06	0.76 ± 0.14	0.70 ± 0.06	0.78 ± 0.12	0.72 ± 0.08	0.78 ± 0.07
ISOVF	0.77 ± 0.03	0.79 ± 0.09	0.74 ± 0.07	0.81 ± 0.06	0.76 ± 0.04	0.80 ± 0.03
L1	0.73 ± 0.07	0.73 ± 0.12	0.72 ± 0.15	0.75 ± 0.10	0.72 ± 0.11	0.79 ± 0.06
L2	0.73 ± 0.07	0.72 ± 0.11	0.72 ± 0.12	0.73 ± 0.11	0.72 ± 0.10	0.77 ± 0.07
L3	0.68 ± 0.08	0.68 ± 0.15	0.66 ± 0.13	0.70 ± 0.11	0.66 ± 0.11	0.75 ± 0.08
MD	0.69 ± 0.06	0.70 ± 0.10	0.68 ± 0.09	0.71 ± 0.09	0.69 ± 0.08	0.76 ± 0.07
MO	0.73 ± 0.08	0.74 ± 0.12	0.71 ± 0.12	0.76 ± 0.08	0.72 ± 0.11	0.77 ± 0.06
OD	0.72 ± 0.05	0.71 ± 0.09	0.72 ± 0.09	0.71 ± 0.04	0.71 ± 0.08	0.78 ± 0.07

RESULTS

Table 1 (continued). Classification Results for 20% Labeling Threshold.

Dataset	Accuracy	Precision	Sensitivity	Specificity	F1	AUC
ASEG	0.71 ± 0.04	0.72 ± 0.10	0.68 ± 0.07	0.75 ± 0.04	0.70 ± 0.08	0.76 ± 0.03
BA_exvivo	0.72 ± 0.04	0.72 ± 0.08	0.71 ± 0.04	0.72 ± 0.08	0.71 ± 0.05	0.75 ± 0.03
DKT	0.68 ± 0.07	0.69 ± 0.10	0.66 ± 0.13	0.70 ± 0.10	0.67 ± 0.09	0.73 ± 0.10
FAST	0.72 ± 0.02	0.72 ± 0.07	0.73 ± 0.04	0.72 ± 0.04	0.72 ± 0.04	0.76 ± 0.05
FIRST	0.72 ± 0.10	0.73 ± 0.18	0.72 ± 0.06	0.74 ± 0.17	0.72 ± 0.11	0.76 ± 0.09
a2009s	0.71 ± 0.04	0.73 ± 0.10	0.69 ± 0.10	0.75 ± 0.08	0.70 ± 0.05	0.76 ± 0.05
desikan_gw	0.72 ± 0.07	0.72 ± 0.12	0.71 ± 0.10	0.74 ± 0.08	0.71 ± 0.10	0.78 ± 0.07
desikan_pial	0.70 ± 0.09	0.69 ± 0.15	0.72 ± 0.08	0.69 ± 0.11	0.70 ± 0.11	0.77 ± 0.09
desikan_white	0.69 ± 0.07	0.71 ± 0.12	0.64 ± 0.12	0.73 ± 0.12	0.67 ± 0.11	0.76 ± 0.08
sub	0.74 ± 0.08	0.74 ± 0.10	0.72 ± 0.11	0.75 ± 0.06	0.73 ± 0.10	0.76 ± 0.08



II. Feature Importance Analysis

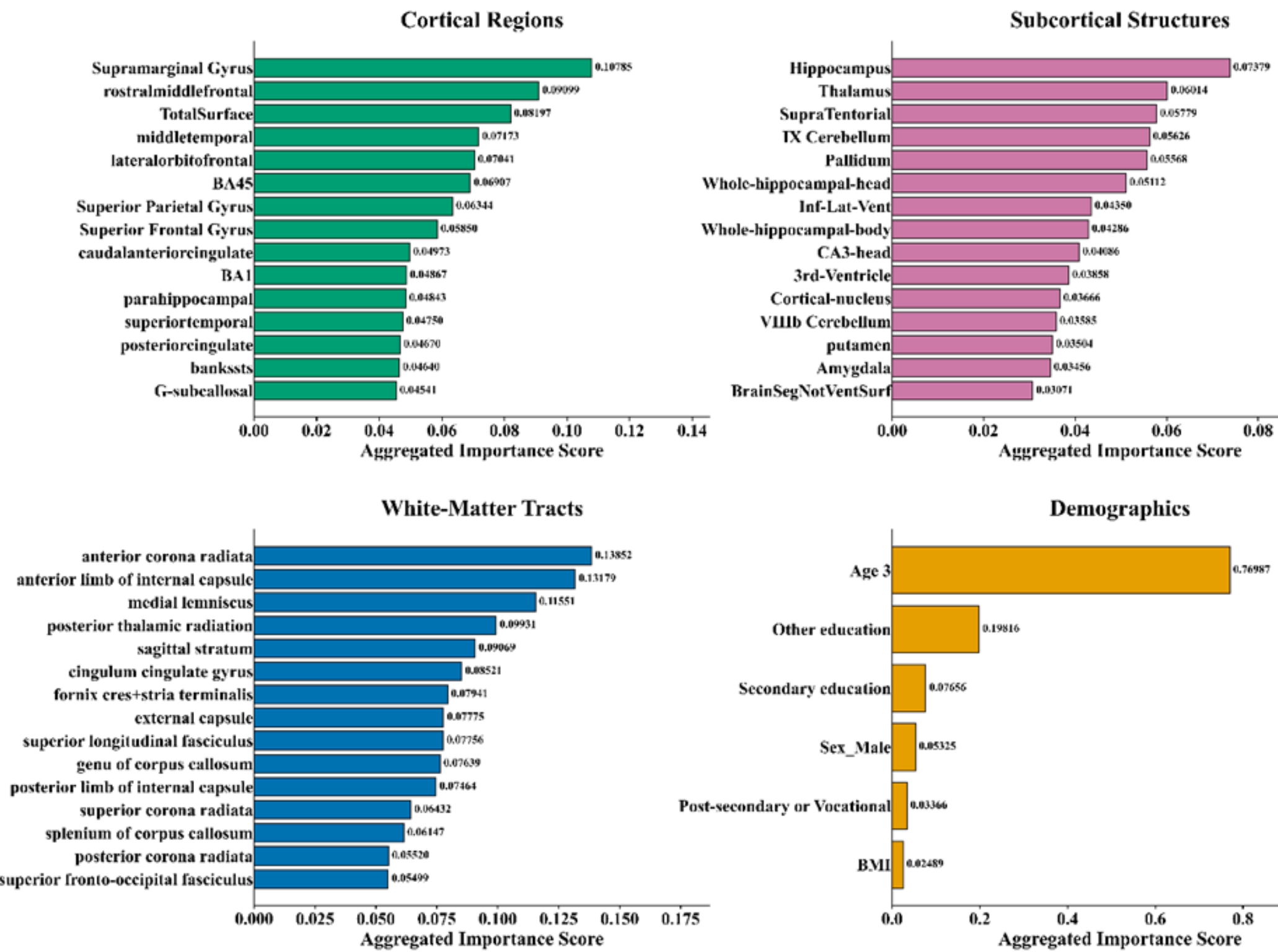


Figure 5. Aggregated SHAP Values Across Cortical Regions, Subcortical Structures, White-Matter Tracts, and Demographic Variables.

CONCLUSION

- rsfMRI, dMRI, and sMRI showed strong and comparable classification performance, with age as the dominant predictor across all models.
- Posterior DMN was the strongest rsfMRI marker, with reduced connectivity linked to poorer cognition and faster AD-spectrum decline.
- Anterior corona radiata was the top dMRI predictor, reflecting white matter integrity loss associated with executive dysfunction in AD.
- Supramarginal gyrus and hippocampus were the strongest sMRI predictors, with cortical thinning and volume loss as established early markers of MCI and AD.