Multi-Modal Prediction of Future Cognitive Impairment in Alzheimer's Disease

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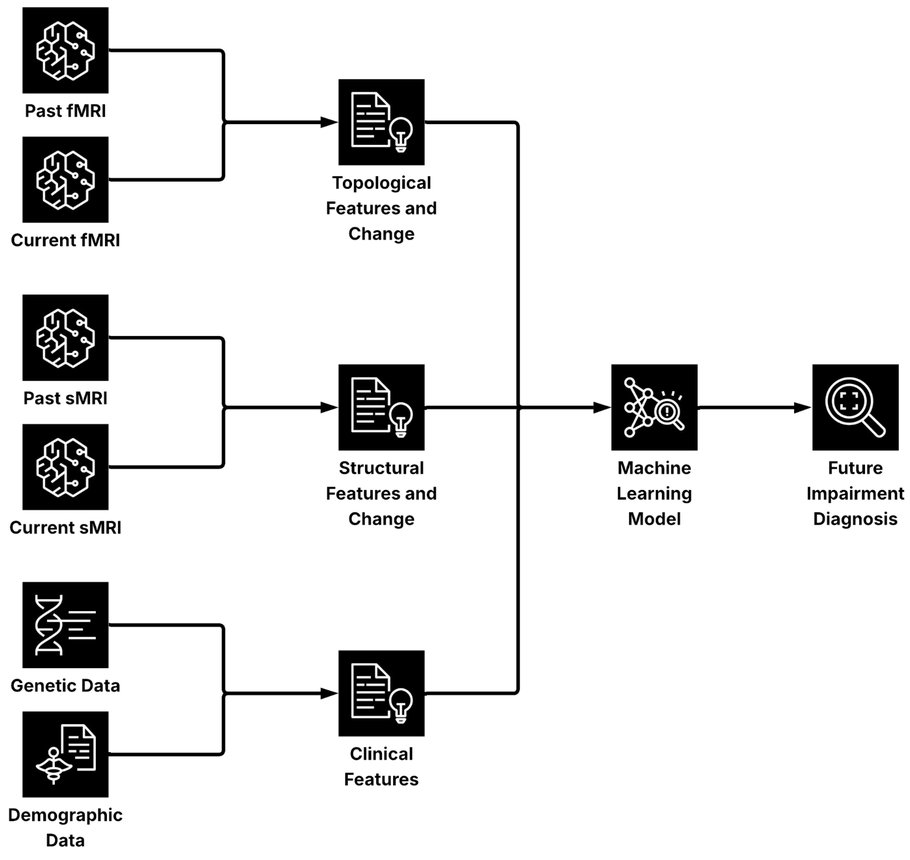
Project Overview

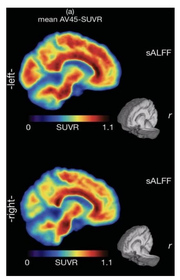
For Alzheimer's disease, prediction of future cognitive impairment is essential for informing patient care decisions, as well as selecting ideal candidates for clinical trials. However, such prediction is complicated by the fact that the rate and pattern of cognitive decline vary widely across individuals.

We present a novel method that integrates the intrinsic 3D geometry of the brain's connectome with graph-based functional connectivity to construct a unified functional connectome. From this, we extract topological features (e.g. mean/max/total persistence, topological difference) to capture its' patterns and structure. We also include structural and clinical variables, along with a set of variables capturing change over the prior year. Using these features, we trained a regression model to predict future cognitive impairment 12 months in the future. Our approach achieves strong performance in both forecasting cognitive scores and identifying cognitive decline, suggesting that using a combined topological and geometric representation, alongside individualized change over time, can meaningfully improve performance.

Model Input Architecture

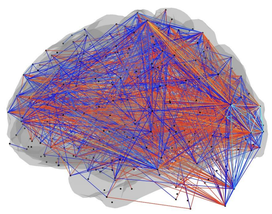


Neuroimaging Processing Pipeline



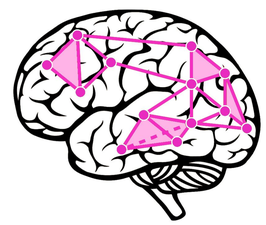
fMRI Scans

Processed into connectomes combining geometric and functional information

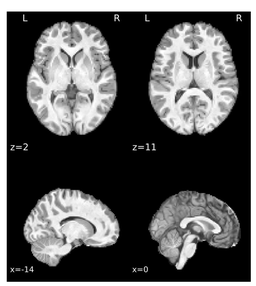


Brain Connectome

Processed into topological features, capturing the pattern and structure of the connectome

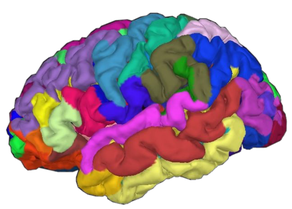


Topological Features



sMRI Scans

Surface reconstruction was performed on T1-weighted scans to get structural volumes and cortical thickness



3D Surface Reconstruction

Results

The regression model aimed to predict a subject's cognitive score 12 months in the future, using log-transformed scores to account for distribution skewness. The final model, trained with randomized hyperparameter search and subject-level cross-validation, achieved strong performance on the testing data, as seen in the regression performance table.

To evaluate the model's ability to identify cognitive decline, we classified subjects as declining if their predicted score was higher than their current score, reflecting a worsening cognitive state. This allowed us to assess decline detection performance using standard binary classification metrics, as seen in the classification performance table. These results demonstrate that the model not only performs well in predicting future cognitive scores but also captures meaningful signals associated with individual risk of decline.

Regression Performance

R^2	76.9%
MAE	0.265
RMSE	0.328

Classification Performance

Accuracy	68.6%
F1 Score	68.3%
Recall	68.5%

Acknowledgements

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