Beyond the MRI: A Nonlinear Machine Learning Framework for Predicting Alzheimer's Progression Using Accessible Clinical Measures in Underserved Latinx Populations

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Alzheimer's disease disproportionately affects Latinx communities, yet most prediction models rely on neuroimaging biomarkers that are costly and inaccessible to underserved populations. This study investigated whether widely available clinical variables, including acculturation measures, can replace imaging biomarkers in predicting cognitive decline. Using the Alzheimer's Disease Neuroimaging Initiative longitudinal dataset, imaging, clinical, and demographic variables were integrated within NeuroLAMA, a novel open machine learning framework designed and coded for longitudinal neuroscience analysis. Neurodegeneration was quantified using SPARE-AD, an MRI-derived biomarker, and functional decline was measured as change in Clinical Dementia Rating Sum of Boxes. Random forest regression predicted longitudinal decline, XGBoost classification distinguished diagnostic groups, and SHAP and response surface analyses examined feature importance and nonlinear interactions. Imaging biomarkers alone provided no predictive signal ($R2=-0.03$), while baseline cognitive status substantially improved performance ($R2=0.72$). Models incorporating acculturation, education, and physical activity achieved strong predictive performance. Diagnostic classification using non-imaging variables exclusively achieved ROC-AUC of 0.99 across cognitively normal, mild cognitive impairment, and Alzheimer's groups. NeuroLAMA-driven nonlinear modeling demonstrates that accessible clinical and acculturation measures directly replicate imaging-based prediction of cognitive decline, eliminating cost-prohibitive MRI requirements and establishing a scalable, culturally inclusive screening pathway for Latinx and underserved communities.

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