

Predicting Longitudinal Progression of Alzheimer’s Disease Brain Morphology From 3D MRI via Latent Space Transformers



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BACKGROUND

- Alzheimer's disease (AD) has a prolonged progression, with brain changes believed to begin two decades or more before clinical symptoms.
- AD progression exhibits substantial inter-individual heterogeneity, with rates and patterns of brain atrophy varying widely across individuals, making individual-level longitudinal analysis essential.
- True longitudinal MRI datasets remain limited, and most available data are cross-sectional.

To address this limitation, we propose a novel transformer-based deep learning model that leverages large-scale cross-sectional MRI data to generate individualized longitudinal MRI and predict disease progression for patients with Alzheimer's disease.

KEY TAKEAWAYS

- Leverages large-scale cross-sectional MRI data to generate individualized longitudinal MRI trajectories.
- Employs a transformer-based framework to capture temporal progression patterns.

METHODS

Stage 1: Latent Feature Representation

Stage 2: Latent Transformer Prediction

We utilized multi-timepoint T1-weighted MRI scans from the ADNI dataset. The proposed framework consists of two key stages.

Stage 1: a 3D Vector Quantized Variational Autoencoder (VQ-VAE) was trained to compress volumetric MRI images into compact, discrete latent codebooks, capturing time-independent anatomical representations of brain structure.

Stage 2: a Transformer-based temporal model was applied in this latent space to learn longitudinal temporal patterns of brain morphological changes.

By modeling sequences of latent representations across time, the Transformer captures disease-related temporal dynamics and predicts future brain morphology at the individual level.

REFERENCES & CONTACT

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RESULTS

Visualization of MRI and Reconstructed Surface

Evaluation of Longitudinal Temporal Pattern

Ground Truth	70.8	71.3	71.8	72.3	72.8	73.8	74.8	75.8	76.8	77.8	78.8	80.1	80.8	
Age	1.000	0.996	0.996	0.995	0.995	0.993	0.987	0.984	0.980	0.977	0.975	0.965	0.964	
	0.996	1.000	0.995	0.994	0.995	0.992	0.986	0.985	0.981	0.978	0.977	0.968	0.967	
	0.996	0.995	1.000	0.994	0.996	0.995	0.989	0.987	0.983	0.981	0.979	0.970	0.969	
	0.995	0.994	0.994	1.000	0.995	0.995	0.992	0.987	0.982	0.978	0.976	0.967	0.967	
	0.995	0.995	0.996	0.995	1.000	0.996	0.990	0.988	0.984	0.981	0.980	0.970	0.970	
	0.993	0.992	0.995	0.995	0.996	1.000	0.992	0.989	0.986	0.984	0.982	0.971	0.972	
	0.987	0.986	0.989	0.992	0.990	0.992	1.000	0.988	0.983	0.981	0.979	0.970	0.970	
	0.984	0.985	0.987	0.987	0.988	0.989	0.988	1.000	0.991	0.991	0.990	0.982	0.982	
	0.980	0.981	0.983	0.982	0.984	0.986	0.983	0.991	1.000	0.995	0.994	0.985	0.985	
	0.977	0.978	0.981	0.978	0.981	0.984	0.981	0.991	0.995	1.000	0.995	0.987	0.988	
	0.975	0.977	0.979	0.976	0.980	0.982	0.979	0.990	0.994	0.995	1.000	0.989	0.989	
	0.965	0.968	0.970	0.967	0.970	0.971	0.970	0.982	0.985	0.987	0.989	1.000	0.994	
	0.964	0.967	0.969	0.967	0.970	0.972	0.970	0.982	0.985	0.988	0.989	0.994	1.000	
	70.8	71.3	71.8	72.3	72.8	73.8	74.8	75.8	76.8	77.8	78.8	80.1	80.8	
Prediction	Age	1.000	0.999	0.999	0.998	0.997	0.994	0.992	0.989	0.986	0.982	0.978	0.972	0.969
		0.999	1.000	0.999	0.999	0.998	0.996	0.993	0.991	0.988	0.984	0.980	0.975	0.971
		0.999	0.999	1.000	0.999	0.999	0.997	0.995	0.993	0.990	0.986	0.982	0.977	0.974
		0.998	0.999	0.999	1.000	0.999	0.998	0.996	0.995	0.992	0.988	0.984	0.979	0.976
		0.997	0.998	0.999	0.999	1.000	0.999	0.997	0.996	0.993	0.990	0.986	0.981	0.978
		0.994	0.996	0.997	0.998	0.999	1.000	0.999	0.998	0.995	0.993	0.989	0.984	0.981
		0.992	0.993	0.995	0.996	0.997	0.999	1.000	0.999	0.997	0.995	0.991	0.987	0.984
		0.989	0.991	0.993	0.995	0.996	0.998	0.999	1.000	0.999	0.996	0.993	0.989	0.987
		0.986	0.988	0.990	0.992	0.993	0.995	0.997	0.999	1.000	0.999	0.996	0.993	0.990
		0.982	0.984	0.986	0.988	0.990	0.993	0.995	0.996	0.999	1.000	0.998	0.995	0.993
		0.978	0.980	0.982	0.984	0.986	0.989	0.991	0.993	0.996	0.998	1.000	0.998	0.996
		0.972	0.975	0.977	0.979	0.981	0.984	0.987	0.989	0.993	0.995	0.998	1.000	0.999
		0.969	0.971	0.974	0.976	0.978	0.981	0.984	0.987	0.990	0.993	0.996	0.999	1.000
		70.8	71.3	71.8	72.3	72.8	73.8	74.8	75.8	76.8	77.8	78.8	80.1	80.8