Table 1.

Demographics for standard 3.0T ADNI 1 dataset (baseline only) from ADNI database			
	Controls (HC)	MCI	AD
N	47	71	33
Age	75.06 <u>±</u> 3.93 y	74.03 <u>±</u> 8.12y	75.08 <u>±</u> 8.07y
Sex (m/f)	18/29	45/26	11/22

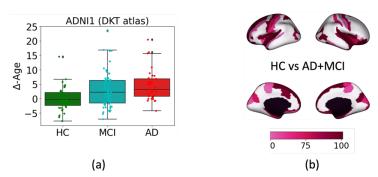


Figure S1. Brain age gap on ADNI dataset curated according to DKT atlas. (a) Distribution of Δ -Age across HC, MCI, Dementia cohorts derived from VNN models trained on OASIS-3. Anatomical covariance matrix from ADNI dataset was used in the VNNs. Δ -Age for controls: 0 ± 3.92 years, Δ -Age for MCI 3 ± 5.74 years, Δ -Age for AD: 4.49 ± 5.34 years. (b) Approach 1 for cross-validation of anatomical interpretability: Across 100 VNNs that had been trained on OASIS-3 dataset, we evaluated the number of times the regional residual mean was smaller for HC group than the AD+MCI group in ADNI1 dataset.

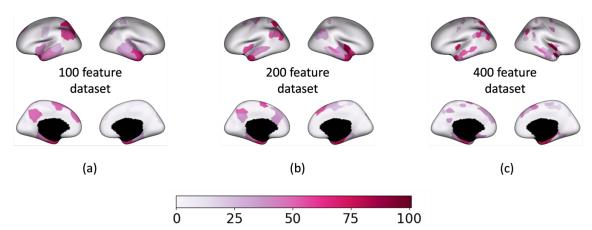


Figure S2. Evaluating brain regions contributing to elevated Δ-Age in ADNI dataset (curated according to different versions of Schaefer's 17-network atlas). Models trained on XYZ dataset (see supplementary material) were used to derive the results in this figure. This figure demonstrates that VNNs can indeed process datasets of different dimensionalities with no re-training and recover consistent patterns of anatomical interpretability across them. This provides evidence that VNNs trained on dataset of one dimensionality can extract the inherent patterns of anatomic interpretability of brain age in datasets of other dimensionalities for a given population. Approach 2 for cross-validation of anatomical interpretability: Across 100 VNNs that had been trained on XYZ dataset, we evaluated the number of times the regional residual mean was deemed to be smaller for HC group than the AD group in ADNI1 dataset using ANOVA (p-value < 0.05) and ANCOVA with age and sex as covariates (p-value<0.05).