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BIOMARKERS

POSTER PRESENTATION

NEUROIMAGING

A multi-class deep learning model to estimate brain age while addressing systematic bias of regression to the mean

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Abstract

Background: Age-related changes in human brain may contribute to the development of age-related neurodegenerative diseases. It may be possible to estimate "brain age" from magnetic resonance imaging (MRI) and the difference between a person's brain and chronological age, Δ_{age}, reflecting whether a person's brain has been aging faster or slower than their chronological age. Deep Learning Models typically regress age on imaging features, leading to systematic biases associated with regression to the mean (RTM), including overestimation of brain age in younger persons and underestimation in older persons. We estimate brain age from a person's MRI as a multi-class classification problem and developed deep learning model to estimate brain age free from RTM bias.

Method: Two 3D ResNet-18 models were implemented: regression and multi-class classification. We transform the task of predicting age as continuous variable to predicting probabilities of discrete age values where age is discretized to closest integer values. Both models were trained on 7,372 T1-weighted MRI scans of 5,848 cognitively normal participants (age: 8-95 years) from public data sources (IXI, ICBM, ABIDE, NACC and OASIS). We create train, validation, and test set in ratio 80:10:10 with matching age distribution. Mean squared error is used as loss function in training regression model. Whereas in the classification model, we introduce two loss terms in addition to standard cross-entropy loss: (1) minimizing the difference between mean ($\sum c * p_c$) of expected age and the actual age, and (2) minimizing variance ($\sum$(c-mean)$^2 * p_c$), where p_c is probability sample belonging to class c.

Result: The regression model achieved MAE = 3.93 years and R^2 = 0.90 on unseen test set whereas classification model achieved MAE = 2.41 and R^2 = 0.96 on same test set. We observe significant decrease in systematic bias using the classification model - for younger (age<30) and older (age>70) subsets, average Δ_{age} improved from 3.17 to 0.2, and from -2.49 to -0.97 respectively (Figure1).

Conclusion: Our proposed classification model with improved loss function to predict brain age from imaging features eliminates systemic bias present in traditional regression approaches and also improves performance by a significant margin. This model

can be used more reliably to study age-related alterations in brain and AD-related deviations from natural aging.

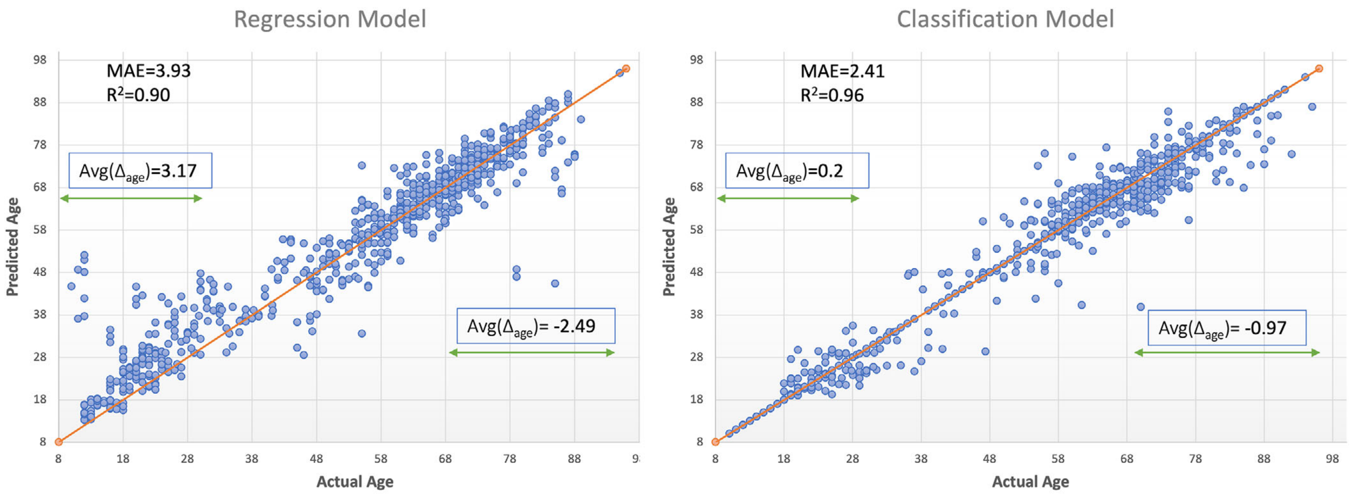

Figure 1. Comparison of actual vs predicted age of regression and classification model