A Deep Decomposition of MRI to Explore Neurodegeneration in Alzheimer's Disease

F. J. Martínez-Murcia, J. M. Gorriz, J. Ramírez, D. Castillo-Barnes, F. Segovia, D. Salas-Gonzalez, A. Ortíz

Department of Signal Theory, Networking and Communications, University of Granada (Spain)

Introduction

Known fact: Cognitive examinations in Alzheimer's Disease often depend on confounding variables such as level of education or repetitions. Deep convolutional autoencoders are an useful way to project large complex imaging datasets to a few features that represent their internal variability.

Hypothesis: Finding a descriptive and objective relation between structural neuroimaging features and cognitive test results could be of great help for understanding the process of neurodegeneration.

We compare the use of convolutional autoencoders and Principal Component Analysis (PCA) applied to structural MRI in order to predict neurocognitive test outcomes.

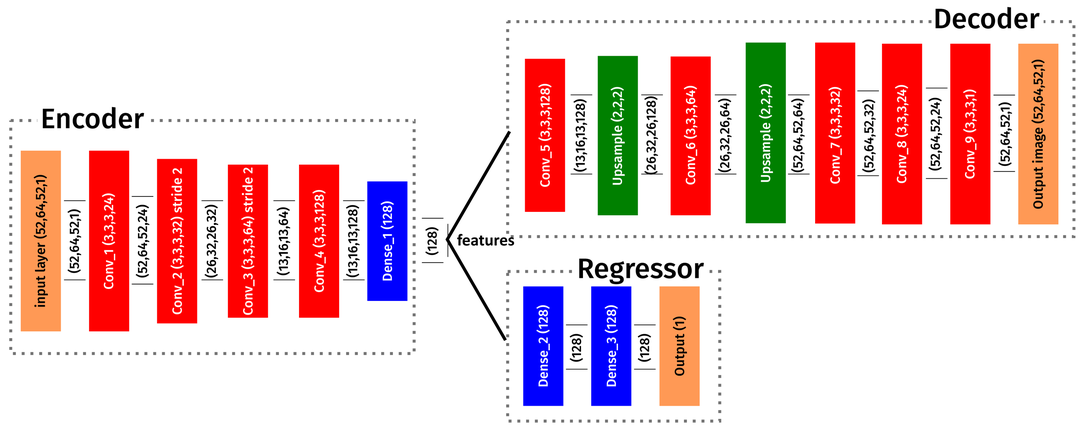

Figure 1. Schema of the proposed Autoencoder - Regression architecture.

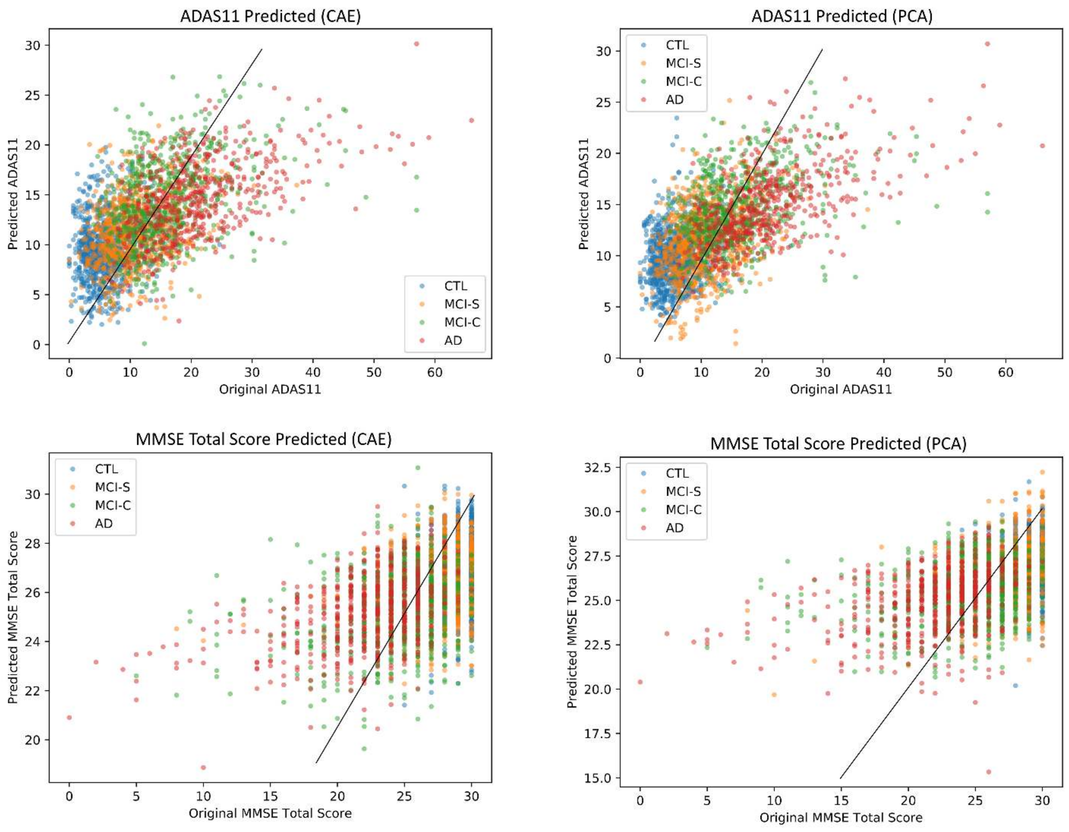

Figure 2. Regression results for MMSE and ADAS-13 cognitive tests.

Materials and Methods

Database and preprocessing: We use **2795** Gray Matter (GM) maps segmented from structural normalized MRI T1-weighted images in **ADNI**, using SPM-12, of which 853 are from Normal Controls (CTL), 769 from Mild Cognitive Impairment (MCI) stable (MCI-S), 645 from MCI converters (MCI-C) and 528 from AD affected subjects. Images were smoothed with a gaussian filter of size 3 and later resampled down to 52 × 64 × 52 for reducing the computational load.

Convolutional Autoencoders (CAEs): CAEs combine a encoder and a decoder convolutional neural network, in which the output layer of the encoder (also known as z-layer) is also the input layer of the decoder. Then, the loss between the reconstructed and the original image is computed

$$\mathcal{L} = \frac{1}{N}\sum_i (I_i - \hat{I}_i)^2$$

In this work we use the CAE architecture displayed at Figure 1. The encoder uses four convolutional layers and one dense layer to obtain an internal representation in the output layer, "Dense 1". The decoder, for its part, uses one dense layer and five convolutional layers to transform back into the original space. Feature reduction in the encoder is achieved via the stride property, since it can completely replace the pooling layer without loss in accuracy, according to a recent study [5]. Its effect is counteracted in the decoder using an upsample layer.

Neural Network Regression: We have implemented a regular non-linear regression algorithm via neural networks (NNR), using a deep architecture with two hidden layers containing 128 neurons each. The network also used ReLU activation, batch normalization and dropout after each layer with probability of 0.5 to prevent overfitting. These layers were connected to the output layer, containing only one neuron, with linear activation. In order to improve convergence, the target variables were normalized by the average of the 5% top values.

Results

The results of regressing the CAE features with the different variables found at Sec. II-A are presented at Table I. Results indicate that there is a medium-to strong correlation of the CAE features, especially with the ADAS-11 and ADAS-13 scores, using both the PCC and the R2, but also with other measures such as Age, FAQ and MMSE.

When plotting scores relevant to Alzheimer's diagnosis, such as ADAS11 or MMSE, we observe clear correlations and distribution of clusters among all four classes found in the database. When compared to a PCA decomposition (see Fig. 2), the CAE decomposition tends to produce less outliers, especially in the CTL and MCI-S classes, but also in abnormal ADAS11 and MMSE scores.

Variable	PCC [STD]	R2 [STD]	MSE [STD]
Age	0.507 [0.109]	0.242 [0.082]	0.005 [0.001]
MMSE	0.501 [0.079]	0.235 [0.069]	0.014 [0.002]
GDSCALE	0.085 [0.078]	-0.017 [0.045]	0.068 [0.010]
Global CDR	0.479 [0.062]	0.212 [0.075]	0.063 [0.006]
FAQ	0.546 [0.075]	0.283 [0.070]	0.064 [0.006]
NPI-Q	0.249 [0.096]	0.049 [0.051]	0.064 [0.014]
ADAS11	0.570 [0.059]	0.312 [0.058]	0.037 [0.004]
ADAS13	0.567 [0.063]	0.307 [0.064]	0.039 [0.004]

Table 1. Regression results for different cognitive tests.

Conclusions

Known fact: The automatic decomposition performed by the autoencoder has proven useful to predict some neuropsychological scores based solely on grey-matter distribution derived features..

Strengths: The prediction of neuropsychological test outcomes achieved R2 rates up to more than 0.3, with correlations higher than 0.5in the case of variables heavily linked to neurogedeneration and cognitive state such as the MMSE or the ADAS11 scores.

Conclusions: This might help to more fully understand the link between neurobiology and cognitive state, as well as pave the way for a future automatic assessment of neurodegeneration via neuroimaging.

References

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