# Classification of Alzheimer's patients and cognitive deficit through MRI

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**Introduction:** Alzheimer's disease (AD) is a type of dementia that affects millions of people around the world. By 2050, more than 14 million people will suffer of AD [1]. To date, there is no cure for AD and its early-diagnosis is a challenging task. Magnetic Resonance Imaging (MRI) has aided in the diagnosis *in-vivo* of various diseases, especially neurodegenerative ones, since it can provide details of tissue and its microstructures therein. The current techniques to predict the diagnosis of AD have explored the microstructural information contained in MRI. Among these techniques, convolutional neural network (CNN) is the most promising and has been used successfully applied to medical imaging problems due to its ability to extract characteristics and transfer knowledge.

**Materials and Methods:** We use the ResNet[4], a well known CNN architecture, to classify the three main stages of AD: controls (NC), mild-cognitive impairment (MCI) and pathologically proven AD stage (AD). We aimed to generalize our model using two datasets. The first dataset was composed by 240 T1-weighted images from the ADNI[2] and the second dataset by 30 T1-weighted images from CADDementia[3]. While the ADNI images were balanced (80 for each class), the CADDementia images were distributed in 12 NC, 9 MCI and 9 AD. For both of two datasets, 50 slices containing the most relevant pixel-wise information were chosen among the coronal plane and cropped at the same size. The ResNet34 model was adapted, by replacing the last layer by a convolution layer, max-pooling, a dense layer, dropout, and lastly another dense layer followed by a softmax. The datasets were divided into train, validation and test sets. The train set was normalized between 0 and 1 and this normalization was applied to validation and test sets. Data-augmentation technique was applied in order to insert more value data by either random 80x80 cropping or mirroring the images. The model was trained using transfer-learning and fine-tuning. To evaluate our results and not insert a bias into our model, k-fold cross-validation was used.

**Results:** The CCN was trained along 100 epochs using cross-validation for 7 folds (Fig.1). From the proposed model an accuracy of 64% was achieved in the test set for the multi-class task (Tab.1).

**Discussion:** Overfitting was registered because of the reduced dataset. The network learned well the training set reducing its error, but the same does not occur in the validation set (Fig.1).

**Conclusion:** Classifying the different stages of AD is not a trivial task. Our results represent a promising approach in classification of AD phases.

**References:** [1] doi: 10.1152/physrev.2001.81.2.741 [2] doi: 10.1002/jmri.21049 [3] doi: 10.1016/j.neuroimage.2015.01.048 [4] doi: 10.1109/CVPR.2016.90 [5] Sørensen, L. et al., *MICCAI 2014 Workshop Proc.: 111-118*, 2014. [6] doi: 10.1109/ISBI.2017.7950647.

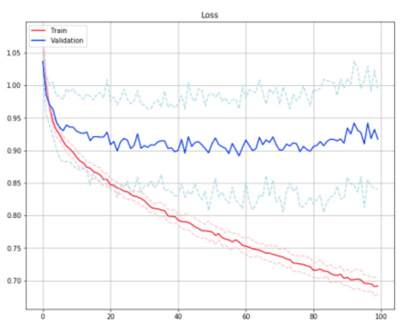


**Figure 1.** Loss for training and validation sets along 100 epochs. The graph depicts the mean and standard deviation along 7 folds.

| Classification task | Validation accuracy | Test accuracy | Literature results |
|---|---|---|---|
| NC vs MCI | 0,69 | **0,7** | 0,58[5] |
| AD vs MCI | 0,82 | **0,625** | 0,61[5] |
| AD vs NC | 0,82 | **0,8** | 0,8[5] |
| Multi-class | 0,71 | **0,64** | 0,63[6] |

**Table 1.** Accuracy results for different tasks when compared with the literature results.