

Evaluation of 5-year disease progression in multiple sclerosis via magnetic-resonance-based deep learning techniques.

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Multiple sclerosis (MS) course variability is guided by chronic inflammation, neuroaxonal degeneration and remyelination. However, it is not clear how these phenomena interact with each other and change over the disease course, making clinical outcome and response to treatment hard to predict [1,2]. In recent years, research interest addressed the possibility to find statistical models able to predict, with a certain degree of probability, the course of the disease over time. The use of advanced statistical techniques and artificial intelligence algorithms could make it possible to identify patients who are at greater risk of disease progression, and to make both pharmacological and rehabilitative treatments more targeted [3, 4].

This study aims at developing a deep learning (DL) classifier for automatically predicting 5-year disease progression in patients, based on 3T magnetic resonance imaging (MRI) scans.

Patients were clinically evaluated twice at 4 to 6 year intervals, at MS Center of S Andrea Hospital, Sapienza University. Demographic and clinical data, i.e. age, disease duration and phenotype, were recorded. The Expanded Disability Status Scale (EDSS) was evaluated on both visits and used to assess disability progression [5]. On their first visit, patients underwent an MRI scan (including T13D images) with a 3T Verio Siemens, hosted at Policlinico Umberto I, Sapienza University. Slices of the sagittal projection of brain-extracted T1-weighted images, registered onto MNI space (FSL toolbox), were used to build models in this study (Figure 1).

Twenty-five DL models were developed from the fine-tuning of a pre-trained inception (V3) image classifier, implemented on the open source Tensorflow library. Multiple DL models were devised by randomly selecting 90% of MRI dataset as the training component, with the remaining 10% used for validation. The discriminating performance of each binary classifier was assessed by plotting true-positive vs. false-positive rates as in Receiver Operating Characteristic (ROC) space (Figure 2).

In this preliminary phase, a sample of 105 patients (38.3+/-9.8 years, 25 males) was studied, including 85 relapsing-remitting and 20 secondary progressive forms. At baseline EDSS distributions (median and range) was 2.0[0.0-7.5]. Disease progression was observed in 36 patients, whose EDSS distributions at baseline and at follow-up were respectively 2.5[0.0-6.5] and 4.5[1.5-7.0]. Disease progression was correctly assessed at 84% true-positive rate (with 16% false-positive), encouraging us to further develop this technique.

Increasing the database of available patients and MRI sequences is fundamental in improving the diagnostic ability and in adapting the tool to single individuals in clinical settings. Application of DL techniques on mildly preprocessed T13D images promises to improve treatment and enable more targeted pharmacological and rehabilitative treatments.

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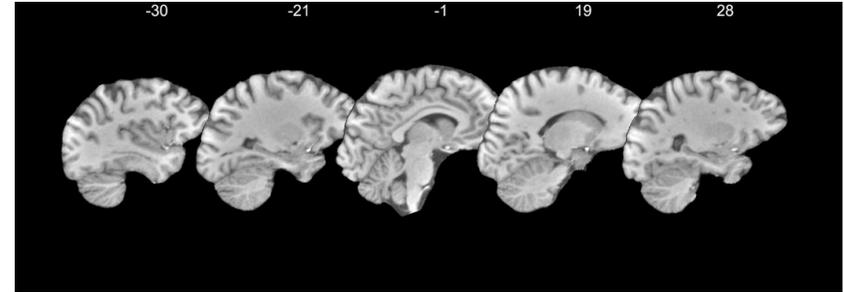


Figure 1. Sagittal projection of T13D, slices -30, -21, -1, 19, 28.

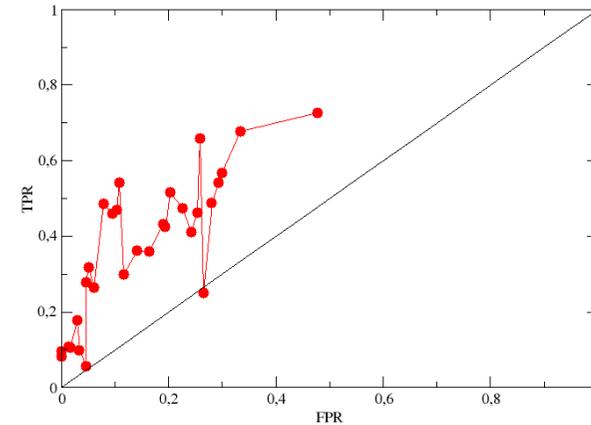


Figure 2. Receiver Operating Characteristic (ROC) space. True-positive rate (TPR) on y-axis, False-positive rate (FPR) on x-axis.