A 3D CONVOLUTIONAL NEURAL NETWORK WITH TRANSFER LEARNING ON MRI FOR INCOMPLETE HIPPOCAMPAL INVERSION CLASSIFICATION

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Introduction

The project defines the potential of transfer learning applied to brain MRI images for diseases classification. Starting from a 3d CNN pre-trained on a large dataset of subjects with hippocampal atrophy, this method uses transfer learning on a subdomain of Incomplete Hippocampal Inversion (IHI). This is atypical anatomical pattern of the hippocampus, mostly described in epileptic patients. The principal aim is to obtain, via transfer learning, an improved task accuracy with a small dataset.

Materials & Methods

Data used for experiments come from two different datasets. The principal 3d CNN is trained on a large dataset (1204 3d scans) of T1-weighted MRI comprising healthy controls and neurological patients with mixed diagnosis. The second target dataset is composed by 42 patients with a diagnosis of temporal lobe epilepsy and positive for Incomplete Hippocampal Inversion (IHI) and 60 patients without malrotation. The presence/absence of IHI was assessed visually on MRI images by an expert neuroradiologist following the international criteria (Fig.2). The structure of 3d CNN contains five blocks, each of them composed by a convolutional layer, followed by a RELU activation function, another convolutional layer, a 3d batch-normalization, a RELU and a max-pooling layer. When learned from scratch, all the parameters of CNN models are initialized with random normed Gaussian distributions. In the transfer learning experiment, the pre-trained convolutional filters of 3d CNN are further adapted to the small target domain to perform task-specific classification of IHI. All experiments described are implemented using open source scientific tools.

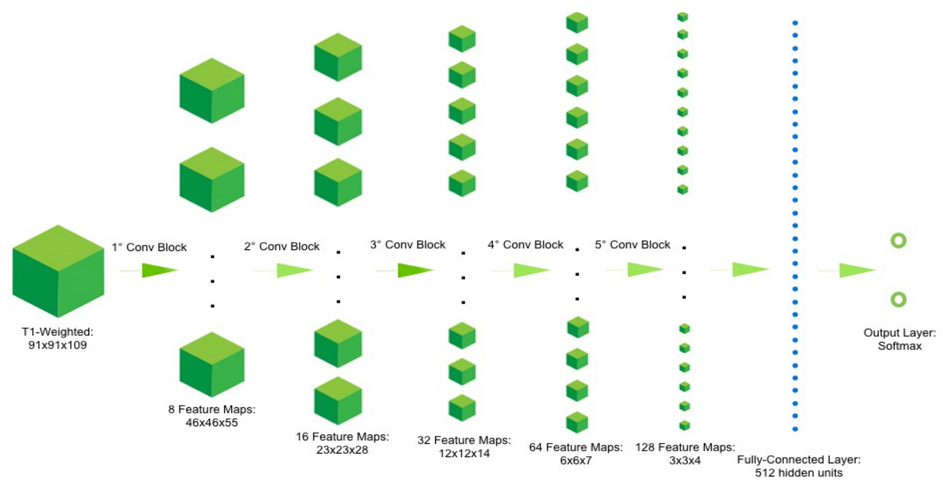


Fig.1: An illustration of our 3d CNN architecture used for classification task.

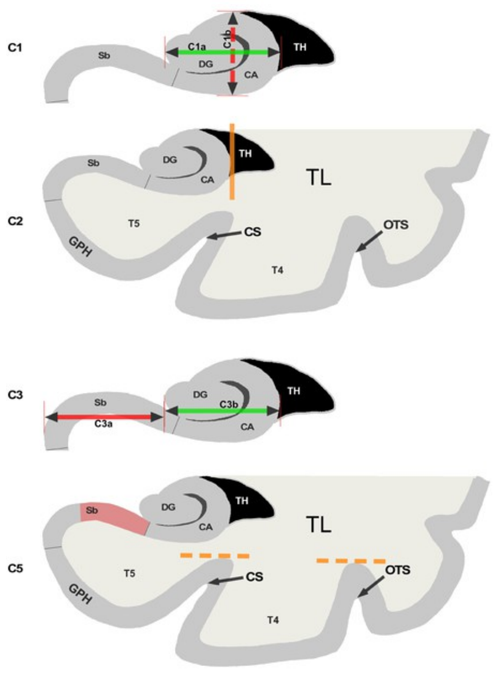
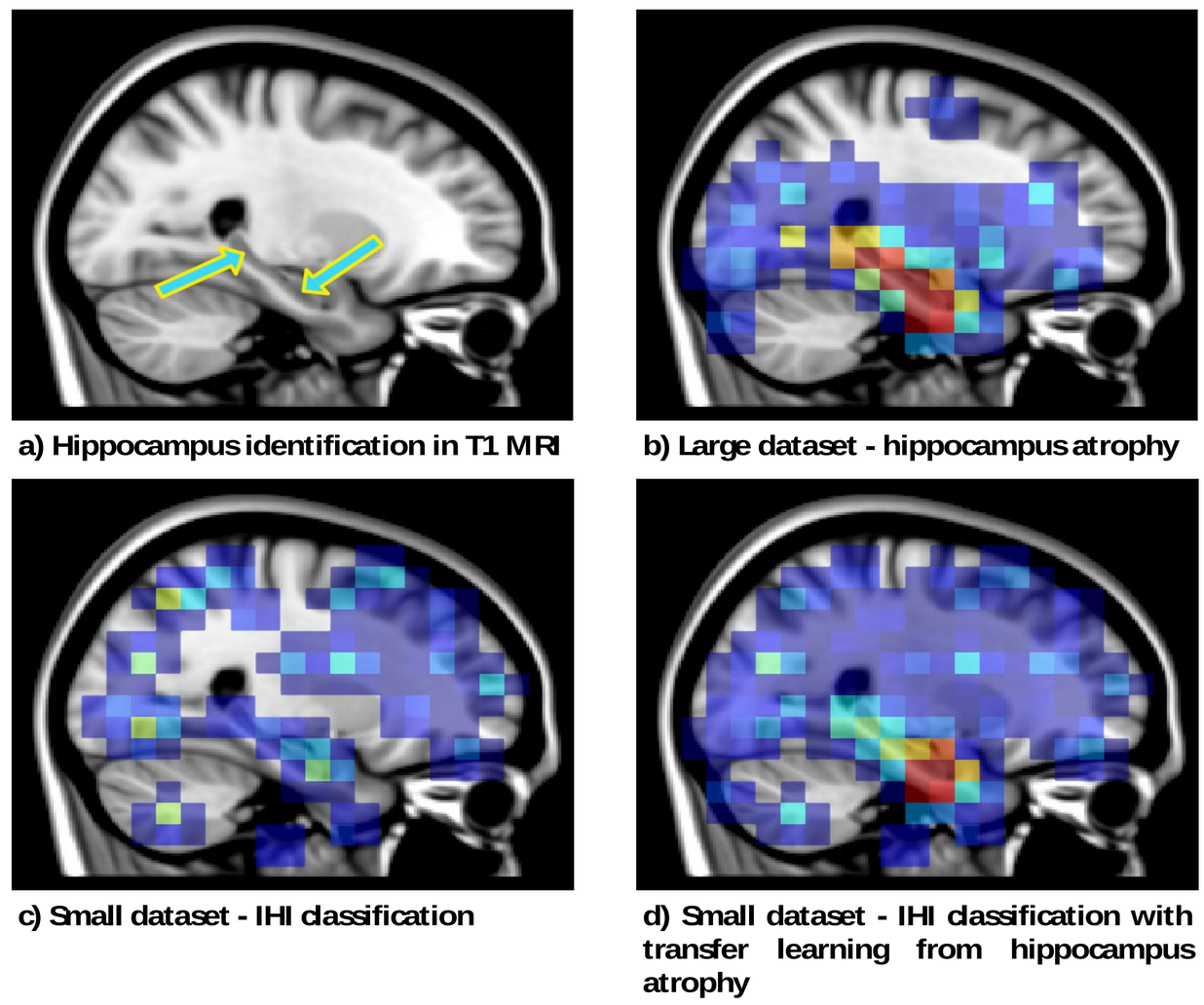


Fig.2: Illustration of the criteria used for the evaluation of Incomplete Hippocampal Inversions. C1: Roundness and verticality. C2: Verticality and depth of the collateral sulcus. C3: Medial positioning. C5: Orientation of the sulci of the fusiform gyrus.



a) Hippocampus identification in T1 MRI

b) Large dataset - hippocampus atrophy

c) Small dataset - IHI classification

d) Small dataset - IHI classification with transfer learning from hippocampus atrophy

Fig.3: a) T1-weighted MRI in the sagittal plane with the hippocampus marked with arrows; b) Heat map superimposed on T1 MRI indicates weights associated to each region from a 3D CNN trained from scratch on source domain dataset composed of subjects with different hippocampal atrophy. There is a clear predominance in the subcortical region of hippocampus compared to the rest of brain; c) Heat map on T1 MRI refers to weight for 3D CNN trained from scratch on target domain dataset of patients with IHI; d) Heat map on T1 MRI reports resulting weights obtained by transfer learning from source domain dataset with hippocampal atrophy to target domain of IHI subjects. In this case, with respect to a training from scratch, features associated to hippocampal regions have greater weight demonstarting the utility of the pre-trained 3D CNN on atrophy domain.

Results & Conclusions

To achieve the goal of diagnosing a very specific and rare anatomical pattern as IHI we used a 3d CNN trained on a large dataset with a common anatomical feature (hippocampus atrophy) whose trained feature where transferred to a second CNN trained on IHI classficiation. It was hypothesized that such a neural network would be able to extrapolate morphological information specific to the structure of interest and use this knowledge as an advantage for the second classification task that involved the same brain region. Choosing the hippocampus atrophy as a model is justified by the fact that IHI pathology affects the same region, altering its appearence on MRI. The accuracy of classification by transfer learning is increased from a value of 0.53 to a value of 0.72.

In this work we have used for the first time the transfer learning technique to understand if, by exploiting a pre-trained network on anatomical variations on a heterogeneous dataset, it is possible to obtain better performance in order to detect the hippocampal variations typical of the IHI pathology.

References

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