WMH Segmentation Challenge MICCAI 2017 – Team Name: caai_amh

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The network architecture of this model is a slightly modified version of the network proposed by Li et al [1]. The network is trained on a local database of 71 multiple sclerosis patients (MS), using transfer learning from the model by Li et al. The challenge dataset is thereby only used for transfer learning and testing of the model.

The Model

The network by Li et al. is a 2D U-net with skip connections including 19 convolutional layers in total, 4 up-sampling and 4 down-sampling blocks [1]. Each block consists of two convolutional layers, each layer followed by a ReLu activation function. The first convolutional block has kernel size 5x5 and the rest 3x3. The network employs the dice loss coefficient for training, in effort to smoothen the class imbalance between lesion voxels and non-lesion voxels.

We made the following changes to the network proposed by Li et al.: We hypothesized an importance of including spatial information to the delineations, and therefore added the neighbouring slice on either side of each relevant axial slice input, to form a stack of slices input. In effort to reduce over-fitting when training, we added a dropout-layer after each convolutional layer in the U-net, with a drop-out fraction of 20%. Lastly, we did not implement the network as an ensemble model, since we have introduced transfer learning, which already decreases variance substantially.

Training

The model was trained on an MS dataset of FLAIR images only, from 71 patients. Only FLAIR images were used, since high-resolution T1-weighted images are not always acquired for MS patients. The model by Li et al. was re-trained on the FLAIR images from the challenge dataset modified to a stack of slices input, and the resulting weights were used for transfer learning to our model.

Input and pre- and post-processing

The model takes a 3-channel 2D input of three consecutive axial FLAIR slices. The output is a binary 2D lesion mask of the middle input slice. The proposed model followed the pre- and post-processing steps of Li et al, including masking of the brain, data normalization and data augmentation (scaling, shearing, rotation, flipping), as well as standardization of all input images to a standard size (200x200). The first 10% of slices in each brain was removed to limit noise.

[1] H. Li, G. Jiang, J. Zhang, R. Wang, Z. Wang, W.-S. Zheng, B. Menze, Fully Convolutional Network Ensembles for White Matter Hyperintensities Segmentation in MR Images MICCAI WMH segmentation challenge, Deep learning, Ensemble models, 2018.