White matter hyperintensities segmentation using a cascade of three convolutional neural networks

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1 Method description

The proposed method is mainly based on our current pipeline designed for multiple sclerosis white matter lesion segmentation [1]. However, various modifications have been proposed to deal with the segmentation of white matter hyperintensities (WMH) of presumed vascular origin.

1.1 Input features

Each of the 60 training images is first subtracted by its mean and divided from its variance. Then, we compute 3D axial patches of size $25 \times 25 \times 5$ centered on the voxel of interest. The set of all computed patches P is stacked as $P = [n \times m \times 25 \times 25 \times 5]$, where n denote the number of training voxels, and $m = 2$ as we use both T1-w and FLAIR available input modalities.

1.2 CNN architecture

Here, the same a 10-layer architecture is proposed for each of the CNN composing our approach. Exact parameters of each of the layers are shown in Table 1.

Table 1: Proposed 10-layer CNN architecture for input image patch size of $25 \times 25 \times 5$ with 2 input modalities as channels. Layer description: 3D convolutional layer (CONV), 3D max-pooling layer (MP) and fully-convolutional layer (FC). Same architecture is proposed for each of the three CNNs.

Layer	Type	Maps	Size	Stride	Pad
0	*input*				
1	CONV	32	$3 \times 3 \times 2$	1^3	1^3
2	CONV	32	$3 \times 3 \times 2$	1^3	1^3
3	MP	-	$2 \times 2 \times 1$	$2 \times 2 \times 1$	0
4	CONV	64	$3 \times 3 \times 1$	1^3	1^3
5	CONV	64	$3 \times 3 \times 1$	1^3	1^3
6	FC	256	1	-	-
7	FC	128	1	-	-
8	FC	64	1	-	-
9	Softmax	2	1	-	-

1.3 Cascade based training

Our proposed cascaded training procedure is shown in Figure 1. Basically, the first network is trained to be more sensitive revealing possible candidate hyperintense voxels. Then, the second network is trained to reduce the number of misclassified voxels coming from the first network. Candidate regions with < 30 voxels coming from the output of the second network are retrained to reduce the number of small false positive hyperintense voxels. A detailed explanation of our proposed approach can be found in Valverde et al. 2017 [1].

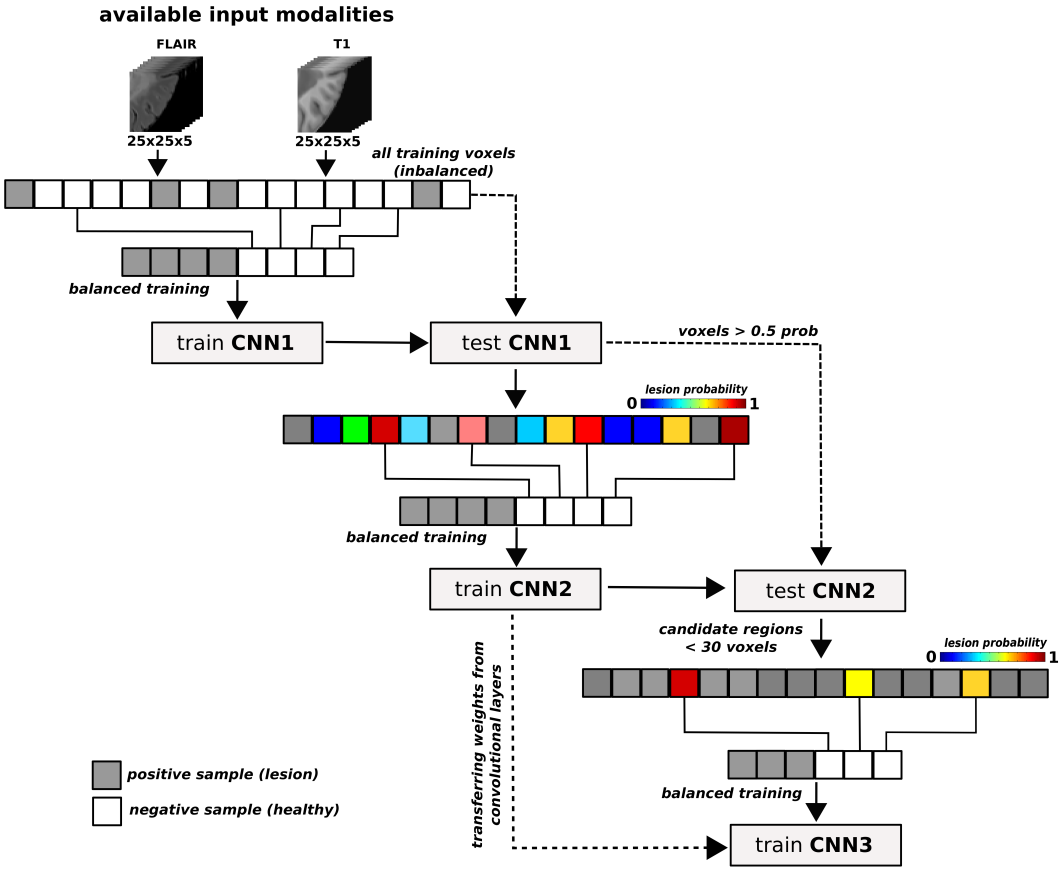

Figure 1: Cascaded based training.

CNN1 and CNN2 are trained individually without parameter sharing, while CNN3 re-trains only the last FC layer. Parametric rectified linear activation functions (p-ReLU) are applied to all layers. Network parameters are learned using ADADELTA with batch size of 128 and categorical cross-entropy as loss cost, using batch-normalization regularization after both convolutional layers, and Dropout with ($p = 0.5$) before the first fully-connected layer. We perform data augmentation on-the-fly at batch time by adding 180 degrees and flip rotations of the input patches.

1.4 CNN Testing

For a given image, all voxel patches are first extracted. For each patch, we also apply the same data augmentation transformations used on training, averaging the predictions. The testing procedure is defined as follows:

1. All patches are evaluated using the CNN1.
2. Voxels with low probability $p < 0.5$ to be lesion are then discarded, while the remaining are re-evaluated using the CNN2.
3. Obtained probability masks are then binarized with $p \geq 0.5$ and all voxels pertaining to regions with < 30 voxels are re-evaluated using the CNN3.
4. Final segmentation is obtained by merging the output segmentations of the CNN2 (for regions > 30 voxels) and CNN3 (for regions < 30 voxels).

References

[1] Sergi Valverde, Mariano Cabezas, Eloy Roura, Sandra González-Villà, Deborah Pareto, Joan C Vilanova, Lluís Ramió-Torrentà, Àlex Rovira, Arnau Oliver, and Xavier Lladó. Improving automated multiple sclerosis lesion segmentation with a cascaded 3D convolutional neural network approach. *NeuroImage*, 155:159–168, 2017.