2D Multi-Scale Res-Net for Stroke Segmentation

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Ischemic stroke is caused by the blockage of the cerebral blood flow. Its penumbral area surrounding the stroke core can be salvaged depending on the time after stroke onset. Efficient neural networks can support the early detection of stroke-related hyper- or hypointensities [1]. As computational power and efficiency of convolutional neural networks (CNN) increase, more complex networks with higher parameter numbers can be applied for inference within clinically demanding time constraints. CNN, like U-Nets [2], have shown competitive performance in different biomedical tasks. Ischemic strokes vary widely in location, shape, and extend of the affected tissue. We propose a fully-convolutional architecture based on U-Nets for segmenting transversal image slices and combine different scale information through further residual connections [3] and losses.

The challenge data is resampled to a common resolution of $1\times1\times5$mm and slices are zero-padded when needed to fully cover the spatial input area of 240×240 voxels. The network is provided 42 image features as input (7 MR sequences, 3 slices including both direct neighboring slices, 2 hemispheric flips). The contracting path additionally includes residual connections enabling the network to propagate information well across the five scale levels of the U-Net (from 240×240 down to 15×15) - the downsampled input in each level is concatenated with the max-pooled activation before it is passed as input to the next level. In the lowest level, 1×1 convolutions are used for the high level classification.

In the upscaling path, at each level a DICE loss is computed on softmax activation and summed up to a total loss for training. The loss of each label is weighted with its inverse prior probability (estimated from training data) to account for class imbalance. To speed up training, the network parameters are optimized using the ADAM algorithm. Moreover, each convolution (in both paths) is followed by a batch normalization (BN), which has already shown advantages in training before [1].

References

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