MR Brain Segmentation Challenge MICCAI 2018

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1 Method

Recent work shows that convolutional networks are getting deeper and deeper. Nevertheless,U-Net will lose more resolution as network goes deeper. In order to gain more precise performance, U-Net may sometimes depend on data augmentation or larger numbers of filters.One of solution to the lost of resolution is using dilated convolution [5]. Dilated convolution can retain sufficient receptive fields without losing resolution even if network goes deeper.

Enlighten by DenseNet [6] and dilated convolution, this project proposes an advanced architecture, Dense U-Net, which implements dense connection and dilated convolution, which can reinforce feature reuse, reduce the numbers of parameters and retain lager receptive fields.

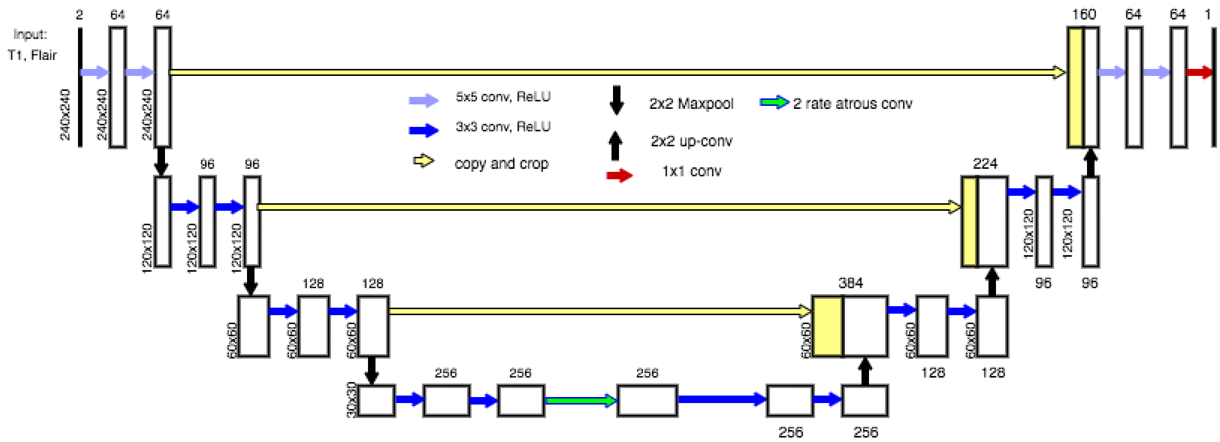
1.1 Preprocessing

Initially, all images were resized to 240x240x48. Then the data (pre/FLAIR.nii.gz,pre/reg_IR.nii,pre/reg_T1.nii,3 channels in all) were combine to X_train.npy, and the segm.nii.gz are combined to Y_train.npy. Especially in training set, 20% of them were used as validation set.

1.2 Network architecture

The network architecture described below contains similar elements to Dense Unet [1].The network architecture described below contains similar elements to Dense Unet [2] .

The architecture is shown below and contains the following elements:



The network has to main innovations, dense connection and dilated convolution. Specifically, this netork has 10 layers. The 5th layer implements dilated convolution, whose dilated rate is equal to 2. In the rest layers from one to nine, batch normalization [3] and pre-activation, LeakReLU [4], are applied before first convolutional layer. As mentioned in the technical report of DenseNet[5], batch normalization can provide a unique scale and bias to previous input while preactivation can reduce the error significantly. In addition, those layers have two convolutional layers with the same numbers of filters. Kernel size is 3x3. The number of filters from layer oneto four is [16, 32, 64, 128]. Symmetrically, The number of filters from layer six to nine is [128,64, 32, 16]. The 10th layer is a output layer with Relu activation function. From layer one to four, 2D MaxPooling layer is used as downsampling. From layer six to nine, deconvolution isimplemented to up-sampling with 2x2 kernel size and strides. Its number of filters reduces 50% compared to the number of filters in previous convolutional layer. Both convolution and deconvolution use "same" padding and "He Normal" initializer [6]. Compared to naive U-Net, most importantly, our model use dense connection in layer seven to nine. For example, both layerone and two are concatenated back to layer nine after deconvolution. Other layers have the same pattern correspondingly.

1.3 Training

During training, 80% of the dataset was used for training and 20% for validation. No additional data outside the competition was used .

Optimizer: Adam optimization with ($lr = 0.0001$ and $\beta_0 = 0.9$, $\beta_1 = 0.999$).
Loss function: Binary dice loss
Notes:

- The network was trained until validation loss stabilized. The network was trained in Google Cloud Platform on NVIDA Tesla K80 (12GB GPU memory).

References

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