Pooling-free fully convolutional networks with dense skip connections for semantic segmentation, with application to segmentation of white matter lesions

Richard McKinley[1], Alain Jungo[2], Roland Wiest[1], Mauricio Reyes[2]

[1] Support Centre for Advanged Neuroimaging Inselspital, University Hospital, University of Bern, Switzerland
[2] Institute For Surgical Technology and Biomechanics, University of Bern, Switzerland,

Introduction

We present a network architecture for semantic segmentation, heavily inspired by the recent Densenet architecture for image classification [1], in which pooling layers are replaced by heavy use of dilated convolutions [2].

The fundamental unit of a densenet architecture is the densely connected block, or dense block. In such a block, the output of each layer (where a layer here means some combination of convolutional filters, nonlinearities and perhaps batch normalization) is concatenated to its input before passing to the next layer.

The layers in our dense blocks have the shape shown in Figure 1. As a nonlinearity, we use Exponential Linear Units (ELU) [3] rather than the combination of rectified linear unit and Batch Normalization [4] used in the original Densenet paper.

Application to WMH segmentation

To account for the relatively small and heterogeneous dataset, we trained two classifiers. The first was trained on a brain mask segmentation (obtained from FSL BET), and segments the brain tissue. This mask is used to identify the relevant brain tissue. A second classifier was then trained on these masked images to find all white matter lesions.

References

[1] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the iEEE conference on computer vision and pattern recognition*, 2017.

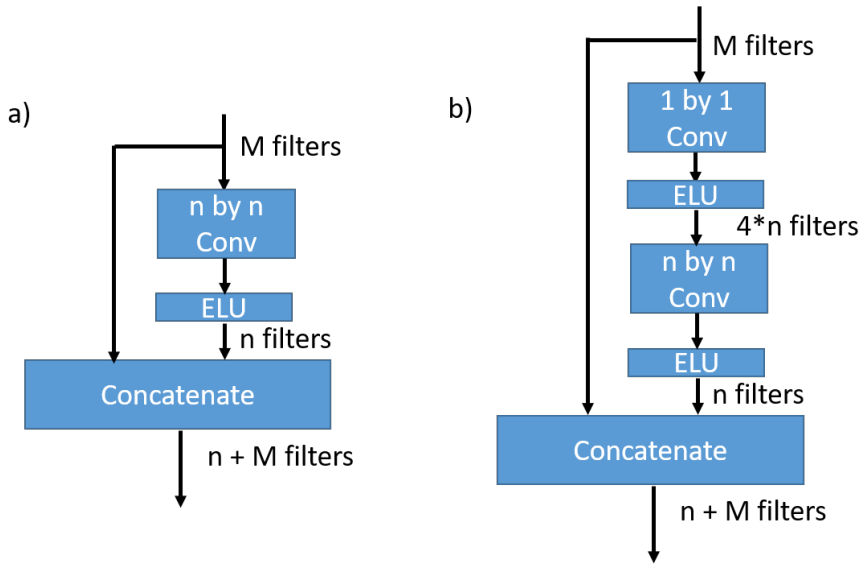

Fig. 1. Dense units, as used in the DeepSCAN architecture a) a dense unit without bottleneck, and b) a dense unit with bottleneck

[2] F. Yu and V. Koltun, "Multi-scale context aggregation by dilated convolutions," in *Proceedings of international conference on learning representations (iCLR 2017)*, 2017.

[3] D. Clevert, T. Unterthiner, and S. Hochreiter, "Fast and accurate deep network learning by exponential linear units (eLUs)," *CoRR*, vol. abs/1511.07289, 2015.

[4] S. Ioffe and C. Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift," *arXiv:1502.03167*, pp. 1–11, 2015.

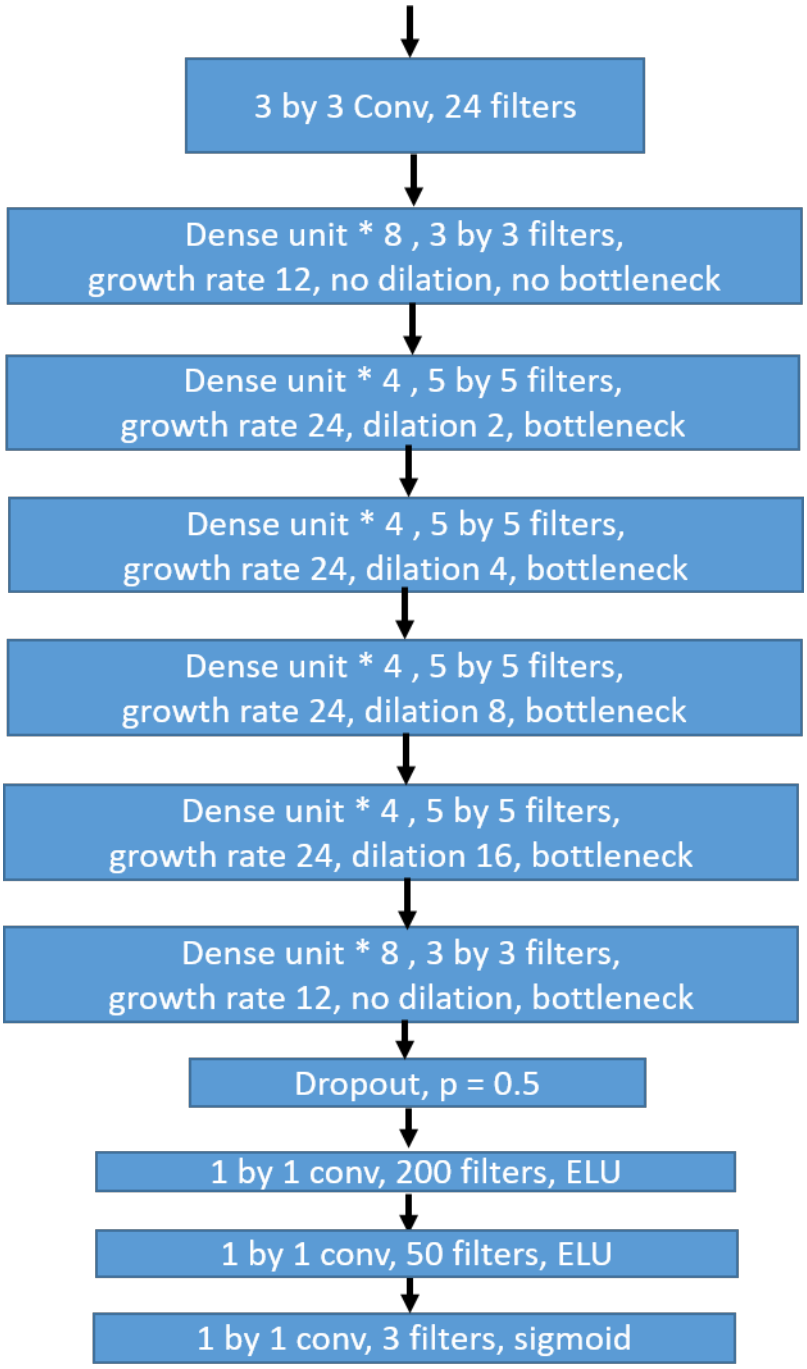

Fig. 2. The DeepSCAN architecture