Ensemble Learning using Deep Neural Patchworks and U-Net for ATLAS R2.0 - Stroke Lesion Segmentation Challenge

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Abstract

In this challenge, we use an ensemble model which consists of one 3D Deep Neural Patchworks model and two patch-based 3D U-Net models where the outputs from these models are averaged to get the final output. Based on our training and validation processes with 600 and 55 scans for training and validation respectively, the averaged output from ensemble learning is better than each individual model. For the final submission, we trained all models using all available data (i.e., 655 scans).

Keywords Deep Neural Patchworks · U-Net · Ensemble

1 Our Models

Deep Neural Patchworks (DNP) is our newly proposed model which automates the process of sampling and augmentation of patches from original images. DNP model exploits the principles of hierarchical attention to seek for important information in images in a coarse-to-fine manner. In each scales, 3D U-Nets are used as backbone segmentation networks but any neural networks can be used as well. Illustrations of scaling and working principle of DNP can be seen in Figure 1 while a more complete explanation of DNP model can be read in [1]. We used DNP's implementation in PyTorch (publicly available in here [1]) while TensorFlow implementation is also available [2]. Sigmoid activation function is used in the segmentation layer, and the size of DNP's patch used for this challenge is $64 \times 64 \times 64$.

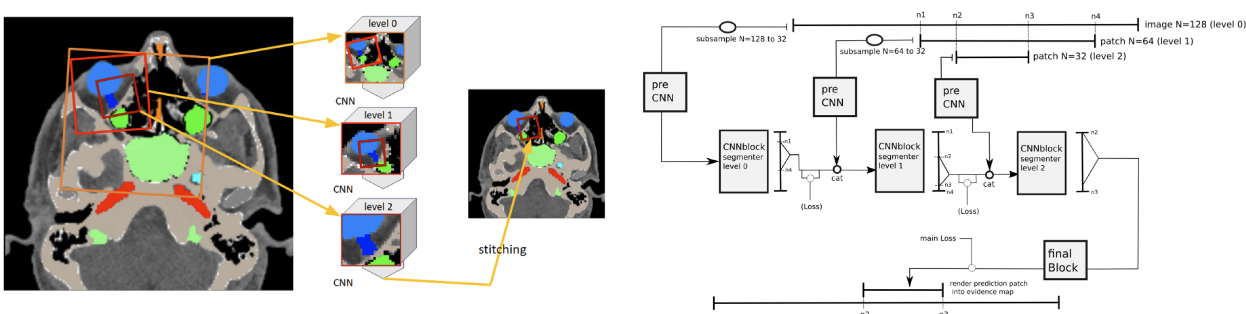

Figure 1: Illustrations of how scaling works in Deep Neural Patchworks (left) and the working principle of patchwork in 1D (right). Left and right figure are Figure 1 and Figure 2 respectively in [1].

[1] https://bitbucket.org/skibbe/deep_patchwork/src/master/
[2] https://bitbucket.org/reisert/patchwork/wiki/Home

To increase generalization, we also trained two different models of 3D U-Net similar to [2] where each of them was trained individually but still using the same training set of $96 \times 96 \times 96$ patches. The only different between these two models are activation functions for segmentation where the first one using sigmoid and the second one is using softmax. MONAI library [3] was used for reproducibility.

2 Data Preprocessing and Postprocessing

All scans were normalized using Zero Mean Unit Variance method. Several data augmentations were also used, such as rotation, scaling, and intensity shifting and scaling. *DiceLoss* was used for DNP while *GeneralizedDiceFocalLoss* from MONAI was used for both U-Net models. Out of 655 scans that are available, 600 of them were used for training while 55 of them were used for validation. All models were roughly trained for 600-800 epochs, and the best models in validation were used as the final models. For final submission, all models were trained using all available data. For models with sigmoid activation function for segmentation, 0.25 and 0.35 were used for threshold values for U-Unet and DNP models respectively. For final output, all outputs from DNP and U-Net were averaged where output from DNP was weighed twice more than the U-Nets' outputs. A simple postprocessing was also used for final output and U-Nets' outputs, where small detected blobs (which are smaller than 27 pixels) are discarded. All codes are available on our GitHub [4].

3 Analysis

Table 1 shows the quantitative results on our validation set. Based on visual analysis, U-Net with sigmoid produced more false positive blobs than the U-Net with softmax. On the other hand, DNP performed better than U-Net with softmax while performed similar to the U-Net with sigmoid but with less false positive blobs. Finally, the final ensemble model performed better than the individual models with higher Dice score in general.

Table 1: Results in Validation. Vol. and diff. stand for volume and difference respectively.

Model	Dice	Per-blob Dice	Blob diff.	Vol. diff.
DNP	0.5422	0.5351	1.6545	6,308.67
U-Net (softmax)	0.5390	0.5757	2.2909	5,467.96
U-Net (sigmoid)	0.5448	0.6040	3.2909	11,037.75
Ensemble (average)	0.5695	0.5891	2.8182	7,408.67

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References

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[2] Özgün Çiçek, Ahmed Abdulkadir, Soeren S Lienkamp, Thomas Brox, and Olaf Ronneberger. 3d u-net: learning dense volumetric segmentation from sparse annotation. In *International conference on medical image computing and computer-assisted intervention*, pages 424–432. Springer, 2016.

[3] `https://monai.io/about.html`

[4] `https://github.com/febrianrachmadi/BIA_ATLAS2`