ATM MICCAI 2022; Satsuma submission 7: 3D full-res nnUNet with morphoclosing

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Abstract. This is short paper describing the Satsuma team's algorithm **7th submission**[3] to the Airway Tree Modelling (ATM) Challenge associated with MICCAI 2022. The nothing new UNet framework (nnUNet)[2] has developed a reputation as a high benchmark in medical image segmentation having demonstrated it generalisability to new medical imaging segmentation challenges. We submit a 3D full resolution nnunet trained on 5 folds of the ATM dataset that at inference, ensembles the folds and removes all but the largest connected component.

Keywords: Segmentation · Deep learning · Computed tomography

1 Introduction

Medical image segmentation is a very active field that is rapidly advancing with the huge surge in developments of deep learning methods. Though many various improvements have advanced deep learning frontiers in natural image segmentation, they have not so easily been transferred to medical imaging. This is likely due to the relatively sparse data available in comparison to natural image datasets, attributed to the private nature of the medical domain. Further confounding the challenge is that natural images are 2D, but modern medical images tend to be in 3D. The extrapolation of techniques to a further dimension is not trivial.

The UNet model architecture [3] has demonstrated that it is well suited to segmentation tasks. It takes a convolutional encoder-decoder configuration. In the encoder stage the input goes 'down' through pooling layers and is then reconstructed 'up' in the decoder by an equal number of upsampling steps which also take input 'laterally' from each corresponding step of the encoder, retaining positional information.

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[3] The same authors are submitting similar methods to the PARSE MICCAI 2022 challenge which runs in a parallel timeline to the ATM MICCAI 2022 challenge. The authors also expect to make future submissions to ATM. It is therefore expected that this paper will have similarities to PARSE and future ATM submissions.

A notable further advance and now benchmark in the medical image segmentation field was the introduction of the 'nothing new UNet' (nnUNet) [2]. An automated framework that amalgamates best practices for optimised training of UNet models to segment 3D medical images. Having come top of the medical segmentation decathlon challenge [1], it has demonstrated great generalisability to new medical imaging segmentation challenges which is why we have used it here.

2 Methods

The main advantage of using nnUNet is its self-configuring nature and out the box compatibility. The model goes through a series of analysing steps before training can begin, during which each image and its corresponding segmentation is considered, the image properties are verified and the images are preprocessed accordingly with a series of augmentations - resampling, intensity scaling, etc. These steps are often overlooked and not reported in studies, but they can significantly influence the model's performance. The advantage of this self-configuring preprocessing is also avoidance of train time inconsistencies and surprises (e.g. an image with an unexpected dimensions or voxel spacing).

The nnUNet framework also works to maximise the use of available compute resources and tunes hyperparameters such as batch size, network depth and width, convolutional kernel sizes, etc.

We trained on a single Nvidia RTX A6000 GPU. The loss function used was an equally-weighted soft DICE loss and Cross-Entropy loss. nnUNet by default initiates with a learning rate of 0.01 and a learning rate decay of 0.001. The initial encoding block of the unet starts with 32 filters. nnUNet augments on the fly with random scaling, mirroring, rotation and gamma (contrast).

2.1 Postprocessing

For the final stage, we propose morphological closing of the output with intensity thresholding. The structuring element used in the morphological operation was a 3×3 square. Voxels identified by this process are only added to the final segmentation if they are of an expected intensity suited to the segmentation task, i.e. pulmonary artery. In this case we empirically chose the intensity interval of [-3000, -775] HU. This helps improve connectivity within the segmentation object as it fills in one voxel gaps without inflating the segmentation, risking oversegmentation of the target.

As required by the competition, we apply a largest connected component filter. This identifies all the 26-voxel neighbour connected components, only keeping the largest in terms of number of voxels. All other connected components are removed. It is assumed that the airway tree, originating from the trachea will always be the largest connected component.

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