### ABSTRACT SUBMISSION FORM

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### PRESENTATION TITLE

Application of a deep convolutional neural network to segment the parotid glands on MR images

### AUTHOR(S)

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### ABSTRACT

**Purpose:** Deep convolutional neural networks (CNNs) have shown great success in solving computer vision tasks, such as object detection and segmentation. To date, there has been only limited application of CNNs to the segmentation of organs-at-risk (OARs) on magnetic resonance (MR) images. We developed and evaluated a CNN-based approach to automatically segment the parotid glands on MR images of head and neck cancer (HNC) patients.

**Materials & Methods:** The proposed method builds upon recent developments in the computer vision community. We implemented the 2D U-net architecture [1], illustrated in Figure 1, using Keras [2] and TensorFlow [3]. Our database consisted of pre-treatment T1-weighted MR images of 13 HNC patients. Each MR image comprised 30 axial slices with 512 x 512 pixels, a slice distance of 4 mm and an in-plane resolution of 0.5 x 0.5 mm². Each slice was downsampled by a factor of 4 before being fed into the network. A clinician manually contoured the parotid glands, which served as the ground truth. For each patient, a leave-one-out cross-validation approach was followed with the test data comprising slices of the patient’s image and the training data slices from the remaining patients’ images. The training data were further split into 90% training and 10% validation in order to optimise hyper-parameters, such as the number of training epochs and the learning rate. One epoch referred to one training cycle over the full training data. We chose 50 epochs and optimised a weighted cross-entropy cost function, accounting for the imbalance between background and foreground pixels. We used the Adam optimiser [4] with a learning rate of 0.00001. Geometric differences between the ground truth and the CNN-derived segmentations were evaluated by calculating the 3D Dice similarity coefficients (DSC) and 95-percentile Hausdorff distances (HD95). Due to their symmetry, we simultaneously segmented both parotid glands and divided them into the left and right part in a post-processing step. Run time was determined for programme execution on a single NVIDIA Titan Xp GPU with 12 GB VRAM.
Results: Figure 2 shows three representative slices from three different patients. Mean DSC ± one standard deviation were 0.82 ± 0.03 for the left and 0.78 ± 0.04 for the right parotid. The mean HD95 were 2.78 ± 0.96 mm for the left and 3.18 ± 1.24 mm for the right parotid. Mean training time was 35.86 ± 0.22 min, whereas mean inference time for the full volume of one image was 0.84 ± 0.05 s.

Conclusion: This preliminary study demonstrates great potential for the application of CNNs to segment OARs for RT treatment planning purposes with the accuracy comparable to state-of-the-art approaches such as atlas-based segmentation (ABS). In comparison to ABS, the segmentation time is much smaller (sub-second compared to minutes or hours). A limiting factor of this study was the amount of training data. With the availability of more training data, the addition of T2-weighted MRI, extended dimensionality to 3D and techniques such as data augmentation we expect to further improve accuracy.

References: