Artificial Intelligence Research and Development
I. Sanz et al. (Eds.)

doi:10.3233/FAIA230674

Development of an Automated CBCT Nerve and Teeth Segmentation Tool Based on Deep Learning

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Abstract. This long abstract details the translation work from research to industry that stems from the collaboration between a research group in Applied Data Sciences and a digital dentistry start-up, with the aim of developing a deep learning-based nerve and teeth segmentation tool for aiding dentist treatment decision-making and diagnosis.

Keywords. Deep Learning, CBCT Image Segmentation, Medical Imaging

1. Translation to develop an automated CBCT segmentation tool

3D Imaging techniques such as Cone-Beam Computed Tomography (CBCTs) and Intra-Oral scans (ICs) have become pivotal in diagnosis and treatment planning in orthodoncy, since they offer the possibility of extracting invaluable volumetric information. In this field, one of the main challenges that stem from implant dentistry and maxillofacial surgery is related to neural and dental damage during the procedure, with the Inferior Alveolar Nerve (IAN) being the most commonly injured nerve [1].

However, a key bottleneck in this workflow is the processing of the DICOM images produced by CBCTs to compute the 3D mesh. This process is tedious and time-consuming, and also requires extensive training, and has to be usually carried out by the dentist.

CBCTs are also commonly performed simultaneously with ICs, and their output has to then be registered to ensure an optimal mapping of the region of interest. Manual segmentation of CBCTs adds human error, and also shows high inter-subject variability.

Ultimately, this might lead to a non-viable alignment between the two image sources. The presence of metal implants introduces artifacts in the scan, increasing the segmentation's difficulty. Therefore, there is great interest in an automated segmentation tool that improves this workflow.

UOC's Applied Data Sciences lab, together with the digital dentistry start-up *Movumtech*, have joined forces to develop a deep learning based tool that will allow dentists to automatically select their anatomical ROI (i.e.: nerve, teeth, mandible, maxilla) and compute an STL mesh from the raw DICOM data.

For these reasons, a comprehensive database of CBCT scans will be assembled from healthy and pathological patients, with manually segmented labels with the oversight from *Movumtech*. Furthermore, IC scans will be used thus greatly improving segmentation accuracy thanks to its high resolution and imperviousness to metal artifacts.

When enough labels have been segmented, an atlas (expert validated reference consisting of the average of a set of templates) will be constructed to compare new input images to, extracting valuable information such as location, number of teeth present, and presence of artifacts.

With regards to the nerve-segmentation tool, we will be using the dataset from the *Toothfairy 2023 MICCAI* challenge, which contains CBCTs and dense labels for the IANs. Our approach follows the so-called triplanar or 2.5D approach, where the original 3D image is sliced along the three orthogonal axes [2] and each slice is predicted using the corresponding 2D model trained using the nnU-Net method [3].

A total of 130 patients were used in training. Data augmentation (gaussian blur, *flipping*) was used to improve the generalization ability of the models. Intensity was rescaled to a range of [0, 2048] to ensure images from different sources can be segmented.

Training was performed with the default nnU-Net hyperparameters except the max epochs, which was reduced to 360. Inference is performed on each slice and then merged obtaining three different 3D masks. These are thresholded and merged obtaining a binary mask. Several methods of postprocessing – majority voting, simple averaging or unanimous voting – will be studied. Preliminary results using probability averaging on 15 test set subjects show a DICE coefficient of 75%. This pipeline will be adapted and applied for teeth-segmentation after a sufficient number of images have been segmented.

Acknowledgements

FPC is partially funded by the National Institute for Health Research Biomedical Research Centre at UCL and UCLH.

References

[1] Tay ABG, Zuniga JR. Clinical characteristics of trigeminal nerve injury referrals to a university centre. International Journal of Oral and Maxillofacial Surgery. 2007;36(10):922-7. Available from: https://www.sciencedirect.com/science/article/pii/S0901502707001269.

[2] Dalbis T, Fritz T, Grilo J, Hitziger S, Ling WX. Triplanar U-net with orientation aggregation for new lesions segmentation. MSSEG-2 challenge proceedings: Multiple sclerosis new lesions segmentation challenge using a data management and processing infrastructure. 2021:57.

[3] Isensee F, Jaeger PF, Kohl SA, Petersen J, Maier-Hein KH. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods. 2021;18(2):203-11.