Master Project: Tooth Presence Classification from Intraoral Scans

Team: TBD

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1 Introduction

Dentists have traditionally relied on clinical examinations and radiographic analysis to diagnose and plan treatment. However, computer-aided design and computer-aided manufacturing (CAD/CAM) as well as digital imaging, such as cone-beam computed tomography (CBCT), have revolutionized clinical protocols. These technologies create precise digital models of the dentition, allowing dentists to simulate procedures such as virtual tooth extraction, tooth movements, and prosthetic outcome simulation. Another layer to automate these tasks is the application of deep learning methods to develop models that segment and label teeth, mostly based on CBCT images (Du et al., 2022; Jang et al., 2022; Polizzi et al., 2023; Zhang et al., 2024a)), and with some contributions considering 3D intraoral scanners (Awari et al., 2024; Ben-Hamadou et al., 2023). Advantages of these 3D intraoral scans (IOS) include faster processing and less radiation exposure of the patients, but there is currently less data available than for CBCT images.

The task of this project is to create an automated dental record from 3D IOS data. This will provide the dentist with an automated summary of the patient's health state in a time-efficient way without need of any personal assistance. Therefore, the goal of the master's project is to develop a deep learning algorithm based on 3D intraoral scans that is capable of labeling the presence or absence of individual teeth to extract a dental record, as shown in the right side of Figure 1. So far, we have about 100 IOS data of upper and lower jaws labeled, which we will use for testing. There are several problems that need to be solved:

1. The task is to provide a total of 32 binary labels, where each of these labels correspond to the presence or absence of a specific tooth. Possibly, we can use upper and lower jaws together so that only 16 labels need to be predicted. Anyway, the distribution of missing teeth is not balanced, and research has shown that data imbalance in the training data leads to biased binary classifiers that have problematic characteristics (Rudd et al., 2016; Zhang et al., 2024b). Therefore, solutions need to be implemented that solve the issue of class imbalance. This includes to select proper evaluation metrics.

2. Due to the little amount of available training data, we want to fine-tune pre-trained networks or foundation models (Liu et al., 2024) for our task, all of which make use of 2D information only. Therefore, the 3D data, which is stored in Standard Tessellation Language (STL) format shall first be converted into 2D data, which requires the application of rendering techniques. The exact alignment (i.e. the viewing angle) of the 3D view and other rendering parameters are subject to optimization, one possible rendering can be found in the left of Figure 1.

3. We will make use of a specific open 3D training dataset, which is part of the 3DTeethSeg22 challenge.[1] In total, this dataset contains 1800 intraoral scans of lower and upper jaws from 900 patients. The scans on this data set are stored in .obj files that need to be converted into .stl files, and the labels of the dataset need to be translated into our task. According to the corresponding article (Ben-Hamadou et al., 2023), the patients required either orthodontic (50%) or prosthetic treatment (50%). Though prosthetic treatment often implies a missing tooth, it is not specified how many of the patients have missing teeth. Additionally, this data was collected in a different way, resulting in differences in the appearance of the 3D data. Therefore, domain adaptation techniques need to be developed to attenuate this difference.

4. The results of the binary classifiers need to be processed to represent their results visually. This includes the automatic creation of a dental record as shown in Figure 1. Additionally, explainable AI tools, such as Grad-CAM (Selvaraju et al., 2017) and its variants (Zhang et al., 2024b), or self-developed methods such as (Weber, 2023) shall be used to highlight the regions of the created 2D images that were used for the classification task.

[1] github repository: `https://github.com/abenhamadou/3DTeethSeg22_challenge`

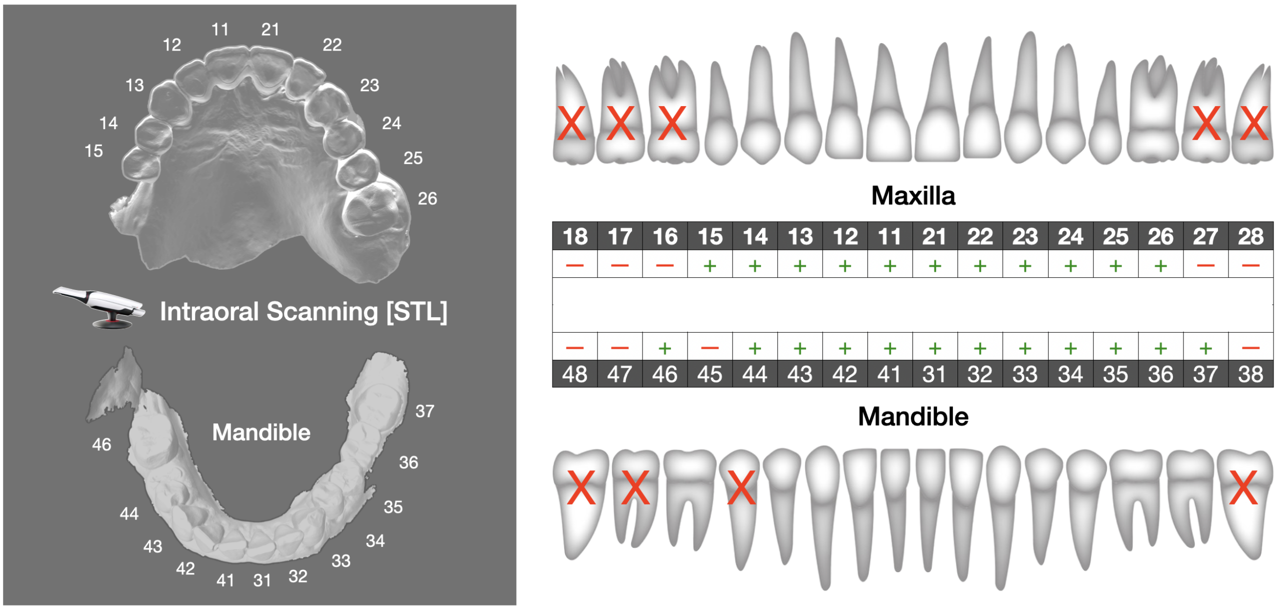

Figure 1: 3D intraoral scan of the upper and lower jaw of a patient indicating the tooth site (left). Sketch of a dental record table to be fill with the information on presence of a tooth (right).

2 Schedule

The project is designed for two to four students. For two students, the focus should be on implementing the basic learning/fine-tuning framework and fine-tuning some pre-trained models for the classification tasks. When more students are present, the domain adaptation techniques and visualization techniques should be added.

Assuming 30 hours of work per week and a total of 15 ECTS with an average of 30 hours per ECTS, we arrive at a total workload of 15 weeks full-time per student. These could be distributed as follows.

Week 1-4 Setting up the work environment, installing all required tools, getting familiar with the data. Provide a first version of 2D data from the 3D OBJ/STL files. Process the target labels to be applicable for our task. Implement a first version of the evaluation.

⇒ Milestone 1: The data is available and a basic learning framework is created.

Week 5-6 Perform a guided literature review and search for available models that can be used for 2D image classification in medical images. Import some of these models into the learning framework, and adapt them for our task.

⇒ Milestone 2: The first pre-trained model is integrated into the framework.

Week 7-11 Fine-tune the pre-trained models using bias mitigation and domain adaptation techniques.

⇒ Milestone 3: New open-set methods are incorporated into the package,

Week 12-15 Run experiments with various versions of pre-trained models, different bias mitigation and domain adaptation techniques, and different evaluation metrics.

⇒ Milestone 4: Experiments have been run and plots have been generated.

>2 students provide a visual representation of the dental record from the results of the classifier. Implement explainable AI tools to highlight the regions of interest for specific teeth.

⇒ Milestone 5: Estimated dental records can be produced automatically directly from the OBJ/STL files.

Writing the project report is part of the Master project. As a template, the LaTeX thesis template from my webpage[2] should be used. I would recommend to start writing early and keep note of what was done when, and by whom. At the end of the project, there will be a joint presentation of the results in my research group.

[2] https://www.ifi.uzh.ch/en/aiml/theses.html

3 References

Awari, H., Subramani, N., Janagaraj, A., Balasubramaniapillai Thanammal, G., Thangarasu, J., and Kohar, R. (2024). Three-dimensional dental image segmentation and classification using deep learning with tunicate swarm algorithm. *Expert Systems*, 41(6).

Ben-Hamadou, A., Smaoui, O., Rekik, A., Pujades, S., Boyer, E., Lim, H., Kim, M., Lee, M., Chung, M., Shin, Y.-G., Leclercq, M., Cevidanes, L., Prieto, J. C., Zhuang, S., Wei, G., Cui, Z., Zhou, Y., Dascalu, T., Ibragimov, B., Yong, T.-H., Ahn, H.-G., Kim, W., Han, J.-H., Choi, B., van Nistelrooij, N., Kempers, S., Vinayahalingam, S., Strippoli, J., Thollot, A., Setbon, H., Trosset, C., and Ladroit, E. (2023). 3DTeethSeg'22: 3D Teeth Scan Segmentation and Labeling Challenge.

Du, M., Wu, X., Ye, Y., Fang, S., Zhang, H., and Chen, M. (2022). A Combined Approach for Accurate and Accelerated Teeth Detection on Cone Beam CT Images. *Diagnostics*, 12(7).

Jang, T. J., Kim, K. C., Cho, H. C., and Seo, J. K. (2022). A Fully Automated Method for 3D Individual Tooth Identification and Segmentation in Dental CBCT. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(10).

Liu, C., Jin, Y., Guan, Z., Li, T., Qin, Y., Qian, B., Jiang, Z., Wu, Y., Wang, X., Zheng, Y. F., et al. (2024). Visual–language foundation models in medicine. *The Visual Computer*, pages 1–20.

Polizzi, A., Quinzi, V., Ronsivalle, V., Venezia, P., Santonocito, S., Lo Giudice, A., Leonardi, R., and Isola, G. (2023). Tooth automatic segmentation from CBCT images: a systematic review.

Rudd, E. M., Günther, M., and Boult, T. E. (2016). MOON: A mixed objective optimization network for the recognition of facial attributes. In *European Conference on Computer Vision (ECCV)*. Springer.

Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., and Batra, D. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. In *International Conference on Computer Vision (ICCV)*. IEEE.

Weber, M. (2023). Visualization of deep features with Grad-CAM and LOTS. Master's thesis, University of Zurich.

Zhang, F., Zheng, L., Lin, C., Huang, L., Bai, Y., Chen, Y., and Luo, X. (2024a). A comparison of U-Net series for teeth segmentation in CBCT images. In Colliot, O. and Mitra, J., editors, *Medical Imaging 2024: Image Processing*, page 84. SPIE.

Zhang, X., Bieri, J. S., and Günther, M. (2024b). Biased binary attribute classifiers ignore the majority classes. In *Swiss Conference on Data Science (SDS)*. **to appear**.