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**Medical Imaging for Dentistry Using Artificial Intelligence**

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**Abstract**

Medical imaging in general and dental imaging in particular are fields where Artificial Intelligence can be applied in order to provide quicker and more accurate results. Providing patients with better care and giving practitioners an opportunity to direct their focus where it is needed most are just two of the objectives such an approach strives towards.

This project uses deep learning techniques for segmenting images and providing dentists with a baseline diagnostic which they can perfect with their expertise, as well as automating screenings. The data used includes Panoramic Dental X-Rays (Abdi, Kasaei, & Mehdizadeh, 2015) and spectral images (Hyttinen, Fält, Jäsberg, Kullaa, & Hauta-Kasari, 2020).

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**1. Introduction**

**1.1**

The problem being tackled here is reliable and fast dental imaging. Progress in this area can lead to an increased quality of life for countless people by providing automated screenings, as well as assistance to practitioners.

The approach is based on deep learning, which has shown significant improvements compared to other methods in the past years. Particularly, this project aims to tweak some existing approaches for the given problem: (Kamnitsas, et al., 2017), (Qin, et al., 2020), (Weber, et al., 2021), while also exploring Graph Neural Networks for image segmentation (Lu, et al., 2021) in the context of dental imaging.

**1.2**

The research presented in this paper advances the theory, design, and implementation of several particular models. The main contribution of this report is to present an intelligent algorithm for solving the problem of dental imaging. The second contribution of this report consists of building an application where medical practictioners as well as patients can have seamless access to these imaging techniques. The application is also meant to encourage the usage of the developed models by integrating them in an intuitive and simple interface meant to digitalize the treatment process.

The present work is structured into five chapters as follows:

The first chapter is introductory, presenting general information and motivation.

The second chapter formulates the scientific problem.

The third chapter presents the current state of the art and work related to this topic.

The fourth chapter presents the particular approaches being investigated in this work.

The fifth chapter presents the application that integrates the developed intelligent algorithms.

**2. Scientific Problem**

**2.1**

**Problem definition**

The problem this project is aiming to solve is that of accurate and efficient segmentation of dental image. The aim is provide doctors with aid in separating the mandible from the skull, as well as spotting dental assymetries through precise pixel-wise measurements

The success of deep learning methods in the past years is the motivation for mainly focusing on such approaches in the present work.

As stated above, a reliable algorithm solving this problem can provide significant improvements to people’s lives’, by improving the reliability, as well as accessibility of diagnostics.

**3. State of the art / Related Work**

Previous work in this area can be broadly considered to be anything regarding image segmentation. DeepMedic (Kamnitsas, et al., 2017) uses Convolutional Neural Networks and Conditional Random Fields to segment brain images. U2Net (Qin, et al., 2020) employs Residual U-blocks (RSU) for general image segmentation. Deeplab (Weber, et al., 2021) is a well-known library comprising several projects employing different deep learning techniques. None of these target dental imaging in particular, but they can be adapted to this task.

**4. Investigated approach**

Apart from using the models mentioned in the previous paragraph, this work aims to train a model based on Graph Neural Networks (Lu, et al., 2021).

As of 17.01.2024, it should be noted that the U-NET architecture seems to do better than U2-NET on segmenting individual teeth, even though U2-NET has a better F-score. This is due to the fact that individual teeth measurements require precise boundaries between the teeth. Both networks have been trained for 150 epochs, but U2-NET might yet be undertrained.

\*For now, some remarks during training.

I had great hopes for using the SAM model combined with prompts from YOLO, but so far it hasn’t turned out great. Using soft thresholding with the sigmoid function makes the decoder forget to segment teeth that have overlapping segmentation masks. Not using thresholding makes it unable to recognize boundaries between instances that have overlap. This is due to the fact that instead of returning a single segmentation mask, the model return a set of masks I have to then add along the detection axis to get the full mask. There is overlap in the central teeth, where the boundaries are very fine. Havng watched the predictions during training, this is the best intuitive explanation I could find for why this approach is performing poorly.

Oriented bounding boxes, on the other hand, have been surprisingly effective. The regular bounding boxes didn’t have orientation and therefore had some overlap between teeth that were heavily angled. Current status: comparing the angled bounding boxes with the unet model. I also have to look into GNNs.

**5. Application**

\*To be Developed

**6. Conclusion and future work**

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