Exploring Automatic Dental Segmentation using U-Net Architecture

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Abstract. Radiology is an essential component of modern healthcare, integral to the diagnosis and treatment of various medical conditions. However, the increasing reliance on radiological services has led to a substantial rise in imaging volumes, outpacing the availability of trained radiologists. This disparity has intensified workloads, resulting in unrealistic expectations for radiologists and elevating the risk of human error. The World Health Organization reports that a significant portion of the global population lacks adequate access to medical imaging.

This project proposes the development of a semantic segmentation model based on U-Net architecture to automate the analysis of dental images. This aims to improve diagnostic efficiency, reduce the workload on radiologists, and enhance patient outcomes. The use of convolutional neural networks within the U-Net framework will allow for precise identification of dental structures, ensuring high accuracy for clinical applications. The model will use robust data preparation and augmentation techniques to create a diverse training dataset that can generalize to real-world scenarios. This project seeks to address the growing demands on radiology and expand access to reliable diagnostic tools globally.

Keywords: Artificial Intelligence · Machine Learning · Convolutional Neural Networks · U-Net Architecture · Radiology.

1 Introduction

1.1 Radiology's Growing Demand

Radiology has become an indispensable tool in modern healthcare, utilised across every sector of the medical field — from diagnosing broken bones to detecting cancer (Smith-Bindman et al. 2008).

The increasing reliance on radiology has led to a surge in the volume of radiological data, which continues to grow at a vastly disproportionate rate compared to the number of trained radiologists available to interpret it (Bhargavan et al. 2002). As the demand for these services continues to rise, global access to radiological expertise remains limited. According to the World Health Organization, 'between two-thirds and three-fourths of the world's population has no or inadequate access to medical imaging' (Welling et al. 2011).

This growing demand has placed significant strain on healthcare providers worldwide, who are forced to compensate by pushing for increased productivity, drastically increasing radiologists' workloads. Studies have reported that, in some instances, radiologists are expected to interpret an image every 3-4 seconds during an 8-hour workday to meet demand (McDonald et al. 2015). Such unrealistic expectations inevitably heighten the risk of human error (Fitzgerald 2001), potentially overlooking critical information in highly sensitive cases (Hosny et al. 2018).

These challenges have been a driving force behind the development of artificial intelligence (AI) in the medical field with substantial efforts focused on research and advancing AI standards within medical imaging (Rubin 2019). Integrating AI into the imaging workflow could significantly improve efficiency and reduce the human input needed for interpreting medical images. This would alleviate the pressure on radiologists, allowing them to focus on more complex cases improving both diagnostic accuracy and patient outcomes. Additionally, AI-powered tools like this project could expand access to radiological imaging worldwide, reducing dependency on highly trained professionals and enabling remote, reliable diagnostics on a global scale (Sharma et al. 2023).

1.2 Addressing These Demands with Artificial Intelligence

This project addresses these challenges by developing a semantic segmentation model that identifies and categorises dental structures, such as teeth, fillings, and implants, from 2D dental images (X-ray images). By automating the analysis of dental images, this project exemplifies how AI and machine learning can enhance diagnostic efficiency, providing dental professionals with a reliable tool to streamline the imaging process and alleviate the workload of radiologists (Shoshan et al. 2022).

I plan to develop this segmentation model using a modified version of the U-Net architecture (Ronneberger et al. 2015), which has demonstrated remarkable effectiveness in various applications within the medical imaging field (Siddique et al. 2021). U-Net's architecture is particularly well-suited for this task due to its use of skip connections, which allow for better feature retention across layers. This is crucial for medical image segmentation, where precise boundaries, such as those between teeth and fillings, are important.

U-Net is built with a Convolutional Neural Network (CNN) at its core which allows for the high performance of CNN-based segmentation models, which excel at learning hierarchical features from images (Kayalibay et al. 2017). In the context of medical imaging, CNNs can effectively capture both low-level features (like edges and textures) and high-level features (like shapes and structures).

This allows CNNs to distinguish between different structures and classify distinct regions within an image, which is likely why they are 'currently the most widely used in (medical) image analysis' (Litjens et al. 2017).

A high level of model accuracy is critical, especially in a clinical setting, where even minor errors can significantly impact patient outcomes. Ensuring that the model can generalize well to unseen data is equally important, as it determines the reliability and effectiveness of the model in real-world applications beyond the training environment (Shorten & Khoshgoftaar 2019). As the journal states, a robust and well-rounded dataset plays a vital role here, providing a solid foundation for the model to learn effectively. Data preparation is a key step in achieving consistency and reliability, as a broader range of data will help prevent biases and gaps in training. Data augmentation will further enhance the model's performance by making the training data more diverse, allowing it to better adapt to differences in clinical images. This is very important as clinics use a wide range of equipment, and the model's ability to adapt to these variations will greatly enhance its effectiveness in real-world applications.

2 Aims and Objectives

2.1 Aims

1. To develop a semantic segmentation model using U-Net architecture, which identifies and categorises teeth, fillings, implants, and other dental structures from 2D dental images. This project addresses the need for automated dental analysis, offering a reliable tool for dental professionals to aid in diagnosis and treatment. The system will be trained on labelled dental images and validated through metrics like pixel accuracy and IoU score to ensure strong performance and reliability in clinical applications.

2.2 Objectives

1. Collect and preprocess a dataset of at least 200 labelled 2D dental images containing teeth, fillings, implants, and other dental structures.
2. Develop a U-Net-based semantic segmentation model capable of identifying and categorizing dental structures with a target pixel accuracy of > 80
3. Apply data augmentation techniques (scaling, blurring, exposure, etc.) on the dataset to improve the model's ability to generalize across images captured from different imaging devices.
4. Perform hyperparameter tuning for optimised segmentation accuracy by systematically adjusting parameters such as the loss function, optimiser, and number of convolutional filters.
5. Organise user testing sessions, ideally with dental professionals, to qualitatively assess the tool's practical value and receive feedback.

6. Conduct a literature review exploring how deep learning models have been applied to dental images. Highlight existing models, their strengths, limitations, and where this project fits within the current state of research.
7. Document and present findings from the development, testing, and evaluation of the model in the dissertation paper.

3 Risk Assessment

1. **Risk:** Failure to find a large enough dataset suitable for training and testing.
   Likelihood: Medium
   Severity: Low
   Mitigation Strategy: Merge multiple dental image datasets, as well as augmentation of valid datasets to artificially increase the amount of data. Manually labelling images is possible if necessary.
2. **Risk:** Overfitting of the machine learning model.
   Likelihood: Medium
   Severity: High
   Mitigation Strategy: Apply cross-validation, monitor training metrics, and use techniques like dropout, early stopping, and hyperparameter tuning to prevent overfitting. Using a large amount of data (augmented or otherwise) will also greatly reduce the likelihood.
3. **Risk:** Imbalanced data leading to poor segmentation of certain dental structures.
   Likelihood: Medium
   Severity: Medium
   Mitigation Strategy: Datasets will be carefully chosen to have a strict balance between the types of classes being segmented. Applying class weighting or undersampling the majority classes is also an option if not enough data can be found or generated.
4. **Risk:** Failure to meet the required accuracy for clinical use (70%).
   Likelihood: Medium
   Severity: High
   Mitigation Strategy: Using as large of a dataset as possible, and fine-tuning the model using techniques such as hyperparameter tuning. The model's performance will be evaluated continuously using metrics such as pixel accuracy and IoU value.
5. **Risk:** Difficulty obtaining expert feedback for model evaluation.
   Likelihood: High
   Severity: Low
   Mitigation Strategy: Reach out to dental professionals early in the project to ensure continuous feedback. If no dental professionals are available for evaluation, ask medical imaging professionals from within the university.
6. **Risk:** Model training taking longer than expected.
   Likelihood: Medium
   Severity: High

Mitigation Strategy: Build buffer time into the project timeline to account for extended training periods. Break down the training process into smaller, testable increments to better monitor progress and adjust appropriately. Welling et al. (2011).

4 Project Timeline

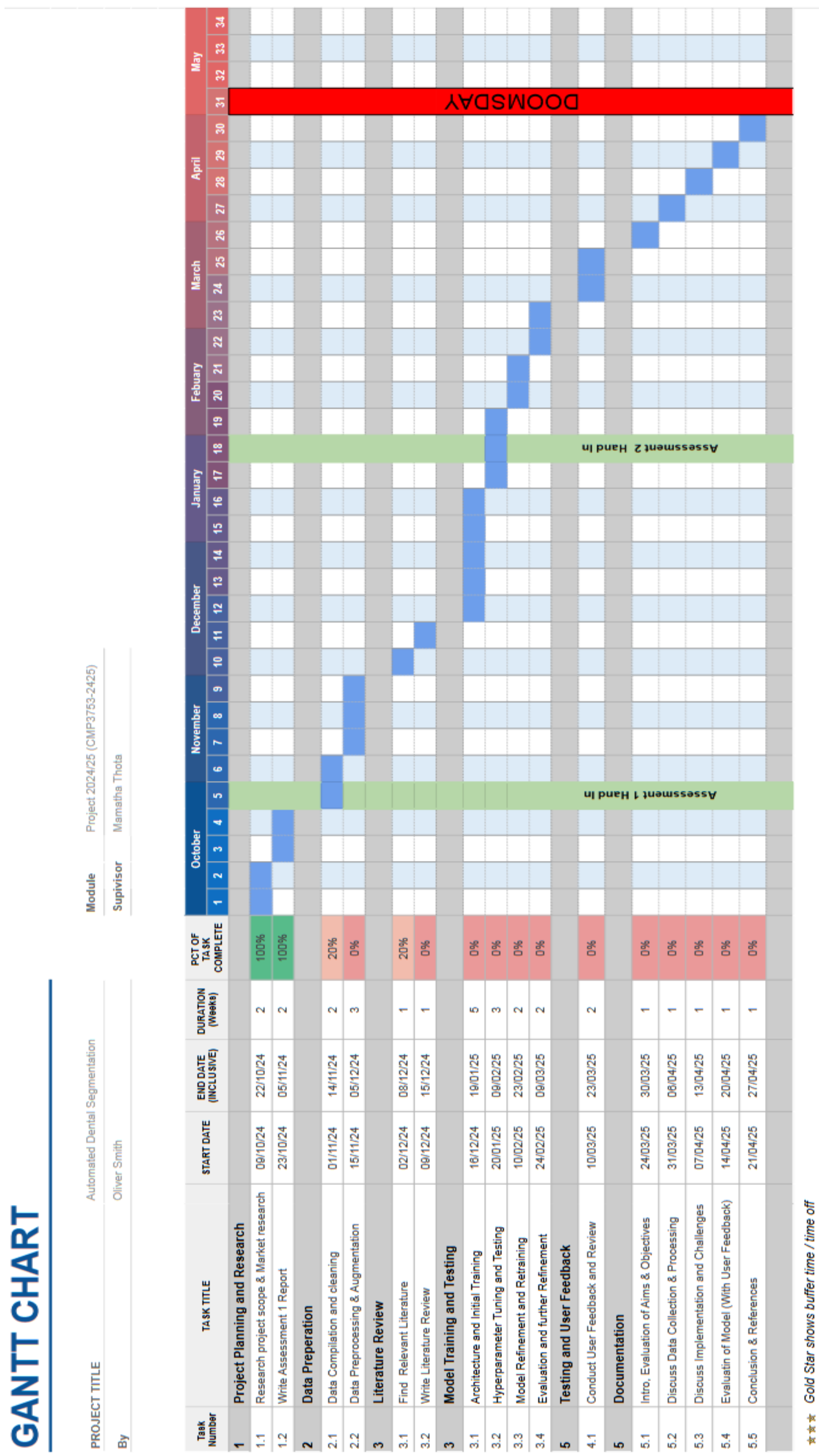

Fig. 1. Project Time Plan.

NOTE: A more granular version of this Gantt chart has uploaded via the supporting documents folder. Please refer to it for a clearer understanding of the estimated timeline.

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