Dental Enumeration in Panoramic Radiographs using Deep Learning

Major Project Synopsis

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Abstract

Dental enumeration plays a critical role in clinical diagnosis, treatment planning, and automated dental analysis. Although recent deep learning approaches have demonstrated promising performance in tooth segmentation on panoramic radiographs, most existing methods primarily focus on pixel-level segmentation accuracy and do not ensure anatomically valid dental enumeration at the patient level. In particular, limited attention has been given to enforcing Fédération Dentaire Internationale (FDI) numbering consistency, detecting missing teeth, and validating complete dental charts.

In this work, a deep learning–based framework for dental enumeration in panoramic radiographs is proposed. Pixel-level annotations are created using the FDI tooth numbering system, where each panoramic image is annotated into 32 tooth classes using polygon-based semantic segmentation. An enhanced U-Net-based architecture with multi-channel sigmoid output is employed to generate precise tooth segmentation masks. Following segmentation, a post-processing enumeration stage is introduced, where connected component analysis and spatial feature extraction are used to convert segmentation masks into individual tooth instances. Anatomical constraints based on jaw separation and left–right ordering are then applied to validate and correct tooth numbering, enabling explicit detection of missing or misnumbered teeth.

The proposed approach is evaluated using both conventional segmentation metrics and clinically meaningful enumeration metrics, including per-tooth numbering accuracy and per-patient complete enumeration accuracy. By separating segmentation from enumeration logic, the framework improves interpretability and robustness while maintaining computational efficiency. The results demonstrate that the proposed method effectively bridges the gap between pixel-level tooth segmentation and clinically reliable dental enumeration, making it suitable for real-world dental diagnostic applications.

Introduction

Dental radiographic imaging plays a vital role in modern dentistry for diagnosis, treatment planning, and monitoring of oral health conditions. Among various imaging modalities, panoramic radiographs provide a comprehensive view of the maxillofacial region, enabling clinicians to examine the full dentition, jaw structure, and surrounding anatomical features in a single image. Accurate identification and numbering of teeth from panoramic radiographs, commonly referred to as **Dental enumeration**, is a fundamental requirement for tasks such as dental charting, disease localization, orthodontic planning, and surgical procedures.

Traditionally, dental enumeration is performed manually by expert dentists through visual inspection of radiographs. However, this process is time-consuming and prone to human error, especially in cases involving overlapping teeth, missing teeth, anatomical variations, or image quality degradation. Incorrect tooth numbering can lead to misdiagnosis, improper treatment planning, and adverse clinical outcomes. As a result, there is a growing interest in developing automated and reliable dental enumeration systems to support clinical decision-making.

Recent advancements in artificial intelligence, particularly deep learning, have demonstrated significant success in medical image analysis, including dental image processing. Convolutional Neural Network (CNN)–based approaches have been widely applied for tasks such as tooth detection, segmentation, and numbering in panoramic radiographs. Many existing methods utilize object detection techniques that predict bounding boxes around teeth, followed by heuristic rules to assign tooth numbers. While these approaches achieve reasonable performance, bounding-box–based detection often fails to capture precise tooth boundaries and struggles in scenarios involving overlapping or closely spaced teeth.

To address these limitations, pixel-level segmentation approaches have gained attention, as they provide detailed delineation of tooth structures and preserve fine anatomical boundaries. Encoder–decoder architectures such as U-Net and its variants have been shown to be particularly effective for medical image segmentation due to their ability to capture both local and global contextual information. Despite achieving high segmentation accuracy, most existing studies primarily evaluate pixel-level performance using metrics such as Dice coefficient or Intersection over Union (IoU), without explicitly validating whether the predicted tooth labels form a complete and anatomically correct dental chart.

This highlights a critical gap in current research: **accurate tooth segmentation does not necessarily guarantee correct dental enumeration**. In many cases, segmentation models may produce visually accurate masks while still assigning incorrect tooth numbers, swapping adjacent teeth, or failing to detect missing teeth. Moreover, anatomical constraints inherent to standardized numbering systems such as the Fédération Dentaire Internationale (FDI) system—including jaw separation, quadrant consistency, and left–right ordering—are often not explicitly enforced or evaluated.

Motivated by these challenges, this project focuses on bridging the gap between pixel-level tooth segmentation and clinically meaningful dental enumeration. **By leveraging pixel-level FDI-based annotations and a U-Net–based segmentation framework, the proposed approach introduces a post-segmentation enumeration stage that converts segmentation masks into individual tooth instances and applies anatomical constraints to validate tooth numbering. This separation of segmentation and enumeration logic enables more reliable and interpretable dental chart generation, addressing limitations observed in existing methods**.

The proposed framework aims to contribute toward the development of an automated dental enumeration system that is accurate, robust, and clinically applicable, thereby supporting dentists in efficient diagnosis and treatment planning using panoramic radiographs.

Proposed Method / Algorithm

The proposed methodology aims to develop an automated framework for **Dental enumeration in panoramic radiographs** by combining pixel-level tooth segmentation with post-segmentation anatomical reasoning. The overall approach is divided into two main stages: **tooth segmentation** and **dental enumeration**. The block diagram of the proposed system consists of data annotation, deep learning–based segmentation, instance extraction, and enumeration validation.

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1. Dataset Preparation and Annotation

Panoramic dental radiographs are annotated using the **Supervisely annotation tool**, where each image is labelled at the pixel level following the **Fédération Dentaire Internationale (FDI)** tooth numbering system. A total of **32 tooth classes (11–48)** are defined, and polygon-based semantic segmentation masks are created for each tooth. Pixel-level annotation ensures accurate representation of tooth boundaries, including crown and root regions, and is particularly effective in handling overlapping or closely spaced teeth.
No additional annotation is performed beyond pixel-level masks. The absence of a mask for a particular tooth class implicitly indicates a missing tooth, which is utilized during enumeration.

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2. Tooth Segmentation Using U-Net-Based Architecture

An enhanced **U-Net–based encoder–decoder architecture** is employed for tooth segmentation due to its effectiveness in medical image analysis and its ability to capture both local and contextual features. The network takes a panoramic radiograph as input and outputs a **multi-channel segmentation map**, where each channel corresponds to one FDI tooth class.

To handle overlapping teeth and class imbalance, the model uses:

- A **multi-channel sigmoid activation function** in the output layer, allowing independent prediction for each tooth class.
- A combined loss function consisting of **Dice loss and Binary cross-entropy**, enabling accurate segmentation of both large and small teeth.

The segmentation model is trained on annotated images and optimized using standard data augmentation techniques such as rotation, scaling, and intensity variation to improve robustness.

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3. Tooth Instance Extraction from Segmentation Masks

Following segmentation, the predicted pixel-level masks are converted into **tooth instances** through post-processing. For each FDI class:

- Binary thresholding is applied to the predicted probability map.
- **Connected component analysis** is used to identify individual tooth regions.

- Spatial features such as **centroid location, bounding box, and area** are extracted from each tooth mask.

This step transforms pixel-level predictions into object-level representations, which are required for dental enumeration.

3.4 Dental Enumeration and Anatomical Validation

Dental enumeration is performed by applying anatomical and spatial constraints to the extracted tooth instances. The following validation steps are implemented:

- **Jaw separation** is achieved by analyzing the vertical position of tooth centroids to distinguish upper and lower dentition.
- **Left–right ordering** is enforced by sorting tooth instances based on horizontal spatial coordinates.
- **FDI numbering consistency** is verified by ensuring correct quadrant placement and sequential tooth ordering.
- **Missing teeth detection** is performed by identifying absent tooth instances corresponding to missing FDI classes.

This post-segmentation enumeration stage ensures that the final output represents a **complete and anatomically valid dental chart**, rather than only visually accurate segmentation masks.

3.5 Evaluation Metrics

The proposed framework is evaluated using both **segmentation metrics** and **enumeration-specific metrics**. Segmentation performance is assessed using Dice coefficient, Intersection over Union (IoU), precision, and recall. Enumeration performance is evaluated using tooth-wise numbering accuracy, missing tooth detection accuracy, and **per-patient complete enumeration accuracy**, which measures whether all present teeth in a radiograph are correctly enumerated.

3.6 Summary of the Proposed Framework

By separating segmentation and enumeration into distinct stages, the proposed methodology addresses limitations of existing approaches that focus solely on pixel-level accuracy. The framework ensures interpretable, robust, and clinically meaningful dental enumeration while maintaining computational efficiency, making it suitable for real-world dental diagnostic applications.

Programming Environment & Tools Used

- **Programming Language:** Python 3.x
- **Core Libraries and Frameworks:**
    - **TensorFlow 2.x / Keras:** Used for designing, training, and evaluating the U-Net–based convolutional neural network for tooth segmentation.
    - **OpenCV (cv2):** Utilized for image loading, preprocessing, resizing, thresholding, and post-segmentation operations such as connected component analysis.
    - **NumPy:** Used for efficient numerical computations, mask processing, and array manipulations.
    - **Matplotlib / Seaborn:** Employed for data visualization, including training and validation curves, segmentation outputs, and evaluation plots.
    - **Scikit-learn:** Used for dataset splitting and calculation of performance evaluation metrics.
- **Annotation Tool:**
    - **Supervisely:** Used for pixel-level annotation of panoramic radiographs, where each image is annotated into 32 classes based on the FDI tooth numbering system.
- **Hardware and Computing Resources:**
    - **GPU:** The project is developed on a system equipped with an NVIDIA GPU to accelerate deep learning model training.
    - **Cloud Platform: Google Colab** is considered as an alternative platform for accessing GPU resources and conducting experiments

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