Detection of Dental Abnormalities in Panoramic Radiographs via Convolutional Neural Networks

Group Members: Alexandre Delgado 58964, Tiago Garcia 54938, Mariia Korepanova 64689

1. Introduction

This project aims to develop a deep learning model for the automatic detection of dental pathologies — including caries, deep caries, periapical lesions, and impacted teeth — in panoramic X-ray images using convolutional neural networks (CNNs). Panoramic radiographs are widely used in routine dental diagnostics, but their interpretation is time-consuming and subjective. Automating this process may improve diagnostic accuracy, speed up workflows, and reduce dentists' workload.

The first phase includes preparing the dataset, choosing the model architecture and methods, and creating a skeleton code. We plan to use CNN-based object detection models, in particular the YOLOv8 architecture, which is widely used to detect multiple objects in images.

2. Problem statement

For this project we will use the publicly available DENTEX Challenge Dataset, which contains over 1000 annotated panoramic dental radiographs labeled by quadrant, tooth number, and diagnosis. Additional unlabeled images may be used for pre-training or augmentation.
We aim to train the model to accurately detect and classify dental anomalies (caries, deep caries, periapical lesions, and impacted teeth) from a single panoramic radiograph.

We will evaluate the model performance in two ways: qualitative and quantitative. The qualitative evaluation will be the visualization of the predicted bounding boxes on the radiographs. The quantitative evaluation will use standard object detection metrics including precision, recall, F1 score, and mean Average Precision (mAP).

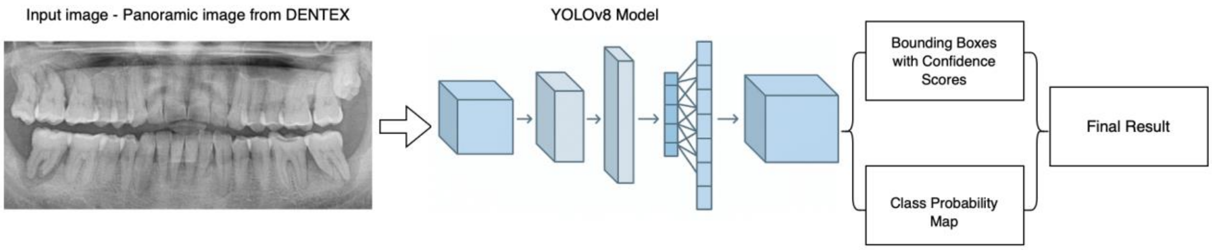
3. Technical Approach

In our project, we will use convolutional neural networks (CNNs), in particular YOLOv8 architecture. This model is efficient and has high performance in multi-object detection tasks in complex images.

This approach involves converting the annotated panoramic radiographs from the DENTEX Challenge dataset to YOLO format. Each anomaly is represented by a bounding box and the corresponding class label. We will split the dataset into training and validation sets. 90% of the images will be used for training and 10% for validation. The configuration file (`data.yaml`) defines the paths to the datasets, the number of classes, and their corresponding labels. During training, the model learns to predict the location and class of anomalies directly from the radiographs. We will use standard data augmentation techniques provided by the YOLO learning framework to improve generalization.

The initial phase focuses on setting up the data pipeline, implementing the training skeleton code, and creating a baseline model that we can optimize in the following phases.

4. Figure describing the approach / methodology.



5. Planned Experiments and Preliminary Results

In this step, we prepared the DENTEX dataset by splitting it into training and validation sets (90/10 split). We also formatted the annotations according to the YOLO object detection format. We chose a YOLOv8-based model architecture and set up the initial training skeleton code, including a configuration file (`data.yaml`).

In the next step, we plan to:

- Training the YOLOv8 model on the prepared dataset with standard hyperparameters.

- Implementing data augmentation techniques to improve generalization.

- Evaluating performance using qualitative assessments (bounding box visualization) and quantitative metrics such as precision, recall, F1-score, and mean Average Precision (mAP).

- Fine-tuning hyperparameters based on initial evaluation results if necessary.

As of now, we have no preliminary results yet, since model training is planned for the next phase.