Ortho-Vision: Optimal therapeutic plan for implants

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Abstract

This report documents the progress of the Ortho-Vision project, an AI-powered system designed for dental implant planning using segmentation models. The project aims to provide an optimal therapeutic plan for dental implants by leveraging deep learning techniques through segmentation and detection using dental imagery from radiographs.

1   Introduction

The Ortho-Vision project aims to assist dental implant planning by leveraging AI for accurate segmentation and detection of dental structures in radiographs. This system is designed to improve the planning process by providing clear and consistent implant guidance.

2   Base Flow

2.1   Application Functionality

The application is designed with functionalities that support end-to-end dental implant planning. It allows users to upload radiographs, segment dental features, and generate suggested implant plans based on segmented regions.

2.2   Problem Description

The goal of this project is to develop a solution for automatic segmentation of dental images, and detection of dental structures. This includes both a descriptive and formal problem analysis, aiming to create a reliable AI-based tool that can assist in identifying key dental regions necessary for implant placement.

2.3   Related Work and Useful Tools and Technologies

We explored existing dental segmentation models, including pre-trained options on Hugging Face, and reviewed literature on segmentation techniques commonly applied in medical imaging. Our toolkit includes TensorFlow, Keras and YOLO for model development, OpenCV and PIL for image processing, with additional experimentation using open-source pre-trained segmentation models to accelerate initial testing.

3 Experimental Phase 1: Segmentation

3.1 Data Collection

We collected a public dataset of multiple dental single-channel radiographs datasets from public sources with corresponding segmentation masks for key dental features. This had 1000 train images and 100 test images. The images have a resolution of 1615 x 840. These were normalized to 256 x 256.

3.2 Methods and Algorithms

We tested two primary models for segmentation:

- **Pre-trained Dental Segmentator (Hugging Face):** A pre-trained model was initially tested, but results were suboptimal, likely due to dataset-specific variations. This model was tested on 100 2-dimensional radiographs and it was not trained on specific masks, as it should have already been trained specifically for dental segmentation.

- **U-Net Model:** Our U-Net model, from an existing deep-learning architecture, implemented with TensorFlow and Keras.

  - **Experiment 1:** Used a partition of 500 images from the public dataset for training with a batch size of 8 and 50 epochs, achieving an accuracy of approximately 92% on the validation set.

  - **Experiment 2:** Used the whole public dataset for training with a batch size of 32 and 30 epochs, yielding slightly higher accuracy at 94.5% on the validation set, indicating that the larger batch size and longer training improved the model's performance.

  The best results were achieved in Experiment 2, where the combination of a larger batch size and additional training epochs allowed the model to converge more effectively.
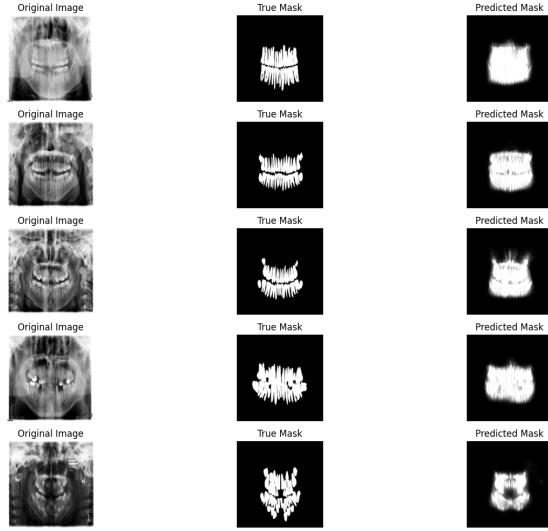
Figure 1: Results from our first experiment of U-Net segmentation model showing accurate predicted masks of dental features.
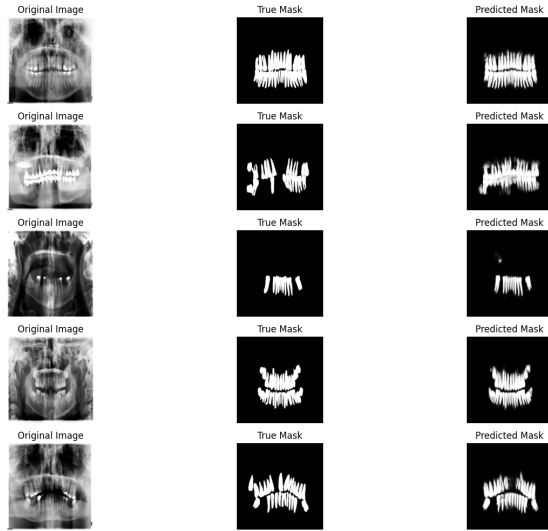

Figure 2: Results from our second experiment of U-Net segmentation model showing accurate predicted masks of dental features.

3.3 Results and Discussion

The U-Net model significantly outperformed the pre-trained Dental Segmentator, especially with the second experiment, achieving accurate and reliable segmentations on our dataset. This model is expected to be central to the overall implant

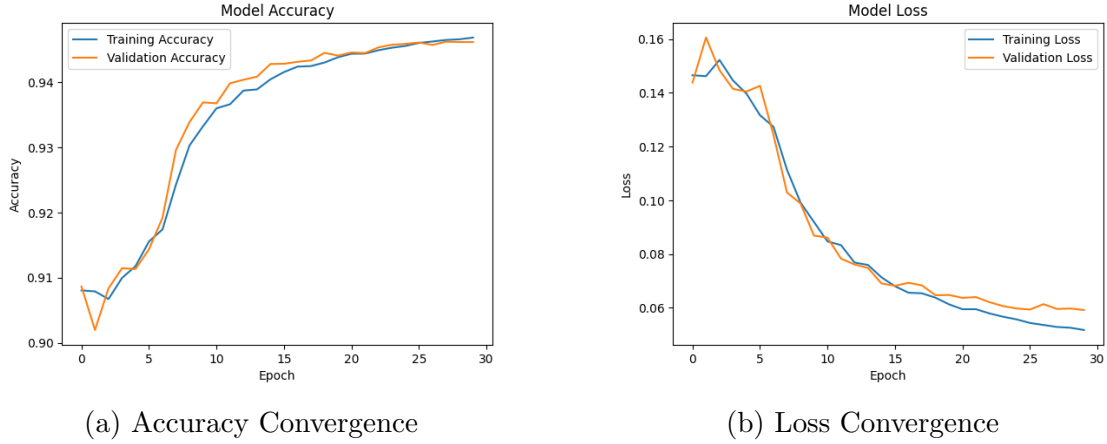planning application, given its robust performance.

(a) Accuracy Convergence   (b) Loss Convergence

Figure 3: Metrics for best performing U-Net

4 Experimental Phase 2: Object Detection

4.1 Data Collection

In this phase, we received proprietary data from UMF University, provided through collaboration with Prof. Mihaela Hedeșiu. The dataset contains 1000 images for training, 100 for validation, and 100 for testing. The images have a resolution of 2775x1475. It contains 12 classes: 'IMP', 'PRR', 'OBT', 'END', 'CAR', 'BON', 'IMT', 'API', 'ROT', 'FUR', 'APS', 'ROR', 'ORD', 'SRD'. Using this dataset, we trained a YOLOv11 model to detect dental structures and extract key characteristics for each tooth. This approach complements the segmentation task by adding object detection capabilities, providing a comprehensive analysis of dental features.

4.2 Methods and Algorithms

We utilized the YOLOv11 model for its state-of-the-art performance in object detection tasks. The model was trained on the proprietary dataset with the following configuration:

- **Training Configuration:** Default configuration from Ultralyitcs library. Trained on the whole recieved dataset.

- **Model Objective:** To detect dental structures and annotate key characteristics for each tooth, such as previous work done by the dentists.
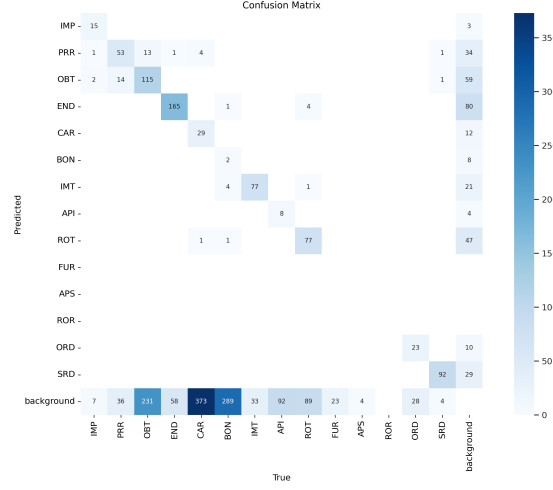

Figure 4: Confusion Matrix from YOLOv11 detection for each annotaion class.

4.3 Results and Discussion

The YOLOv11 model Successfully identified individual teeth and their attributes, providing valuable insights for dental implant planning.
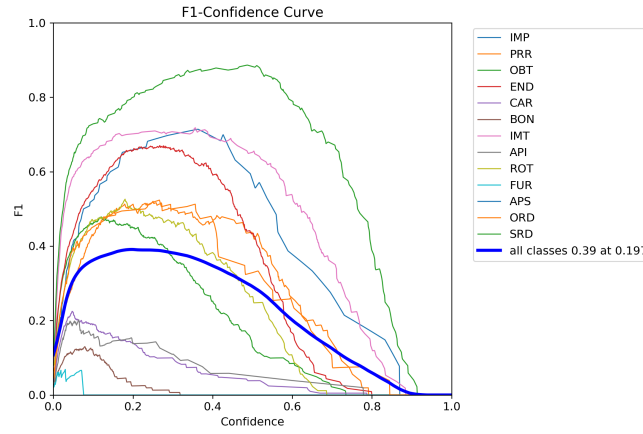

Figure 5: Validation F1 score.

Table 1: Detection Metrics for Classes

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
all	153	1972	0.549	0.386	0.369	0.167
IMP	10	25	0.713	0.595	0.632	0.342
PRR	49	103	0.477	0.592	0.467	0.240
OBT	80	359	0.539	0.401	0.413	0.135
END	79	224	0.655	0.747	0.679	0.269
CAR	108	407	0.617	0.0688	0.124	0.0364
BON	49	297	0.200	0.0168	0.0332	0.00999
IMT	46	110	0.666	0.652	0.600	0.299
API	45	100	0.486	0.060	0.121	0.0391
ROT	43	171	0.457	0.474	0.397	0.136
FUR	15	23	1.000	0.000	0.0142	0.00403
APS	1	4	0.000	0.000	0.000	0.000
ORD	18	51	0.646	0.471	0.404	0.200
SRD	20	98	0.682	0.939	0.916	0.466

The results indicate that YOLOv11 is an effective tool for detecting dental structures and extracting detailed characteristics. This capability will be integrated into the final application to enhance the planning process by combining segmentation with object detection.
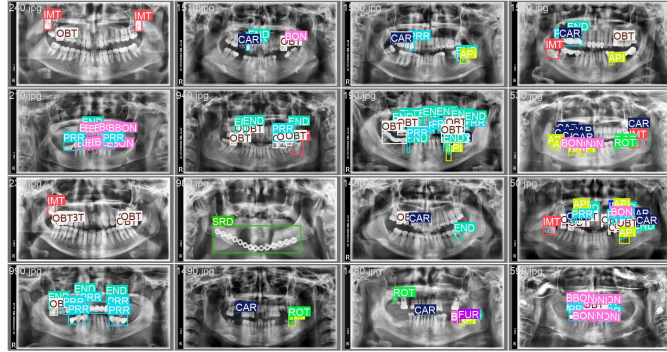

Figure 6: Results from YOLOv11 detection, highlighting dental structures and annotations for each tooth.

4.4 Future Steps

Moving forward, we aim to:

- Compare the performance of YOLOv11 with other object detection models to identify the optimal approach for our use case.

- Integrate the detection and segmentation modules into a unified pipeline for comprehensive dental implant planning.

5 Experimental Phase 3: Model Improvements and Pipeline

This phase will focus on further optimizing our winning models model, introducing additional data preprocessing steps, and experimenting with ensemble methods or advanced architectures to improve accuracy further.

5.1 Results and Discussion

We expect that these improvements will lead to higher accuracy and more reliable segmentation and detection outputs, particularly in complex or noisy images. Results from these experiments will be detailed as they are completed.

6 Future Work

Future improvements will focus on integrating post-processing techniques for refinement of segmentation, expanding the dataset with 3-dimensional radiographs, and evaluating additional model architectures. We also aim to implement the system as a complete dental implant planning tool with a user-friendly interface and easy-to-interpret outputs.