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مجلة جامعة دمشق للعلوم ....
المجلد ... العدد... : الصفحات.

الاستفادة من خوارزميات تعليم الآلة لتصنيف الأسنان في صور البانوراما السنية

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الملخص

يعمل هذا البحث على اكتشاف إمكانات خوارزميات تعليم الآلة والتعليم العميق على تحليل صور الأشعة السينية للأسنان والفكين. تحتوي صور الأشعة السينية للفم والفكين على معلومات عن كامل المجموعة السنيّة في الفكين العلوي والسفلي والذي يجعلها من أكثر التقنيات استخداماً من قبل أطباء الأسنان. يمكن للأطباء بتحليل هذه الصور اكتشاف الحالات السنية مثل الزرعات والحشوات والأسنان الطامرة والنخر.

يقدم هذا البحث خوارزمية تتألف من ثلاث مراحل تدمج بين تقنيات معالجة الصور وتقنيات التعليم العميق لمعالجة صور بانوراما الأسنان واكتشاف حالات الأسنان غير الطبيعية, كما يقارن البحث الخوارزمية المقترحة مع خوارزميات التعليم العميق الأخرى بعد تدريبها على نفس مجموعة البيانات. حصلنا على دقة كشف 97% ودقة تعرف على كامل النظام وصلت لـ 92% والذي يوحي بالإمكانات الواعدة لتقنيات تعليم الآلة في مجال تحليل الصور السنية للمساعدة على التشخيص وتحديد الخطة العلاجية. بشكل عام, يسلط هذا البحث الضوء على مدى فعالية خوارزميات تعليم الآلة في مجال تحليل صور بانوراما الأسنان والذي يزيد من سرعة ودقة التشخيص وبالتالي يحسن من مدى الاهتمام بالمرضى.

تاريخ الايداع

تاريخ القبول

الكلمات المفتاحية: معالجة الصور الطبية, صور بانوراما الاسنان, النخر, الحشوات, الزرعات.

Utilize ML for Abnormal Tooth Classification in Dental Radiography

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Abstract:

This research explores the potential of deep learning for analyzing panoramic dental X-rays. Panoramic X-rays provide a wide-angle view of all the teeth in the upper and lower jaws, making them valuable tools for dentists. By analyzing these X-rays, dentists can identify various dental features, including Implants, Fillings, Impacted teeth, and Caries.

The study proposes a new, three-stage method that combines image processing techniques and deep learning models for simultaneously recognizing these crucial features. The study compares its deep learning approach to existing, advanced algorithms. The high detection accuracy of 97% and overall recognition accuracy of 92% suggest that deep learning has great promise for more precise diagnoses and can optimize treatment planning. Overall, this research highlights the potential of deep learning to revolutionize dental X-ray analysis, leading to faster, more accurate diagnoses and improved patient care.

Keywords: Medical image processing, Dental Radiography, Panoramic X-ray, Teeth, caries, impacted teeth, fillings, implants

Received:
Accepted:

1. Introduction

Oral diseases, particularly common ones like caries and gum disease (periodontitis), pose a significant global public health concern. Periodontitis is primarily caused by the buildup of dental plaque, a sticky film on teeth that triggers inflammation and damages the supporting tissues around the teeth. Research suggests caries might not only worsen gum disease (periodontitis) but also increase the risk of cardiovascular disease and potentially be linked to other serious health problems (Falcao and Bullón, 2019). Dental caries is a disease that can damage tooth structure and is mainly caused by acid erosion. The acid is mostly produced by intraoral bacteria. Dental caries are one of the main oral diseases with high prevalence that influence the quality of life. Caries are a leading oral health concern globally, affecting a large number of people. this disease can have a profound impact on oral health and overall well-being. Therefore, the prevention of dental caries is an important task for dentists. Moreover, early diagnosis has always been a crucial part of the treatment of caries. Beyond diagnosis, dental X-rays are valuable for tracking treatment progress, assessing fillings and implants, and evaluating impacted teeth to inform treatment plans. The detection of dental caries and treatment progress mainly depends on clinical and radiographic examinations. Dentists typically evaluate various aspects of a patient's oral condition to provide a comprehensive diagnosis and treatment plan. Using AI-assisted technology to concurrently recognize dental caries and case details aligns closely with how dentists diagnose patients in clinical practice. Saving time and reducing loading for dentists and minimizing patients' discomfort associated with multiple examinations can be realized.

Dental X-ray imaging has become the foundation for dental professionals globally. This technology allows dentists to detect abnormalities within the teeth structure (Kumar et al., 2021). For dentists, radiography assists in providing accurate clinical diagnosis and dental structure examination. A manual examination of X-ray images can be time-consuming and prone to error. The recent surge in deep learning (DL) and machine learning (ML) has revolutionized the field of medical image processing, with a significant impact on DXRI analysis.

This is primarily driven by the power of Convolutional Neural Networks (CNNs). Unlike traditional algorithms, CNNs excel at handling large and intricate image datasets like dental X-rays. Their secret lies in their multi-layered structure. Each layer acts as a filter, progressively extracting increasingly complex features from the raw image data. Through this hierarchical processing, CNNs can learn to identify subtle patterns and variations within the X-ray that might be missed by the human eye. This capability is particularly valuable in dental diagnosis, where early detection of caries, impacted teeth, and other abnormalities is crucial for successful treatment (Schmidhuber, 2015; Hwang et al., 2019). Pre-trained convolutional neural networks (CNNs) such as AlexNet, VGG, and GoogLeNet were successfully employed in classifying various tooth disorders and enhancing dental X-ray analysis. Researchers are actively developing new machine-learning algorithms in the area of image segmentation, the process of isolating specific regions of interest within the X-ray and using them for dental radiography (Hatvani et al., 2018; Lee et al., 2018a; Yang et al., 2018; Hwang et al., 2019; Khanagar et al., 2021). The field of dentistry is undergoing a transformation with the rise of AI-powered automated analysis of dental X-rays (AbuSalim et al., 2022). Yet, developing automated algorithms for panoramic X-ray analysis remains a significant challenge due to the inherent variability in human jaw and tooth anatomy (Yuksel et al., 2021) and the shortage of publicly accessible annotated data (El Joudi et al., 2022). While challenges exist, integrating AI into dental

X-ray analysis holds immense promise. This approach has the potential to significantly improve treatment outcomes and patient satisfaction (Pauwels et al., 2021). The potential benefits of AI in dentistry necessitate further research to refine and develop robust AI algorithms for dental X-ray analysis.

2. Literature Review

In (Lee et al., 2018) A deep learning-based CNN was implemented for periodontal prediction of the compromised teeth (PCT), premolars, and molars individually. The study used 16 convolutional layers and 3 dense layers in the model to classify teeth into healthy, moderate PCT, and severe PCT. (Li et al., 2021) used a vector of the severity of alveolar bone loss from the teeth as an input feature of XGBoost to classify the four-class severity degree of periodontitis from a panoramic radiograph. In (Chang et al., 2022), periapical radiographs were used to calculate the radiographic bone loss (RBL) values and classify the severity of RBL into mild or severe, and also classify the defect morphology. they used a multi-task classification approach with the InceptionV3 model.

(Sornam et al., 2017) combined the modified linearly adaptive particle swarm optimization with a backpropagation neural network to distinguish between normal and caries-affected teeth. In (Lee et al., 2018), a pre-trained GoogLeNet InceptionV3 CNN network was used to predict of dental caries of premolars and molars. In (Geetha et al., 2020), they developed a system for predicting dental caries using Laplacian filtering, window-based adaptive thresholding, morphology, statistical features, and backpropagation. In (Jusman et al., 2021), Hu's moment was used to train the support vector machine and k-nearest neighbors for the classification of four levels of dental caries. In (Imak et al., 2022), they used both raw and enhanced images as inputs to an ensemble deep convolutional neural network model for dental caries detection. (Bui et al., 2020) extracted features from teeth on panoramic radiographs using deep learning networks and each extracted feature set was used to train the classification model. The caries screening was determined by a majority voting method.

(Chen et al., 2021) used a deep convolutional neural network with region proposal techniques to detect decay, periapical periodontitis, and periodontitis on periapical radiographs. The three diseases were individually classified into mild, moderate, and severe levels. In (Li et al., 2022), the periapical radiograph subregion was cropped to obtain a single-tooth image. Then, the crown region and the root region were cropped according to the identified cervical line. The detection of caries from the crown region and periapical periodontitis from the root region was based on a deep learning model constructed of two cascaded ResNet-18 backbones and two individual convolutional layers.

(Chen et al., 2023) used YOLOv7 to detect individual teeth. Then cropping the tooth and passing it to contrast-limited adaptive histogram equalization to enhance the local contrast, and bilateral filtering to eliminate noise while preserving the edge. They built the classifier on a pre-trained EfficientNet-B0 and fully connected layers that output two labels by the sigmoid activation function. It used a dataset of 1525 periapical x-ray images obtained from a dental clinic in Hualien, Taiwan. (Hamamci1 et al., 2023) proposed a challenge at the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI) 2023, DENTEX Challenge. They proposed an algorithm based on HierarchicalDet (Hamamci et al., 2023). it utilizes a diffusion-based model for hierarchical object detection. the method comprises two components, an image encoder that extracts high-level features from the input image and a detection decoder that refines the noisy boxes to object boxes.

3. Materials and Methods

Medical data are hard to acquire and harder to label! Medical information is strictly confidential and applicable to privacy concerns which makes it hard to acquire, and labeling medical data requires high-level specialists with years of experience. Most previous studies in the field of dental image processing used locale data provided by certain clinics or organizations and didn't share their dataset due to privacy concerns. However, with the increased interest in ML, new datasets were provided. There are two main annotated datasets for dental image processing, The Dental Radiography Dataset (DRD 2023) and Dentex (Hamamci1 et al., 2023). DRD provides 1075 training and 121 validation panoramic dental X-rays. It includes annotations for four dental abnormalities: caries (or cavities), implants, impacted teeth, and fillings. Figure 1 shows the number of instants for each class in the dataset and Figure 3 shows sample images.

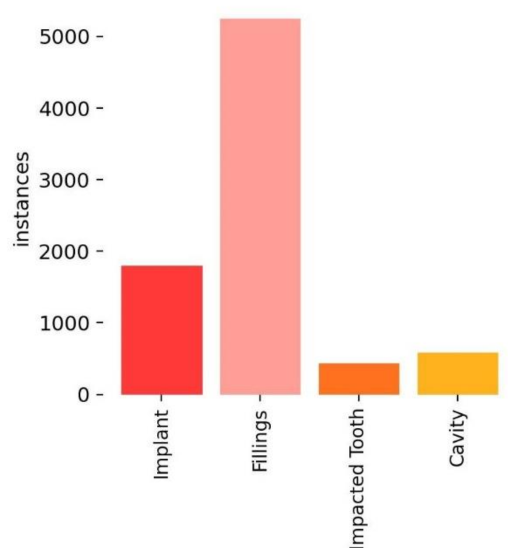

Figure 1- Dental Radiography dataset number of instants for each class

Dentex offers 705 annotated images for training and 51 unlabeled images for validation. It also provides annotations for quadrant and teeth enumeration for tooth location recognition. Dentex contains 4 abnormalities classes: caries, deep caries, impacted teeth, and periapical lesions. Figure 2 shows the number of instants for each class and Figure 4 shows samples of the dataset images.

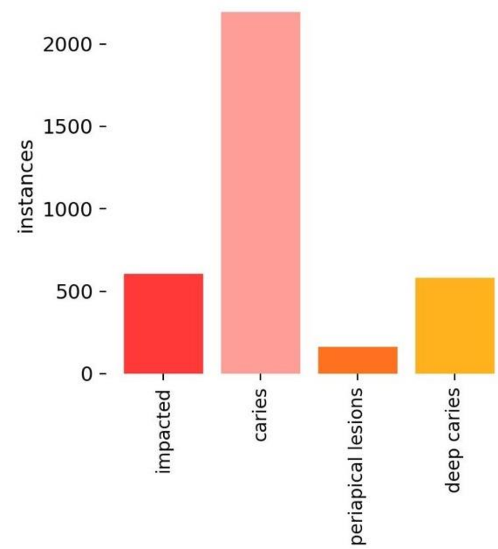

Figure 2 - Dentext dataset number of instants for each class

Table 1 and Table 2 provide more details about datasets and their class instants.

For this study, we opted to utilize the Dental Radiography Dataset (DRD) due to its extensive collection of annotated data, which is crucial for training and validating machine learning models effectively.

YOLO was chosen as a reference for both detection and recognition of teeth abnormalities. YOLO, which stands for "You Only Look Once", is a real-time object detection algorithm. Unlike some object detection methods that analyze images in stages, YOLO is a single-stage detector. It processes the entire image at once, making it faster for real-time applications. It relies on CNNs, which are artificial neural networks particularly adept at image recognition.

Table 1 - dental datasets details, number of training images, number of validation images and number of classes

dataset	Training #	Validation #	Classes #
Dental Radiography dataset	1075	121	4
Dentex	705	51	4

Table 2 - dental datasets classes details, number of abnormal teeth in each class

Dataset	Class	Instances #
Dental Radiography dataset	Caries	576
	Implant	1784
	Impacted Teeth	428
	Filling	5242
Dentex	Impacted Teeth	604
	Caries	2188
	Periapical lesions	158
	Deep caries	578

By analyzing the image through a series of filters, CNN can identify objects and their locations within the image. predicts bounding boxes around detected objects in the image. These boxes indicate the location and size of the object. Additionally, YOLO assigns a probability score to each bounding box, indicating the confidence level that the identified region contains a specific object class (e.g., caries, implant, filling). We have trained YOLOv7, YOLOv8, and YOLOv9 on DRD for both detection and recognition.

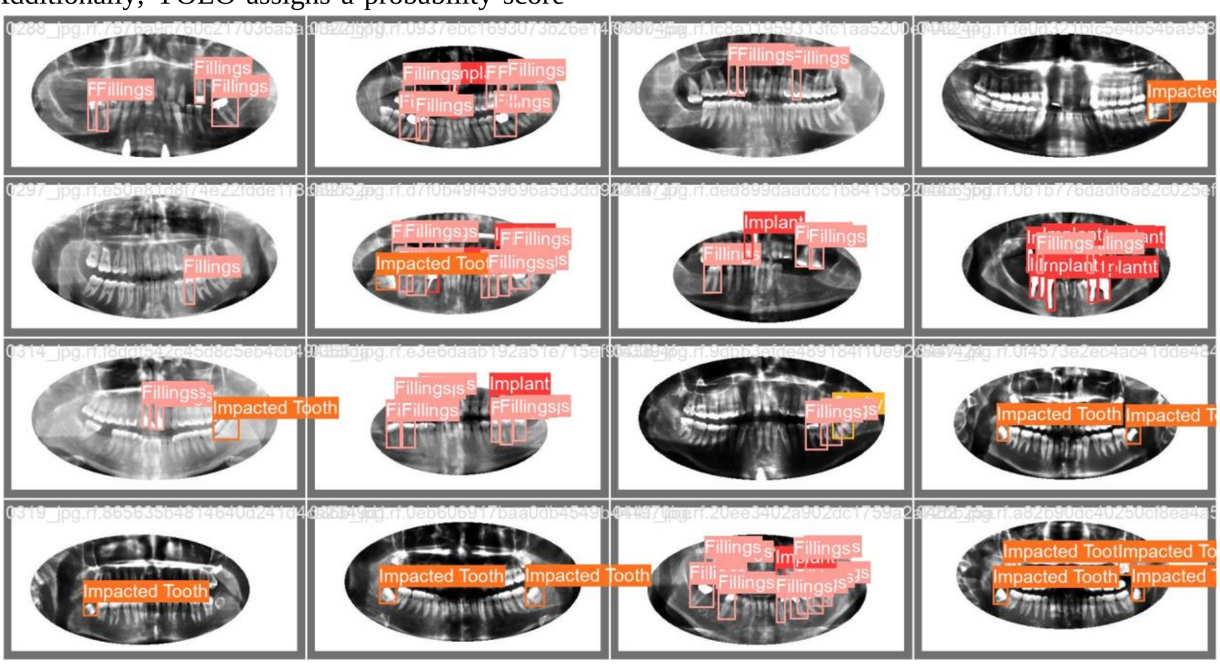

Figure 3 - sample images from dental radiography with annotated classes

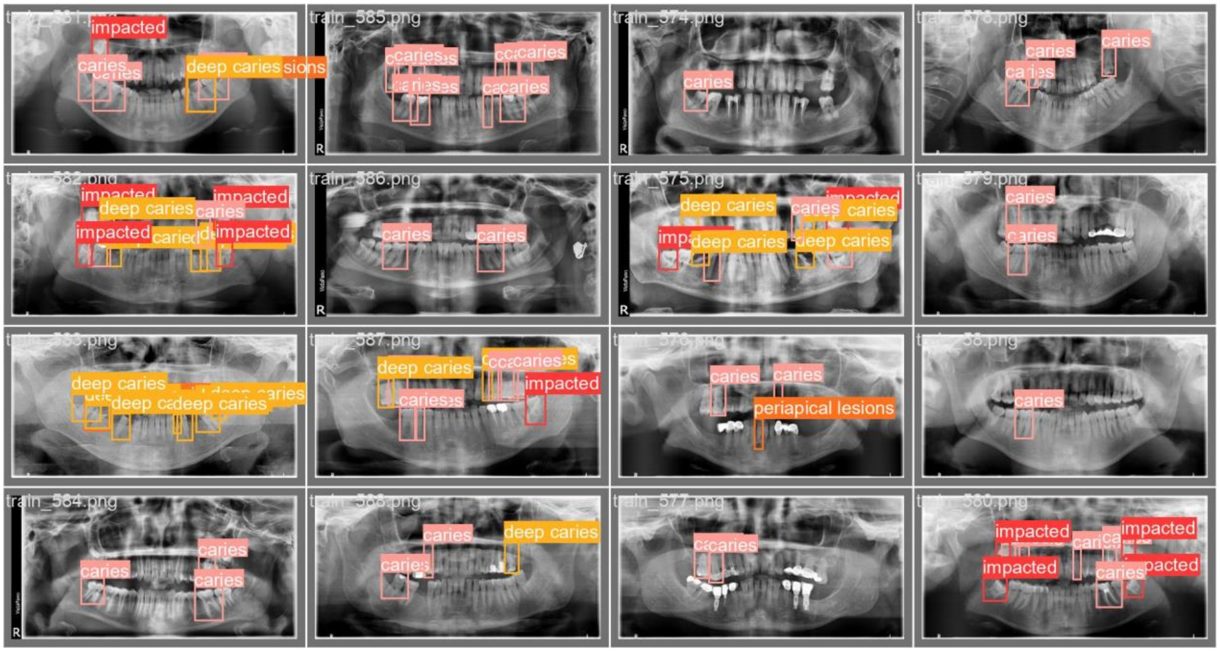

Figure 4 - sample images from dentex with annotated classes

4. Proposed algorithm

We propose a three-stage recognition approach as shown in Figure 5. In the first stage, we applied YOLO for single-tooth detection (first row of Figure 5). YOLOv8 was the most effective architecture for tooth detection due to the Path Aggregation Network (PAN) blocks within its feature pyramid architecture. PAN blocks effectively combine features from different scales within the network, allowing it to capture both fine-grained and coarse details of objects, leading to improved accuracy in object localization and recognition. It also leverages a Dilated Convolution (DCN) module within its detection head. DCN allows the network to capture information from a wider surrounding area, improving its ability to detect objects even when partially occluded by other objects in the image.

At the second stage (second row of Figure 5) we cropped each tooth and applied a custom convolutional filter. A few convolutional matrixes were examined and tested; a gain of 2% in the overall accuracy was achieved using the proposed matrix.

In the third and final stage, Resnet achieved the best accuracy. Resnet was designed to overcome the vanishing gradient issue in deep neural networks allowing the use of hundreds or even thousands of layers. It uses “skip connections” to bypass some layers in the network. The results are discussed in the results section

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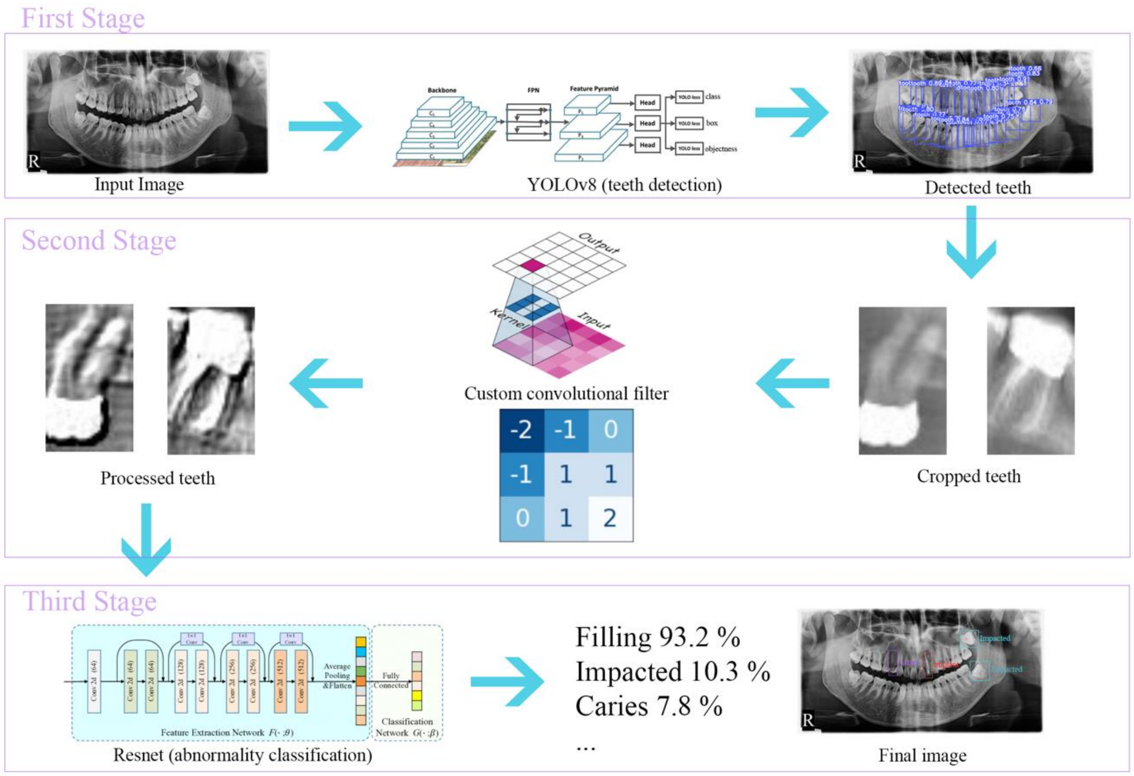


Figure 5 - Block diagram of the proposed algorithm, each stage is illustrated in one row

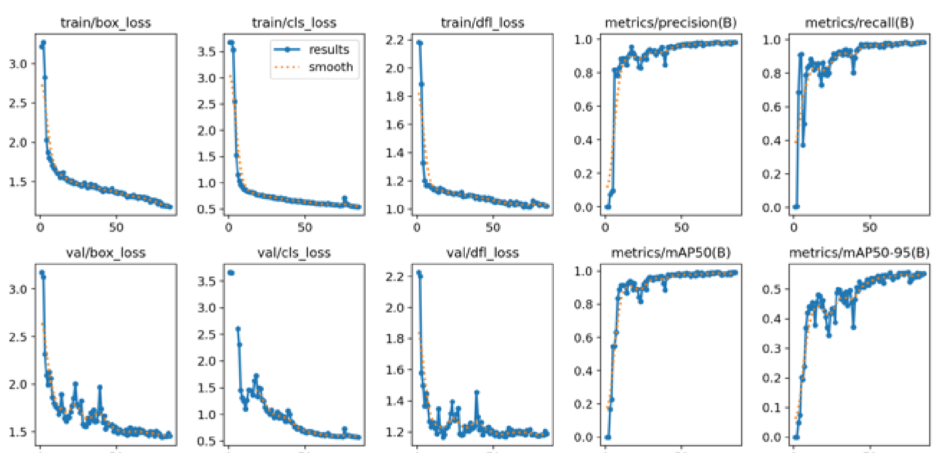


Figure 6 - YOLO v8 training and validation plots

Figure 7 - YOLO v8 tooth detection prediction sample

Table 3 - proposed algorithm results

Algorithm	P (All) %	P (Implant) %	P (Filling) %	P (Impacted) %	P (Caries) %	R (All) %	R (Implant) %	R (Filling) %	R (Impacted) %	R (Caries) %	mAP 0.5 (All) %	mAP 0.5 (Implant) %	mAP 0.5 (Filling) %	mAP 0.5 (Impacted) %	mAP 0.5 (Caries) %
YOLOv7	66.6	87.2	79.3	70.6	29.3	64.2	90.0	76.7	76.3	14.0	40.3	59.4	51.1	45.0	5.8
YOLOv8	76.4	95.5	82.4	77.2	50.3	71.1	93.6	84.8	71.1	34.9	76.6	97.8	86.8	79.5	42.2
YOLOv9	71.9	93.0	87.5	66.0	41.1	74.2	95.6	85.9	71.1	44.2	75.9	96.9	91.5	75.5	39.5

5. Results

To compare different approaches, we trained versions 7, 8, and 9 of the YOLO object detection. We trained them end-to-end to identify and recognize teeth abnormalities in DRD. To speed up training we used transfer learning by using weights from a pre-trained model on the COCO dataset. The results for our models, including their learning curves, and confusion matrices are presented in Appendix A and the accuracy, recall, and mean Average Precision (mAP), are presented in Table 3.

Our analysis shows similar performance between YOLO v8 and v9. While YOLO v8 achieves the highest overall accuracy, YOLO v9 demonstrates a superior ability to recall abnormalities. This suggests that YOLO v9 might be better at finding teeth anomalies, but for this specific task of teeth abnormality detection in dental radiographs, YOLO v8 remains the preferable choice. This is likely because YOLO v9 prioritizes general object detection over the specific classification required for this application.

According to the research paper, the core idea behind YOLO v9 is "programmable gradient information" which essentially allows the model to focus on learning what's important during training.

Analyzing class-related results revealed an imbalance in the dataset, leading to lower accuracy for caries detection. The dataset contained significantly fewer caries images (576) compared to implants (1784) and fillings (5242). This limited data for caries detection likely explains the lower accuracy in this class compared to the high accuracy achieved for implants and fillings.

Our proposed algorithm utilizes YOLO v8 in the first stage to detect individual teeth. To achieve this, we trained YOLO v8 for 85 epochs. In order to both accelerate training and enhance accuracy, we employed transfer learning by leveraging pre-trained weights from the COCO dataset. The training and validation loss and accuracy curves are visualized in Figure 6. Sample detection results on several images are presented in Figure 7. An accuracy of 97 % was achieved for single-tooth detection. Single-tooth detection learning curves and confusion matrix can be found in Appendix B.

In the second stage, we resized each tooth image to 55x32 pixels and then applied the custom convolutional filter mentioned in the proposed algorithm section. Not applying the filter resulted in about 3% lower overall classification accuracy (89 %).

For the final stage of tooth abnormality classification, we employed ResNet50. To expedite training and enhance accuracy, we implemented transfer learning with a pre-trained model based on the ImageNet dataset and trained the model for 85 epochs. This approach achieved an overall classification accuracy of 92%. As shown in Table 3, the proposed algorithm exceeded YOLO end-to-end models. However, similar to the YOLO, the dataset imbalance impacted the trained model. Caries detection accuracy remained the lowest (81%) compared to fillings (96%) and implants (97%).

6. Conclusion

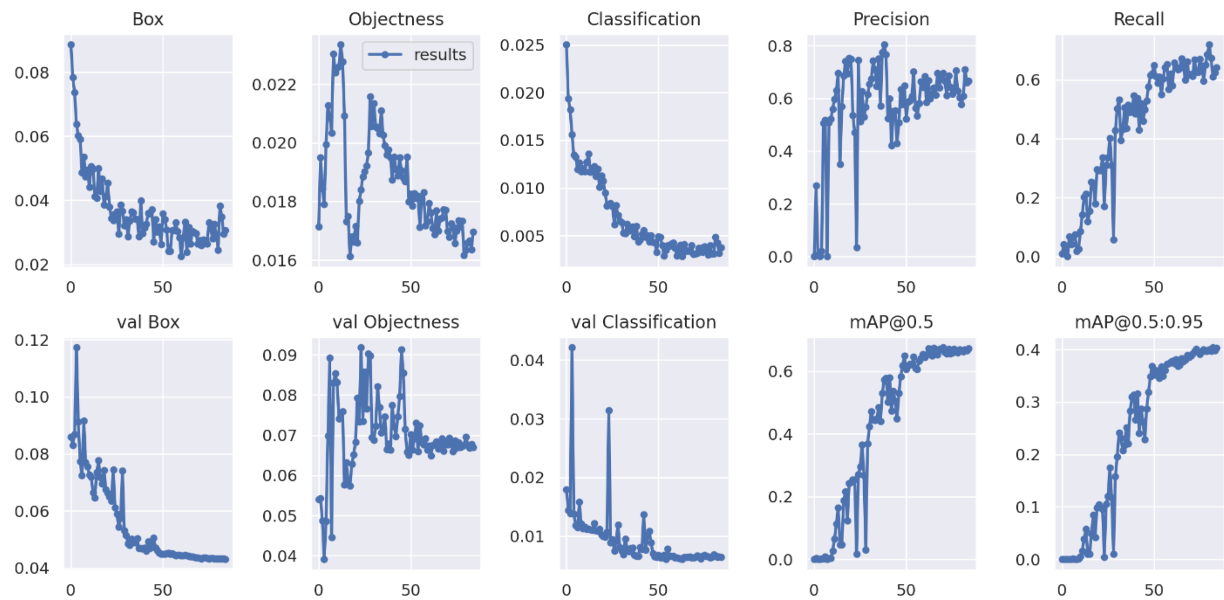
This study proposes a three-stage algorithm for abnormal teeth detection. The encouraging results demonstrate good recall and mAP values for all four tooth abnormality classes. However, the dataset imbalance undeniably impacted the accuracy, particularly for caries detection. We believe a more balanced dataset can significantly enhance the overall performance.

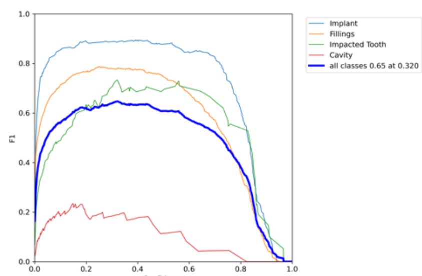
To address this limitation, future work could involve merging the DRD dataset with the Dentex dataset. This would significantly increase the number of instances available for training and validation, leading to a more robust model. Additionally, data augmentation techniques could be explored to artificially generate more images for classes with fewer instances, further improving the model's ability to handle imbalanced data.

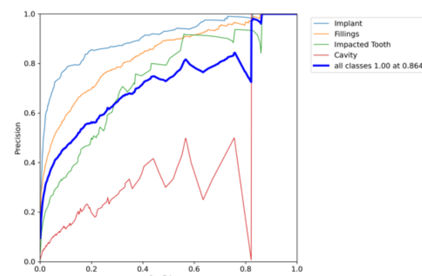
Appendix A

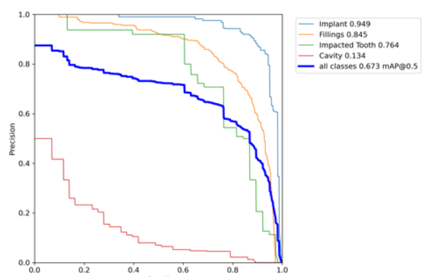
Learning curves for YOLO versions 7, 8, and 9 end-to-end models

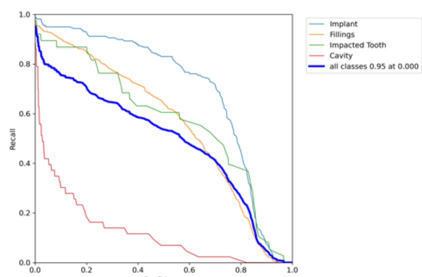
YOLOv7

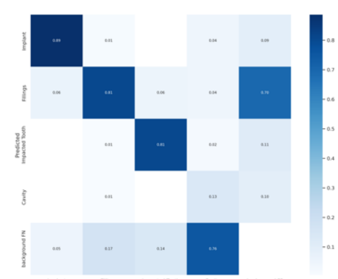




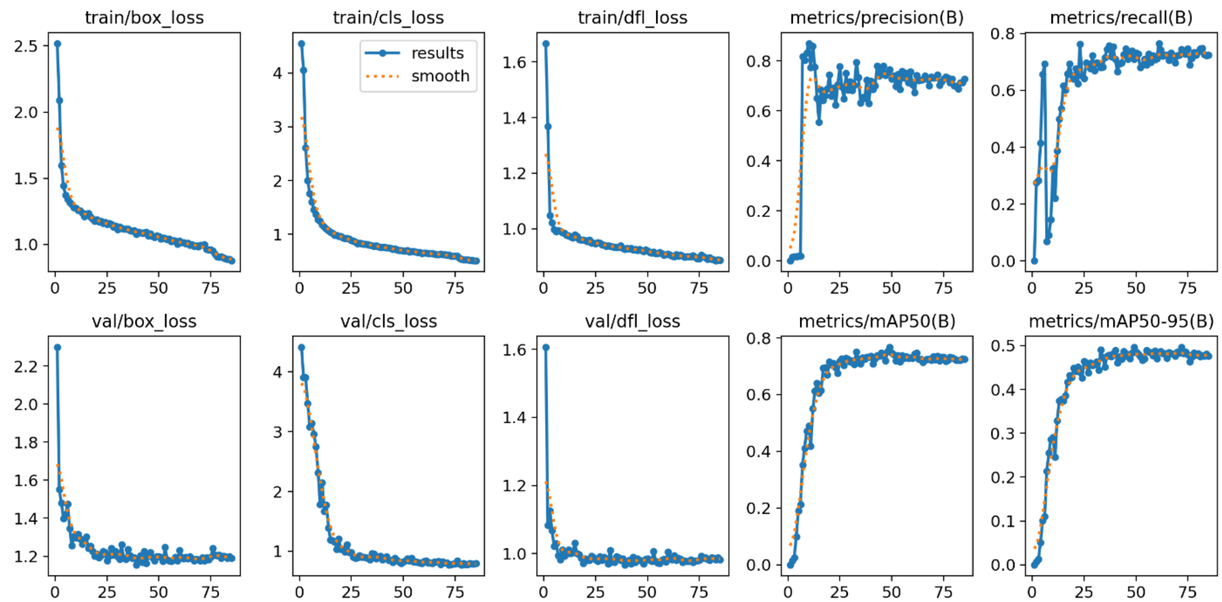








YOLO v8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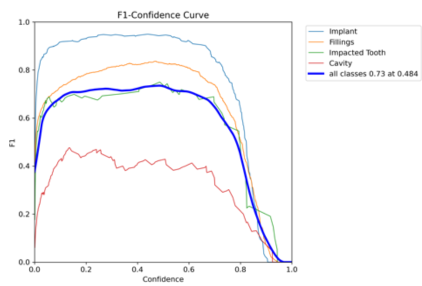
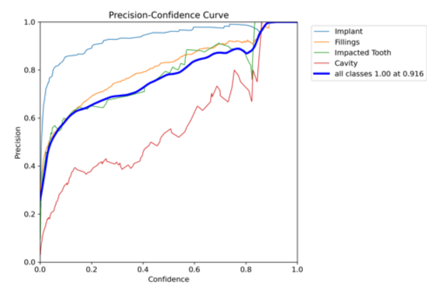
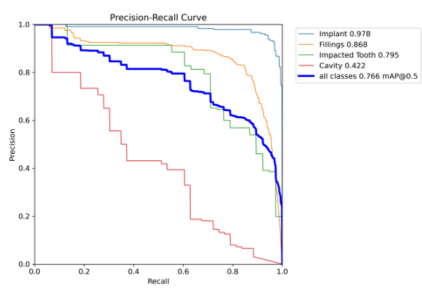
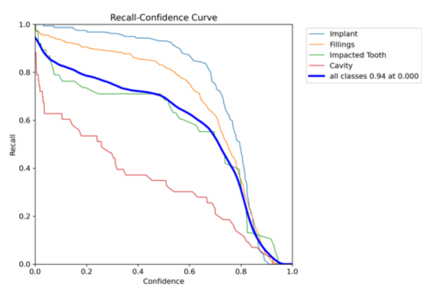
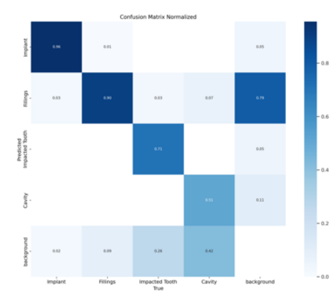
train/cls_loss
results
smooth
train/dfl_loss
metrics/precision(B)
metrics/recall(B)
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP50(B)
metrics/mAP50-95(B)


F1-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 0.73 at 0.484
F1
Confidence

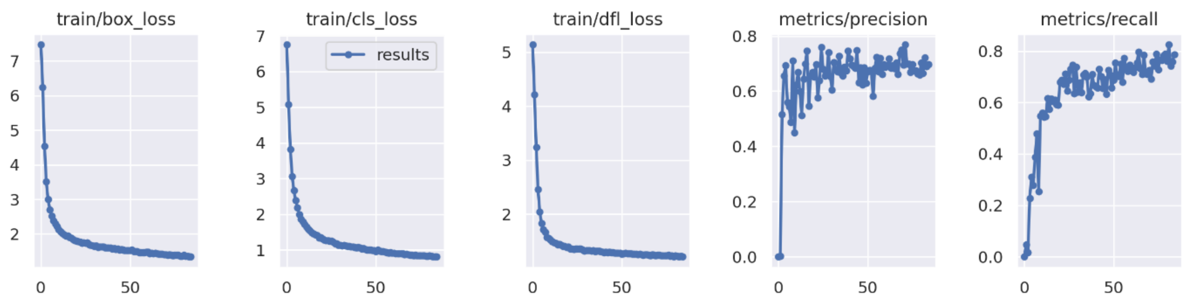

Precision-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 1.00 at 0.916
Precision
Confidence


Precision-Recall Curve
Implant 0.978
Fillings 0.868
Impacted Tooth 0.795
Cavity 0.422
all classes 0.766 mAP@0.5
Precision
Recall


Recall-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 0.94 at 0.000
Recall
Confidence


Confusion Matrix Normalized

YOLO v9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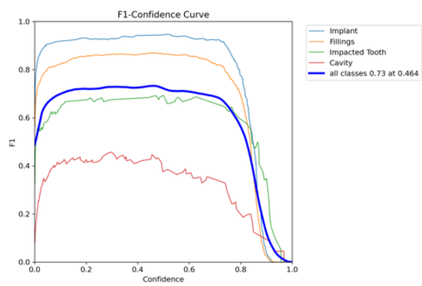
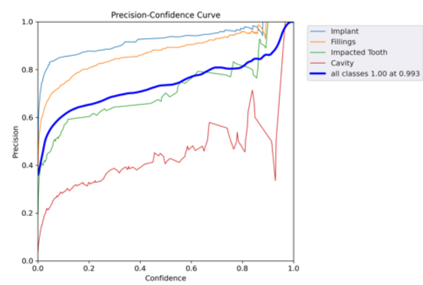
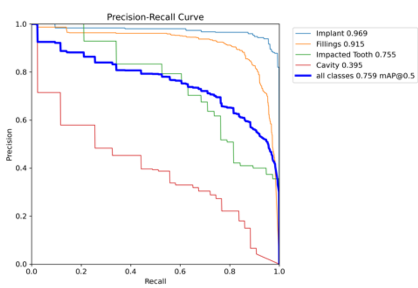
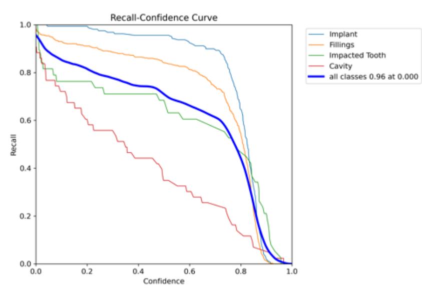
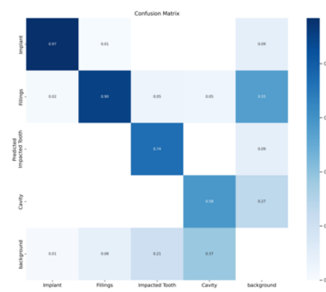
train/cls_loss
results
train/dfl_loss
metrics/precision
metrics/recall


F1-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 0.73 at 0.464
F1
Confidence


Precision-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 1.00 at 0.993
Precision
Confidence

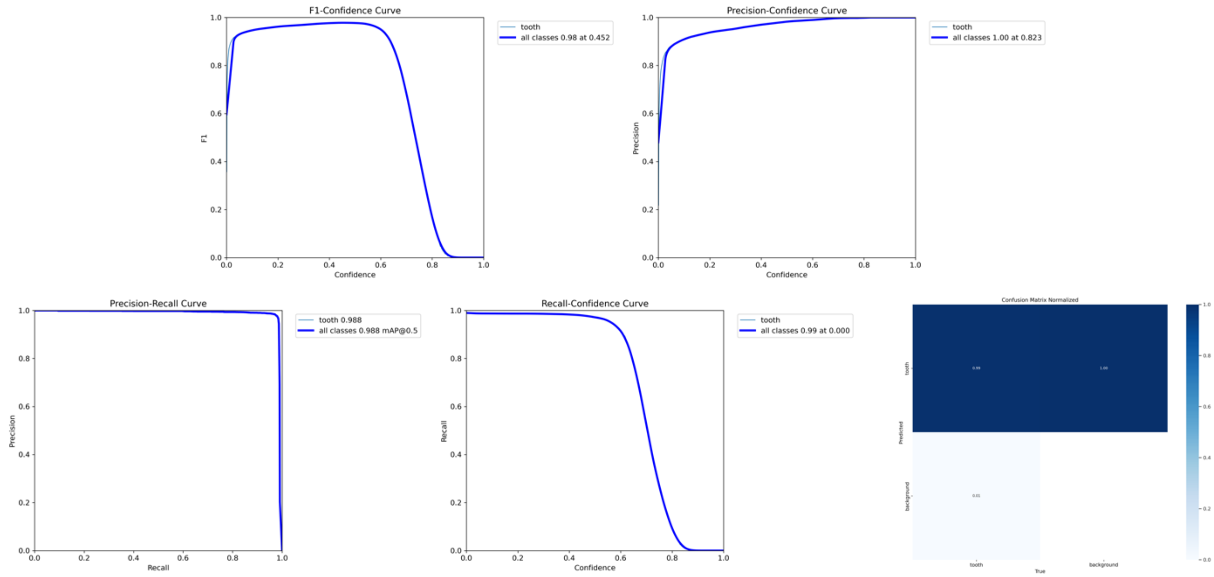

Precision-Recall Curve
Implant 0.969
Fillings 0.915
Impacted Tooth 0.755
Cavity 0.395
all classes 0.759 mAP@0.5
Precision
Recall


Recall-Confidence Curve
Implant
Fillings
Impacted Tooth
Cavity
all classes 0.96 at 0.000
Recall
Confidence


Confusion Matrix

Appendix B

YOLOv8 teeth detection learning curves



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