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# AI-Powered Dental Disease Detection and Treatment Recommendation using YOLOv8

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**ABSTRACT:** Dental diseases can affect oral health and quality of life, and image-based screening may help organize visible findings for further professional assessment. This paper presents DentalAI V2, a Python desktop prototype that integrates task-specific YOLOv8-based models for selected dental image-analysis tasks. The interface provides separate workflows for intraoral photographs and panoramic dental radiographs (OPG), including enamel-caries classification, intraoral caries detection, gingivitis detection, calculus and oral-ulcer detection, and OPG finding detection. The application displays predicted classes and confidence values and, for detection tasks, bounding boxes and finding counts. A rule-based module maps selected outputs to informational oral-health guidance. Earlier project records report 94.67% accuracy for a three-class enamel-caries classifier, 55.38% mAP@0.5 for a four-class OPG detector, and 80.39% mAP@0.5 for a two-class intraoral caries detector; these values are provisional and must be verified against the original checkpoints, held-out splits, and evaluation reports before publication. Additional colour-image and gingivitis experiments are maintained as separate model workflows and should be reported quantitatively only after their evaluation is verified. The prototype is intended for research and educational demonstration and is not a clinically validated diagnostic system or a substitute for assessment by a qualified dental professional.

**KEYWORDS:** Dental disease detection, YOLOv8, deep learning, object detection, dental radiographs, intraoral images, decision support, Tkinter

## I. INTRODUCTION

Dental conditions such as caries, gingival inflammation, calculus accumulation and oral lesions can require timely professional assessment. Intraoral photographs and panoramic radiographs provide different visual evidence: photographs show visible tooth surfaces and soft tissues, while panoramic radiographs provide a broad view of teeth and surrounding structures. Interpreting these images requires clinical expertise, and image quality, lighting, camera angle, anatomical variation and annotation differences can complicate automated analysis.

Deep-learning methods have become useful for image classification and object detection because they can learn visual patterns from annotated data. Classification assigns a label to an image, whereas object detection identifies localized regions and associates them with class labels and confidence scores. These tasks require different datasets and evaluation metrics, and a model trained for one image modality or label set should not be assumed to generalize to another.

This work presents DentalAI V2, a modular desktop application that routes an uploaded image to a task-specific model. The visible interface includes four intraoral-photo screening modes—enamel-caries classification, intraoral caries detection, gingivitis detection, and calculus/ulcer detection—and a separate panoramic OPG workflow. Predicted labels, confidence values, bounding boxes, counts and a findings summary are displayed where supported by the selected model. The application also presents rule-based informational guidance for selected findings.

The contribution of this work is the integration of separate dental-image models into a single desktop workflow, with modality-specific routing and a user interface for reviewing model outputs. The paper distinguishes implemented interface functions from experiments whose evaluation remains to be verified. The system is a research prototype; its outputs should not be interpreted as definitive diagnoses or individualized treatment prescriptions.

The remainder of this paper is organized as follows. Section II reviews related dental-image analysis work. Section III describes the proposed system, architecture, data flow, models and implementation. Section IV presents the available preliminary results and application demonstrations. Section V concludes the paper and identifies future work

## **II. LITERATURE SURVEY**

The concept of image inpainting was first introduced by Bertamio et al. [1]. The method was inspired by the real inpainting process of artists. The image smoothness information interpolated by the image Laplacian is propagated along the isophotes directions, which are estimated by the gradient of image rotated by 90 degrees. Exemplar Based method proposed by Criminisi et al. [2] used a best exemplar patch to propagate target patch including missing pixels. This technique uses an approach which combine structure propagation with texture synthesis and hence produced very good results. In [3], the authors decompose the image into sum of two functions and then reconstruct each function separately with structure and texture filling-in algorithms. Morphological technique is used to extract text from the images presented in [4]. In [5], the inpainting technique is combined with the techniques of finding text in images and a simple algorithm that links them. The technique is insensitive to noise, skew and text orientation. The authors in [6] have applied the CCL (connected component labelling) to detect the text and fast marching algorithm is used for Inpainting.

The work in this paper is divided in two stages. 1) Text- Detection 2) Inpainting. Text detection is done by applying morphological open-close and close-open filters and combines the images. Thereafter, gradient is applied to detect the edges followed by thresholding and morphological dilation, erosion operation. Then, connected component labelling is performed to label each object separately. Finally, the set of selection criteria is applied to filter out non text regions. After text detection, text inpainting is accomplished by using exemplar based Inpainting algorithm.

## **III. METHODOLOGY**

### **1) System Architecture**

Fig. 1 presents the high-level architecture of DentalAI V2. The input layer accepts intraoral colour photographs or panoramic OPG images. The Tkinter application routes each input according to the user's selected workflow. Separate model components perform enamel-caries classification, intraoral object detection, gingivitis detection, calculus/ulcer detection, or OPG object detection. Their outputs are formatted by the application as class labels, confidence values, bounding boxes and counts where the model task supports them. A presentation and decision-support layer displays the results and provides rule-based informational guidance for selected findings.

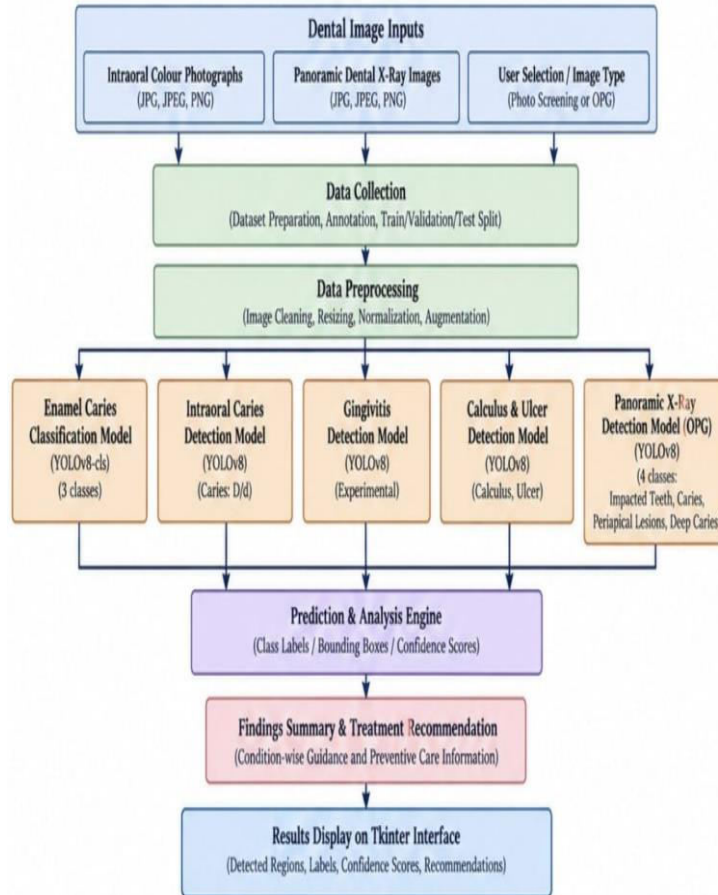


Fig. 1: System architecture of the proposed Dental AI framework.

## 2) Data Flow

Fig. 2 shows the data flow through the application. The user selects the image modality and screening mode, then uploads an image in a supported format. The application reads the image and prepares it for the selected model using that model's expected input procedure. Inference produces class probabilities or detection outputs. For object-detection workflows, post-processing collects class labels, confidence scores, bounding-box coordinates and counts. The interface then displays the image and prediction summary, along with informational guidance when configured. Preprocessing operations and thresholds must be reported from the actual implementation rather than assumed from a generic YOLO pipeline.

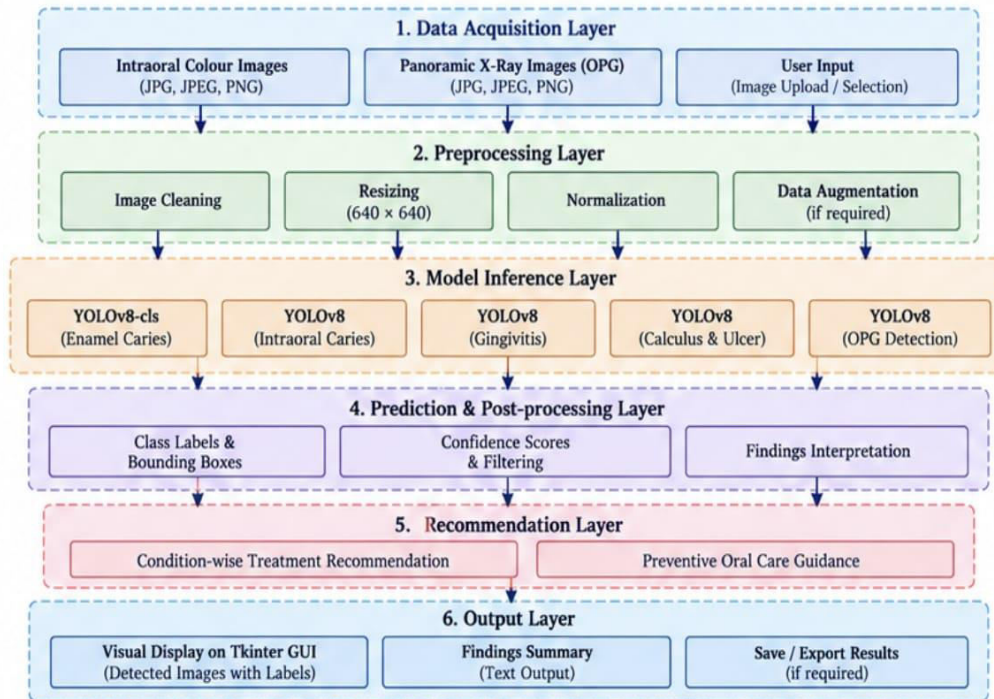


Fig. 2: Data flow diagram of the proposed system.

### 3) Model Workflows

A. Enamel-carries classification: The interface provides a three-class workflow with the displayed classes Advance Enamel Caries, Early Stage Enamel Caries, and No Enamel Caries (Healthy). The project specification screen identifies the model as YOLOv8n-cl with a  $224 \times 224$  input. Classification returns a class-probability distribution rather than localized bounding boxes.

B. Intraoral caries detection: A separate object-detection workflow uses two configured labels, D (Permanent Caries) and d (Primary Caries), as recorded in the earlier project notes. Its outputs are displayed as localized detections. The exact model checkpoint, test partition and evaluation output must be confirmed before reporting final performance.

C. Gingivitis detection: The interface displays detected gingival regions with bounding boxes, confidence values and a total finding count. The screenshot provided for this workflow also displays a warning that healthy-region false-positive risk has not been quantified. This workflow should therefore be described as experimental until a verified independent evaluation and class-wise error review are available.

D. Calculus and oral-ulcer detection: The interface has a separate workflow for calculus and oral-ulcer findings, showing counts and confidence values for detected regions. The precise configured class names and the model checkpoint should be checked against the current model metadata before the final submission.

E. Panoramic OPG detection: The OPG screen displays four configured categories: impacted teeth, caries, periapical lesions and deep caries. The project specification screen identifies YOLOv8s object detection with a  $1024 \times 1024$  model input. The application displays bounding boxes, category counts, confidence values and inference time for the selected image. These outputs are automated visual predictions and require professional dental review.

### 4) Dataset Preparation

The project uses distinct datasets for classification and detection tasks. The earlier records refer to a three-class enamel-carries classification dataset, a DENTEX-derived OPG detection dataset, a two-class intraoral caries dataset, and additional colour-image and gingivitis experiments. These datasets should not be merged into a single total because

their modalities, labels and experimental purposes differ. For each experiment, the final paper should specify the source, version, number of images, class distribution, annotation format, train/validation/test split and licensing terms.

Earlier notes record a 2,227-image intraoral caries dataset with 6,687 bounding boxes and splits of 1,557 training, 334 validation and 336 test images. A separate Oralalytics subset audit recorded 331 images split into 216 training, 48 validation and 67 test images; the audit found a small number of gingivitis examples and therefore a class-imbalance concern. These figures must be checked against the current dataset manifests before publication. Exact duplicate checks do not rule out near-duplicates or patient-level leakage.

### 5) Implementation

The application is implemented in Python and uses Tkinter for its desktop graphical interface. The project specification screen identifies Python 3.8.10, Ultralytics YOLOv8, PyTorch, Pillow and CPU-only execution for the documented setup. The interface includes navigation between the home screen, dental-photo screening modes, panoramic OPG analysis and project specifications. The model variants and image dimensions differ by task; the final paper should preserve the exact values from the running environment and training configuration.

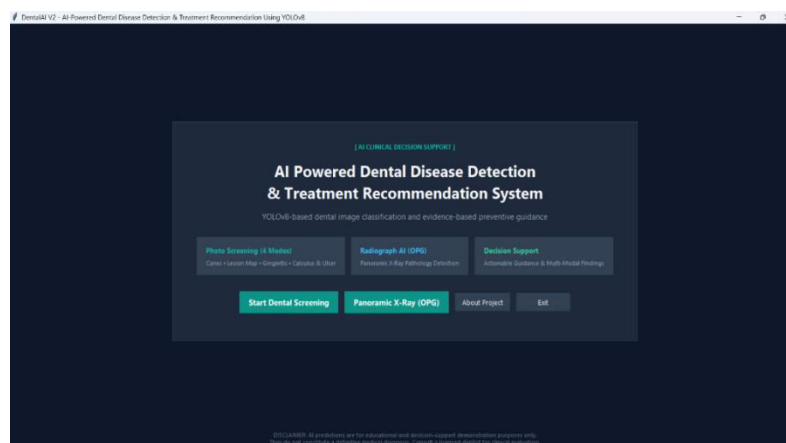
The recommendation component presents informational guidance based on detected labels. Unless an independent clinical validation study has been performed, it should be described as rule-based decision support rather than a validated treatment-planning system. The user interface itself explicitly states that the predictions are for educational and decision-support demonstration purposes and do not constitute a definitive diagnosis.

### 6) Evaluation Methodology

Classification performance should be reported using accuracy, macro F1-score, weighted F1-score and per-class precision, recall and F1-score, together with a confusion matrix. Object-detection performance should include precision, recall, mAP@0.5 and mAP@0.5:0.95, with per-class results where possible. Inference time should specify the hardware, input dimensions, number of runs, warm-up procedure and whether pre-processing and post-processing are included. The held-out test set should not be used to select model settings. All values below remain provisional until reconciled with the original evaluation files.

## III. EXPERIMENTAL RESULTS

The proposed Dental AI V2 system was implemented using Python, Tkinter, and YOLOv8 models for dental disease detection and analysis. The application supports enamel caries classification, intraoral caries detection, gingivitis detection, calculus and oral ulcer detection, and panoramic dental X-ray analysis. It displays predicted findings, confidence scores, bounding boxes, and informational recommendations where applicable. Preliminary evaluation records report 94.67% accuracy for enamel caries classification, 55.38% mAP@0.5 for panoramic X-ray detection, and 80.39% mAP@0.5 for intraoral caries detection. These results require verification against the original evaluation reports before publication. The system provides an integrated platform for dental image analysis, but further testing and clinical validation are necessary before practical clinical use.



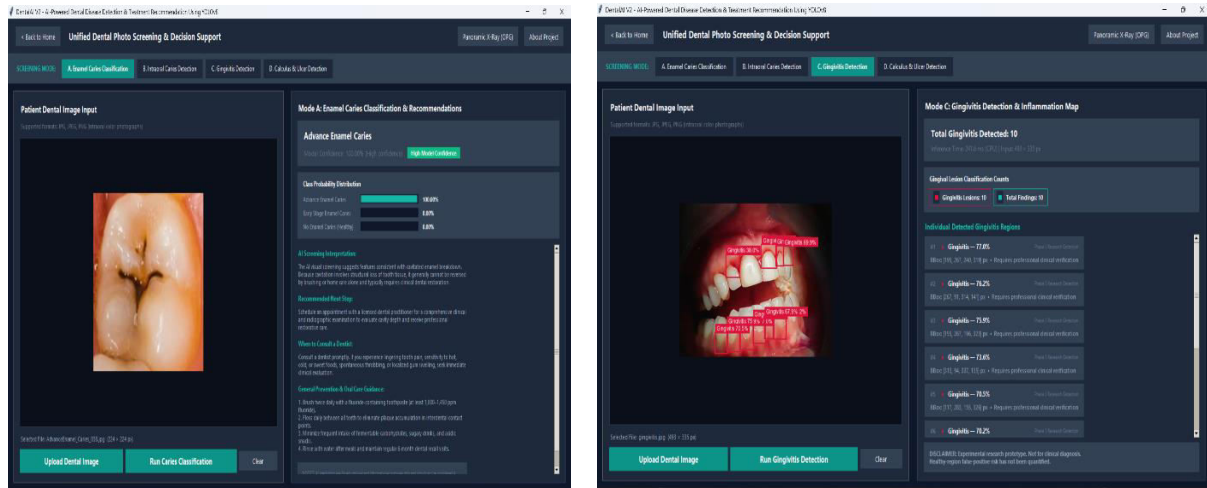


Fig. 3: Graphical User Interface Showing Dental Disease & Predicted Results

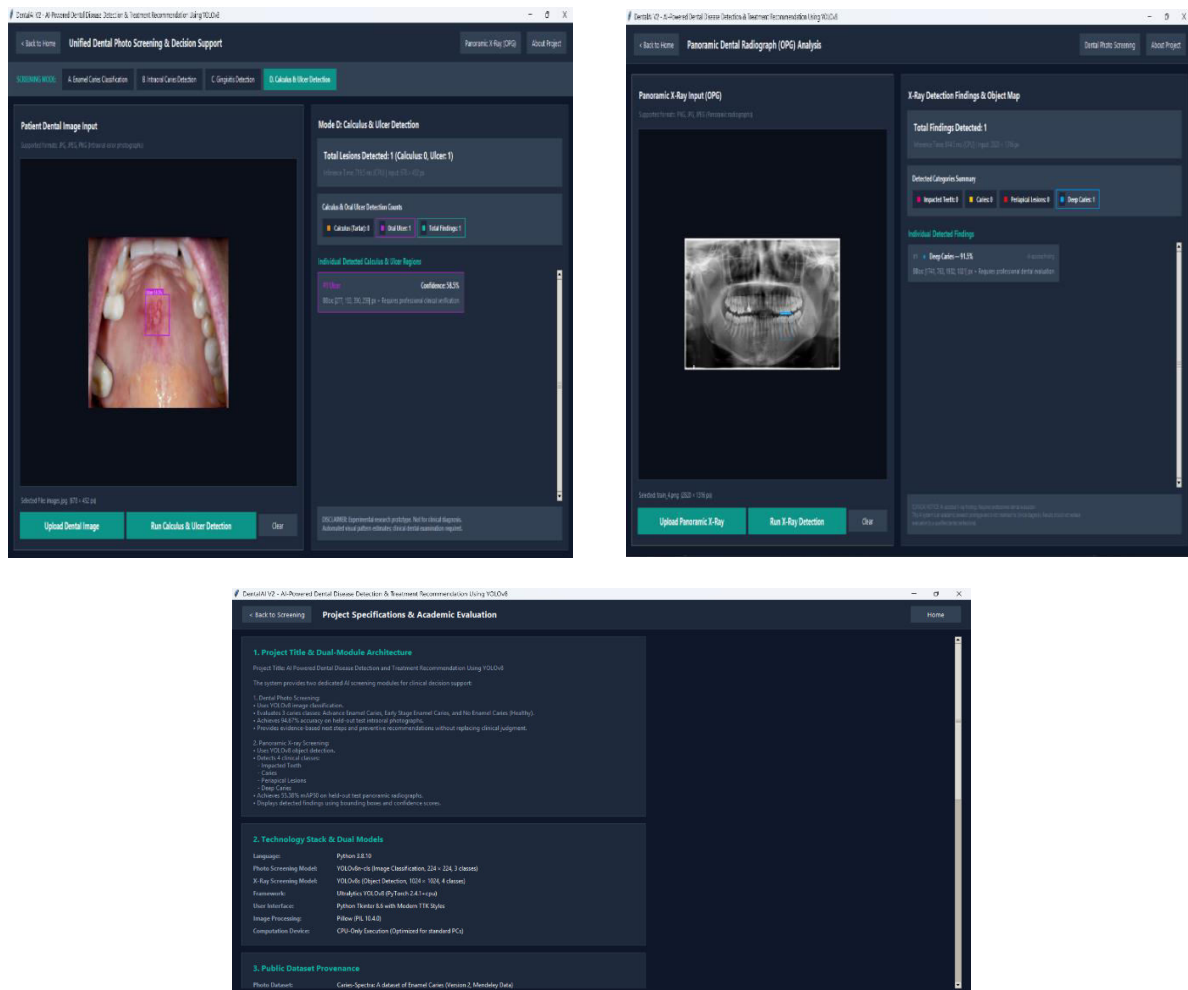


Fig.4: YOLOv8-Based Dental Image Analysis & Prediction Interface

#### **IV. CONCLUSION**

This paper presents DentalAI V2, a desktop prototype that integrates task-specific YOLOv8-based models for selected dental-photo and panoramic OPG analysis workflows. The Tkinter interface provides image upload, model selection, prediction visualization, finding summaries and rule-based informational guidance. Preliminary project records include evaluation metrics for enamel-carries classification, OPG detection and intraoral caries detection, but these values must be verified against original model checkpoints and held-out evaluation reports before publication. The separate gingivitis experiment and the audited Oralalytics subset require further quantitative analysis and class-wise review. Future work includes reproducible evaluation, improved class balance, independent testing, expert review of false positives and false negatives, and validation of the informational recommendation rules. The prototype is intended for research and educational demonstration and should not replace a qualified dental professional.

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