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Deep Learning Approach for Dental Anomalies X-ray Imaging using YOLOv8

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ABSTRACT

Dental X-ray imaging is a critical diagnostic tool for identifying various dental anomalies. However, manual interpretation is time-consuming, prone to human error, and requires specialized expertise. Deep learning models, particularly object detection frameworks like YOLO, have demonstrated promising results in automating medical image analysis. This study aims to develop and evaluate a YOLOv8-based deep learning model for automated detection and classification of 14 dental anomaly categories, including Caries, Crowns, Fillings, Implants, and Periapical lesions. The proposed approach addresses limitations in previous YOLO versions by leveraging anchor-free detection and enhanced feature extraction for improved accuracy. The model was trained on a dataset of annotated dental X-ray images and preprocessed with data augmentation techniques to improve generalization. Performance was evaluated using Precision, Recall, F1-score, and Mean Average Precision (mAP). Additional insights were obtained from confusion matrices, precision-recall curves, and training-validation loss curves. The model achieved high precision in detecting Implants (0.90), Crowns (0.89), and Root Canal Treatment (0.69), demonstrating strong potential for clinical applications. However, Caries (0.30) and Periapical lesions (0.15) were detected with lower accuracy, indicating the need for further optimization. Analysis of training loss curves and label distributions suggested that class imbalance and anomaly co-occurrence influenced detection performance. YOLOv8 presents a promising AI-based solution for dental anomaly detection, capable of improving diagnostic efficiency and accuracy in clinical practice. The model's integration into dental healthcare systems can reduce radiologists' workload and enhance early disease detection, particularly in resource-limited settings.

I. Introduction

Dental X-ray imaging is crucial in diagnosing and planning treatments for various dental anomalies [1]. Accurate detection of conditions such as caries, crowns, fillings, implants, and periapical lesions is essential for effective dental healthcare [2]. However, manual interpretation of X-ray images is time-consuming, prone to human error, and highly dependent on the expertise of dental radiologists [3]. These challenges highlight the need for an automated and reliable approach to improve diagnostic accuracy and efficiency.

Several deep-learning approaches for dental anomaly detection using object detection models have been proposed. Previous versions of YOLO, such as YOLOv4 and YOLOv5, have been successfully implemented in medical imaging, including dental radiographs [4][5]. Studies have demonstrated that these models accurately detect common dental conditions. However, they still exhibit limitations in identifying subtle anomalies like caries and periapical lesions [6][7]. Additionally, many existing methods rely on anchor-based detection, which increases computational complexity and requires extensive hyperparameter tuning [8][9]. These gaps indicate the need for further improvements in model efficiency, accuracy, and generalization across diverse dental conditions.

To address these challenges, this study introduces an automated dental anomaly detection system using YOLOv8, a state-of-the-art deep learning model with an anchor-free detection strategy. YOLOv8 enhances feature extraction efficiency through its CSPDarknet53 backbone and C2f module,

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enabling real-time and high-precision object detection [10]. The primary objective of this research is to develop and evaluate a YOLOv8-based model for detecting and classifying 14 dental anomaly categories, improving upon the limitations of previous YOLO versions.

This study contributes to the field by offering a novel implementation of YOLOv8 in dental X-ray analysis, demonstrating its effectiveness in detecting a broad range of dental conditions. The key contributions of this work include (1) developing a robust deep learning model tailored for dental anomaly detection, (2) providing a comparative analysis of YOLOv8's performance against previous models, and (3) identifying areas for further improvements in automated dental diagnostics. The findings of this research can serve as a foundation for future advancements in AI-driven dental healthcare solutions.

II. Method

A. Data Collection and Preprocessing

The dataset used in this study consists of annotated dental X-ray images collected from multiple sources, including publicly available dental imaging repositories and clinical datasets. Each X-ray image is labeled with one of 14 predefined dental anomaly categories: Caries, Crown, Filling, Implant, Malaligned Teeth, Mandibular Canal, Missing Teeth, Periapical Lesion, Retained Root, Root Canal Treatment, Root Piece, Impacted Tooth, and Maxillary Sinus. The dataset was curated to ensure a balanced representation of each anomaly class, as a class imbalance can lead to biased model predictions. Additionally, experienced dental radiologists reviewed and validated images to ensure accurate labeling and minimize annotation errors.

Several data augmentation techniques were applied. These include geometric transformations such as rotation, flipping, and scaling, which help the model learn invariant features across different dental structures [11]. Contrast-limited adaptive histogram equalization (CLAHE) was employed to enhance image contrast, particularly in cases where X-rays exhibited poor visibility due to variations in exposure settings [12]. Furthermore, Gaussian noise and random brightness adjustments were incorporated to simulate real-world variations in radiographic imaging conditions [13]. All images were resized to 640×640 pixels before training to maintain consistency in input dimensions, ensuring compatibility with the YOLOv8 model architecture.

B. YOLOv8 Model

YOLOv8 introduces several advancements over its predecessors, making it a powerful tool for object detection, including dental anomaly classification in X-ray imaging [14]. Unlike earlier YOLO versions, YOLOv8 adopts an anchor-free detection strategy, eliminating the need for predefined anchor boxes and reducing computational overhead [15]. This approach improves model efficiency while maintaining high detection accuracy across multiple classes. Additionally, YOLOv8 employs adaptive spatial feature fusion, which enhances the model's ability to detect objects at varying scales—crucial for identifying dental anomalies that differ in size, shape, and intensity [16]. The architecture integrates CSPDarknet53 as its backbone, utilizing cross-stage partial networks (CSPNet) to optimize gradient flow and improve feature representation.

A key improvement in YOLOv8 is its C2f module (Cross-Stage Partial with Fusion), which refines feature extraction by allowing deeper interactions between feature maps at multiple levels [17]. This enhancement is particularly beneficial for dental X-ray analysis, where subtle differences in grayscale intensity and texture can indicate the presence of conditions such as caries or periapical lesions. Moreover, YOLOv8 incorporates an improved loss function based on Complete Intersection over Union (CIoU), ensuring more precise bounding box predictions by accounting for object shape and scale variations [18]. Another notable aspect is integrating a multi-label classification mechanism, enabling the model to detect multiple anomalies in a single X-ray image—a crucial capability in real-world clinical settings where patients often exhibit more than one dental condition.

Furthermore, YOLOv8 supports dynamic computational graphs, allowing flexible network modifications during training. This adaptability makes fine-tuning the model for specific medical imaging tasks easier without significant architecture redesigns. The model also benefits from improved augmentation techniques, including mosaic augmentation and mixup strategies, which help enhance robustness against variations in X-ray quality, noise, and contrast levels. These advancements collectively position YOLOv8 as a highly effective tool for automated dental diagnostics, outperforming previous YOLO versions regarding precision, recall, and overall inference speed.

C. Training Process

The YOLOv8 model was trained using a dataset of annotated dental X-ray images, focusing on detecting 14 distinct dental anomalies. The training was conducted on an NVIDIA RTX 4060 GPU, leveraging approximately 3072 CUDA cores to accelerate computation. The model was trained with a batch size of 16 over 100 epochs using the Adam optimizer with an initial learning rate of 0.01 [19]. The loss functions used were binary cross-entropy for classification and Complete Intersection over Union (CIoU) for bounding box regression, which helped refine object localization accuracy [20]. Early stopping and learning rate scheduling were employed to mitigate overfitting, ensuring that the model adapted efficiently without excessive weight updates. Additionally, batch normalization was applied to stabilize training and accelerate convergence.

Extensive data augmentation techniques such as rotation, flipping, contrast adjustment, and Gaussian noise addition were applied to the training dataset to enhance generalization. These augmentations helped simulate real-world variations in dental X-ray images, making the model more robust to different lighting conditions, image quality variations, and anatomical differences among patients. Furthermore, stratified sampling was used to maintain a balanced distribution of anomaly classes. This prevented the model from being biased toward more frequent conditions like implants and fillings while ensuring it learned to recognize rarer conditions such as periapical lesions. The model's training performance was monitored using real-time visualization tools, allowing adjustments to hyperparameters when necessary.

D. Evaluation Metrics

Multiple key metrics were employed to comprehensively evaluate the performance of the YOLOv8 model for dental anomaly detection, including Precision, Recall, F1-score, and Mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5. Precision measures the proportion of correctly identified anomalies out of all predicted anomalies [21]. At the same time, Recall indicates the proportion of correctly identified anomalies out of all actual anomalies in the dataset [22]. The F1-score, as the harmonic mean of Precision and Recall, provides a balanced assessment of the model's effectiveness [23]. Additionally, mAP serves as an overall measure of detection accuracy by computing the area under the Precision-Recall curve, which is particularly useful for evaluating object detection models across multiple classes [24].

Beyond these standard evaluation metrics, we further analyzed the model's performance through confusion matrices, precision-recall curves, and F1-confidence curves to gain deeper insights into classification strengths and weaknesses. The confusion matrix provides a breakdown of true positive, false positive, and false negative classifications for each anomaly category, highlighting specific conditions where the model performs well or struggles. The precision-recall curve helps determine the optimal confidence threshold for classification by visualizing the trade-off between Precision and Recall. The F1-confidence curve, on the other hand, illustrates the consistency of model predictions across different confidence levels, which is crucial for fine-tuning decision thresholds in clinical applications. These comprehensive evaluation techniques ensure a robust assessment of the model's reliability and effectiveness for real-world dental anomaly detection.

III. Result and Discussion

Following the training of the YOLOv8 model, its performance was rigorously evaluated using multiple assessment techniques, including confusion matrices, precision-recall curves, and comparative visual analysis between model predictions and ground truth labels. The normalized confusion matrix (Figure 1) provides a detailed breakdown of the classification performance across 14 dental anomaly categories, offering crucial insights into the model's strengths and areas for improvement. The results indicate that the model excels in detecting highly distinct anomalies, such as Implants (0.90 precision), Crowns (0.89 precision), and Root Canal Treatment (0.69 precision), which are typically well-defined and contrast clearly against surrounding dental structures in X-ray images.

However, the detection accuracy drops significantly for Caries (0.30 precision) and Periapical lesions (0.15 precision), suggesting that these anomalies are more challenging to differentiate due to their subtle visual features, overlapping characteristics with surrounding tissues, or inherent variability in manifestation. The confusion matrix also reveals instances of misclassification, particularly among closely related categories, indicating the potential benefit of hierarchical classification approaches, refined feature extraction techniques, and additional dataset augmentation to enhance model performance.

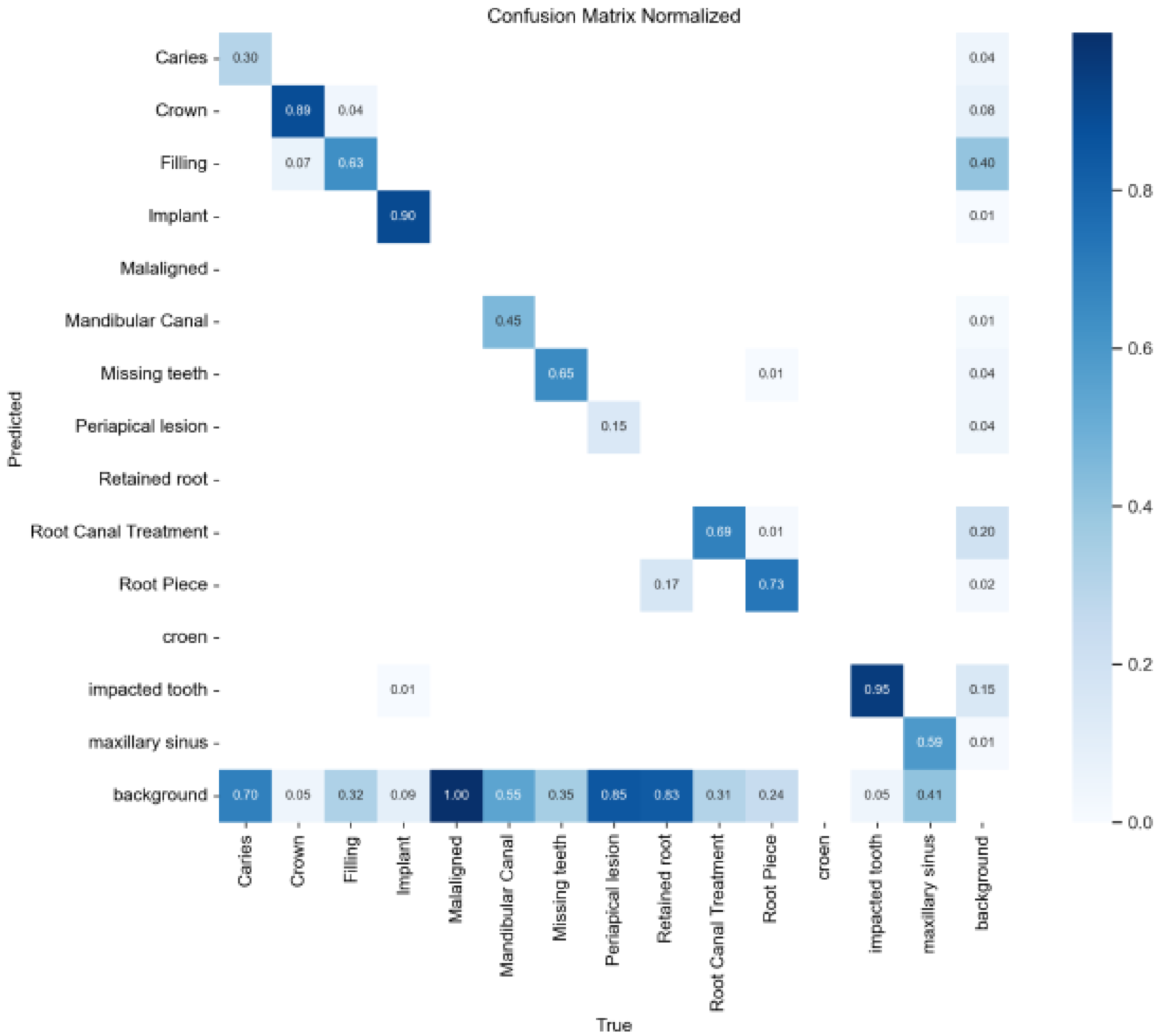

Fig. 1. Output showing bounding boxes around detected anomalies with confidence scores

The input X-ray images and corresponding model predictions, as illustrated in Figure 2 and Figure 3, visually represent the YOLOv8 model's detection capabilities across multiple dental anomaly classes, revealing varying confidence levels depending on the anomaly type. The model demonstrates high confidence in detecting "Filling" and "Root Canal Treatment," likely due to their distinct radiographic features and well-defined structural contrasts in X-ray images. In contrast, "Caries" is often detected with lower confidence, attributed to its subtle appearance, overlapping features with adjacent dental structures, and varying intensities across different X-ray scans. These variations suggest that while YOLOv8 excels in identifying well-defined anomalies, its performance diminishes when detecting conditions with less pronounced visual characteristics or those that frequently co-occur with other anomalies.

The bounding box visualizations in Figure 2 highlight the precision of the model in localizing anomalies. In contrast, Figure 3 further illustrates instances where model predictions closely align with the ground truth labels, reinforcing the reliability of YOLOv8 in automated dental diagnostics. However, the occasional misclassification observed, particularly in "Caries" detection, suggests further fine-tuning, possibly through enhanced feature extraction techniques, additional training data, or adaptive thresholding strategies to improve sensitivity for subtle conditions.

Fig. 2. Output showing bounding boxes around detected anomalies with confidence scores

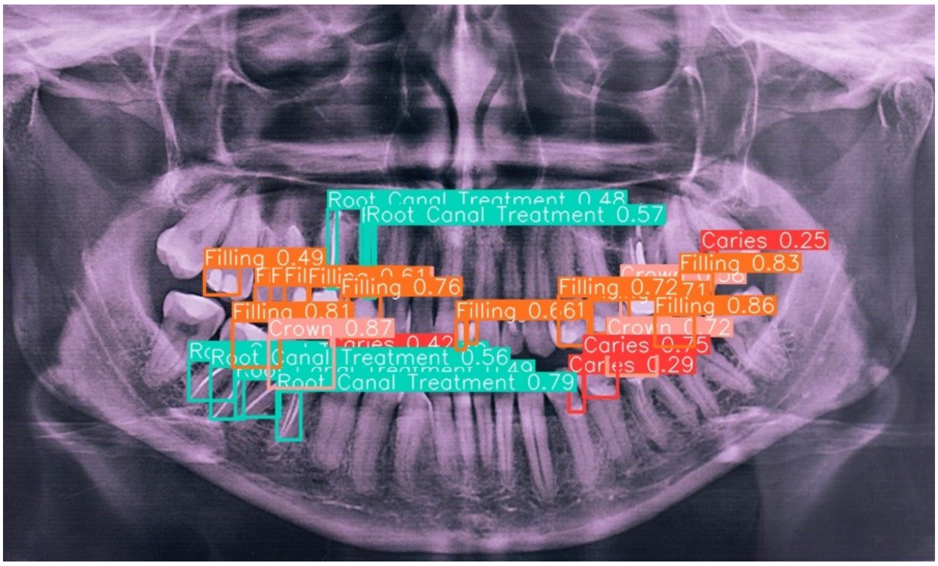

Fig. 3. Raw input X-ray image for comparison

The validation batch results presented in Figure 4 and Figure 5 provide crucial insights into the generalization capability of the YOLOv8 model in detecting dental anomalies across diverse X-ray samples. Figure 4 illustrates instances where the model accurately identifies anomalies such as Fillings, Crowns, and Root Canal Treatments, demonstrating its robustness in detecting well-defined dental structures with high confidence. Conversely, Figure 5 highlights cases where the model's predictions deviate from ground truth labels, particularly for Caries and Periapical Lesions, which exhibit lower contrast and more ambiguous visual patterns in X-ray imaging. These discrepancies suggest that while identifying distinct anomalies effectively, the model occasionally struggles with conditions that share overlapping features or appear in less pronounced radiographic forms.

Figure 6 and Figure 7 provide critical insights into the model's training process, showcasing its capacity to generalize across multiple dental anomaly categories. The visualizations of predictions on a set of training batches illustrate how the YOLOv8 model effectively handles multi-class detection scenarios, accurately identifying anomalies such as Crowns, Fillings, and Implants with high confidence while struggling with more subtle conditions like Caries and Periapical lesions. These discrepancies suggest that certain anomaly classes may be underrepresented in the training data or exhibit higher intra-class variability, making them harder to detect.

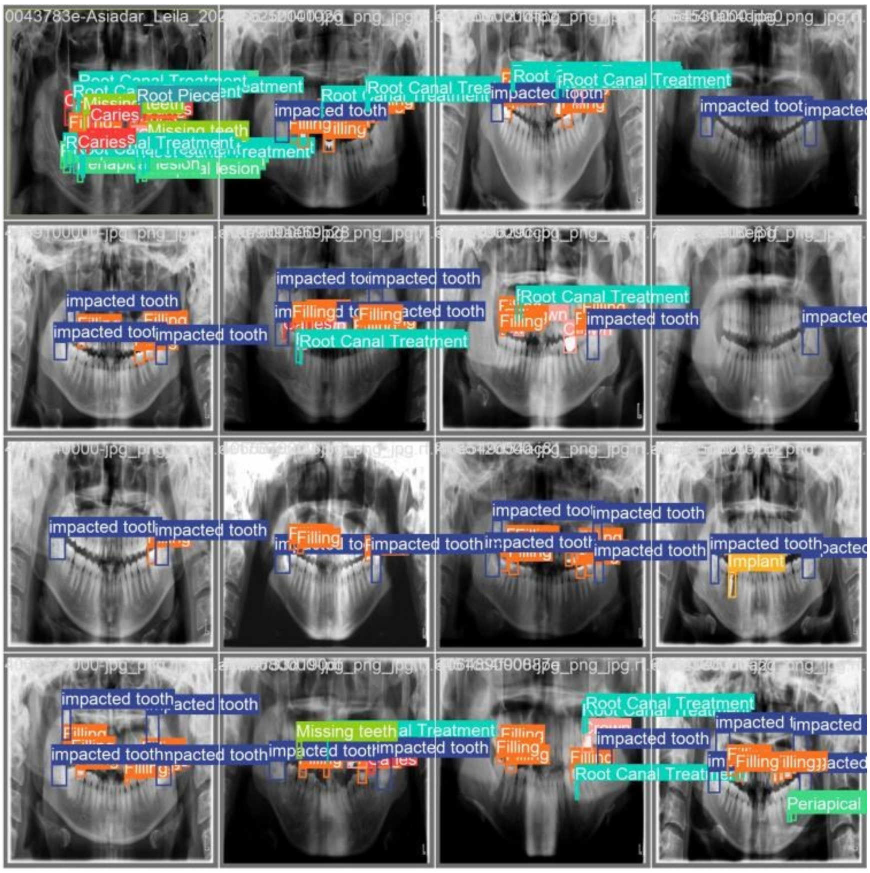

Fig. 4. Validation of true labels

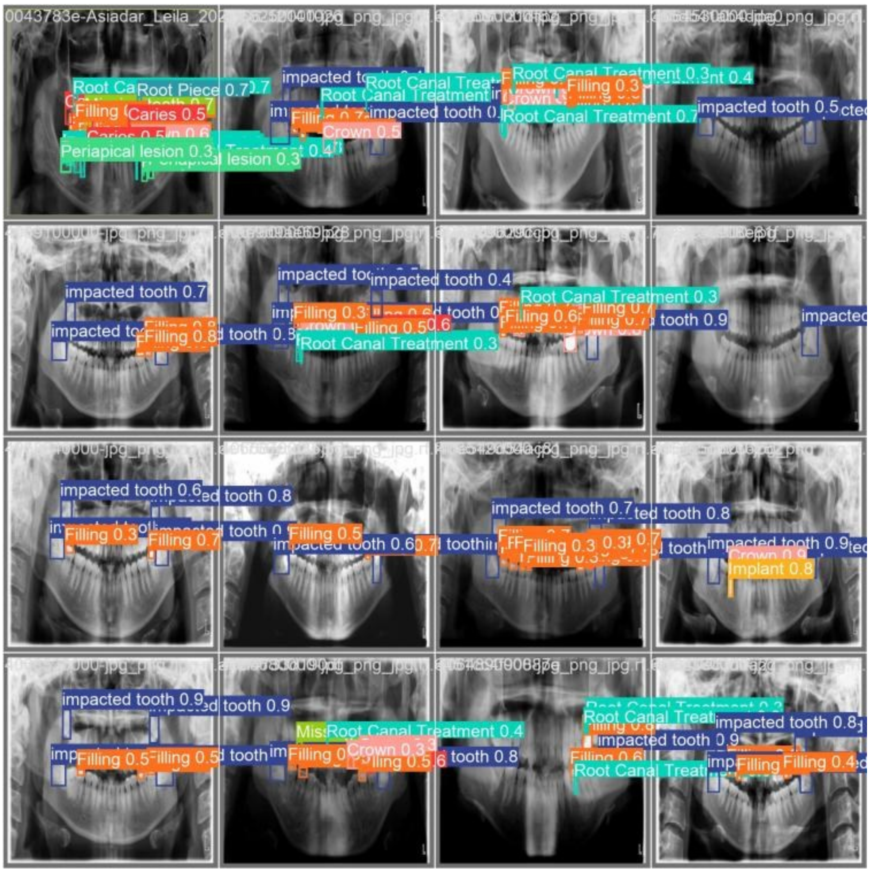

Fig. 5. Validation of predicted labels

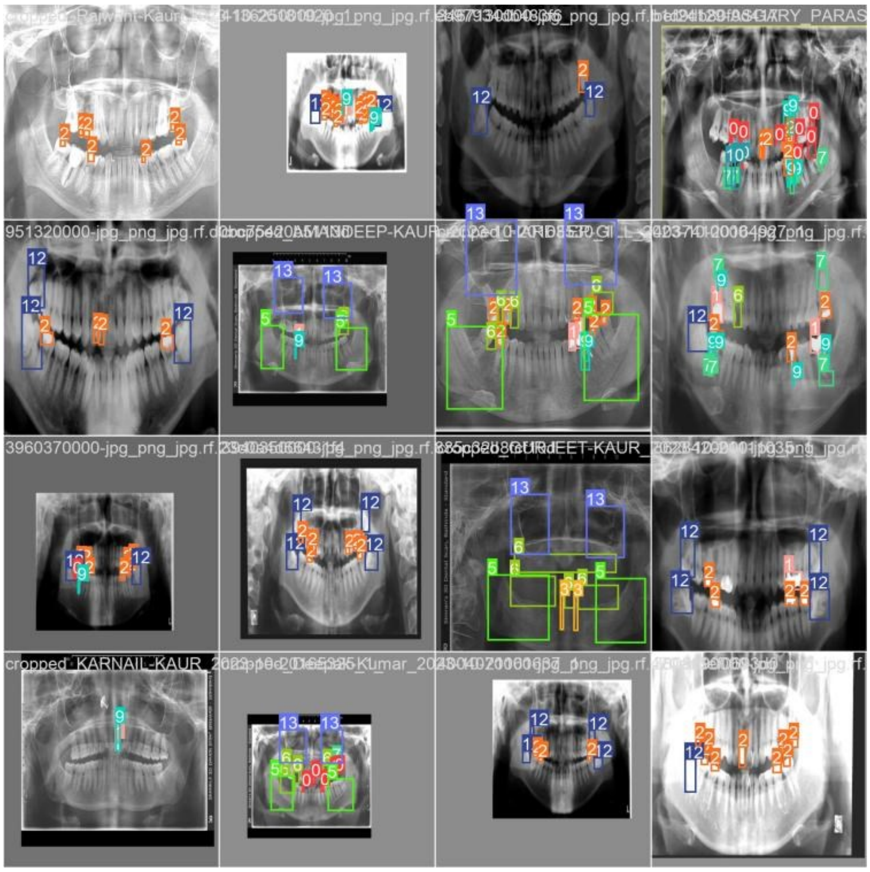

Fig. 6. Batch no. 8972 of the training model

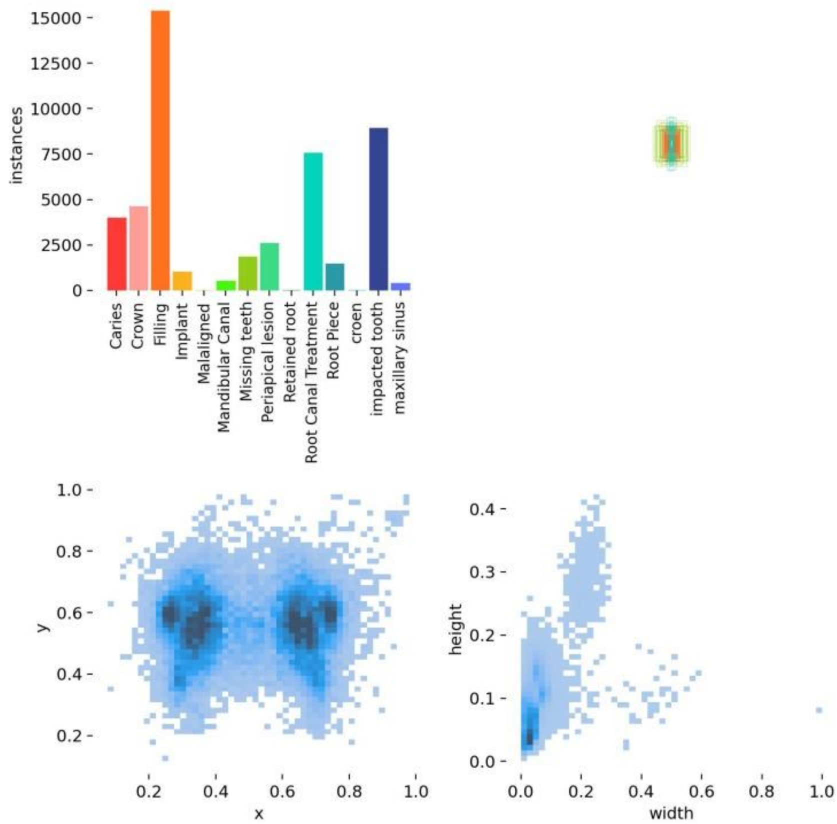

Fig. 7. Labels of the trained model

Furthermore, label distribution analysis (Figure 8) reveals an uneven representation of dental conditions, with some classes being significantly more frequent than others, potentially influencing the model’s bias toward well-represented categories. The correlogram further reinforces this finding by highlighting co-occurrence patterns between dental anomalies, indicating that certain conditions, such as Root Canal Treatment and Periapical lesions, often appear together in X-rays. This correlation suggests incorporating hierarchical classification strategies or multi-label learning techniques could improve detection accuracy for interrelated conditions.

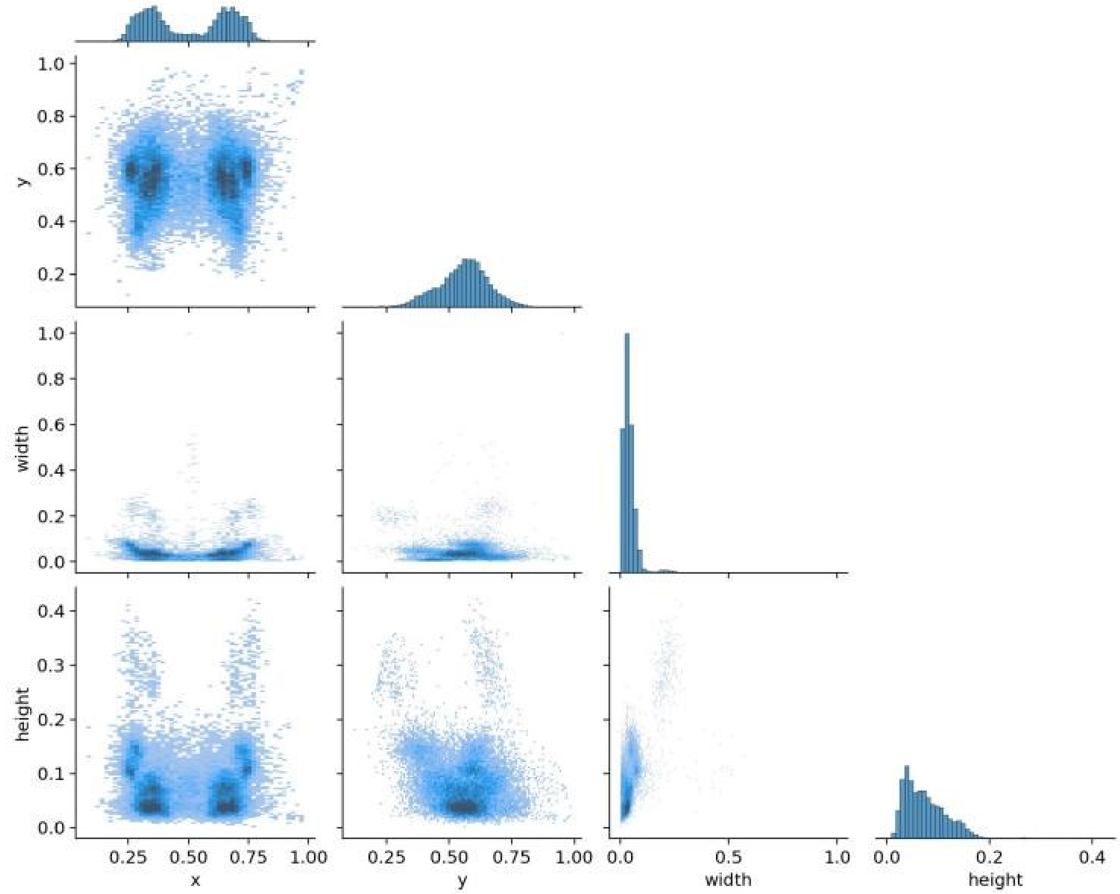

Fig. 8. Labels Correlogram of the trained model

The precision-recall (PR) curve (Figure 9) and the F1-confidence curve (Figure 10) provide crucial insights into the trade-offs between precision and recall at varying confidence thresholds, offering a comprehensive view of the model's classification performance across different dental anomaly categories. The PR curve demonstrates that the model maintains high precision for well-defined anomalies such as "Implants" and "Crowns," reflecting its robustness in detecting these conditions with minimal false positives. However, a notable decline in recall is observed for "Caries" and "Periapical lesions," indicating that while the model minimizes false detections, it may also miss true instances of these anomalies, likely due to their subtle and less distinguishable radiographic features. The F1-confidence curve further complements this analysis by illustrating how the model’s classification balance shifts with changes in confidence thresholds; an optimal threshold range around 0.5 to 0.6 is identified, where F1-scores peak, signifying the best equilibrium between precision and recall.

The training and validation loss curves (Figure 11) provide crucial insights into the learning dynamics of the YOLOv8 model throughout the training process. The steady decline in box and classification loss indicates that the model successfully learned spatial representations and class features over successive epochs. However, noticeable fluctuations in validation loss at specific points suggest potential overfitting, particularly in later epochs, where the model begins to memorize specific training samples rather than generalize effectively to unseen data. This phenomenon is likely exacerbated by a class imbalance in the dataset, as anomalies such as "Implants" and "Crowns" exhibit a higher frequency compared to "Caries" and "Periapical lesions," leading the model to prioritize learning dominant classes while struggling with underrepresented ones. Additionally, the periodic spikes in validation loss could indicate sensitivity to hard-to-classify instances, where the model oscillates between different decision boundaries when encountering ambiguous dental structures.

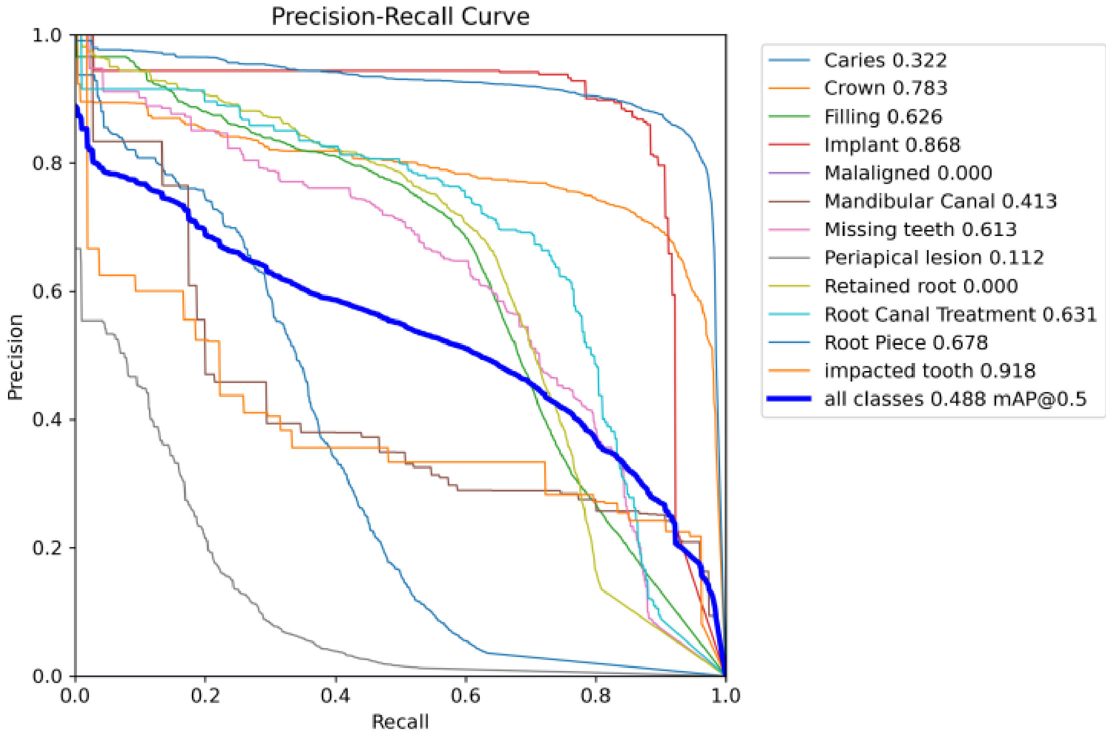

Fig. 9. Precision-recall curve of the trained model

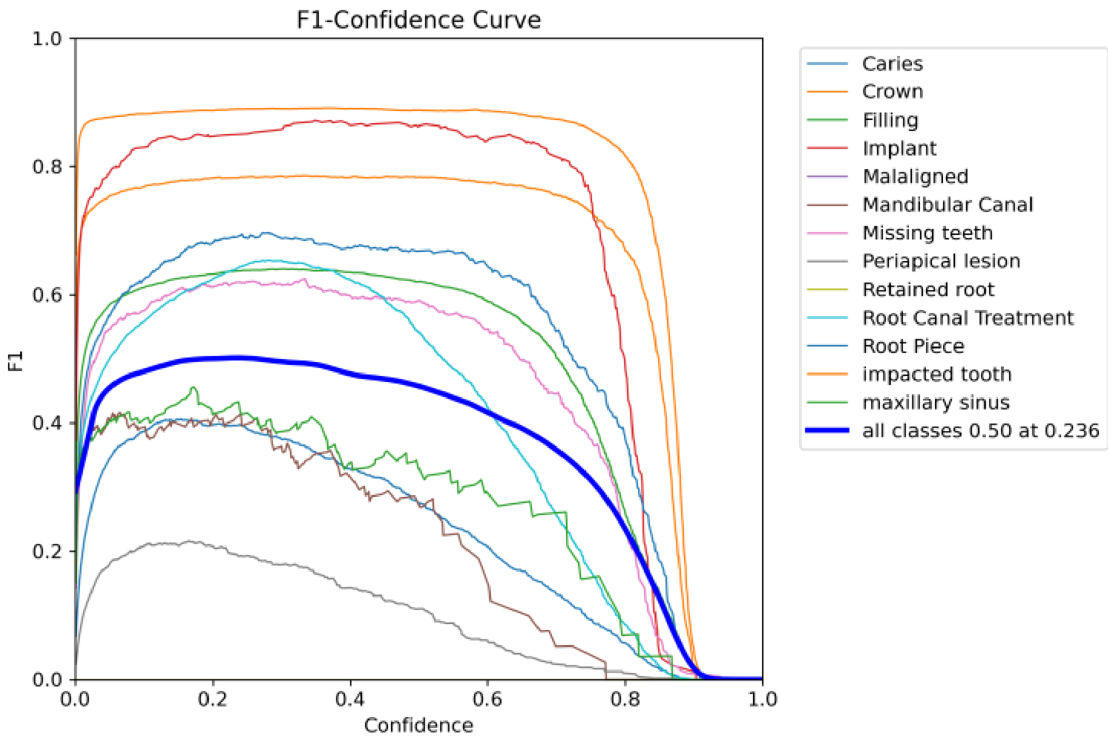

Fig. 10. F1-Confidence curve of the trained model

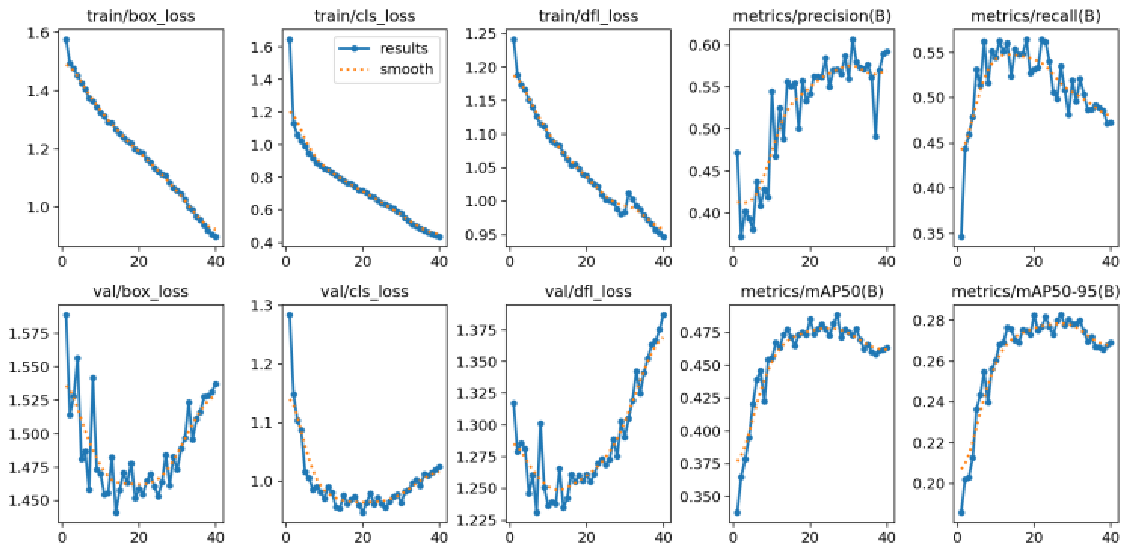

Fig. 11. Loss curves

The results from this study indicate that YOLOv8 is a powerful tool for automating the detection of dental anomalies in X-ray images [25]. The model performed exceptionally well in detecting "Implant" and "Root Canal Treatment" anomalies, typically more distinct in X-rays. However, detecting more subtle conditions such as "Caries" requires further improvement. Data augmentation and increasing the dataset size for underrepresented conditions are potential avenues for improving model performance. The precision-recall and F1-confidence curves further highlight the strengths and weaknesses of the model.

The findings of this study demonstrate the potential of YOLOv8 as an advanced tool for automated dental anomaly detection, offering significant implications for dental radiology, AI-driven healthcare, and medical imaging. The model's high precision in detecting implants and crowns indicates strong feasibility for integration into clinical decision support systems, aiding dentists in rapid and accurate anomaly detection [26]. However, the lower performance on more subtle anomalies like caries and periapical lesions highlights the need for custom AI-driven preprocessing techniques tailored to enhance feature extraction for these conditions.

Additionally, the automated detection approach introduced in this study can reduce diagnostic workload, minimize human error, and enable real-time dental screening in resource-limited settings. Future research should incorporate multimodal AI techniques, such as hybrid CNN-transformer architectures or self-supervised learning models, to refine detection accuracy. Expanding the dataset to include diverse patient demographics and X-ray variations can enhance model robustness, ensuring applicability across clinical scenarios.

IV. Conclusion

This study successfully demonstrated the application of YOLOv8 for automated dental anomaly detection in X-ray imaging, significantly advancing AI-driven dental diagnostics. The model achieved high accuracy in detecting anomalies such as Implants, Crowns, and Root Canal Treatments, indicating its potential for real-world implementation in clinical decision support systems. However, the results also highlighted detection challenges for Caries and Periapical lesions, suggesting that additional improvements in data augmentation, feature enhancement, and model optimization are necessary to enhance detection performance for these subtle conditions.

A detailed evaluation using confusion matrices, precision-recall curves, F1-confidence curves, and training-validation loss curves provided critical insights into the model's strengths and limitations. The label distribution and correlogram analyses further emphasized the impact of class imbalance and anomaly co-occurrence, which could mitigate by hierarchical classification techniques or cost-sensitive learning approaches. Future work should explore hybrid deep learning architectures, domain-specific preprocessing methods, and multimodal AI strategies to refine detection accuracy further.

From a practical standpoint, integrating YOLOv8 into dental healthcare systems can significantly reduce diagnostic workload, enhance detection efficiency, and minimize human error, particularly in resource-limited settings. The findings of this study contribute to the growing body of research on AI in medical imaging, paving the way for future innovations in automated dental anomaly detection and real-time AI-assisted diagnosis.

Declarations

Author contribution

All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

Conflict of interest

The authors declare no known conflict of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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