A Multi-Method Fusion for Improving Missing Teeth Detection in Intraoral Images

Muhammad Fakhrurrifqi
Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia | Department of Electrical Engineering and Informatics, Vocational College, Universitas Gadjah Mada, Yogyakarta, Indonesia
rifqi_ilkom@mail.ugm.ac.id

Sri Mulyana
Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia
smulyana@ugm.ac.id

Asikin Nur
Department of Biomedical Sciences, Faculty of Dentistry, Universitas Gadjah Mada, Yogyakarta, Indonesia
asikin@mail.ugm.ac.id

Wahyono
Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia
wahyo@ugm.ac.id (corresponding author)

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ABSTRACT

Monitoring Decayed, Missing, and Filled Teeth (DMFT) provides valuable insights into the prevalence and severity of tooth decay. However, existing algorithms often struggle with detecting missing teeth, as they can be overly sensitive to incomplete features. To address this limitation, this study proposes a novel YOLOv8 framework for tooth detection integrated with linear regression, DBSCAN clustering, and Lagrange interpolation for identifying missing teeth. A dataset of 983 frontal intraoral images acquired through smartphone-based imaging was considered. Experimenting on 197 images demonstrated that the proposed method enhances system performance, achieving precision of 64.27%, recall of 75.34%, and mean Average Precision (mAP) of 52.03%. Compared to the standard YOLOv8 model, the proposed approach improves precision by 2.27%, recall by 20.66%, and mAP by 6.83%. These findings highlight the potential of the proposed method as an effective tool for monitoring DMFT, contributing to improved diagnostic accuracy in enhancing missing teeth detection.

Keywords-clustering; missing teeth; interpolation; intraoral image; regression; YOLOv8

I. INTRODUCTION

Around 3.5 billion people in the world suffer from teeth and mouth disease, with the most common problems including decay (carries, calculus, tooth color change) and hypodontia (missing teeth) [1]. Detection and assessment of Decayed, Missing, and Filled Teeth (DMFT) play a crucial role in understanding oral health trends, providing valuable insights into the prevalence and severity of tooth decay [2, 3]. Many applications and automated models leveraging Artificial Intelligence (AI) have been developed for tooth decay detection. These AI-driven models have demonstrated satisfactory performance and are increasingly being integrated into clinical practice to enhance diagnostic accuracy, improve treatment quality, and optimize patient outcomes. Additionally, they can aid in identifying individuals at a higher risk of developing tooth decay, enabling early intervention and preventive care [4-6]. When comparing technology-based examinations with direct ones, there is no big difference [7]. However, technology might perform slightly better [8]. Several studies have explored the use of deep learning techniques for detecting and evaluating DMFT, showing their potential to improve oral health assessment and even be more accurate than humans [5, 9, 10]. However, a significant weakness of these techniques is that they were not efficient in detecting missing teeth [8, 11]. However, dental health services are highly dependent on accurate diagnosis [12]. The identification of missing teeth has been extensively studied, with numerous research efforts leveraging object detection models to improve accuracy and reliability. Object detection models have been applied using segmentation and detection approaches on panoramic images with moderate results [13], whereas classification models like Inception-ResNet-V2 achieved good accuracy [14]. Although panoramic radiographic images have been extensively studied in dental research, studies focusing on intraoral imaging remain relatively limited. However, several investigations have explored teeth detection techniques using intraoral images, emphasizing their potential for dental diagnostics and analysis. To address these challenges, this study proposes an integrated approach that combines YOLOv8 with regression, clustering, and interpolation techniques to improve missing teeth detection in intraoral images. This integration represents a novel improvement over existing methods, aiming to improve detection reliability and overcome the shortcomings of previous models.

II. THE PROPOSED METHOD

The proposed research workflow is illustrated in Figure 1. The process begins with data collection, followed by data preprocessing, which involves applying resizing and padding, Contrast Limited Adaptive Histogram Equalization (CLAHE), and annotation to the images. Subsequently, the dataset is split into training, validation, and test sets in a 6:2:2 ratio. A detailed breakdown of the data splitting process is provided in Table I. The proposed model for missing teeth detection is trained on the training set, and its performance is assessed by comparing its prediction results with those of the state-of-the-art YOLO model in the final evaluation stage.

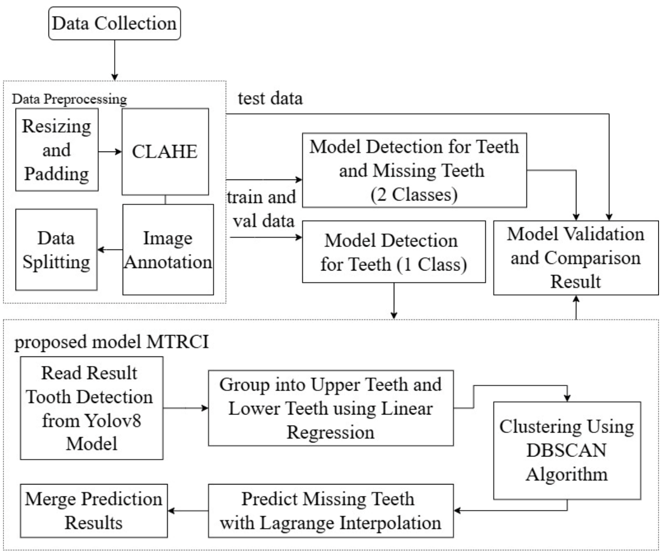


Fig. 1. The proposed method.

The utilized intraoral images were obtained by dentists at Puskesmas Kebayoran Baru (Kebayoran Baru Community Health Center), South Jakarta, as part of the School Dental Health Unit program conducted within the Community Health Center area between 2022 and 2023. Ethical approval for this research was granted by the Research Ethics Committee of the Faculty of Dentistry – RSGM UGM Prof. Soedomo, Universitas Gadjah Mada (No. 63/UN1/KEP/FKG-RSGM/EC/2024). The dataset consisted of frontal intraoral images capturing the front teeth of each patient, taken by dentists using smartphone cameras. To ensure optimal image quality, certain images were excluded from the dataset. These included images where the tooth surface was obscured by saliva, food, braces, or other artifacts that hindered clear diagnosis. Additionally, blurry or out-of-focus images, as well as those containing persistent teeth with overlapping structures that could interfere with missing tooth detection, were removed. The final dataset comprised two categories: images of intact teeth and images of missing teeth. A total of 983 images were collected. The detailed distribution of the data is presented in Table II.

TABLE I. DATA SPLITTING

Data	Number of images	Number of teeth	Number of missing teeth
Train	589	9,028	234
Val	197	2,935	76
Test	197	2,932	81

TABLE II. DATASET DISTRIBUTION

Image Type	Overall number of images	Overall number of teeth	Missing teeth
Intact teeth images	714	11,152	0
Images with missing teeth	269	3,743	391
Sum of all images	983	14,895	391

The data preprocessing stage aimed to optimize images for model training. The first step is resizing the original images to 640 × 640 pixels. To achieve this resolution, both resizing and padding techniques were applied. CLAHE was applied during preprocessing to enhance image contrast while preserving important details. The next stage is annotation, where each tooth in the intraoral images was labeled and assigned a bounding box based on its type. The annotation process focused on two primary object categories: Teeth and Missing Teeth. Two trained experts, under the guidance of a professional dentist, carried out the annotation by identifying and marking all visible teeth and the missing tooth areas using bounding boxes. To facilitate the annotation process, the open-source platform VGG Image Annotator (VIA), developed by the Visual Geometry Group (VGG) and released under the BSD-2-Clause License, was utilized. The results of the preproccessing process are presented in Figure 2.

Fig. 2. Preprocessing.

A. YOLOv8 Model for Teeth Detection

In this study, two models were developed to enhance dental image analysis. The first model was designed specifically for tooth detection, while the second model was trained to identify both teeth and missing teeth simultaneously. Both models were implemented using YOLOv8 [15, 16]. The YOLOv8 architecture comprises three main components: (1) Backbone, which extracts features from input images utilizing a Feature Pyramid Network (FPN), (2) Neck, which refines the extracted features to enhance detection performance, and (3) Detection Head, which identifies objects through the use of Cross-Layer Connection (CLC) mechanisms [17]. YOLOv8 incorporates advanced features that enhance its precision in object detection, particularly through its anchor-free detection head, which improves localization accuracy and adaptability [18, 19]. YOLOv8n was selected due to its efficient computational performance.

B. The Proposed MTRCI (Missing Teeth detection using Regression, Clustering, and Interpolation) Model

The proposed MTRCI model is designed to enhance the detection of missing teeth by leveraging tooth detection results from YOLOv8. This approach integrates regression, clustering, and interpolation techniques to improve detection accuracy. Specifically, linear regression [20-22] is used to classify the teeth into the upper and lower teeth groups, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm [23] is employed to group the detected teeth, while Lagrange Interpolation [24] is utilized to estimate the positions of missing teeth based on the existing tooth patterns. Figure 3 illustrates the workflow of the proposed model for missing teeth detection.

The first stage is to group the teeth into upper and lower teeth using a regression model. This grouping is essential, as anterior teeth are typically positioned closely together and exhibit a more complex spatial distribution. By distinguishing between upper and lower teeth, the analysis can be refined to focus on specific tooth groups. The subsequent step involves clustering. In this study, DBSCAN is utilized to group teeth by identifying clusters of closely positioned teeth while distinguishing them from other, more distant groups. The distance calculation formula between box i and box j, $D[i,j]$, is given in (1):

$$D[i,j] = \begin{cases} 1 - IoU(b_i, b_j), & i \neq j \\ 0, & i = j \end{cases} \quad (1)$$

where b_i represents the coordinate of the i-th bounding box, and $IoU(b_i, b_j)$ describes the Intersection over Union (IoU) value between bounding boxes b_i and b_j. The IoU function is:

$$IoU = \frac{\text{Area of overlap}}{\text{Area of union}} \quad (2)$$

The clustering results serve as the basis for identifying potential missing teeth. Specifically, if multiple clusters are detected in a given tooth position, they indicate possible missing teeth. Missing teeth are identified by analyzing two adjacent clusters, with interpolation applied to estimate the position of the missing tooth located between them. The overall process for missing tooth identification follows these key steps:

1) Generate Point Pairs

To provide a complete context for Lagrange interpolation, data from two adjacent clusters (left and right) are merged. The left cluster consists of elements with lower x-values, while the right cluster contains elements with higher x-values. The space between these clusters is left as an empty list, representing potential missing teeth. The number of missing teeth candidates is dynamically determined to accommodate multiple missing teeth. The Generate Point Pairs algorithm is then employed to establish reference points along the x-axis. For instance, if the left cluster has five teeth, the right cluster has one tooth, and one missing tooth is expected, the reference points are defined as [1, 2, 3, 4, 5, 7]. These reference points are essential for accurately scaling the interpolation, ensuring that each y-value is computed with the correct reference.

2) Missing Prediction

The core process involves applying Lagrange interpolation to estimate each coordinate of the missing bounding box. These values are derived from the coordinate patterns generated by the Generate Point Pairs algorithm. Once predictions are made, the algorithm validates them using the IoU. If the IoU exceeds the maximum threshold, the prediction is considered invalid due to overlapping with existing bounding boxes. Conversely, if the IoU is below the minimum threshold, the algorithm adjusts by increasing the number of predicted missing teeth and recursively refining its calculations. Valid predictions fall within the acceptable IoU range and are assigned class attributes to ensure proper classification.

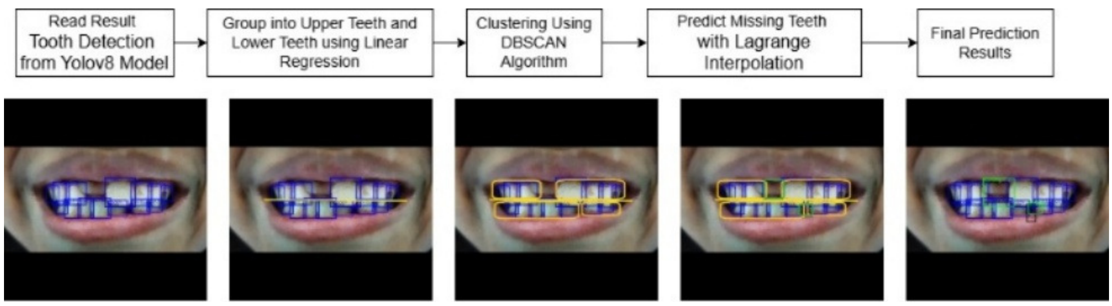


Fig. 3. Workflow of the YOLOv8 integrated with the MTRCI model.

C. Evaluation Metrics

The performance is evaluated using precision, recall, and mean Average Precision (mAP) scores [25-27] with an IoU threshold of 0.5, which is the standard metric for object detection in deep learning. The detection results must have a confidence score greater than 0.5.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (3)$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (4)$$

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n}(AP_i) \quad (5)$$

III. EXPERIMENTAL RESULTS

Table III presents the performance comparison between the state-of-the-art YOLOv8 model and the proposed YOLOv8 + MTRCI model in detecting teeth and missing teeth. The performance comparison was evaluated on the testing dataset consisting of 197 images without missing teeth. Overall, the proposed model demonstrates varying performance across different detection tasks. For tooth detection, both YOLOv8 and the proposed model achieve identical results, with a precision of 96.58%, recall of 86.56%, and mAP of 83.60%, indicating that the integration of MTRCI does not impact the detection of intact teeth. However, when the model detects missing teeth, a noticeable decline in performance is observed in the YOLOv8 model, achieving a precision of 44.12%, a recall of 18.52%, and an mAP of 8.17%. This suggests that the standard YOLOv8 model struggles with accurately identifying missing teeth. In contrast, the proposed YOLOv8 + MTRCI model significantly improves the detection of missing teeth, with precision increasing to 53.06%, recall to 64.20%, and mAP to 34.06%, demonstrating the effectiveness of integrating MTRCI in enhancing missing tooth identification.

For joint tooth and missing tooth detection, YOLOv8 alone achieves a precision of 62.00%, a recall of 54.68%, and an mAP of 45.20%, indicating that the model finds it challenging to simultaneously detect both classes. The proposed YOLOv8 + MTRCI model improves overall performance, achieving a precision of 64.27%, a recall of 75.34%, and an mAP of 52.03%. These results suggest that the MTRCI integration enhances the ability to detect missing teeth while maintaining the effectiveness of tooth detection. The significant improvement in recall and mAP for missing tooth detection highlights the potential of the proposed approach in real-world dental applications, where accurately identifying missing teeth is critical for diagnosis and treatment planning.

The recall of 18.52% suggests that YOLOv8 struggles to identify a substantial number of missing teeth, likely due to the varying shapes, occlusions, and lighting conditions present in intraoral images. This limitation underscores the need for a more advanced approach, such as the proposed integration of MTRCI, which leverages regression, clustering, and interpolation techniques to improve the detection process. By incorporating these additional steps, the proposed model effectively addresses the challenge of false negatives in missing tooth detection, leading to a significant improvement in recall (64.20%) and mAP (34.06%).

Furthermore, the improved performance in joint tooth and missing tooth detection suggests that the MTRCI framework contributes to a more robust detection mechanism without compromising the accuracy of intact tooth recognition. The precision of 64.27% and recall of 75.34% for the joint detection task indicate that the proposed approach effectively balances the detection of both object classes, which is crucial in practical dental diagnostic applications. The increase in recall is particularly important in clinical settings, where missing teeth must be identified with high sensitivity to ensure proper treatment planning.

TABLE III. COMPARATIVE ANALYSIS OF DETECTION MODEL PERFORMANCE

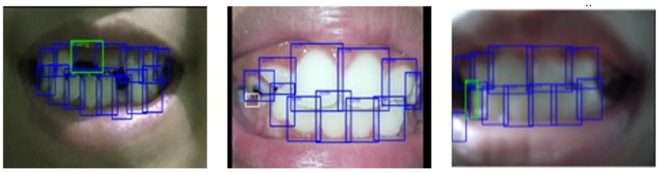
Task	YOLOv8			YOLOv8 + MTRCI (proposed)		
	Precision	Recall	mAP	Precision	Recall	mAP
Tooth Detection	96.58%	86.56%	83.60%	96.58%	86.56%	83.60%
Missing Tooth Detection	44.12%	18.52%	8.17%	53.06%	64.20%	34.06%
Tooth and Missing Tooth Detection	62.00%	54.68%	45.20%	64.27%	75.34%	52.03%

IV. DISCUSSION

The teeth detection model using YOLOv8 has demonstrated excellent performance, with high precision, recall, and mean mAP. This indicates that the model can accurately recognize and detect teeth. However, the addition of missing teeth detection has not produced satisfactory results. The recall rate for missing teeth detection is significantly low, meaning the model fails to detect a large portion of missing teeth. The impact of this low recall rate in missing teeth detection is significant, as it may lead to misdiagnosis, where a missing tooth is mistakenly assumed to be present. Several studies have looked into ways to deal with missing teeth cases by excluding the handling of missing teeth [8, 28]. In healthcare applications, recall is more critical than precision since misidentifying missing teeth can affect patient treatment planning.

Authors in [11] tried to use deep learning methods for detecting teeth area, including missing teeth. They used three different convolutional neural network models to build an AI system that can classify malocclusion. But the result was not very satisfactory because accuracy and were much lower when many teeth were missing in the same quadrant. Authors in [29] used two models, Mask R-CNN for segmenting the teeth, and then Faster R-CNN for finding missing teeth in panoramic X-ray images. The result of this research was also not optimal. Also, the use of many detection models made computational cost heavier [29].

Authors in [30] used statistical shape modeling for finding mandible teeth and to detect missing teeth automatically in 3D medical images. This method needs shape estimation of the tooth, so it only works well on the front side and not that well on the others. For this reason, in this study we combined detection models and other statistical methods to identify missing teeth. This study introduces a method to enhance the model's capability in identifying missing teeth by analyzing patterns within detected tooth clusters. This approach aims to improve the prediction of missing tooth locations by leveraging spatial relationships between the detected teeth. As illustrated in Figure 4(a), this method balances detection outcomes and provides additional insights into potential missing teeth. However, the method has limitations, particularly in detecting missing teeth outside identified clusters, as shown in Figure 4(b). Since it relies on clustering, detection is restricted to areas between detected tooth groups. As a result, missing teeth at the far left or right of an intraoral image may go undetected. This limitation highlights the need for a more adaptive approach to handle diverse missing tooth cases.



(a) (b) (c)

Fig. 4. (a) Accurate detection results, (b) undetected missing teeth, (c) detection inaccuracies.

Furthermore, the accuracy of the proposed method is highly dependent on the performance of the YOLO-based tooth detection stage. As demonstrated in Figure 4(c), errors such as misdetections or undetected teeth can directly affect the reliability of missing tooth predictions. If a tooth is not accurately identified in the initial detection phase, the subsequent clustering-based approach may fail to infer the correct missing tooth positions. This dependency emphasizes the necessity of further refining the detection pipeline, possibly by integrating additional contextual cues or employing more advanced interpolation techniques to mitigate the impact of detection errors and improve overall model robustness.

V. CONCLUSION

This study demonstrates that YOLO-based tooth detection achieves high accuracy, confirming its effectiveness in identifying intact teeth. However, integrating missing tooth detection presents several challenges, primarily due to data imbalance and low recall values. The proposed approach, which incorporates the MTRCI (Missing Teeth detection using Regression, Clustering, and Interpolation) model, successfully enhances the detection balance by improving precision, recall, and mAP of the YOLO's direct detection of both present and missing teeth. This improvement highlights the effectiveness of combining object detection with additional analytical techniques to address the limitations of conventional deep learning models. Nevertheless, further refinements are needed to optimize the model's ability to detect missing teeth in various clinical scenarios, particularly in cases where missing teeth fall outside detected clusters.

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