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IDCCD: evaluation of deep learning for early detection caries based on ICDAS

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ABSTRACT

Dental caries is a common oral disease in children, influenced by environmental, psychological, behavioral, and biological factors. The American academy of pediatric dentistry recommends screening from the time the first tooth erupts or at one year of age to prevent caries, which mostly affects children from racial and ethnic minorities. In Indonesia, the 2023 health survey reported a caries prevalence of 84.8% in children aged 5-9 years. This research introduces early caries detection using three deep learning models: faster-RCNN, you only look once (YOLO) V8, and detection transformer (DETR), using Indonesian dental caries characteristic datasets (IDCCD) focused on Indonesian data with international caries detection and assessment system (ICDAS) classification D0 to D6. The results showed that YOLO V8-s and DETR gave good results, with mean average precision (mAP) of 41.8% and 41.3% for intersection over union (IoU) 50, and 24.3% and 26.2% for IoU 50:90. Precision-recall (PR) curves show that both models have high precision at low recall (0 to 0.2), but precision decreases sharply as recall increases. YOLO V8-s showed a slower and more regular decrease in precision, indicating a more stable performance compared to DETR.

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1. INTRODUCTION

Dental caries is the most common chronic oral illness, especially in young children. Carious lesions are a complex etiological infectious disease that progress over time. Environmental factors, psychology, behavior, and biology all play a role in dental caries. Important contributing factors are metabolic alterations brought on by sugars, carbohydrates that ferment, and dental biofilms. Other factors included fluoride, salivary flow, and oral bacteria. Understanding the connections between sugars and dietary habits, health-related behaviors, socioeconomic variables, and psychological elements is critical [1]-[3].

According to the American academy of pediatric dentistry, children should begin preventive dental examinations and cleaning as soon as their first tooth erupts or at age one to prevent dental caries. Recent data indicate that dental caries, including untreated caries, are more common in children of racial and ethnic minorities than in non-Hispanic white children [1]. Previous research has shown that Asians have a high risk of caries [4]. Dental caries are the most prevalent chronic illness among children in Indonesia.

According to an Indonesian health survey conducted by the Health Government of Indonesia in 2023, the prevalence of tooth decay in children aged 5-9 according to-Indonesian health survey was 84.8% [5]. The estimated average prevalence of caries in deciduous teeth worldwide is 43%, with prevalence rates of over 40% in 134 of 194 WHO member states or 69% of all countries. Indonesia had the highest rate of dental caries according to data from WHO. Research has shown that the prevalence of caries is high in both urban and non-urban areas [6]. Differences in dental surface morphology and post-eruption enamel maturation have been considered reasons for the varied susceptibility to caries [7]. A study on Sulawesi Island found that Besoa people consume peanuts and onions as food ingredients in various diets. This difference in diet causes several dental diseases such as tooth decay and attrition [8].

Dental caries detection has been performed using a mirror glass and probe; however, with the increase in digitalization, dental caries detection can be performed using a computer system. Various research results for dental caries detection using intraoral camera artificial intelligence (AI) systems. The results showed that the sensitivity of dental caries detection using intraoral photography with an AI system was 80% [9]. A previous study evaluated the you only look once (YOLOv5x) model to detect white spot lesions in post-orthodontic mouth photos using training data from as many as 349 images with 1589 labels. The training results obtained precision, recall, and F1-score values for detecting white spot lesions of 0.786, 0.618, and 0.692, respectively [10]. This research evaluated the effectiveness of three deep learning models, faster R-CNN, YOLOv8, and detection transformer (DETR), in detecting early caries using a new dataset created specifically for this research, the Indonesian dental caries characteristic dataset (IDCCD). The IDCCD dataset offers a comprehensive and representative collection of high-fidelity dental images, with labels indicating the presence of carious lesions in classes D0-D6 of the index of dental caries and early detection (ICDAS) classification [11]. The ICDAS is a classification system that assesses caries from the beginning or early detection of white spots until caries reaches the pulp. The ICDAS classification is also used to assess the health status of a community [12]. Deep learning models were evaluated by training the models on the IDCCD dataset and then assessing their ability to accurately identify carious lesions on new dental images. This research aimed to compare the performances of the three models and determine the most effective approach for early caries detection. This could potentially lead to improved dental care practices and early interventions for caries prevention in Indonesia.

2. METHOD

This research aimed to build the IDCCD and evaluate deep learning models in early caries detection tasks using several deep learning models. The proposed method for automatic early caries detection is based on the development of object-detection techniques. The proposed research and method flow are illustrated in Figure 1.

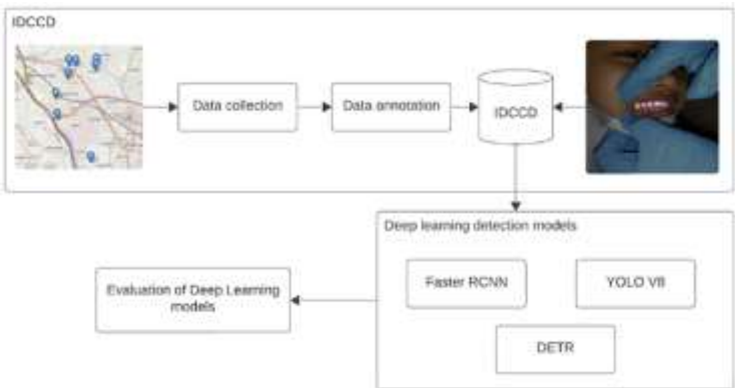


Figure 1. Propose method and research flow

2.1. IDCCD

The IDCCD, an initiative that aims to compile a detailed dataset of dental caries characteristics in Indonesia. The project involved a careful and thorough data collection process conducted by researchers in Indonesia. The main objective of IDCCD is to provide a complete and representative dataset on the prevalence, distribution, and characteristics of dental caries in Indonesia to provide a solid basis for the development of more effective dental health policies and interventions. The data collection process includes various methods ranging from field surveys to electronic data collection through online forms and the Hibogi application. Thus, the IDCCD is not only a collection of data but also a valuable source of information for researchers, dental health practitioners, and policy makers to understand and address the problem of dental caries in Indonesia more effectively.

2.1.1. Data collection

In an effort to collect the data needed to compile the dataset in this research, the researcher found that there are differences in dental characteristics between the Indonesian population and populations from other countries, with the differences being more pronounced in white and Asian races [4]. Detailed information on the data collection sites is shown in Figure 2. In this research, primary data were collected directly by the researchers with the help of doctors and dental students. Data collection was conducted in accordance with research ethical procedures at several locations, namely *Puskesmas Cimahi Utara, Puskesmas Cimahi Tengah, Puskesmas Cimahi Selatan, SDN Mandiri 02, SDN Mandiri 04, SDN Baros Mandiri Cimahi, SDN Melong Mandiri 04, and SDN Cibabat 2*, as shown in the map in Figure 2(a). Data collection was carried out by several research teams divided into several groups, each consisting of eight dentists, young dentists, and four dental students. The data collection is shown in Figure 2(b).

(a)

(b)

Figure 2. Data collection results (a) data collection location and (b) data collection techniques

2.1.2. Data annotation

In the data annotation process, the researcher involved several individuals with specific expertise in labeling the data that had been collected. This collaboration included the participation of labeling experts with in-depth experience and knowledge in the field of dentistry, especially in the case of dental caries. This is because the main focus in labeling the data is on the dental caries class using guidelines from the index of dental caries and early detection ICDAS [11], [13]. This approach aims to perform early detection of dental caries in the severity range from D0 to D6 according to the ICDAS classification system. Involving special expertise in data labeling and in-depth knowledge of dental caries will result in an accurate and relevant dataset, which can be a strong foundation for further research and interventions to prevent and manage dental caries using a deep learning approach. The workflow of data annotation is shown in Figure 3. After the dataset was collected, dentists, who were experts in caries classification, categorized the collected images into caries classes using a table in Excel. The data were then received by a labeling expert and labeled using RoboFlow. After all the datasets were labeled, the data were re-verified by two dentists to avoid labeling errors. The labeling results for data images with classes D0-D6 can be seen in Table 1. This grouping was a sample of caries classes with reference to the field of dentistry experts based on the ICDAS classification.

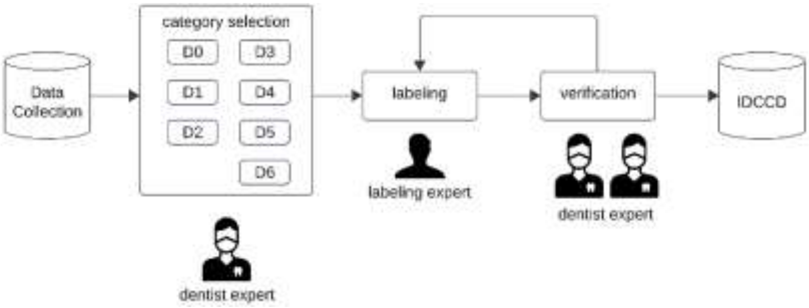


Figure 3. Datasets labeling workflow

Table 1. Sample caries classes in IDCCD datasets

No	Data images	Class/caries stage	Caries extension
1		D0	No clinically detectable lesion. Dental hard tissue appears normal in color, translucency, and gloss.
2		D1	Earliest clinically detectable lesion compatible with mild demineralization. Lesion limited to enamel or to shallow demineralization of cementum/dentin. Mildest forms are detectable only after drying. When established and active, lesions may be white or brown and enamel has lost its normal gloss.
3		D2	
4		D3	Visible signs of enamel breakdown or signs the dentin is moderately demineralized.
5		D4	
6		D5	Enamel is fully cavitated and dentin is exposed. Dentin lesion is deeply/ severely demineralized
7		D6	

2.2. Image pre-processing

The proposed research methodology involves a three-step data-preprocessing pipeline to enhance the quality and consistency of the image dataset. First, the images were scaled to a uniform dimension of 640×640 pixels to ensure consistent processing. Second, histogram equalization (HE) is applied to enhance contrast and improve feature visibility [14], potentially boosting the model training accuracy. Finally, data normalization was performed by scaling the pixel values to the range [0, 1] [15], reducing the impact of varying lighting conditions and promoting model generalization. This comprehensive preprocessing approach aims to prepare an image dataset for effective model training and potentially improve overall model performance.

2.3. Deep learning detection model

This research focuses on three deep learning models for object detection: faster R-CNN, YOLO V8, and DETR. Each model was analyzed in depth to assess its effectiveness for the early detection of dental caries. A comparative analysis was conducted to highlight the strengths and weaknesses of each model and provide insights into their practical implementation in dental healthcare.

2.3.1. Faster RCNN

In faster R-CNN, the object detection model is divided into three parts: convolution layer, region proposal network (RPN), and class and bounding box [16]. This research uses the VGG16 architecture for feature extraction on input images with a fixed size of 640×640 pixels. VGG16 consists of 16 layers with 3×3 convolution filters and 1-pixel steps to maintain spatial resolution. A 1×1 filter was used for linearity before the ReLU activation function. The architecture includes four 2×2 window max-pooling layers with two steps to support post-convolution pooling. The layer depth of VGG16 increases the ability of the network to capture complex features, thereby rendering it effective for image classification [17], [18]. The next step is the RPN stage, which uses the feature map generated by the backbone feature extraction network to obtain dental caries suggestion boxes. Initially, the feature map is processed using 3×3 convolution layers, and then nine a priori boxes are assigned to each feature map grid. Next, the feature map is processed using two 1×1 convolution layers, where a SoftMax classifier distinguishes the foreground and background, generating a caries-suggestion box by scoring and adjusting the specific a priori box [19]. The results of the RPN process and backbone feature extraction are then combined and processed by the ROI-pooling layer, then combined into two fully connected layers and ReLU as the activation function, and then divided into two fully connected networks only to distinguish between caries and background and predict the coordinates of the caries position. The relevant procedure is illustrated in Figure 4.

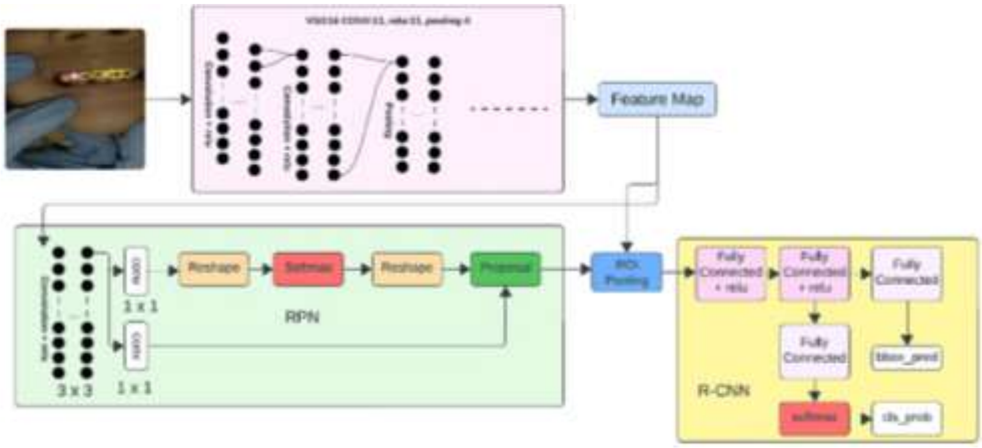


Figure 4. Faster CNN model architecture [20]

2.3.2. Yolo V8

YOLOv8, the latest version in the YOLO series, is an advanced object detection model designed for real-time applications that offers significant improvements in accuracy and performance [21]. It uses the CSPDarknet53 as its backbone, an enhanced version of the Darknet architecture, incorporating cross-stage partial (CSP) networks to improve learning capacity and efficiency. In addition, YOLOv8 employs a path aggregation network (PANet) for its neck architecture, facilitating better feature fusion across different scales, which enhances its ability to detect objects of varying sizes more effectively. The architecture of YOLOv8 consists of three main components: backbone, neck, and head. The CSPDarknet53 backbone extracts hierarchical features from the input image, thereby providing a detailed visual representation. The PANet neck combines multi-scale features to improve detection accuracy, whereas the YOLO head generates bounding box predictions, objectness scores, and class probabilities [22], [23], as shown in Figure 5. Furthermore, YOLOv8 incorporates advanced training techniques, such as rectified Adam (RAdam) optimization and data augmentation methods, such as MixUp, contributing to faster convergence and better generalization during training. These enhancements make YOLOv8 highly adaptable to various datasets and application scenarios, ensuring superior performance in diverse computer vision tasks including real-time object detection, segmentation, and pose estimation.

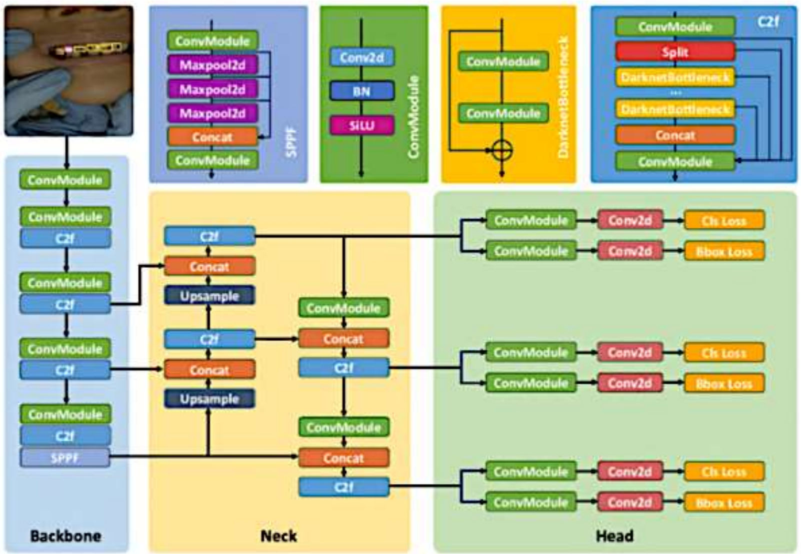


Figure 5. YOLO v8 model architecture [24]

2.3.3. DETR

DETR combines a conventional CNN with transformers for object detection. The model first used a CNN backbone to extract 2D features from the input image. These features are then flattened and positional coding is added before being fed to the transformer encoder. The transformer encoder enriches this feature representation using an attention mechanism [25]. The transformer decoder receives a fixed number of learned position embeddings, called "object queries," and pays additional attention to the encoder output [26]. Each embedding output from the decoder is then passed to a shared feed-forward network (FFN) that predicts object classes and bounding boxes [27]. With this approach, DETR simplifies the object detection process by eliminating the need for anchor boxes, and offers a more efficient end-to-end method. An illustration of the DETR architecture is shown in Figure 6.

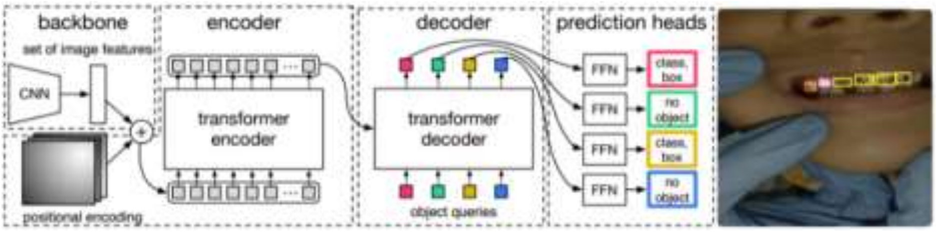


Figure 6. DETR model architecture [27]

2.4. Training and evaluation

In the training phase of this research, a Google Colab Pro platform equipped with an A100 GPU and 54GB of RAM was used. This platform was chosen because of its superior ability to handle computationally intensive deep learning tasks. Model training was conducted for 100 epochs. Each epoch represents one full cycle through the entire dataset, during which the model learns to refine its weights based on the previous prediction errors. This large number of epochs allows the model to absorb complex patterns in the data, which is expected to improve prediction accuracy.

For model evaluation, several metrics essential for assessing object detection performance are used. These metrics include intersection over union (IoU), mean average precision (mAP), and average precision (AP) [21]. Precision is a measure of the accuracy of the model in correctly identifying positive samples, that is, the percentage of correct positive predictions out of all positive predictions made by the model using the mathematical equation in (4) [10]. Recall is a measure of the sensitivity of the model in detecting positive samples, which is the percentage of positive samples that are actually detected out of all positive samples with the mathematical equation in (5) [10]. The IoU measures the extent to which the bounding box prediction of the model overlaps with the ground truth using the mathematical equation in (1) [28]. The mAP, which is the average AP for different object classes, provides an overall picture of the detection accuracy of the model on the dataset used in the mathematical equation in (2) [29]. The AP itself is a metric that evaluates the precision of the model for each class at various IoU threshold levels, providing a more detailed view of the model's performance in detecting each object type with the mathematical in (3).

$$IoU = \frac{(groundTruth \cap prediction)}{(groundTruth \cup prediction)} \tag{1}$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \tag{2}$$

$$AP = \sum_{k=0}^{K}\big(R_r(k) - R_r(k+1)\big)Rr_{interp}(R_r(k)) \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

Where:
– TP: true positive when the model correctly predicts the positive sample.
– FP: false positive; when the model predicts a positive sample, it is negative.
– FN: false negative; when the model predicts a negative sample, it is positive.

The use of these comprehensive evaluation metrics allows for a more in-depth and accurate assessment of the performance of the model, ensuring that the resulting model is not only correct in detection but also efficient in processing various objects in the IDCCD dataset.

3. RESULTS AND DISCUSSION

The results of this study show that the deep learning model that best fits the IDCCD dataset in Table 2 is the YOLO V8-s model compared to other models. This is evidenced by the mAP value of 41.8% at IoU 50 in Table 3, which is the highest value compared to other models, such as the DETR and faster R-CNN. The YOLO V8-s model proved to be very effective in detecting and classifying several caries classes, as shown in Table 4, particularly for advanced classes such as D2, D4, D5, and D6, where this model showed high AP values. Previous research shows that the evaluation of the YOLO v3 model is good enough to get the highest sensitivity value compared to other models, namely 74% for evaluation results of C vs. NC classification and 36.9% for evaluation results of VNC vs. NSC classification shown in research conducted by Mai Thi Giang Thanh [30] in addition, research by Aayush Juyal shows that the sensitivity of YOLO v3 is much better but on other evaluation criteria the value is less good than faster RCNN [28]. In subsequent studies using the YOLO v5 model showed even better results where the highest precision (0.853) occurred in the YOLOv5l model [31]. In addition, previous research on caries detection for the classification of white spot lesions showed good results with the YOLOv5x model [10], indicating that the architecture of the YOLO model can effectively detect objects, particularly work in detecting objects, especially caries.

The proposed research resulted in a dataset called IDCCD, which has undergone a thorough labeling process using a dental decoder. The total labeled dataset included various dental caries data collected from various locations in Indonesia. The distribution of the data contained in these datasets is presented in detail in Table 2. Furthermore, these data will be used to train machine learning models with the aim of making accurate predictions about dental caries using several machine learning models. The number of instances in each caries data class used in the model training process is shown in Figure 7. The number of instances in each class of caries data used in the model training process is as follows: class D0 has approximately 1,000 instances, class D1 has approximately 900 instances, class D2 has approximately 1,200 instances, class D3 has approximately 1,100 instances, class D4 has approximately 900 instances, class D5 has approximately 1,300 instances, and class D6 has the highest number of instances, which is approximately 1,400 instances. This number of instances shows a fairly balanced distribution of data among the various caries classes, with class D6 having the highest number of instances and classes D1 and D4 having the lowest number of instances.

Table 2. Dataset distribution

	Training	Testing	Validation
Datasets	2266	320	635

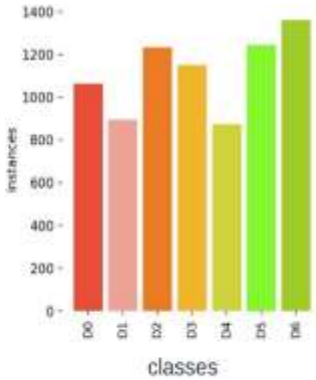


Figure 7. Instances of each caries class

Model training results using three different model architectures: faster R-CNN, YOLO V8, and DETR. The training results showed that the YOLO-V8 and DETR models provided the most satisfactory performances compared to the other two models. Specifically, at an IoU metric of 50, the YOLO-V8 model achieved a mAP of 41.8%. At the more stringent IoU metric of 50:95, the DETR model achieved a mAP of 26.2%. These results show that the DETR model has a better ability to detect and classify objects with higher accuracy than the Faster R-CNN and YOLO V8 models. A comparison of the results is presented in Table 3. In the YOLO V8-s model, the caries classes with the highest AP values were D2, D4, D5, and D6, indicating that this model performed exceptionally well in accurately identifying and classifying caries within these specific categories. This suggests that the YOLO V8-s model is particularly effective in detecting more advanced stages of caries and provides reliable results for these categories. In contrast, the DETR model demonstrated the highest AP values in classes D0, D1, and D3, demonstrating its proficiency in correctly identifying and categorizing early to moderate stages of caries. This performance difference highlights the strengths of each model in handling the various stages of caries progression.

Table 3. Model training results with IDCCD datasets

Model	Class	AP (%)	IoU	mAP (%)
Faster R-CNN	D0	3.1	50	2.6
	D1	0.075		
	D2	0.22	50:95	0.9
	D3	1.02		
	D4	0.143		
	D5	0.13		
	D6	1.58		
YOLO V8	D0	33.2	50	**41.8**
	D1	33.4		
	D2	**38.1**	50:95	24.3
	D3	32.3		
	D4	**35.4**		
	D5	**54.3**		
	D6	**65.6**		
DETR	D0	**33.7**	50	41.3
	D1	**35.7**		
	D2	37.3	50:95	**26.2**
	D3	**33.8**		
	D4	32.3		
	D5	52.9		
	D6	63.1		

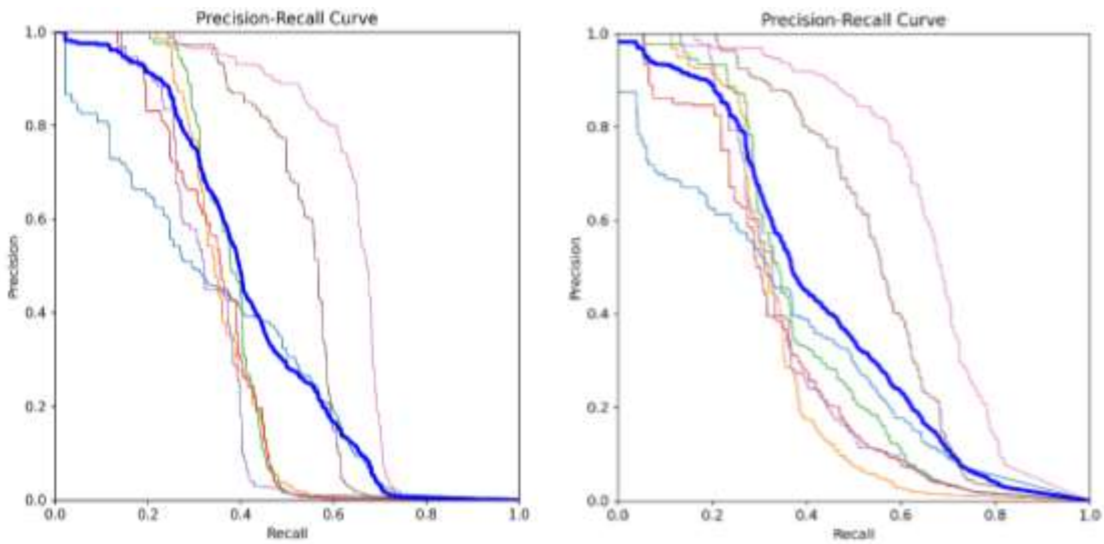
Furthermore, this research observes the training results of the YOLO V8 model with various sizes available in the model architecture. YOLO V8 has several size variants, namely YOLO V8-n (nano), YOLO V8-s (small), YOLO V8-m (medium), YOLO V8-l (large), and YOLO V8-x (extra large). Each of these model sizes has a different configuration and complexity, which affect the performance of the model in terms of detection speed and accuracy. The results show that the YOLO V8-s model achieves a fairly high mAP value compared with the other models, with a mAP of 41.8% at IoU 50. However, when using the IoU 50:95 metric, the YOLO V8-x model showed better performance, with a mAP of 25.7%. The details of the results are listed in Table 4.

Table 4. YOLO V8 model training results with various sizes

Model	IoU	mAP(%)
YOLO V8-n	50	35.5
	50:95	18.6
YOLO V8-s	50	**41.8**
	50:95	24.3
YOLO V8-m	50	41.4
	50:95	25.5
YOLO V8-l	50	40.9
	50:95	24.4
YOLO V8-x	50	40.5
	50:95	**25.7**

The overall results of this research show that the YOLO V8 and DETR deep-learning models perform quite well. The YOLO V8-s model shows that some caries classes have a fairly high AP compared to the DETR model. In the YOLO V8-s model, the caries classes with the highest AP values were D2, D4, D5, and D6. The highest AP values in the DETR model were found in classes D0, D1, and D3. In addition, the highest mAP value at IoU 50 was achieved by the YOLO V8 model with a mAP value of 41.8%, whereas the DETR model had a mAP of 41.3%, and the faster R-CNN model only achieved a mAP of 2.6%.

Evaluation of the precision-recall (PR) curves for the DETR and YOLO V8-s models shows that both models have high precision at low recall (0 to 0.2), but the precision decreases sharply as the recall increases. The YOLO V8-s model exhibited a slower and more regular decrease in precision than the DETR model, indicating more stable performance Figure 8. In Figure 8(a), The DETR model graph shows the average at recall 0.7 the precision value decreases very drastically until it reaches 0.01. In Figure 8(b), the YOLO V8-s model graph shows a fairly good average, where at a fairly high recall of 0.7, the AP value is 0.1. The variability between classes was significant in both models, with some classes showing a rapid decline in precision. Overall, YOLO V8-s has a slightly superior performance stability across recall levels compared to DETR.



(a) (b)

Figure 8. Visualization of PR curve results (a) curve of DETR model and (b) curve of YOLO V8 s model

Comprehensive ICDAS-guided exploration of IDCCD primary data using deep learning models has revealed significant insights into caries detection. Recent studies have shown that although the ICDAS framework provides a structured approach to caries classification, the adequacy of IDCCD datasets in representing different stages of caries remains an important topic in deep learning model training. For example, Turchiello *et al.* [32] emphasized the importance of systematic reviews for evaluating the effectiveness of caries detection methods, indicating that further validation of the dataset is essential for accurate diagnosis. In our research, we found that the YOLO v8s model outperformed other models, such as faster R-CNN and DETR, in terms of robustness and accuracy in detecting caries. This aligns with the findings from Chen *et al.* [33] who demonstrated that deep learning methods significantly improve the sensitivity of caries detection, particularly in complex cases. Furthermore, the potential for expanding IDCCD datasets across diverse regions in Indonesia could enhance the ability of the model to generalize across different populations, as suggested by the need for varied datasets in AI applications [34]. This approach not only addresses the limitations of current datasets but also aligns with the growing recognition of AI's role in preventive dentistry, as highlighted by Ayhan *et al.* [35] work on early caries detection. Thus, the integration of comprehensive datasets and advanced deep-learning models holds promise for improving caries detection and management in clinical practice.

4. CONCLUSION

The accuracy and sensitivity of the faster R-CNN, YOLOv8-S, and DETR models for detecting caries remained lower than those expected for practical applications. However, in this study, it was found that the YOLOv8-S model was better at detecting advanced caries and the DETR model was better at detecting early caries. However, this research is a promising and acceptable detection method compared with previous studies. The current research provides initial insights to be further improved by developing the IDCCD dataset with new data from all regions in Indonesia, sampling from each island and different ethnic groups to determine the diversity of datasets in Indonesia for training, and applying modifications to the deep learning algorithm.

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