TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 1, February 2026, pp. 151~161
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i1.27507

Dental caries detection and treatment cost prediction using YOLOv11

Salsabila Qotrunnada[1], Bayu Taruna Widjaja Putra[1,2], Mei Syafriadi[1,3]
[1]Graduate School of Public Health Sciences, Faculty of Public Health, Jember University, Jember, Indonesia
[2]Centre of Excellence on Artificial Intelligence for Industrial Agriculture, Faculty of Agricultural Technology, Jember University, Jember, Indonesia
[3]Oral Pathologybiomoleculer and Biomedical Sciencespathobiology, Faculty of Dentistry, Jember University, Jember, Indonesia

Article Info

Article history:

Received Aug 25, 2025
Revised Nov 14, 2025
Accepted Dec 8, 2025

Keywords:

Artificial intelligence
Deep learning
Dental caries detection
Treatment cost estimation
YOLOv11

ABSTRACT

Dental caries is one of the most prevalent oral diseases, progressively damaging tooth structure and often leading to significant treatment costs. Variations in dental service fees across clinics can become a financial barrier, discouraging timely and appropriate care. This study introduces an artificial intelligence (AI)-based framework that utilises smartphone camera images to detect dental caries and predict treatment costs. A total of 1,200 images of carious and normal teeth were collected from dental clinics in Denpasar, Bali, Indonesia, and classified by three dental experts. Data augmentation expanded the dataset twentyfold to 23,060 images to address variation and class imbalance. The you only look once version 11 (YOLOv11) deep learning algorithm was employed for caries detection, and its performance was evaluated using mean average precision (mAP), precision, and recall metrics. The model demonstrated high accuracy, achieving an mAP of 96.1%, a precision of 95.5%, and a recall of 93.0%. This study provides the first integration of YOLOv11 with RGB-intensity-based cost prediction in digital dentistry. The proposed system offers a fast, accessible, and cost-efficient approach for early caries detection and treatment cost estimation. These findings highlight its potential to support real-time, AI-assisted preventive dentistry and contribute to more equitable access to oral healthcare.

Corresponding Author:

Bayu Taruna Widjaja Putra
Center of Excellence on Artificial Intelligence for Industrial Agriculture
Faculty of Agricultural Technology, Jember University
Jember 68121, East Java, Indonesia
Email: bayu@unej.ac.id

1. INTRODUCTION

Dental caries is a major global health problem and one of the most prevalent oral diseases, progressively damaging tooth structure and leading to significant treatment needs [1], [2]. It develops through multifactorial interaction among carbohydrate intake, microorganisms, susceptible tooth surfaces, and saliva composition [3]. According to the World Dental Federation (FDI), modern dental care emphasizes minimal intervention dentistry (MID), which focuses on preventing disease, preserving healthy tooth structure, and providing cost-effective treatment [4].

Socioeconomic status, gender, environmental factors and individual behaviours significantly influence the need and demand for dental treatment [5], [6]. High treatment costs, time constraints, and varying clinical fees often discourage individuals from seeking timely care, leading to delayed intervention and greater financial burden [7], [8].

Recent technological development in dentistry have enable automated oral examination that provide real-time feedback for clinicians and patients. Using a simple smartphone-based imaging system, users can now identify possible dental problems and estimate treatment costs at minimal expense [9]–[11]. Artificial intelligence (AI) and internet of things (IoT) technologies have accelerated this transformation, providing real-time image analysis, remote diagnosis, and data-driven decision-making in healthcare [12]–[15].

The use of AI in the health sector is widely discussed by several researchers, such as Zhou *et al.* [16], using deep learning algorithms to detect ulceration using intra-oral images. Makarim *et al.* [17] used deep learning methods to detect and classify carious teeth on the tooth surface. Welikala *et al.* [18]. Use deep learning and IoT methods to detect and classify oral cancer. However, research focusing on AI-based caries detection combined with cost estimation remains limited. Most prior works only addressed detection accuracy, without linking diagnostic outcome to clinical treatment costs, which could support patients in financial planning and decision-making.

Therefore, this study aims to develop an Ai-based dental caries detection system using you only look once version 11 (YOLOv11,) integrated with red-green-blue (RGB)-based cost estimation. This approach not severity with predicted treatment costs, promoting accessibility, transparency, and affordability in dental healthcare services.

2. METHOD

This study is quantitative experimental research aimed at developing and evaluating an AI-based dental caries detection system. A total of 1,200 intraoral images were collected through purposive sampling from several dental clinics in Denpasar, Indonesia. Only permanent teeth were included in the dataset. Teeth showing carious lesions were categorised as cases, while non-carious teeth were used as controls. Images with poor quality (blurred, too dark, or overexposed), incomplete crown visibility, or extrinsic stains that could interfere with caries detection were excluded from analysis.

As illustrated in Figure 1, the research workflow began with data preprocessing to filter images based on clarity and a 1:1 aspect ratio. Images that met the criteria were then labelled by dental experts using the Greene Vardiman (GV) Black classification. The dataset was expanded through augmentation techniques to increase image variability, and subsequently divided into training, validation, and testing subsets. Model training was conducted using the YOLOv11 architecture. In addition to the detection process, the mean RGB pixel values of the detected caries region were extracted to estimate treatment costs based on the severity of the lesions. This methodological framework was designed to produce a clinically relevant and accurate AI model capable of early caries detection and reliable cost prediction.

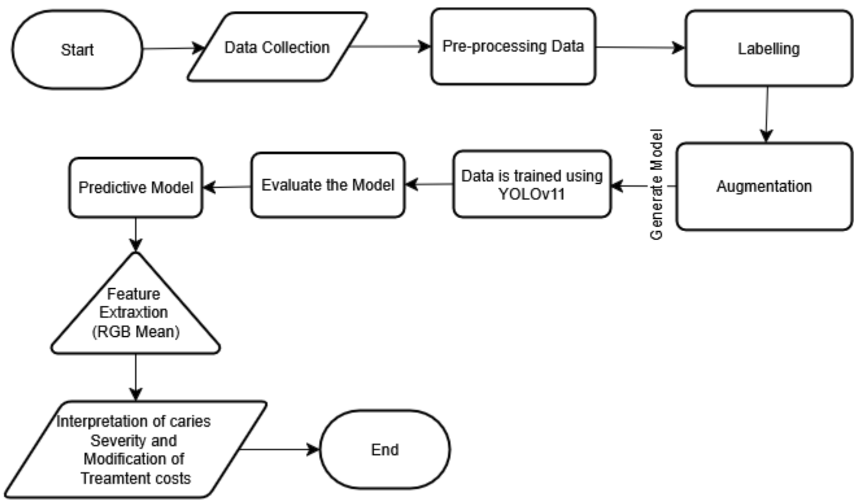


Figure 1. Development framework of AI system for dental caries detection

2.1. Data collection

This study collected a total of 1,200 intraoral dental images obtained through purposive sampling. The images were taken by dentists using smartphone cameras with a 1:1 aspect ratio to ensure consistency in image quality. The dataset included both caries and non-caries teeth and was gathered from five different dental clinics to ensure sufficient variation in dental conditions and visual characteristics. To maintain the quality and diagnostic relevance of the dataset, exclusion criteria were applied to eliminate images with visual obstructions such as stains, dental calculus, and anatomical anomalies. Specifically, images of teeth with developmental disorders such as dentinogenesis imperfecta and amelogenesis imperfecta, as well as teeth with malformed shapes, were excluded to avoid bias and ensure model generalizability

2.2. Image pre-processing and data augmentation

To enrich the variety of datasets without reducing the validity of the original condition of the teeth, an augmentation method was used to increase the volume of training data [19]. In this case, all images were flipped vertically and horizontally, rotated 90 °, and cropped 1:1. In the current study, data augmentation increased the number of images by about 20 times. This resulted in a dataset of 23,060. This is done to help overcome the problem of a lack of data variation or class imbalance in the dataset, as well as to enable the model to better recognise common patterns in the data. In addition, augmentation can help reduce overfitting, which is a condition where the model is too specific to certain training data and cannot generalise well to new data [20]–[22]. Although qualitative balance was maintained during augmentation, no quantitative analysis was conducted to measure class distribution after augmentation. Future research could further investigate how augmentation techniques, such as rotation or flipping, may influence model bias or impact the clinical interpretation of caries features.

2.3. Image annotation

Annotation of the dataset was conducted with the assistance of dental professionals using the GV Black classification system, which categorizes dental caries based on the location and type of lesion on the tooth surface. Class I includes caries in pits and fissures on the occlusal surfaces of molars and premolars and the lingual surfaces of anterior teeth. Class II involves caries on the proximal (mesial or distal) surface of premolars and molars. Class III refers to caries affecting the proximal surfaces of anterior teeth without involving the incisal edge. Class IV includes caries on the proximal surfaces of the anterior teeth, involving the incisal angle. Class V comprises caries on the cervical third of the facial or lingual surfaces of anterior or posterior teeth, usually near the gum line [23].

Labelling was performed using the Roboflow platform, where each image was segmented polygonally to delineate the area affected by caries according to its class Figure 2. After annotation and segmentation, the complete dataset was divided into three subsets: training data (21,240 images), validation data (1,217 images), and testing data (603 images), representing 92%, 5%, and 3% of the dataset, respectively.

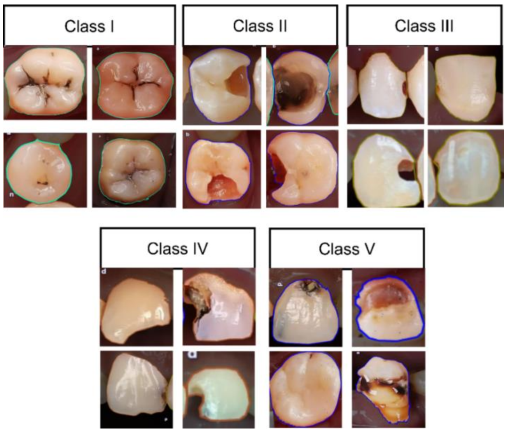


Figure 2. Image annotation

2.4. YOLOv11 and network setting

YOLOv11 is the latest release of the YOLO series. YOLOv11 is designed to be fast, accurate and easy to use for object detection, image segmentation, image classification, and real-time object tracking. YOLOv11 further develops the framework by introducing the cross-stage partial with spatial attention (C2PSA) block, which significantly improves spatial awareness by allowing the model to more effectively focus on critical regions in images. This innovation proved to be very beneficial in complex scenarios, such as healthcare applications, where precision and accuracy are crucial [24].

The model achieved a final mAP50 of 0.958 in several rejects. In particular, YOLO11m, with an average speed of 2% faster than YOLOv10. YOLOv11 is optimized for real-time applications, which require fast processing even in demanding environments [25], [26]. Model performance was evaluated using the mean average precision (mAP) metric to assess tooth detection accuracy. The applied network tuning included several important parameters, such as learning rate, batch size, and number of epochs. The learning rate was adjusted incrementally to ensure the model could converge well without getting stuck in a local minimum. The batch size was set to maximize memory usage, while the number of epochs was chosen based on the result of evaluating the model's performance on validation data. In addition, data augmentation such as rotation, flipping, and cropping was used to improve the generalization ability of the model to variations in the position and size of dental caries in the image [27].

The model was trained on a system equipped with an Intel Core i7 processor, 16 GB RAM, and integrated Intel Iris Xe graphics. A total of 150 epochs were completed in approximately six hours using the YOLOv11 architecture initialised from the Microsoft common objects in context (MSCOCO)-seg checkpoint. The YOLOv11 model was trained using default hyperparameter settings provided by the ultralytics framework, as this study primarily focused on evaluating model applicability for dental caries detection and subsequent cost estimation rather than hyperparameter optimization. The default configuration included a batch size of 16, a learning rate of 0.001, and the Adam optimizer. The training process was conducted for 150 epochs with early stopping enabled to prevent overfitting. Data augmentation, such as rotation, brightness, adjustment, and horizontal flipping, was applied automatically by the framework to enhance generalization.

2.5. RGB-based cost mapping

The RGB-based cost estimation method was chosen because variation in mean RGB intensity is correlated with enamel translucency and lesion severity, where darker regions (lower RGB values) typically indicate deeper or more extensive carious lesions. Mean RGB values were grouped into three severity levels: Mild (RGB>170), moderate (150-170), and severe (< 150), and mapped to corresponding estimated treatment costs. The mapping was derived from average clinical tariffs in Denpasar, Indonesia, with cost ranges of IDR 150,000-300,000 for mild, IDR 300,000-600,000 for moderate, and above IDR 600,000 for severe lesions. This approach provides a quantifiable and practical framework linking image-based intensity data with clinical cost estimation.

In this study, mean RGB intensity values were used to represent colour variations on tooth surfaces, offering a simple yet effective approach to assess enamel translucency and lesion severity. Unlike texture-based methods such as the grey level cooccurrence matrix (GLCM), which analyse pixel spatial relationship and require complex feature extraction, mean RGB provides a more direct correlation with optical changes in enamel brightness and translucency. Since demineralisation primarily alters light transmission rather than surface texture, intensity-based analysis is considered more support that enamel translucency and light transmission can be represented through colour intensity variation [28]. Thus, darker or lower-intensity RGB regions were interpreted as areas of more severe caries, which also informed the estimation of treatment costs.

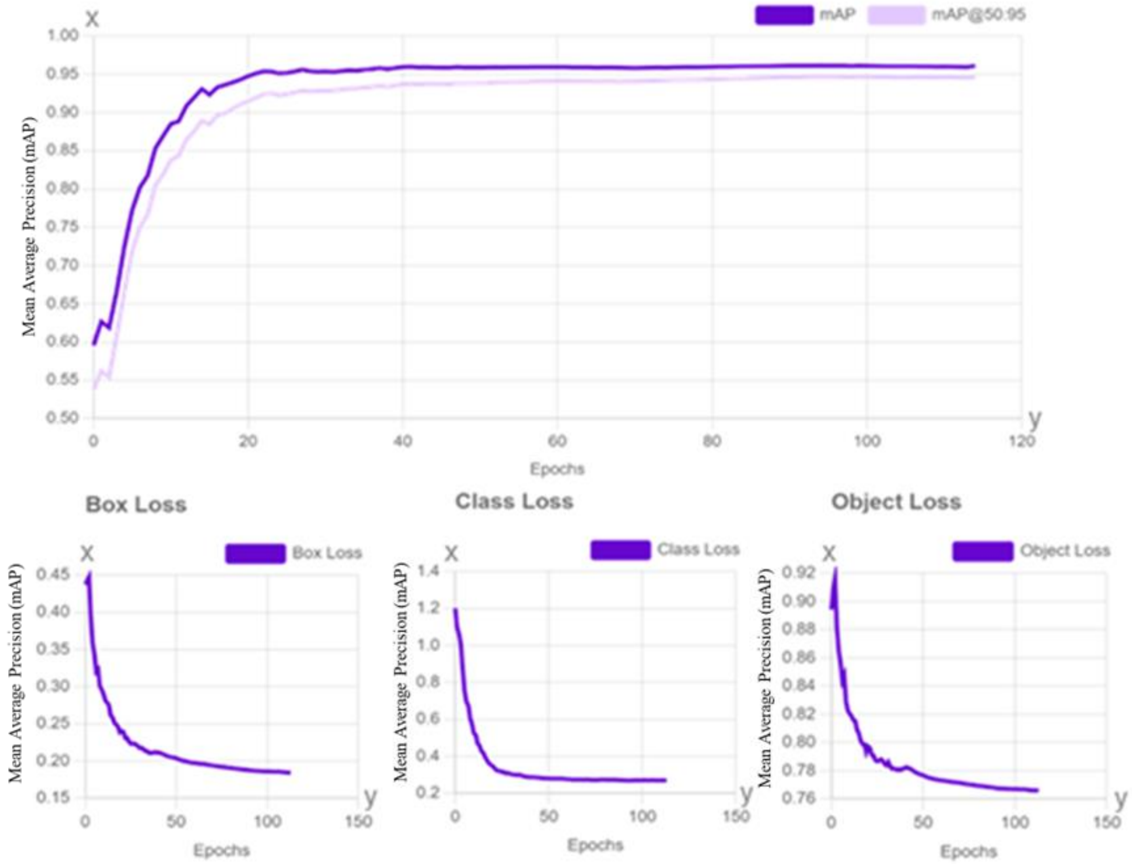
3. RESULTS AND DISCUSSION

3.1. Training and performance validation

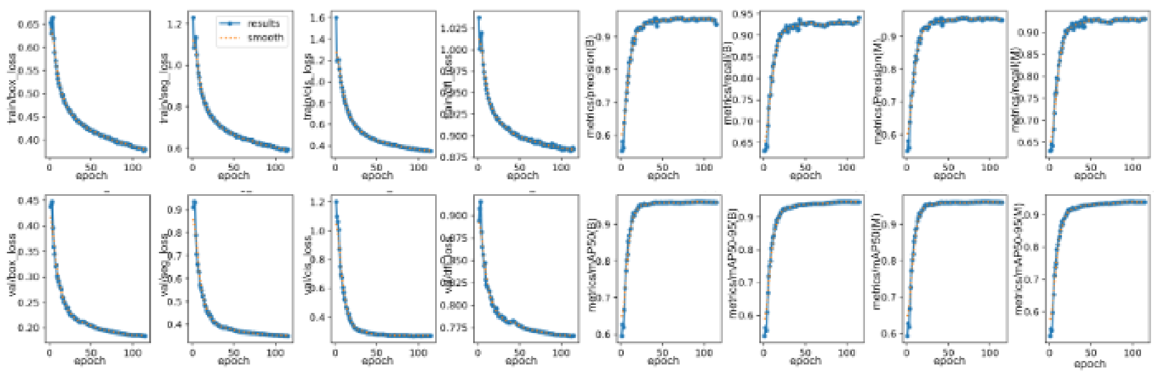
The dental caries detection using the YOLOv11 architecture was trained with the instance segmentation technique based on the MSCOCO-seg checkpoint. The model achieved strong and reliable performance, evaluated using mAP and loss metrics (box loss, class loss, and object loss) as shown in Figure 3.

As illustrated in Figure 3(a), the model achieved an mAP of 0.961 and an mAP@50-95 of 0.964 for both training and validation datasets. These high values indicate that the detection results closely match the ground truth, reflecting a well-balanced trade-off between precision and recall [29]. Figure 3(b) shows a substantial reduction in Box Loss during the early training epochs, followed by convergence after approximately 50 epochs, implying improved bounding-box localisation accuracy. Similarly, Class and Object Losses decreased consistently, signifying enhanced classification and object detection performance throughout training.

During the training process, the box loss, class loss, and object loss graphs steadily decrease, indicating that the model continues to learn well as the training progresses. The decreasing box loss reflects the model's ability to detect the location and size of caries with high accuracy, while the class loss shows that the model can distinguish caries in other areas of the tooth well. Object loss that drops to a stable value indicates reliability in detecting the presence of caries without much error. A graph that shows a consistent decrease in all three graphs Figure 3(a) shows that the model has reached convergence, where the learning process is optimised. Other studies have also found that the stability of the loss function value is critical to avoid overfitting and allow generalisation of results [30].



(a)



(b)

Figure 3. Model performance curves showing: (a) mAP, precision, and recall metrics and (b) box loss, class loss, and object loss trends

To ensure result consistency, the training runs were performed under identical hyperparameter settings. The mean mAP variance across runs was ±0.8%, indicating stable learning behaviour and minimal fluctuation. This suggests that the model's performance is reproducible and not significantly affected by random initialization or dataset shuffling.

YOLOv11 introduces innovative features and improves performance in various optimized computer vision tasks. The YOLOv11 model uses enhanced training techniques that have produced better results on data sets [25], [26], [31]. The research results confirm that the developed AI and IoT-based dental caries detection model shows excellent performance. Although no direct experimental comparison was conducted with alternative models on the same dataset, performance benchmarks from previous studies indicate that YOLOv11 outperforms earlier YOLO versions in the dental imaging task Table 1, outperforming YOLOv5 (mAP 90%, F1= 0.87) and Detection transformer (DETR) (mAp 85%, F1 = 0.82) reported in Ying *et al.* [32], the review by Radha *et al*. [33], highlights that most machine learning-based studies rely on radiographic images for detecting periodontitis and dental caries, whereas studies focusing on smartphone-based caries detection are still limited. The improvement of approximately 10-15% in mAP highlights YOLOv11's enhanced backbone, decoupled head architecture, and optimized training strategy, which collectively enhance feature extraction and inference speed.

Table 1. Performance comparison between YOLOv11 and previous deep learning models for dental caries detection

Model	Dataset type	mAP (%)	Precision (%)	Recall (%)	Source
DETR	Radiographic caries images	82.0	-	-	[32]
YOLOv5	Radiographic caries images	87.0	-	-	[32]
YOLOv11 (this study)	Smartphone clinical images	96.1	95.5	93.0	Present Study

These findings reinforce that YOLOv11 provides strong and consistent performance for dental caries detection, particularly on smartphone-acquired images where illumination, reflection, and positional variations are more challenging than radiographic data.

Data augmentation expanded the dataset from 1,200 to 23,060 images, effectively reducing overfitting during training. However, the class distribution after augmentation was not quantitatively verified. Although the balance between carious and non-carious images was maintained qualitatively, the statistical proportions were not calculated. Geometric transformations such as rotation and flipping may introduce slight interpretational bias, particularly when lesions appear in uncommon orientations. Nevertheless, these augmentations were intended to enhance model generalization and replicate natural variations in patient imaging. Future research should include a quantitative assessment of class balance and evaluate how augmentation strategies influence diagnostic robustness.

This study primarily focused on developing and validating a single optimized YOLOv11 model to evaluate its technical feasibility and diagnostic potential rather than performing comparative statistical testing. Hence, statistical variance measures such as confidence intervals or standard deviations were not applied to all metrics. Furthermore, specificity is less relevant in object detection frameworks like YOLO, which emphasize localization accuracy rather than binary classification outcomes. Qualitative visual inspection of misclassified samples revealed that errors primarily occurred in images with uneven lighting or overlapping restorations. These insights provide a useful foundation for future refinement of the model through improved preprocessing and image normalization techniques. Overall, the model achieved an average mAP of 96.1%, precision of 95.5%, and recall of 93.0% Table 2, demonstrating that YOLOv11 can accurately localize, classify, and detect dental caries with high consistency and reliability.

The findings are consistent with previous studies reporting strong and reliable YOLO-based performance in medical and dental imaging applications [34]–[37]. This study focused on developing and validating a single optimized YOLOv11 model to evaluate its technical feasibility and diagnostic potential rather than performing comparative statistical testing. Therefore, statistical variance measures such as confidence intervals or standard deviations were not applied. In addition, specificity is less relevant in object detection frameworks like YOLO, which emphasize localization accuracy rather than binary classification outcomes. Quantitative error analysis was not performed since the individual prediction logs were not stored during training; however, qualitative visual inspection of misclassified samples provided valuable insights into common error patterns and areas for future model refinement.

Table 2. The value of precision, recall, and accuracy obtained

Model type	Checkpoint	mAP	Precision	Recall
YOLOv11 instance segmentation (accurate)	COCOs-seg	96.1%	95.5%	93.0%

3.2. Performance test

Model testing was conducted to evaluate the actual performance of the test dataset. The test results show that the model achieved an overall mAP of 96.1%, which reflects a good ability to detect and classify dental caries with high accuracy on a dataset that has never been seen before. With a precision of 95.5%, the model demonstrated an excellent level of accuracy in detecting caries, while a recall of 93% demonstrated the model's ability to capture as many caries as possible without missing too many relevant instances Table 3. With these results, the model is proven ready to be used for a better IoT-based dental caries detection system based on the caries classification generated by the AI model.

Table 3. Precision average each class (mAP50)

Average precision by class mAP50	Validation set	Test set
Class I	98	99
Class II	97	98
Class III	94	95
Class IV	97	96
Class V	95	98
Normal	95	96

3.3. Visual test

The automatic detection and localization of dental caries were conducted based on the predefined classification scheme, as illustrated in Figure 4. The YOLOv11 model successfully identifies and segments carious lesions with high accuracy. Each labelled region (a-e) corresponds to caries categories from Class I to Class V, as determined by standard clinical classification. The model demonstrates strong capability in distinguishing caries type across various tooth surfaces and, notably, can detect more than one caries class within a single tooth through separate bounding boxes. This finding highlights the model's robustness in recognising distinct lesion patterns that differ in depth and severity within the same tooth structure.

A few instances of misdetection were observed in regions affected by saliva reflection, food debris, or discolouration, which may visually resemble carious areas. Nevertheless, the overall segmentation results indicate that YOLOv11 can accurately localise, classify, and delineate caries lesions under realistic intraoral imaging conditions, supporting its potential for clinical diagnostic assistance.

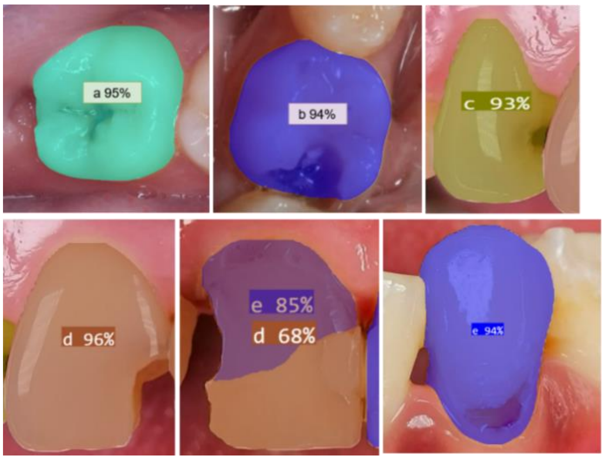


Figure 4. Detection and segmentation of dental caries using the YOLOv11 model

3.4. RGB-based validation and cost estimation integration

To validate the detection model, a quantitative analysis was conducted using the mean pixel intensity (RGB Mean) from carious and non-carious regions. The analysis demonstrated that healthy teeth generally exhibited higher average pixel values (±184.31) compared to carious teeth (±153.44), indicating greater light reflection due to intact enamel surfaces. Conversely, carious lesions appeared darker and less uniform, reflecting enamel demineralization and tissue loss. RGB intensity values were further analyzed across severity levels (mild, moderate, severe), with lighter areas corresponding to milder lesions and darker areas indicating more extensive damage. Standard deviation values supported intra-class variation, particularly within moderate and severe categories.

This RGB-based approach was selected because pixel-intensity variations demonstrate a direct correlation with both the degree of enamel demineralization and the surface area of the lesion, allowing for an objective quantification of caries severity. This severity index was then integrated with treatment cost estimation. Detected caries were automatically classified I-V, with severity determined based on the proportion of affected surface area relative to healthy enamel. A smaller ratio represents more extensive demineralization, indicating higher severity Table 4.

Treatment cost estimation was derived by mapping each class and severity level to a modified cost range based on average restorative treatment tariffs in Denpasar, Indonesia, adapted from the "*Persatuan Dokter Gigi Indonesia* (PDGI)" standards. This integration demonstrates the model's potential to provide not only accurate early diagnosis but also predictive treatment cost estimation, thereby enhancing clinical decision support and promoting more transparent, patient-centred dental care.

Validation using 100 images excluded from the training process showed consistently high confidence levels (>90%). These findings confirm that the system can accurately detect and classify carious lesions even on previously unseen data, demonstrating the model's stability and reliability under internal testing conditions.

Table 4. Dental treatment cost estimate based on caries severity

Caries class	Caries severity	Affected area (%)	Estimated treatment cost (IDR)
I	Mild	(86-99)%	300.000 - 350.000
II		(90-82)%	350.000 – 400.000
III		(95-80)%	400.000 – 450.000
IV		(99-76)%	400.000 – 450.000
V		(89-76)%	450.000 – 500.000
I	Moderate	(85-76)%	350.000 – 400.000
II		(81-69)%	400.000 – 450.000
III		(79-68)%	450.000 – 500.000
IV		(75-62)%	500.000 – 550.000
V		(75-63)%	500.000 – 550.000
I	Severe	≤75%	450.000 – 500.000
II		≤68%	500.000 – 550.000
III		≤67%	500.000 – 550.000
IV		≤61%	600.000 – 650.000
V		≤61%	600.000 – 650.000
I	Severe with symptoms	≤75%	500.000 – 2.500.000
II		≤68%	550.000 – 2.500.000
III		≤67%	550.000 – 1.500.000
IV		≤61%	650.000 – 1.500.000
V		≤61%	650.000 – 1.500.000

3.5. Ethical and regulatory considerations

This study obtained ethical approval and was submitted to the Ethics Committee of the Faculty of Dentistry, University of Jember, under approval No.3036/ un25.8/ KEPK/DL/2025. All participants or their legal guardians provided written informed consent before image collection. All patient images were securely stored on encrypted, password-protected servers, and fully anonymized to remove any identifiable information and stored on secure, password-protected servers to ensure privacy and compliance with applicable health data regulations. The research followed the principles of the Declaration of Helsinki and adhered to Indonesian health-research guidelines. Although this investigation was conducted in a controlled research setting, future implementation of the AI-based caries detection system in routine dental practice will require continued oversight, compliance with national health authority regulations, and transparent patient communication to maintain safety, privacy, and public trust.

4. CONCLUSION

This study demonstrates that the YOLOv11-based deep learning model can accurately detect and classify dental caries from smartphone images while also estimating potential treatment costs through RGB-based pixel intensity mapping. The model achieved a mAP of 96.1%, supporting its potential as an accessible and low-cost tool for early caries detection and clinical decision support in dentistry.

Compared with models reported in previous studies, such as convolutional neural network (CNN) - and YOLOv5-based frameworks, YOLOv11 achieved higher detection accuracy and faster inference speed, as documented in recent literature. These advantages reinforce the suitability of YOLOv11 for real-time mobile and point-of-care dental screening applications. The key contribution of this work lies in integrating a state-of-the-art object detection model (YOLOv11) with an RGB-based cost estimation approach, providing both diagnostic and economic insight from a single image-processing pipeline.

However, several limitations should be acknowledged. The dataset was collected exclusively from dental clinics in Denpasar, which may limit generalizability to other populations. All images were captured using smartphone cameras, potentially introducing bias due to lighting and device variability. Moreover, real-world clinical validation has not yet been conducted to assess usability in daily practice.

Future work will involve multi-centre data collection, inclusion of larger and more diverse datasets, and prospective validation in clinical environments. Additionally, expanding the cost estimation model to include region-specific tariffs and economic variables will further enhance generalizability and practical utility.

ACKNOWLEDGMENTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING INFORMATION

The authors state no funding is involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Salsabila Qotrunnada	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Bayu Taruna Widjaja Putra	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓		✓
Mei Syafriadi	✓	✓		✓			✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

[1] L. R. Costa *et al.*, "Socio-economic status, psychosocial factors, health behaviours and incidence of dental caries in 12-year-old children living in deprived communities in Manaus, Brazil," *Journal of Dentistry*, vol. 133, Jun. 2023, doi: 10.1016/j.jdent.2023.104504.

[2] Z. Li, C. Yu, and H. Chen, "Global, regional, and national caries of permanent teeth incidence, prevalence, and disability-adjusted life years, 1990-2021: analysis for the global burden of disease study," *BMC Oral Health*, vol. 25, no. 1, May 2025, doi: 10.1186/s12903-025-06086-z.

[3] X. Li *et al.*, "Global burden of dental caries from 1990 to 2021 and future projections," *International Dental Journal*, vol. 75, no. 5, Oct. 2025, doi: 10.1016/j.identj.2025.100904.

[4] J. C.-L. Lui, W. Y.-H. Lam, C.-H. Chu, and O. Y. Yu, "Global Research Trends in the Detection and Diagnosis of Dental Caries: A Bibliometric Analysis," *International Dental Journal*, vol. 75, no. 2, pp. 405–414, Apr. 2025, doi: 10.1016/j.identj.2024.08.010.

[5] T. Kries, S. Rupf, M. Hannig, J. Naim, and M. P. Gund, "The impact of general medical health status, demographical, and patient-specific variables on need for dental treatment of children and adolescents under general anesthesia," *Clinical Oral Investigations*, vol. 27, no. 8, pp. 4245–4257, May 2023, doi: 10.1007/s00784-023-05041-y.

[6] N.-H. Kim, H. W. Elani, and I. Kawachi, "Did dental insurance expansion improve dental care needs among Korean adults? difference in difference analysis," *Journal of Epidemiology*, vol. 33, no. 2, Feb. 2023, doi: 10.2188/jea.JE20200596.

[7] S. Yaddanapalli, S. Parveen Sultana, A. Lodagala, P. Babu, S. Ravoori, and S. Pachava, "Oral healthcare-seeking behavior and perception of oral health and general healthcare among WHO indexed age groups in East-Coast India," *Journal of Family Medicine and Primary Care*, vol. 9, no. 7, 2020, doi: 10.4103/jfmpc.jfmpc_350_20.

[8] I. R. Santana, A. Mason, N. Gutacker, P. Kasteridis, R. Santos, and N. Rice, "Need, demand, supply in health care: working definitions, and their implications for defining access," *Health Economics, Policy and Law*, vol. 18, no. 1, pp. 1–13, Jan. 2023, doi: 10.1017/S1744133121000293.

[9] P. R. E.d. Melo, M. A. Monteiro, N. V. d. A. Lopes, and J. L. S. Cunha, "In response to the reply on 'Advancing oral cancer diagnosis in Brazil: Integrating artificial intelligence with teledentistry for enhanced patient outcomes'," *Oral Oncology*, vol. 154, Jul. 2024, doi: 10.1016/j.oraloncology.2024.106856.

[10] E. Kayalar and B. Küçükkurt, "Applications and effectiveness of teledentistry in orthodontic practice during the COVID-19 restrictions," *Journal of the World Federation of Orthodontists*, vol. 12, no. 3, pp. 118–124, Jun. 2023, doi: 10.1016/j.ejwf.2023.04.002.

[11] N. M. Aly, M. K. El Kashlan, N. Giraudeau, and M. El Tantawi, "Comparison of intraoral cameras and smartphones in early childhood caries detection: A diagnostic accuracy study," *Journal of Evidence-Based Dental Practice*, vol. 24, no. 4, Dec. 2024, doi: 10.1016/j.jebdp.2024.102041.

[12] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. Upper Saddle River, NJ, USA: Pearson Education, Inc., 2010.

[13] A. Zahlan, R. P. Ranjan, and D. Hayes, "Artificial intelligence innovation in healthcare: Literature review, exploratory analysis, and future research," *Technology in Society*, vol. 74, Aug. 2023, doi: 10.1016/j.techsoc.2023.102321.

[14] A. A. Nancy, D. Ravindran, P. M. D. Raj Vincent, K. Srinivasan, and D. Gutierrez Reina, "IoT-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning," *Electronics*, vol. 11, no. 15, Jul. 2022, doi: 10.3390/electronics11152292.

[15] P. Arun, N. Prajith, C. Melvin, S. N. Sreejith, and S. Sandesh, "Design and development of an IoT based intelligent multi parameter screening system," *Materials Today: Proceedings*, vol. 58, pp. 7–12, 2022, doi: 10.1016/j.matpr.2021.12.071.

[16] M. Zhou *et al.*, "Deep learning algorithms for classification and detection of recurrent aphthous ulcerations using oral clinical photographic images," *Journal of Dental Sciences*, vol. 19, no. 1, pp. 254–260, Jan. 2024, doi: 10.1016/j.jds.2023.04.022.

[17] A. F. Makarim, T. Karlita, R. Sigit, B. S. Bayu Dewantara, and A. Brahmanta, "Deep learning models for dental conditions classification using intraoral images," *JOIV : International Journal on Informatics Visualization*, vol. 8, no. 3, Sep. 2024, doi: 10.62527/joiv.8.3.1914.

[18] R. A. Welikala *et al.*, "Automated detection and classification of oral lesions using deep learning for early detection of oral cancer," *IEEE Access*, vol. 8, pp. 132677–132693, 2020, doi: 10.1109/ACCESS.2020.3010180.

[19] R. Esmaeilyfard, H. Bonyadifard, and M. Paknahad, "Dental caries detection and classification in CBCT images using deep learning," *International Dental Journal*, vol. 74, no. 2, pp. 328–334, Apr. 2024, doi: 10.1016/j.identj.2023.10.003.

[20] K. Tong, Y. Wu, and F. Zhou, "Recent advances in small object detection based on deep learning: A review," *Image and Vision Computing*, vol. 97, May 2020, doi: 10.1016/j.imavis.2020.103910.

[21] T. Islam, M. S. Hafiz, J. R. Jim, M. M. Kabir, and M. F. Mridha, "A systematic review of deep learning data augmentation in medical imaging: Recent advances and future research directions," *Healthcare Analytics*, vol. 5, Jun. 2024, doi: 10.1016/j.health.2024.100340.

[22] S. K. Manoharan, R. K. Megalingam, G. A, G. Jogesh, A. K, and A. R. Kunnambath, "AI based early identification and severity detection of nutrient deficiencies in coconut trees," *Smart Agricultural Technology*, vol. 9, p. 00575, Dec. 2024, doi: 10.1016/j.atech.2024.100575.

[23] D. Macri and A. Chitlall, "Caries classification," *Dimensions*, 2017. [Online.] Available: https://dimensionsofdentalhygiene.com/article/caries-classification/

[24] M. L. Ali and Z. Zhang, "The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection." Oct. 23, 2024. doi: 10.20944/preprints202410.1785.v1.

[25] R. Sapkota, Z. Meng, and M. Karkee, "Synthetic meets authentic: Leveraging LLM generated datasets for YOLO11 and YOLOv10-based apple detection through machine vision sensors," *Smart Agricultural Technology*, vol. 9, Dec. 2024, doi: 10.1016/j.atech.2024.100614.

[26] R. Sapkota, Z. Meng, M. Churuvija, X. Du, Z. Ma, and M. Karkee, "Comprehensive performance evaluation of YOLO11, YOLOv10, YOLOv9 and YOLOv8 on detecting and counting fruitlet in complex orchard environments." *Institute of Electrical and Electronics Engineers (IEEE)*, Oct. 21, 2024. doi: 10.36227/techrxiv.172954111.18265256/v1.

[27] G. Vimalarani and U. Ramachandraiah, "Automatic diagnosis and detection of dental caries in bitewing radiographs using pervasive deep gradient based LeNet classifier model," *Microprocessors and Microsystems*, vol. 94, Oct. 2022, doi: 10.1016/j.micpro.2022.104654.

[28] R. D. Paravina, P. Cevik, J. C. Ontiveros, and W. M. Johnston, "Translucency of enamel and dentin: A biomimetic target for esthetic dental materials," *Journal of Esthetic and Restorative Dentistry*, vol. 37, no. 4, pp. 1127–1134, Apr. 2025, doi: 10.1111/jerd.13382.

[29] T. Zirek, M. Ü. Öziç, and M. Tassoker, "AI-Driven localization of all impacted teeth and prediction of winter angulation for third molars on panoramic radiographs: Clinical user interface design," *Computers in Biology and Medicine*, vol. 178, Aug. 2024, doi: 10.1016/j.compbiomed.2024.108755.

[30] X. Zhang, T. Lu, J. Wang, S. Fu, and F. Gao, "Small object detection by Edge-aware Neural Network," *Engineering Applications of Artificial Intelligence*, vol. 138, Dec. 2024, doi: 10.1016/j.engappai.2024.109406.

[31] A. Awad and S. A. Aly, "Early diagnosis of acute Lymphoblastic Leukemia using YOLOv8 and YOLOv11 deep learning models," *Prepr. arXiv.2410.10701*, Jan. 2025. [Online]. Available: http://arxiv.org/abs/2410.10701

[32] S. Ying, F. Huang, X. Shen, W. Liu, and F. He, "Performance comparison of multifarious deep networks on caries detection with tooth X-ray images," *Journal of Dentistry*, vol. 144, May 2024, doi: 10.1016/j.jdent.2024.104970.

[33] R. C. Radha, B. S. Raghavendra, B. V. Subhash, J. Rajan, and A. V. Narasimhadhan, "Machine learning techniques for periodontitis and dental caries detection: A narrative review," *International Journal of Medical Informatics*, vol. 178, Oct. 2023, doi: 10.1016/j.ijmedinf.2023.105170.

[34] M. Estai *et al.*, "Evaluation of a deep learning system for automatic detection of proximal surface dental caries on bitewing radiographs," *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, vol. 134, no. 2, pp. 262–270, Aug. 2022, doi: 10.1016/j.oooo.2022.03.008.

[35] H. M.-Rahimi *et al.*, "Deep learning for caries detection: A systematic review," *Journal of Dentistry*, vol. 122, Jul. 2022, doi: 10.1016/j.jdent.2022.104115.

[36] F. A. Umer, M. F. Ahmed, S. Aijaz, and N. Adnan, "Deep learning model for caries detection: A validation study," *International Dental Journal*, vol. 74, Oct. 2024, doi: 10.1016/j.identj.2024.07.914.

[37] E. T. Chaves *et al.*, "Detection of caries around restorations on bitewings using deep learning," *Journal of Dentistry*, vol. 143, Apr. 2024, doi: 10.1016/j.jdent.2024.104886.

BIOGRAPHIES OF AUTHORS

Salsabila Qotrunnada is a graduate student at Jember University. She completed her undergraduate studies in Dentistry at the University of Jember in 2020, followed by her professional education, and graduated as a dentist in 2022. She has demonstrated a strong dedication to advancing her expertise in healthcare management and public health. Currently, she is pursuing a Master's degree in Public Health at Jember University Postgraduate Program, specializing in health service management. With her commitment to continuous learning and professional growth, she aims to bridge clinical practice the effective healthcare management and technology, contributing to the development of innovative solutions for improving health services. She can be contacted at email: sasanada9@gmail.com.

Bayu Taruna Widjaja Putra Professor in Precision Agriculture at the Faculty of Agricultural Technology, Jember University, Indonesia. He completed his undergraduate degree in the Agricultural Engineering Study Program at Jember University, and later earned his Master of Engineering (M.Eng) and Doctor of Philosophy (Ph.D.) degree from Asian Institute of Technology (AIT), Thailand in 2013 and 2017, respectively. Since 2017 he was entrusted with becoming the Information Technology Division of the Indonesian Society of Agricultural Engineering (PERTETA). In 2022, he was appointed as a Country representative of International Society of Precision Agriculture (ISPAG). He also a member of several Professional Affiliations, namely The Institute of Electrical and Electronics Engineers (IEEE), the International Society for Photogrammetry and Remote Sensing (ISPRS). His managerial experiences in Higher Education Institution are including the Head of Laboratory of Precision Agriculture and Geoinformatics, and since 2020, he has appointed as Head of the Technical Service Unit of Information and Communication Technology, University of Jember. He works on the application of precision agriculture technologies such as remote sensing, GIS, artificial neural networks, machine learning, computer vision, and deep learning on commercial farms. He can be contacted at email: bayu@unej.ac.id.

Mei Syafriadi is a professor and researcher in Oral Pathology at the University of Jember, Indonesia. He obtained his Doctoral degree in Oral Pathology and has published extensively in national and international journals, particularly on precancerous lesion transformation through p53 expression. In recent years, his research has increasingly integrated information technology, focusing on the application of artificial intelligence (AI), computer vision, and machine learning for medical image analysis, especially in detecting oral lesions and supporting the development of digital health systems. Beyond cancer research, he is actively involved in public health studies, including adherence analysis of antiretroviral therapy among people living with HIV in Situbondo. With his wide-ranging academic contributions and dedication to education, he plays a key role in advancing oral pathology, public health, and the implementation of intelligent technologies in dental medicine. He can be contacted at email: didiriadihsb.fkg@unej.ac.id.