A Mobile Application for the Detection of Pre-Carious Lesions in Peruvian Patients based on YOLOv7

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ABSTRACT

Dental cavities represent a significant global health challenge, particularly in low- and middle-income countries, where early detection and diagnosis can substantially improve clinical outcomes. This study presents the development of a mobile application that utilizes YOLOv7 to detect early carious lesions on intraoral images, intending to provide dental professionals with a tool for timely diagnosis and intervention. The research was carried out in three key phases: analysis of YOLOv7, system development, and validation. The application was trained in a real clinical environment in Peru in collaboration with two independent dentists and their patients in two private clinics. Intraoral images were collected and processed from 40 participants, ensuring complete adherence to the ethical and privacy standards required for clinical studies. The experimental results demonstrated that the application achieved an average accuracy of 94%, with both accuracy and Positive Predictive Value (PPV) exceeding 90% in most cases. The results demonstrated consistent diagnostic accuracy and efficiency, validating the application's performance. Patient surveys reflected high satisfaction, with average scores of 4.4 for usability, 4.2 for efficiency, and 4.6 for functionality. Similarly, dentists rated the usability, functionality, and efficiency of the application with average scores of 4.5. These findings highlight the potential of the application to improve clinical workflows and accuracy in detecting early carious lesions.

Keywords- YOLOv7; pre-carious lesions; dental diagnosis; mobile application; intraoral images

I. INTRODUCTION

A recent study published by the World Health Organization highlighted the growing and alarming issue of dental cavities in the global population, particularly in low- and middle-income countries. This situation is especially concerning due to the multiple complications that can arise if not addressed in time, such as tooth loss, oral infections, and, in extreme cases, systemic diseases. Moreover, poor dental health has a direct and negative impact on overall quality of life and general well-being [1]. In this context, in [2], the knowledge and attitudes of parents about oral health during the primary dentition stage were highlighted. The results revealed that a high percentage of children suffer from dental problems due to a lack of access to quality dental services, exacerbating the public health situation. In [3], policies on fluoride use and sugar consumption reduction in Latin America and the Caribbean were evaluated, identifying significant differences in the implementation and effectiveness of these policies among countries.

Many approaches have been proposed for the detection and classification of dental pathologies using artificial intelligence techniques. Notable among these approaches are models such as YOLOv7 [4] and AI-Dentify [5]. These models have been designed with various objectives, such as detecting specific pathologies in dental radiographs, improving the classification of dental cavities, detecting proximal cavities in bitewing radiographs, simultaneously detecting dental cavities and fissure sealants in intraoral images, comparing the performance of various deep neural network architectures, and detecting secondary cavities around restorations. Previous studies have employed different datasets, including periapical X-ray images [6], bitewing radiographs [7], intraoral photographs [8], and more recently, dental X-ray images and panoramic radiographs [9], for various purposes. Although most of these studies have utilized their own images, there is notable variability in the accuracy and effectiveness of each proposed technique.

Regarding specific research on the detection of pathologies in dental radiographs, YOLOv7 [10] has been used to detect periodontitis and dental cavities on 1,525 periapical X-ray images, achieving an accuracy of 94.94%. AI-Dentify [5] also focused on the detection of proximal cavities on bitewing radiographs, using a dataset of 13,887 images and reaching an accuracy of 92%. The simultaneous detection model in [8] explored the ability to simultaneously detect dental cavities and fissure sealants in 5,000 intraoral images, achieving an accuracy of 89%. The accuracy of the models varies considerably depending on the type of image and the technique employed. For instance, a performance comparison on 8,000 dental X-rays reported an accuracy of 94.00% [12]. For the detection of secondary cavities, another study used 7,500 bitewing radiographs, achieving an accuracy of 91.00% [13]. An AI-assisted diagnosis [14] on 6,000 periapical radiographs showed an accuracy of 88.00%, while an application for dental students [15] on 3,000 dental radiographs achieved an accuracy of 87.00%. In [16], the effectiveness of Mask RCNN combined with ResNET101 FPN was demonstrated, achieving an accuracy of 88.48% for bounding boxes and 76.42% for segmentation, further underscoring the importance of pixel-level precision in dental diagnostics. More recent studies, such as [17], have further reinforced the importance of pixel-level precision by achieving 98.4% accuracy in tooth detection and a dice coefficient of 0.87 in segmentation tasks. These efforts highlight the importance of meticulously segmenting areas of interest and combining advanced strategies to improve the quality of dental diagnosis.

This study proposes a mobile application based on YOLOv7 for the early and accurate detection of pre-carious lesions. The main objective is to provide dentists with an effective tool for accurate diagnosis and timely interventions.

II. MATERIALS AND METHODS

This section presents the development of the mobile application for early detection of pre-carious lesions based on YOLOv7. The first stage of the study was described in [18].

A. *Analysis of YOLOv7*

The Tooth Cavities Detection dataset contains 9,327 intraoral images labeled into three dental categories: teeth with amalgam, healthy teeth, and teeth with cavities, as described in Table I. This dataset, labeled by dentists, is available in [19]. To ensure a comprehensive and unbiased evaluation of the YOLOv7 model, the dataset was divided into 69% (6,559 images) for training, 22% (1,845 images) for validation, and 9% (923 images) for testing. This stratification ensures a proportional representation of each dental category across all subsets, maintaining dataset integrity and preventing overfitting. Figure 1 shows examples of each category.

TABLE I. DENTAL CONDITION CLASSES [19]

Id	Class	Quantity
0	Teeth with amalgam	2,918
1	Teeth with cavities	3,373
2	Healthy Teeth	3,036

(a) (b) (c)

Fig. 1. Types of images in the dataset: (a) teeth with amalgam, (b) healthy teeth, and (c) teeth with cavities.

The performance of the YOLOv7 model was evaluated using various metrics that measure the model's effectiveness:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1 - score = \frac{2 \cdot Precision \cdot Recall}{Precision+Recall} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

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

where TP denotes the number of cases correctly identified as teeth with cavities, TN denotes the number of cases correctly identified as healthy teeth or teeth with amalgam (if they do not have cavities), FP denotes the number of cases incorrectly identified as teeth with cavities, FN denotes the number of cases incorrectly identified as healthy teeth or teeth with amalgam (if they have cavities), and mAP is the mean average precision across different classes or thresholds.

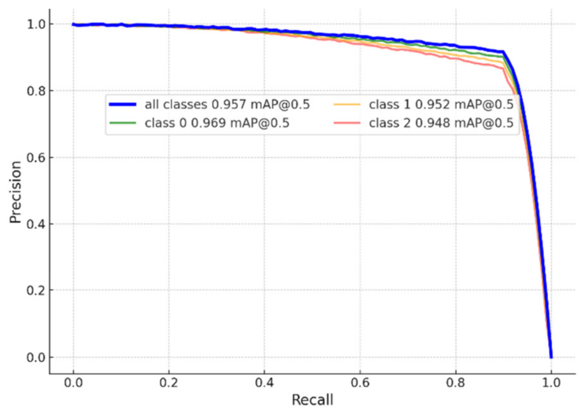


Fig. 2. *Precision-Recall* curve of YOLOv7.

The results of implementing the YOLOv7 model for detecting dental health states were notably positive. The analysis of the PR curve (Figure 2) shows consistent performance across all categories, achieving an mAP of 0.957 with a threshold of 0.5. Specifically, the class of teeth with cavities obtained an AUC of 0.969. The ROC curve (Figure 3) indicates a mean accuracy of 0.91 with a confidence level of 0.351 for all combined classes. The confusion matrix (Figure 4) provides a detailed view of the model's performance.

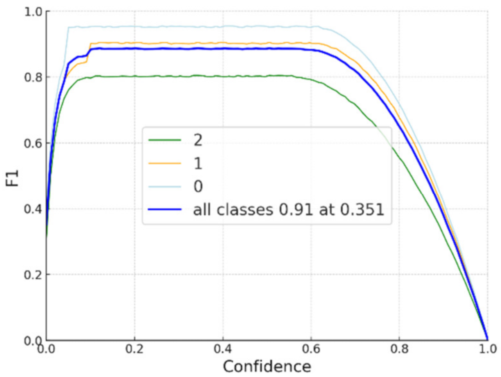


Fig. 3. ROC curve of YOLOv7.

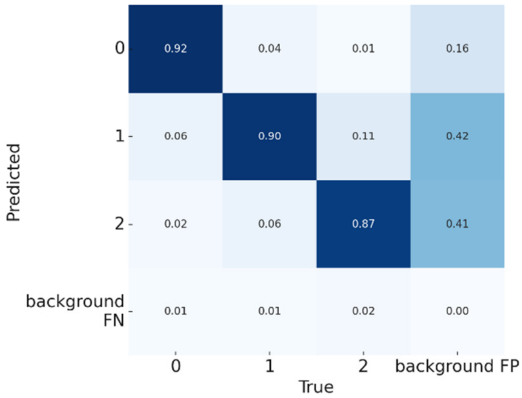


Fig. 4. Confusion matrix of YOLOv7.

B. Construction of the Application

1) System Architecture Design

The YOLOv7 model was used for the development of the mobile application, which performed the best in [18]. This algorithm was selected for its ability to process images with high accuracy, enabling early and precise identification of carious lesions.

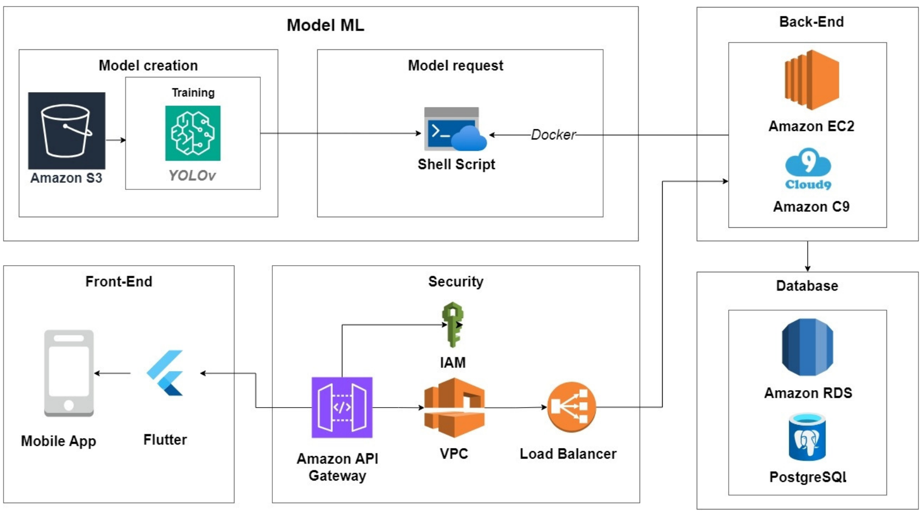


Fig. 5. Application architecture.

The initial step in the architecture of the mobile application (Figure 5) involves creating a machine-learning model capable of predicting the presence of anomalies (cavities) in the user's oral cavity. To achieve this, a training dataset was collected containing examples that the model used to learn to make accurate predictions. YOLOv7 was selected for its high precision in object detection, and the training data was stored on Amazon S3, providing a secure and scalable repository. The training process was carried out in a specialized machine-learning environment, where YOLOv7 was trained to recognize specific patterns associated with carious lesions. Once the model was trained, it was deployed to be accessible through an endpoint managed by a shell script hosted in a Docker container running on Amazon Cloud9. This approach ensures efficient integration and management of the development and execution environment, with inference requests handled by the container communicating with the trained model to process images submitted by users.

The system backend was hosted on an Amazon EC2 instance, which facilitates application deployment and resource management by hosting the development and execution environment. Furthermore, Amazon Cloud9 provides an Integrated Development Environment (IDE) that supports efficient coding, debugging, and execution. For database management, the system uses Amazon RDS (Relational Database Service) with PostgreSQL. Amazon RDS allows for easy configuration, operation, and scalability, while PostgreSQL securely stores image data and inference results. The connection between the backend and the database is established by configuring the EC2 and RDS instances appropriately, ensuring secure and efficient communication.

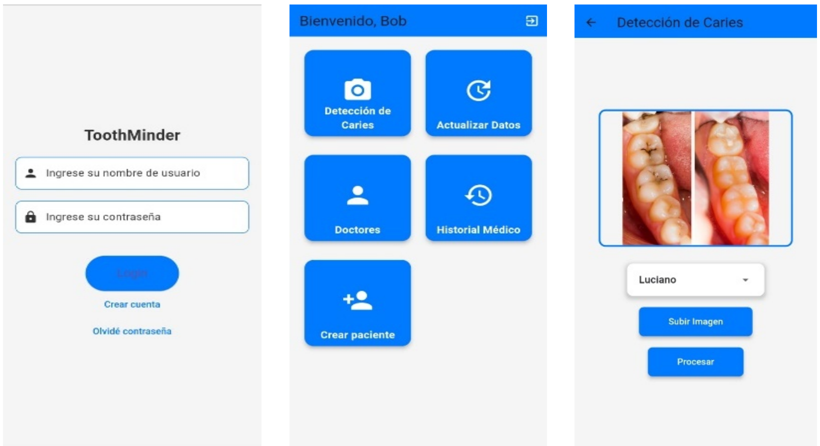
In the front end, the system was developed in Flutter, offering a user-friendly and accessible interface for mobile devices. This mobile application enables users to upload images and receive detection results intuitively and quickly. Flutter facilitates the development of native applications for both Android and iOS from a single codebase, ensuring a consistent and high-quality user experience.

To ensure security, the system incorporates multiple layers of protection. First, Amazon Cognito manages user authentication and authorization, ensuring that only registered and authorized users can access the system. Additionally, a firewall and Amazon API Gateway provide an extra layer of security, protecting communications and access to backend services. The use of VPC (Virtual Private Cloud) further ensures that AWS resources remain isolated and secure. To enhance reliability, the load balancer distributes requests among server instances, ensuring high availability and system reliability. Lastly, AWS Identity and Access Management (IAM) manages permissions and roles, ensuring that only authorized users and services can access critical system resources.

By integrating these components, the architecture of the mobile application ensures robust performance, security, and a seamless user experience, making it a powerful tool for the early detection of carious lesions.

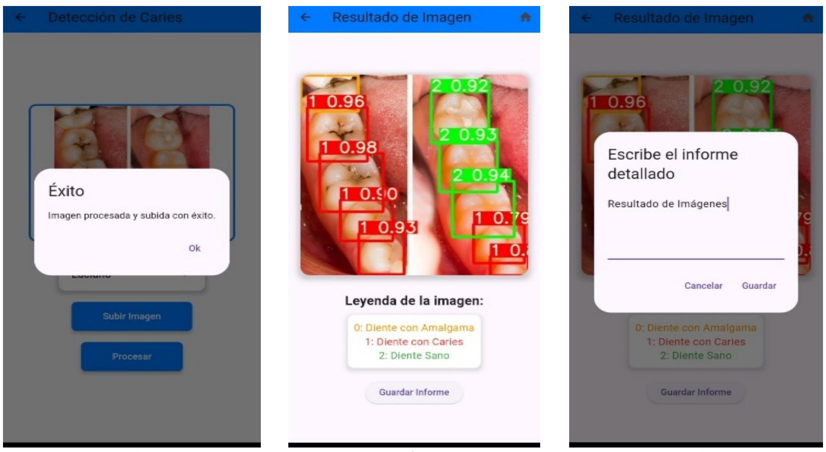
2) Definition of Functionalities

The mobile application has the following functionalities: User login, Main menu, Cavities detection, Patient data registration and update, Doctor consultation, new patient registration, user data update, consultation of available doctors, viewing patient medical history, sending processed image reports to doctors, and receiving notifications of processed images by email.



(a) (b) (c)

Fig. 6. Main application interfaces: (a) User login, (b) Main menu, (c) Cavity detection.



(a) (b) (c)

Fig. 7. Cavity detection function interfaces: (a) Successful image processing confirmation, (b) detection results with image legend, (c) writing a detailed report on the results.

Figure 6 shows the main interfaces of the mobile application: User login (a), Main menu (b), and Cavities detection (c). Figure 7 shows the interfaces of the Cavities detection function: Successful image processing confirmation (a), Detection results with image legend (b), and writing a detailed report on the results (c).

C. Validation

1) Experimentation

For system validation, an exhaustive experiment was designed in a real clinical environment. The validation included two main experimental phases, conducted with the collaboration of independent dentists and their respective patients at two private clinics in Lima, Peru (Table II). Each clinic included 20 patients, totaling 40 participants in the experiment. These phases were crucial for evaluating the accuracy and effectiveness of the application in diagnosing pre-carious lesions. Informed consent was obtained from all participating patients for the use of their images and data in the research, ensuring compliance with the ethical and privacy standards required for clinical studies.

TABLE II. DETAILS OF THE EXPERIMENTS

Groups	Participants	Data type
Experiment 1: Dentist Diagnosis		
Group 1	20 patients, 1 dentist	Intraoral photos
Group 2	20 patients, 1 dentist	Intraoral photos
Experiment 2: Diagnosis with the Application		
Group 1	20 patients, 1 dentist	Intraoral photos
Group 2	20 patients, 1 dentist	Intraoral photos

In addition to the clinical experimentation, surveys were administered to both patients and dentists to assess their perceptions regarding the application's usefulness and effectiveness. These surveys were designed to gather both qualitative and quantitative data, categorized according to the quality characteristics outlined in the ISO/IEC 25010 standard. Table III presents the data collected from dentists, evaluating the application's usability, efficiency, and functionality based on their hands-on experience with the pre-carious lesion detection process. Similarly, Table IV presents the patients' perspectives, focusing on their interaction and satisfaction with the application.

TABLE III. QUALITY EVALUATION OF THE APPLICATION BY DENTISTS

#	Question	Attribute
Q1	How easy was it for you to use the application to detect pre-carious lesions?	Usability
Q2	How intuitive and easy to navigate did you find the application?	
Q3	How fast and efficient do you consider the pre-carious lesion detection process?	Efficiency
Q4	Do you think the application allowed you to detect pre-carious lesions more efficiently than traditional methods?	
Q5	How accurate and reliable do you consider the pre-carious lesion detection performed by the application?	Functionality

TABLE IV. QUALITY EVALUATION OF THE APPLICATION BY PATIENTS

#	Question	Attribute
Q1	How easy is it to learn to use the application to detect pre-carious lesions?	Usability
Q2	How intuitive and easy to navigate do you find the application's user interface?	
Q3	Based on your experience, how accurate do you find the application's detection of pre-carious lesions?	Functionality
Q4	How would you rate the application's processing speed for detections?	Efficiency
Q5	How much does the application contribute to improving the efficiency of your daily workflow?	

2) Metrics

The following metrics were used in the research to obtain the expected validation:

$$NPV = \frac{TN}{\mathrm{TN+FN}} \quad (6)$$

$$PPV = \frac{\mathrm{TP}}{TP+FP} \quad (7)$$

Negative Predictive Value (*NPV*) indicates the proportion of identified negative cases that were truly negative (without cavities). Positive Predictive Value (*PPV*) is the proportion of identified positive cases that were correctly identified as positive (with cavities). Assisted Diagnosis Time (*DT*) is a measurement of the speed and efficiency of the diagnosis performed with the help of the application compared to manual methods.

III. RESULTS AND DISCUSSION

A. Experiment 1: Dentist Diagnosis

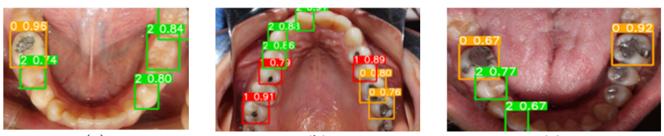
As part of the validation process, dentists conducted evaluations on a total of 20 patients each, diagnosing multiple conditions within each patient's teeth. Table V presents a summary of the diagnoses, including healthy teeth, amalgam fillings, and cavities, as well as the average time required for each evaluation. This table provides a detailed analysis of the application's clinical performance, highlighting its precision and efficiency in supporting dentists with accurate diagnoses.

B. Experiment 2: Diagnosis with the Application

In this experimental phase, the application was used to diagnose cavities in patients, and its results were compared with the manual diagnoses made by dentists. The process involved several steps. First, 40 patients were selected, with 20 in each of the two private clinics located in Lima, Peru. Intraoral photos of each patient's teeth were taken using high-end smartphones. Then, the dentists logged into the application using their credentials. Once inside, they created profiles for the patients in the system, recording their basic information. From the main menu, the dentists selected the Caries Detection option and uploaded the patients' intraoral images for analysis. The system processed the images and displayed success confirmation for each processed image. The detection results were displayed with a legend indicating the condition of the teeth, including detected cavities and healthy areas. Figure 8 shows examples of these detection results, illustrating the predictions for patients 16, 5, and 19. These images highlight the application's ability to identify specific carious lesions and categorize them with varying confidence levels, demonstrating their effectiveness in real-world scenarios. Finally, the dentists wrote detailed reports on the results obtained, describing observations and recommendations for each patient. Table VI presents the diagnosis metrics for Dentist 1, detailing accuracy, VPN, VPP, and the average time required per diagnosis for each patient.

TABLE V. DIAGNOSIS METRICS OF THE APPLICATION BY DENTISTS

Dentist experiment 1			Dentist experiment 2		
Patient	**Diagnosis**	**DT (m)**	**Patient**	**Diagnosis**	**DT (m)**
1	Healthy: 8, Amalgam: 8	15.36	1	Healthy: 10, Amalgam: 6	11.77
2	Healthy: 10, Cavities: 6	15.18	2	Healthy: 11, Cavities: 5	12.46
3	Healthy: 12, Amalgam: 4	14.3	3	Healthy: 9, Amalgam: 7	12.2
4	Healthy: 9, Cavities: 7	15.32	4	Cavities: 10, Healthy: 4	12.38
5	Healthy: 8, Amalgam: 6, Cavities: 2	16.22	5	Healthy: 12, Cavities: 4	12.27
6	Healthy: 14, Cavities: 2	15.42	6	Healthy: 10, Amalgam: 4	12.25
7	Cavities: 8, Amalgam: 6	14.62	7	Healthy: 8, Cavities: 8	12.06
8	Healthy: 8, Amalgam: 4, Cavities: 4	15.24	8	Healthy: 9, Amalgam: 5, Cavities: 2	12.55
9	Healthy: 12	15.89	9	Healthy: 14	11.68
10	Amalgam: 3, Healthy: 13	14.55	10	Amalgam: 14	12
11	Cavities: 9, Healthy: 5	14.95	11	Cavities: 8, Healthy: 6	11.8
12	Amalgam: 10, Healthy: 4	14.95	12	Healthy: 8, Amalgam: 8	12.45
13	Cavities: 6, Amalgam: 6, Healthy: 2	14.94	13	Cavities: 10, Amalgam: 2, Healthy: 2	12.26
14	Cavities: 10, Healthy: 4	15.68	14	Healthy: 9, Cavities: 7	11.62
15	Healthy: 9, Amalgam: 7	15.36	15	Amalgam: 8, Healthy: 6	11.75
16	Cavities: 8, Healthy: 8	16.02	16	Cavities: 10, Healthy: 4	11.95
17	Amalgam: 9, Healthy: 7	14.4	17	Amalgam: 8, Healthy: 6	12.58
18	Healthy: 12, Cavities: 4	14.95	18	Cavities: 9, Healthy: 5	12.16
19	Amalgam: 8, Cavities: 6, Healthy: 2	15.48	19	Healthy: 10, Amalgam: 4	11.66
20	Healthy: 10, Cavities: 4	15.18	20	Cavities: 8, Healthy: 8	12.22



(a) (b) (c)

Fig. 8. Application results for Dentist 1 and patients: (a) 16, (b) 5, (c) 19.

TABLE VI. DIAGNOSIS METRICS OF THE APPLICATION BY DENTIST 1

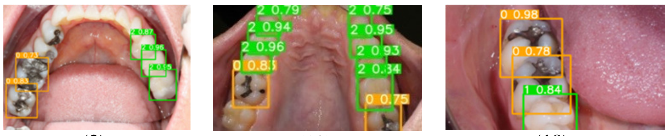
Patient	***Accuracy (%)***	***VPN (%)***	***VPP (%)***	**Average time per diagnosis (minutes)**
1	92.99	91.98	86.62	9.36
2	92.52	90.09	85.85	9.18
3	93.96	91.59	83.70	8.30
4	91.68	89.02	85.21	9.32
5	91.00	83.00	79.00	8.50
6	90.85	89.23	84.77	9.42
7	91.18	89.10	83.57	8.62
8	94.20	92.60	84.00	9.24
9	94.15	91.60	84.87	9.89
10	90.80	87.99	87.87	8.55
11	91.88	89.83	84.11	8.95
12	92.60	89.90	86.54	8.95
13	90.26	89.48	85.88	8.94
14	93.00	90.46	87.04	9.68
15	94.42	92.16	84.83	9.36
16	96.00	84.00	80.00	9.00
17	91.62	89.50	86.79	8.40
18	91.27	90.08	82.41	8.95
19	92.00	77.00	67.00	9.20
20	92.64	89.27	86.97	9.18

Additionally, the dentist noted: "The application represents an innovative tool for the early detection of cavities across patients of all age groups. Although some improvements to the user interface could enhance the overall experience, the system is intuitive and easy to navigate. Continued development and clinical validation are crucial to ensure its long-term effectiveness and reliability in everyday practice."

Similarly, the application was used by Dentist 2 to diagnose cavities, following the same steps outlined previously. Examples of detection results for patients 2, 12, and 18 are shown in Figure 9, illustrating the system's predictions with corresponding confidence levels. Table VII presents the diagnosis metrics for Dentist 2, providing a comparative view of the application's performance across different cases.

TABLE VII. DIAGNOSIS METRICS OF THE APPLICATION BY DENTIST 2

Patient	***Accuracy (%)***	***VPN (%)***	***VPP (%)***	**Average time per diagnosis (minutes)**
1	95.99	93.00	87.90	8.77
2	96.03	86.97	55.12	9.47
3	96.96	94.23	88.13	9.20
4	94.68	90.82	88.97	9.38
5	95.54	92.69	87.99	9.27
6	93.85	91.45	87.42	9.25
7	94.18	92.50	87.51	9.06
8	97.20	95.11	88.12	9.55
9	97.15	93.76	87.60	8.68
10	93.80	92.13	89.87	9.00
11	94.88	93.29	88.60	8.80
12	95.08	78.95	34.25	8.72
13	93.26	91.85	89.02	9.26
14	96.00	93.16	87.04	8.62
15	97.42	95.21	88.77	8.75
16	96.31	94.32	87.58	8.95
17	94.62	92.36	87.29	9.58
18	97.95	78.12	83.87	8.38
19	94.82	94.38	87.17	8.66
20	95.64	91.27	88.47	9.22



(2) (12) (18)

Fig. 9. Application results for Dentist 2 and patients: (a) 2, (b) 12, (c) 18.

Likewise, the second expert stated: "The application demonstrates significant potential for the early detection of cavities. However, expanding its capabilities to address more complex diagnoses, such as identifying resins or advanced cavities, would be advantageous. Continued development and clinical validation are essential to ensure its precision and applicability in diverse clinical settings."

C. Joint Analysis

In the validation experiments of the dental diagnostic application, dentists evaluated 20 patients each, diagnosing healthy teeth, amalgam fillings, and cavities, with average diagnosis times ranging from 14.3 to 16.22 minutes for the first dentist and from 11.66 to 12.58 minutes for the second. The application, evaluating the same patients, showed accuracy between 90.26% and 94.42% for the first dentist and between 93.26% and 97.42% for the second, with average diagnosis times of around 9 minutes. Experts highlighted the application's effectiveness in the early detection of cavities and suggested improvements to the user interface and expansion of its diagnostic capabilities.

D. Patient Survey

A brief survey was conducted with the patients to evaluate their experience with the application. The questions and average ratings on a Likert scale of 1 to 5 (where 1 indicates Strongly Disagree and 5 indicates Strongly Agree) are illustrated in Figure 10, showing the average evaluation of the application across different categories.

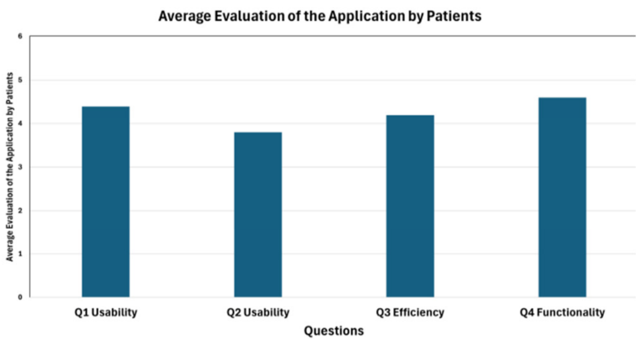


Fig. 10. Average application evaluation by patients.

The results showed that patients rated the "Usability" of the application with an average score of 4.4, indicating that they found the application easy to use and navigate. The "Efficiency" of the detection process was rated with an average score of 4.2, suggesting that patients perceived the process as fast and efficient. Finally, the "Functionality" of the application received an average score of 4.6, reflecting high accuracy and reliability in detecting pre-carious lesions. These results were discussed with patients during feedback sessions, where they reviewed the results and commented on the application's effectiveness. Despite some individual variations, the overall scores indicate a positive perception of the application's usability, efficiency, and functionality in a real clinical environment.

E. Dentist Survey

A similar survey was conducted with the dentists to evaluate their perception of using the application in their clinical practice. The questions and average ratings on a Likert scale of 1 to 5 (where 1 indicates Strongly Disagree and 5 indicates Strongly Agree) are shown in Figure 11, which summarizes the evaluation results.

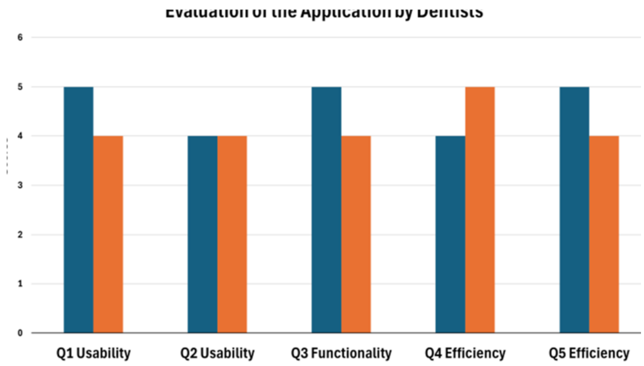


Fig. 11. Application evaluation by dentists.

The results show that dentists rated the "Usability" of the application with scores of 5 and 4 for ease of use (Q1) and interface intuitiveness (Q2). Regarding "Functionality," the accuracy of pre-carious lesion detection was rated with scores of 5 and 4 (Q3). The "Efficiency" of the application was evaluated with scores of 4 and 5 for processing speed (Q4) and with scores of 5 and 4 for its contribution to improving workflow (Q5). These results were discussed with the dentists during feedback sessions, where they reviewed the scores and commented on the application's effectiveness. Despite some individual variations, the overall scores indicate a positive perception of the application's usability, functionality, and efficiency in a real clinical environment. Dentists highlighted the application's ability to effectively integrate into their workflow and improve the detection process of pre-carious lesions.

F. Comparison with Other Studies

The comparison of the proposed YOLOv7 model with other state-of-the-art approaches for dental caries detection was evaluated using key performance metrics, including precision, recall, and F1 score for the labeled classes. As shown in Table VIII, YOLOv7 consistently outperformed the other models across all metrics and classes, achieving a precision of 94.0% for caries detection, a recall of 93.5%, and an F1 score of 93.75%. Furthermore, YOLOv7 demonstrated a superior ROC value of 91.0%, surpassing the 88.0% achieved by other models in similar studies. These performance indicators, as presented in Table VIII, highlight YOLOv7 as the most proficient model in this comparative study.

TABLE VIII. COMPARATIVE TABLE OF MODELS

Model	*Precision (%)*	*Recall (%)*	*F1 score (%)*	*ROC (%)*
YOLOv7 [18]	94.0	93.5	93.75	91.0
AI-Dentify [5]	92.0	90.0	91.0	89.5
Simultaneous Detection [8]	89.0	88.0	88.5	87.0
Multifarious Deep Networks [11]	94.0	92.5	93.25	93.0
AI-aided Diagnosis [9]	88.0	87.0	87.5	86.0
Dental Student Application [14]	87.0	85.5	86.25	84.5
Rapid Detection using Mask R-CNN [15]	93.0	92.5	92.75	92.0

AI-Dentify [5] demonstrated strong accuracy (92.0%) in detecting proximal caries in bitewing X-rays, but its complexity and high computational cost limit its applicability in real-time scenarios. Simultaneous Detection [8] showed good performance in detecting fissure sealants, but its lower recall (88.0%) suggests a higher likelihood of missing true caries cases. Multifarious Deep Networks [11] achieved high precision (94.0%) but relied heavily on pre-training, which may restrict its adaptability to diverse imaging conditions. AI-aided Diagnosis [9] and the Dental Student Application model [14] showed lower recall and F1-score values, making them less effective for general caries detection. Meanwhile, Rapid Detection using Mask R-CNN [15] excelled in segmentation but remained computationally expensive, limiting its real-time deployment.

Table IV shows the ranking of AI-based detection models based on accuracy. YOLOv7 achieved the highest accuracy (94.0%), demonstrating superior performance in detecting pre-carious lesions in intraoral images. AI-Dentify [5] followed with 92.0%, excelling in proximal caries detection but with higher computational demands. Simultaneous Detection [8] and AI-aided Diagnosis [9] showed competitive accuracy (89.0% and 88.0%, respectively) but had limitations in recall and adaptability. Multifarious Deep Networks [11] matched YOLOv7 in accuracy (94.0%) but relied heavily on pre-training, affecting generalizability. Rapid Detection using Mask R-CNN [15] (93.0%) performed well but required significant computational resources. The Dental Student Application [14] had the lowest accuracy (87.0%), highlighting its educational rather than clinical focus. These results confirm YOLOv7 as the most effective and scalable approach for real-time dental caries detection.

TABLE IX. DETECTION MODELS SORTED BY ACCURACY

AI Models	Samples	*Accuracy (%)*
YOLOv7 [18]	9327	94.0
AI-Dentify [5]	13887	92.0
Simultaneous Detection [8]	5000	89.0
Multifarious Deep Networks [11]	8000	94.0
AI-aided Diagnosis [9]	6000	88.0
Dental Student Application [14]	3000	87.0
Rapid Detection using Mask R-CNN [15]	9000	93.0

IV. CONCLUSIONS

The study showcases the effectiveness of a mobile application based on the YOLOv7 architecture for the early detection of pre-carious lesions, providing a transformative tool for dental diagnostics. This application enables precise and timely diagnosis of caries, reducing complications associated with untreated conditions and improving overall dental care. Validation in clinical environments demonstrated the system's robustness, achieving an average accuracy of 94% and a PPV exceeding 90% in most cases. Dentists highlighted the application's accuracy, ease of use, and seamless integration into workflows, while patients rated its usability, efficiency, and functionality at 4.4, 4.2, and 4.6, respectively. These results, coupled with a notable reduction in diagnostic time, underscore the application's potential to enhance workflow efficiency and provide a high-quality user experience.

A comparative analysis with other state-of-the-art approaches further emphasized the superiority of YOLOv7, achieving a precision of 94.0%, recall of 93.5%, F1 score of 93.75%, and ROC of 91.0%. These metrics outperform alternative models such as AI-Dentify [5] and Mask R-CNN [15], solidifying YOLOv7 as the most competent framework for caries detection. Despite the larger datasets utilized by some models, YOLOv7 excels due to its balance of simplicity, accuracy, and implementation efficiency, making it a more practical and scalable solution.

This study not only demonstrates the application's technical and clinical viability but also its acceptance by both patients and clinicians, paving the way for its broader adoption. Future work will focus on improving the user interface, expanding diagnostic capabilities to include more complex dental pathologies, and conducting longitudinal studies to further validate its clinical effectiveness. These efforts aim to solidify the application as a cornerstone for advancing dental diagnostics and improving patient outcomes worldwide.

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