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Detection of dental caries under fixed dental prostheses by analyzing digital panoramic radiographs with artificial intelligence algorithms based on deep learning methods

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Abstract

Background The aim of this study was to evaluate the efficacy of detecting dental caries under fixed dental prostheses (FDPs) through the analysis of panoramic radiographs utilizing convolutional neural network (CNN) based You Only Look Once (YOLO) models. Deep learning algorithms can analyze datasets of dental images, such as panoramic radiographs to accurately identify and classify carious lesions. Using artificial intelligence, specifically deep learning methods, may help practitioners to detect and diagnose caries using radiograph images.

Methods The panoramic radiographs of 1004 patients, who had FDPs on their teeth and met the inclusion criteria, were divided into 904 (90%) images as training dataset and 100 (10%) images as the test dataset. Following the attainment of elevated detection scores with YOLOv7, regions of interest (ROIs) containing FDPs were automatically detected and cropped by the YOLOv7 model. In the second stage, 2467 cropped images were divided into 2248 (91%) images as the training dataset and 219 (9%) images as the test dataset. Caries under the FDPs were detected using both the YOLOv7 and the improved YOLOv7 (YOLOv7 + CBAM) models. The performance of the deep learning models used in the study was evaluated using recall, precision, F1, and mean average precision (mAP) scores.

Results In the first stage, the YOLOv7 model achieved 0.947 recall, 0.966 precision, 0.968 mAP and 0.956 F1 scores in detecting the FDPs. In the second stage the YOLOv7 model achieved 0.791 recall, 0.837 precision, 0.800 mAP and 0.813 F1 scores in detecting the caries under the FDPs, while the YOLOv7 + CBAM model achieved 0.827 recall, 0.834 precision, 0.846 mAP, and 0.830 F1 scores.

Conclusion The use of deep learning models to detect dental caries under FDPs by analyzing panoramic radiographs has shown promising results. The study highlights that panoramic radiographs with appropriate image features can be used in combination with a detection system supported by deep learning methods. In the long term, our study may allow for accurate and rapid diagnoses that significantly improve the preservation of teeth under FDPs.

Keywords Deep learning, Dental caries, Detection, Digital panoramic radiography, Fixed dental prosthesis

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Background

Fixed dental prosthesis (FDP) is a good treatment option for patients with partial edentulism [1]. Despite the advances in the techniques and materials, the treatment may fail, resulting with replacement of crowns and bridges [1, 2]. The most common cause of failure in FDPs is dental caries [3]. The difficulties inherent in diagnosing caries under FDPs with traditional methods underscore the necessity for the development of alternative caries detection methods. The impracticality and potential distress associated with the removal of a permanently cemented prosthesis for caries detection under FDPs highlight the need for alternative approaches [4]. In such cases, intraoral and extraoral radiographic methods are used [5]. Panoramic radiography is an extraoral imaging technique that is frequently employed in the context of dental examinations. Panoramic radiography offers a comprehensive visualization of the anatomical structures of the face in a relatively short time. Furthermore, the low radiation dose represents an additional advantage when the imaged area and other imaging modalities are considered [3–7]. In this sense, it is important to conduct studies that will accelerate caries detection using panoramic radiography and provide practical benefit to physicians [3].

Panoramic radiography provides valuable information to physicians in the process of deciding on the treatment to be performed. However, it should be noted that panoramic radiography may not be a comprehensive solution for the detection of caries [7]. This is due to the resolution and detail issues inherent to panoramic radiography, as well as the formation of metal artefacts, caries presence in the subgingival region, and the radiopacity of FDPs, which impedes the visualization of caries [7, 8]. These limitations for caries detection under fixed dental prostheses indicate the necessity for more sensitive and specific diagnostic methods [3]. The need for computer-aided diagnostic systems that will provide a second opinion to physicians is increasing day by day and new computer aided dental caries detection methods have been searched [3–6].

In recent years, by using artificial intelligence (AI) and deep learning methods, especially convolutional neural network (CNN), successful results have been obtained for caries detection on dental periapical [9–13], bitewing [14–18], and panoramic [19–21], radiographic images with promising clinical applications. You Only Look Once (YOLO) is a CNN-based algorithm inspired by the human visual system's ability to simultaneously detect where objects in the image are and how they interact with each other [22]. The YOLOv7 algorithm is one of the YOLO algorithms that have been developed over the years. The accuracy and speed of YOLOv7 have increased compared to the previous YOLO algorithms [23].

It is arguable that the use of AI systems on radiologic images in clinical practice may be better than or equivalent to the ability of clinicians to analyze radiologic images [15, 24]. However, it is thought that increasing the effectiveness of dental caries detection with deep learning algorithms in dental radiography will greatly benefit dentists in their clinical practice [15, 21]. Therefore, the aim of this study was to evaluate the effectiveness of detecting dental caries under FDPs by analyzing panoramic radiographs with the YOLO based CNN models. The null hypothesis of this study was that the AI algorithms based on deep learning methods would not be effective in detecting caries under FDPs by analyzing panoramic radiographs.

Materials and methods

Dataset

The ethical approval (Decision No: 2022.09.22) of the Non-Interventional Research Ethics Committee of the University was obtained for the study. The dataset was obtained from the university's database. The panoramic radiographs of 1004 patients aged 25–75 years who came to the faculty for examination and/or treatment and had fixed dental prosthesis between the years of 2016 and 2023 were recorded in JPEG format. The inclusion criteria were that at least one of the extraction, filling, root canal treatment or prosthesis renewal procedures because of the progression of caries had been performed in the teeth under the FDPs. This condition was validated from the university's patient registration system. The exclusion criteria were the absence of FDPs in the radiographic images, the presence of artifacts and super positions that would prevent the optimum evaluation of caries, abutment tooth and missing tooth areas under the FDPs observed on panoramic radiographs. In this study, a panoramic x-ray device having 66 kVp, 10 mA, 16 s irradiation (Gendex GXDP-700, Gendex) was used. Data labelling was performed by two prosthodontists (BA with 4 years of experience and SA with 27 years of experience) making simultaneous decision and consensus on the same computer screen. Labelling was not performed when the diagnoses of two dentists did not match in the dataset. The dataset for this study was determined based on a power analysis conducted using G*Power 3.1 (Heinrich Heine University). The analysis indicated that a total sample size of 1003 was required (sample size group 1 = 903 and sample size group 2 = 100), with 95% power (1-β error probability), a proportion of P1/H1 = 0.71, and a significance level of $\alpha = 0.05$.

Study design

This study had two stages. In the first stage, a dataset of 1004 digital panoramic radiographs were divided into a training dataset ($n = 904$ [90%]) and a test dataset ($n = 100$

[10%]). [20,21,25] In the training and test datasets, teeth restored with FDPs were labeled to include their roots. On the test dataset, a CNN-based deep learning model called YOLOv7 achieved a high detection score, and FDPs on all radiographs were automatically detected and cropped (selectively extracted from the original radiographic images) by the same model [21–26]. In the second stage, the new dataset of cropped images was divided into a training dataset ($n = 2248$ [91%]) and a test dataset ($n = 219$ [9%]). [20,21,25] Caries under the FDPs were detected with the YOLOv7 model and the improved YOLOv7 model that uses the convolutional block attention module (CBAM) [27]. The performance of the deep learning models was evaluated with recall, precision, mAP, and F1 scores [18, 27]. The study plan and number of labels are shown in Fig. 1.

Data labelling process

A total of 1004 panoramic radiographs from the dataset were resized to 640 × 640 pixels and converted into JPEG file format [14]. In the labelling process, FDPs, abutments and missing teeth areas (regions of interest [ROI]) on the panoramic images were all labeled. Totally 2248 labels were made on the training dataset of 904 images and 243 labels were made on the test dataset of 100 images. After the trained YOLOv7 model detected FDPs, ROIs were automatically cropped from the main radiographic images (Fig. 2B, E, H). Then, dental caries, caries-free abutment teeth and missing teeth under the FDPs were labeled by the BA and SA using the cropped images (Fig. 2C, F, I). All abutment teeth that were found to be caries-free were labeled as "healthy". The cropped images were resized to the dimensions accepted by YOLOv7. After resizing, it was not possible to label the abutments in some images as healthy or caries. Considering the factors mentioned above, it was decided to exclude 24 images from the test dataset. This is because the test dataset will affect the final outcome of the study. In the 2248 training dataset, 950 labels for caries, 1978 labels for missing teeth, and 4158 labels for healthy abutment were obtained. In the 219 test datasets, 110 labels for caries, 258 labels for missing teeth and 502 labels for healthy abutments were obtained (Table 1). Predictions (Fig. 2D, G, J) of the trained deep learning models were obtained with the test dataset. Representative examples of the cropped radiographs, unlabeled and labeled images, and prediction of the YOLOv7 model are presented in Fig. 3.

Caries detection on panoramic radiographs with YOLOv7 and YOLOv7 + CBAM

In this study, the YOLOv7 algorithm, which comprises the input, spine, neck, and head components, is employed to identify dental caries under FDPs. The default setting of the YOLOv7 model is 640 × 640 pixels. This input image size allows to minimize the calculation cost of the model. Consequently, in the present study, the input module resized the input images to 640 × 640 pixels, the accepted size for the YOLOv7 architecture, prior to feeding them to the spine network [14, 23, 28, 29].

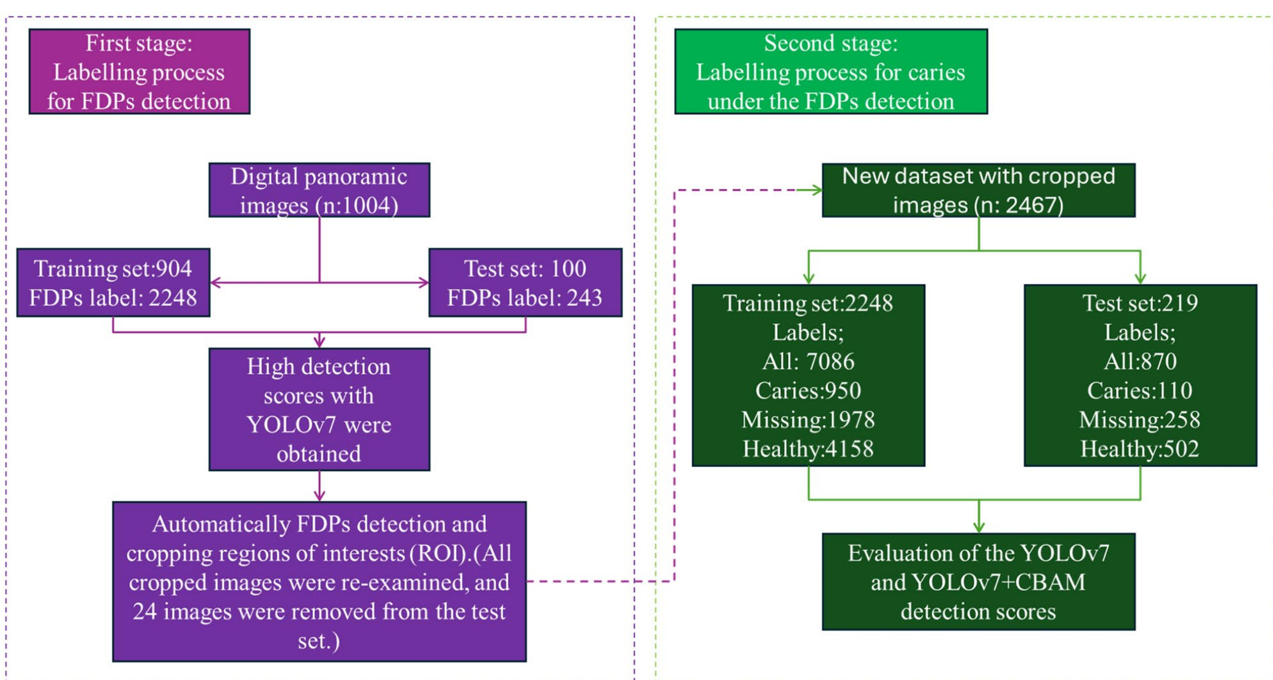

Fig. 1 The design of the study

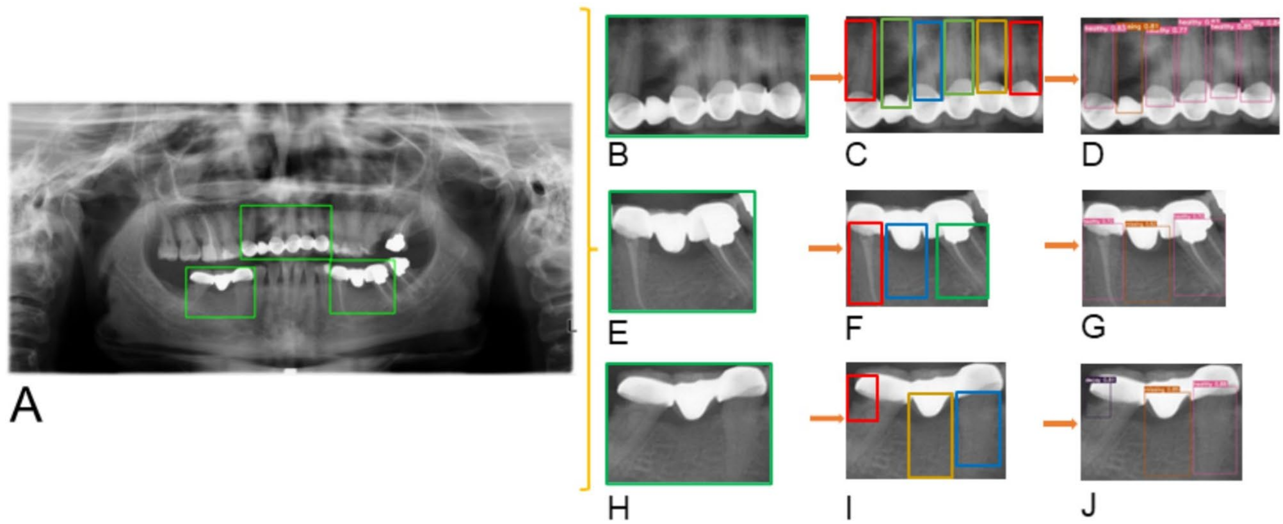

Fig. 2 Representative radiograph from the dataset **(A)**, ROIs cropped from the radiographs **(B**, **E**, **H)**, Labelling made by the experts **(C**, **F**, **I)**, YOLOv7's predictions **(D**, **G**, **J)**

Table 1 The dataset used in the study

	FDPs detection	Caries, missing, and healthy teeth under FDPs detection	
Training Data	Number: 904 Label: 2248	Number: 2248 Label: 7086	Caries: 950 Missing: 1978 Healthy: 4158
Test Data	Number: 100 Label: 243	Number: 219 Label: 870	Caries: 110 Missing: 258 Healthy: 502

In this study, the Convolutional Block Attention Module (CBAM), which is one of the attention mechanisms that have been shown to improve caries detection performance under FDPs, was integrated into the YOLOv7 model [23–27]. Although the CBAM modules increase performance, they can cause degradation instead of increasing performance if the number of the CBAM modules is not chosen correctly. In this study, CBAM modules were integrated into various regions within the architecture, and using three CBAM modules after the ELAN modules achieved the best detection performance (Fig. 4).

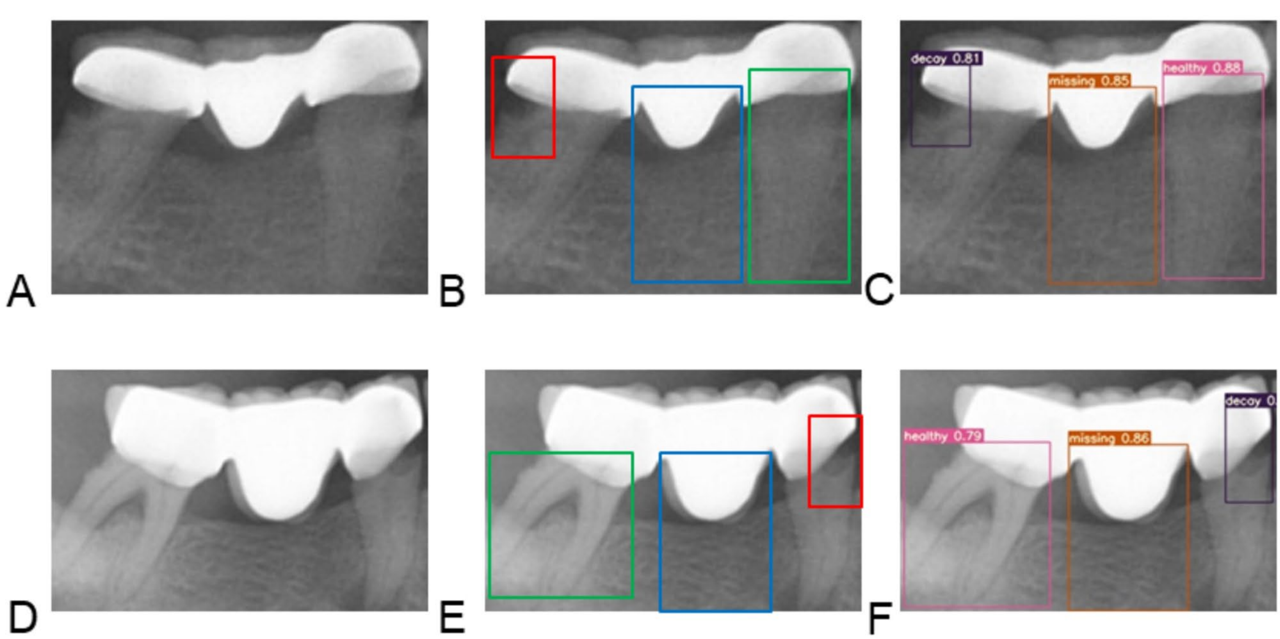

Fig. 3 Examples from cropped radiographs: Unlabeled images **(A**, **D)**, Labeled images **(B**, **E)**, Predictions of the YOLOv7 model **(C**, **F)**

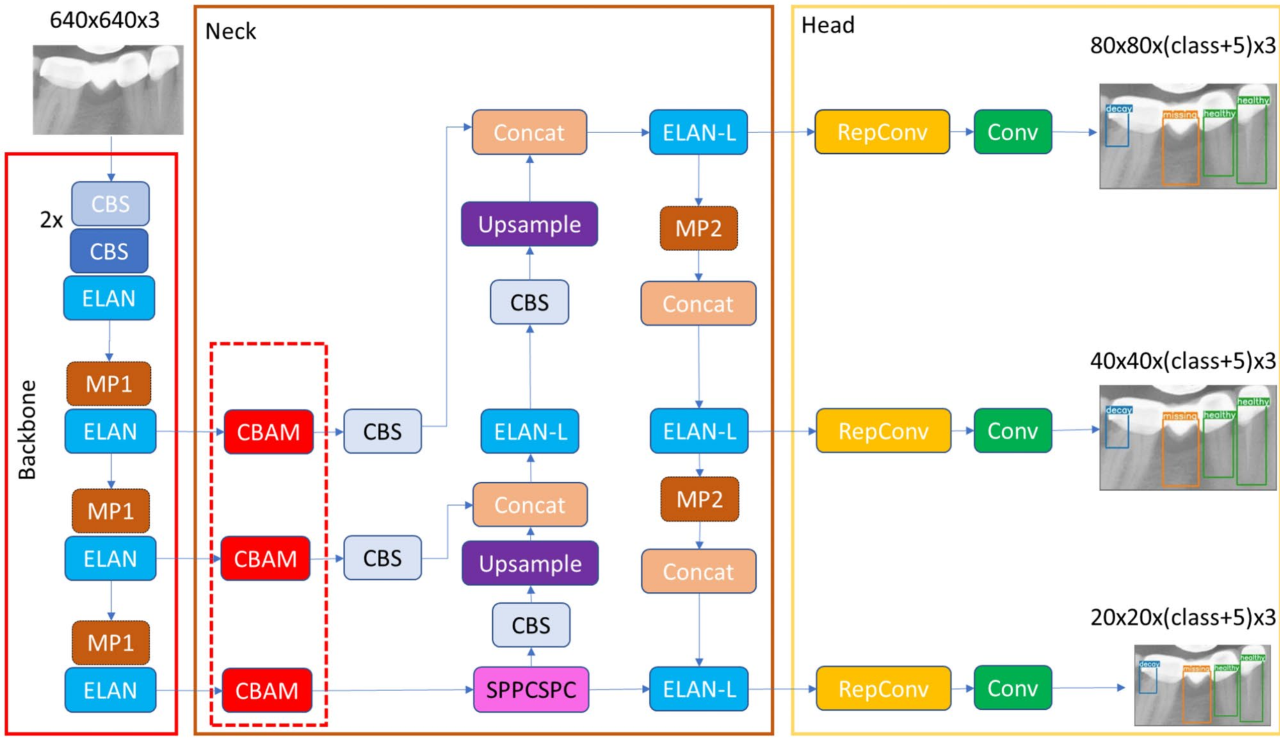

Fig. 4 The YOLOv7 + CBAM module was developed with three CBAM modules integrated into the neck section of the original YOLOv7 architecture

Development environment and model hyperparameters

The deep learning models were improved using the Python programming language. PyTorch and OpenCV libraries were used in the setup and testing of the models. The whole process was carried out using a computer having a Nvidia 1080Ti graphics card, two Xenon processors, 32 GB of RAM and Ubuntu 20.04 operating system [14].

The training process was configured with the following hyperparameters: The model was trained for 200 epochs with a batch size of 16. The Intersection over Union (IoU) threshold was set to 0.50, while the confidence threshold was set to 0.20. The Adam optimizer was employed with a learning rate of 0.01. The momentum value was set to 0.93, and the weight decay parameter was configured as 0.0005. The input size for the model was defined as $640 \times 640 \times 3$.

Performance analysis

Performance metrics were used to compare the success of the developed deep learning models. In deep learning, the similarity between the values labeled on the test data (ground truth) and the predicted value of the model is measured by the IoU value [18–25]. The object detection success of the model is evaluated by comparing the threshold and IoU values. In our study, the threshold value was set as 0.5 [25]. The predictive values of the model trained with real values in binary classification or multi classification tasks are shown in the confusion matrix that is a significant table that sums up the actual and predicted circumstances [30, 31]. The confusion matrix and the terminology used for the matrix in this study were as follows: True Positive (TP): In the area where the object is labeled, the model indicates the object exists. False Positive (FP): In the area where the object is not labeled, the model indicates the object exists. False Negative (FN): In the area where the object is not labeled, the model indicates the object does not exist. True Negative (TN): In the area where the object is labeled, the model indicates the object does not exist. TN value is generally not used in object detection [32].

After TP, FP, and FN values were obtained, model performance evaluation was made by calculating recall, precision, mAP, and F1 scores together with these values. Precision (P) was the ratio showing how many of the positive predictions were correctly predicted. Recall (R) was the percentage of positive samples that are correctly predicted. The F1 score was the harmonic average of the P and R values reduced to a single number. It was used instead of accuracy. The mean average precision (mAP) is a metric used to evaluate the performance of a model for tasks such as information extraction and object detection [32]. The equations are given below (Eqs. 1–4).

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \quad (1)$$

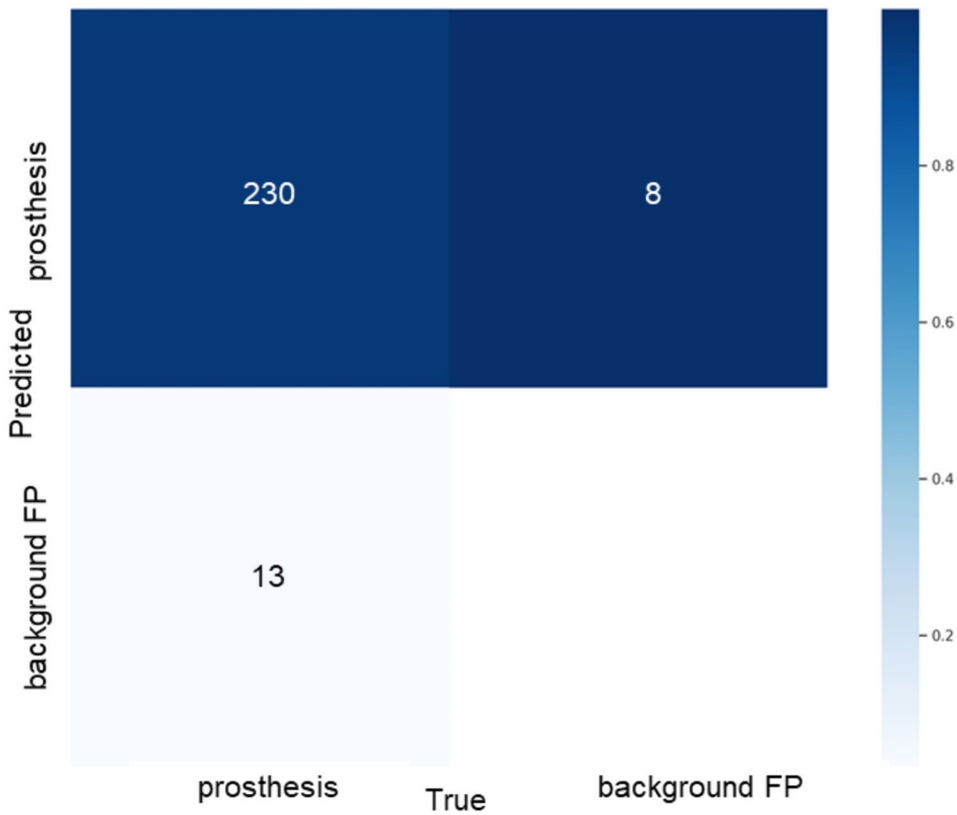

Fig. 5 Confusion matrix for FDP detection with YOLOv7

Table 2 The detection scores of the FDPs, caries, missing, and healthy teeth

		Recall	Precision	mAP	F1
FDPs Detection with YOLOv7		0.947	0.966	0.968	0.956
Caries Detection with YOLOv7	All	0.902	0.862	0.903	0.881
	Caries	0.791	0.837	0.800	0.813
	Missing	0.939	0.804	0.931	0.866
	Healthy	0.976	0.945	0.978	0.960
Caries Detection with YOLOv7 + CBAM	All	0.905	0.866	0.918	0.885
	Caries	0.827	0.834	0.846	0.830
	Missing	0.922	0.821	0.933	0.868
	Healthy	0.964	0.945	0.973	0.954

$$Recall = \frac{True\ Positive}{(True\ Positive + False\ Negative)} \quad (2)$$

$$F1 - Score = \frac{2\,(Precision \times\ Recall)}{(Precision + Recall)} \quad (3)$$

$$mAP = \frac{1}{N}\sum\ {}_{i=1}^{N} AP_i \quad (4)$$

Results

Evaluation of the YOLOv7 model for detecting FDPs on panoramic radiography

Of the 1004 panoramic radiographs, 904 were identified as the training dataset and 100 were identified as the test dataset. The trained YOLOv7 model evaluated 230 of the 243 FDP labels in 100 images in the test group as TP, 8 as FP and 13 as FN (Fig. 5). As result of this evaluation, 0.947 recall, 0.966 precision, 0.968 mAP, and 0.956 F1 scores were obtained (Table 2).

Detection scores of caries under FDPs with YOLOv7 and YOLOv7 + CBAM

After the trained YOLOv7 model detected FDPs, ROIs were automatically cropped from the main radiographic images and 2491 images were obtained. Among the cropped images, 2248 images were used as the training

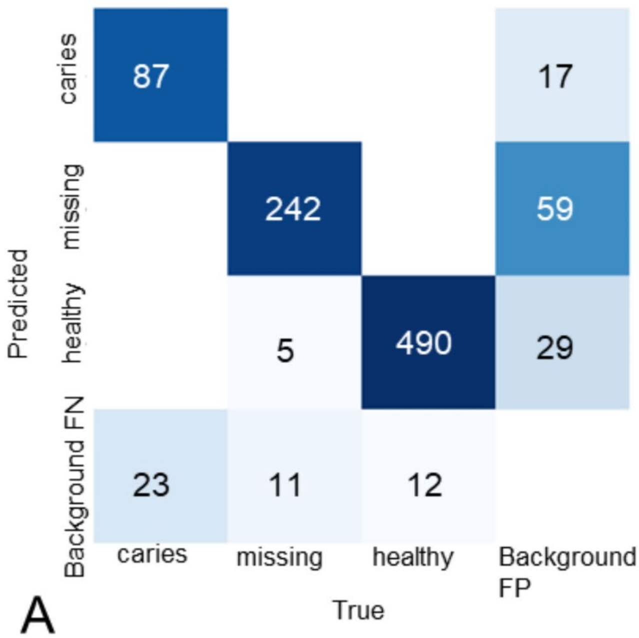

Fig. 6 Confusion matrix for caries, missing and healthy teeth predictions with YOLOv7 (**A**) and YOLOv7 + CBAM (**B**)

dataset and 219 images were used as the test dataset. The trained YOLOv7 model predicted 87 of the 110 caries labels in the test group as TP, 17 as FP and 23 as FN. Of the 258 missing tooth labels, 242 were TP, 59 were FP, and 16 were FN. Of the 502 caries-free abutment labels, 490 were predicted as TP, 29 as FP and 12 as FN (Fig. 6A). The YOLOv7 model had 0.791 recall, 0.837 precision, 0.800 mAP, and 0.813 F1 scores for dental caries labelling on the cropped images; 0.939 recall, 0.804 precision, 0.931 mAP, and 0.866 F1 scores for the missing teeth. For the caries-free abutments, 0.976 recall, 0.945 precision, 0.978 mAP, and 0.960 F1 scores were obtained (Table 2). After training with the original YOLOv7 model, attention mechanisms (CBAM) were integrated into this model to better detection, and it was observed that the caries detection performance of the model increased. The trained YOLOv7 + CBAM model identified 91 of the 110 caries labels in the test group as TP, 18 as FP and 19 as FN. Of the 258 missing tooth labels, 238 were TP, 52 were FP, and 20 were FN. Of the 502 caries-free abutment labels, 484 were predicted as TP, 28 as FP, and 18 as FN (Fig. 6B). As a result of training with the YOLOv7 + CBAM model, 0.827 recall, 0.834 precision, 0.846 mAP, and 0.830 F1 scores for the caries labels, 0.922 recall, 0.821 precision, 0.933 mAP, and 0.868 F1 scores for the missing tooth labels, and 0.964 recall, 0.945 precision, 0.973 mAP, and 0.954 F1 scores for the caries-free abutment labels were obtained (Table 2).

Discussion

In this study, promising results were obtained using deep learning models to detect dental caries under FDPs by analyzing digital panoramic radiographs. While the original YOLOv7 model obtained 0.791 recall, 0.837 precision, 0.800 mAP, and 0.813 F1 scores for the caries labels, 0.827 recall, 0.834 precision, 0.846 mAP, and 0.830 F1 scores were obtained for the caries labels as a result of training with the YOLOv7 + CBAM model. Therefore, the null hypothesis, which states that the detection of dental caries under FDPs by analyzing digital panoramic radiographs with artificial intelligence algorithms based on deep learning methods would not be efficient, was rejected.

Bitewing radiography is the most used imaging technique for the detection of approximal caries [6]. In the study conducted by Bayraktar et al. [14], in which approximal caries lesions were detected using the YOLOv3 algorithm on bitewing radiographs, the recall and precision scores were obtained as 0.7226 and 0.9819, respectively. In another study by Panyarak et al. [33] using the YOLOv7 algorithm on bitewing radiographs, 0.605 precision and 0.512 recall scores for caries detection were obtained. In this study, it was shown that model detection scores obtained with bitewing imaging using panoramic radiographs can be obtained within the specified inclusion and exclusion criteria.

Several studies focused on dental caries detection by using deep learning on panoramic radiographs [19–21, 25, 34]. One of these studies used The AI model on panoramic images, the recall scores were 0.9674 for crown, 0.3026 for caries detection, and precision scores were 0.8600 for crown, 0.5096 for caries detection [34]. Although the recall score (0.947) and precision score (0.966) of crown detection of the present study were consistent with this study, recall and precision scores for caries detection were found lower than the scores of the present study, which were 0.791 (without the CBAM module) and 0.827 (with the CBAM module) for recall scores, and 0.837 (without the CBAM module) and 0.834 (with the CBAM module) for precision scores. The higher scores in the current study can be explained by the different models, the use of the CBAM module and the presence of a larger number of ground truths. In another study, the detection of FDPs on panoramic radiographs with the YOLOv4 model was performed using 521 panoramic radiographs selected from 5126 panoramic radiographs as test data. In that study, 0.79 recall, 0.74 precision, and 0.76 F1 scores were obtained for crown labels and 0.95 recall, 0.84 precision, and 0.89 F1 scores were obtained for bridge labels [25]. The authors are not aware of any study in the literature evaluating the detection of caries under FDPs. Therefore, the results of the present study could not be compared with the results of other studies.

The application of image cropping in this study had two aims. Firstly, to augment the quantity of data and secondly, to enhance the model's detection of caries, healthy abutments, and missing teeth under FDPs. In a similar study by Chen et al. [35] 1525 periapical radiographs were converted into single-tooth images using image cropping and detection scores were obtained using different CNN algorithms for simultaneous detection of periodontitis and caries on periapical radiographs.

In present study, attention mechanisms (CBAM) were integrated into the YOLOv7 to better predict the study parameters and dental caries under FDPs [26]. Another study, which used the CBAM module with the original YOLOv7 algorithm, concluded that the prediction scores of the algorithm increased for recall and mAP in comparison to the original YOLOv7 algorithm [27]. These results are consistent with the present study, where the caries detection scores of recall, mAP, and F1 increased by using the YOLOv7 + CBAM model (Table 2). Although the recall values for caries detection under the FDPs were 0.791 with the YOLOv7 model and 0.827 with the YOLOv7 + CBAM model, they still need improvement for clinical practice.

Bitewing radiographs are widely preferred for detecting dental caries due to their superior resolution and sensitivity. However, their exclusion from this study represents a significant limitation. The absence of bitewing radiographs means that certain advantages of this modality, such as reduced artifact interference and higher detail resolution, were not evaluated in comparison to panoramic radiographs. Future studies could address this by adopting a study design that incorporates both panoramic and bitewing radiographs, enabling a more comprehensive comparison of diagnostic effectiveness and elucidating the scenarios where each modality performs best. On the other hand, panoramic radiographs are commonly employed in clinical practice due to their ability to provide simultaneous visualization of all teeth and associated structures. For this reason, they were chosen in this study to evaluate their utility in detecting caries beneath fixed dental prostheses (FDPs). However, relying solely on panoramic radiographs may amplify the limitations of this method, such as challenges in detecting subgingival caries or lesions obscured by metal artifacts from FDPs. These inherent drawbacks could have influenced the results and need to be addressed in future research. To enhance the reliability and applicability of deep learning models in clinical settings, future research should consider integrating multimodal datasets combining panoramic and bitewing radiographs. Training deep learning algorithms with data from both modalities may leverage their complementary strengths, improving diagnostic accuracy and robustness. Additionally, including radiographic images from a variety of dental imaging devices could enhance the generalizability of the algorithms to different clinical environments. Furthermore, incorporating patient-specific factors such as age, dental condition, or type of restoration into model training could refine diagnostic performance and yield more precise results. In conclusion, while this study demonstrated promising results in detecting caries under FDPs using non-bitewing radiographic techniques, the integration of diverse imaging modalities and datasets is necessary to build a more robust and reliable foundation for future clinical applications.

Conclusion

Within the limitations of this study, it was demonstrated that AI algorithms based on deep learning models, particularly YOLOv7 + CBAM, achieved promising results in detecting dental caries under fixed dental prostheses (FDPs) using panoramic radiographs. The improved recall (0.827) and precision (0.834) scores highlight the potential of attention mechanisms in enhancing diagnostic accuracy. However, the exclusive use of panoramic radiographs limits the findings, as bitewing radiographs or multimodal imaging could provide greater sensitivity and detail. Future research should incorporate diverse datasets, multimodal approaches, and clinical validation to enhance the generalizability and practical application of these AI models in dental diagnostics.

Abbreviations

AI	Artificial Intelligence
CBAM	Convolutional Block Attention Module

CNN	Convolutional Neural Network
FDPs	Fixed Dental Prostheses
FN	False Negative
FP	False Positive
mAP	Mean Average Precision
ROI	Regions Of Interest
TN	True Negative
TP	True Positive
YOLO	You Only Look Once

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Author contributions
B.A. contributed to conceptualization, visualization, methodology, the investigation, data curation, and writing (original draft and review & editing). E.A. contributed to the software development, the formal analysis, visualization and writing (original draft and review & editing). S.A. contributed the conceptualization and supervision, writing (original draft and review & editing) and project administration. All authors read and approved the final manuscript.

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Data availability
The datasets generated and/or analyzed during the current study are not publicly available due to the fact that the data were obtained from anonymized radiographs by labeling them in a way that prevents reverse engineering. The raw data cannot be shared without the consent of the patients, and the data has been anonymized to remove any personal information. However, they are available from the corresponding author upon reasonable request.

Declarations

Ethical approval and consent to participate
This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Non-Interventional Research Ethics Committee of the Kırıkkale University (Date: 28 September 2022, Decision No: 2022.09.22). There was no need for individual consent, and the need for informed consent was waived by the Non-Interventional Research Ethics Committee of the Kırıkkale University for this retrospective study because the data and patient details were anonymized.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Clinical trial number
Not applicable.

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