

Evaluation of an Artificial Intelligence-based software in the detection of caries in Panoramic Radiographs

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Aim: To evaluate the clinical diagnostic accuracy of WediagnostiX artificial intelligence-based software for helping dental professionals in the automatic detection and identification of dental caries in panoramic radiographs.

Materials and methods: A dataset of 325 anonymized panoramic radiographs (PR) were selected. First, the images were manually evaluated by two experienced oral radiologists, where consensus was established by a third evaluator to set the “ground truth”. The evaluators classified their findings as follows: (DC) for dental caries, (M) for missing teeth and all teeth were numbered and labelled with Federation Dentaire Internationale (FDI) nomenclature. The OPGs were then anonymously uploaded and analyzed by the AI-based software (WeDiagnostiX). Caries detection module was operated using the specific confidence threshold of the software. Results were recorded on excel spreadsheets, and a statistical analysis was performed to compare the automated diagnosis of the software to the ground truth in terms of Sensitivity (S), Specificity (E), Positive Predictive Value (PPV), Negative Predictive Value (NPV), Diagnostic Accuracy (DA), and their presentation in the area under (AUC) the Receiver Operating Characteristic (ROC) curve.

Results: Diagnostic metrics for each variable obtained in this study were as follows: (DC) S=50%, E=91.8%, PPV=50.4%, NPV=91.7%, DA= 85.9%, AUC=0.709; (M) S=82.4%, E=93.9%, PPV=72.1%, NPV=96.5%, DA=92%, AUC=0.882; (FDI) S=90.3%, E=87.7%, PPV=69.7%, NPV=96.7, DA=74.6%, AUC=0.89.

Conclusion: Results of this study suggest that WeDiagnostiX can provide reliable evaluation for dental caries and other variables on PRs improving diagnostic quality and performance of dental clinicians.

Keywords: Artificial Intelligence, Convolutional neural network, Machine learning, Caries, Panoramic radiography

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Introduction

Scientists and computer engineers have attempted for centuries to humanize inanimate objects for several purposes¹ The concept of creating non-human objects with human-like qualifications is the basis of artificial intelligence. Artificial intelligence (AI) is the ability of a machine to intelligently imitate human behavior² In 1956, the concept of AI research was coined by John McCarthy³, a pioneer in AI.

The use of AI has taken a leading role in healthcare as more medical and dental professionals seek to make diagnosis faster and more accurate, saving time and effort while reducing cost and errors² Two important subsets of AI are machine learning (ML) and deep learning (DL). ML is a subset of AI, in which algorithms are applied to study the intrinsic statistical patterns and details of structures in data, which allows for predictions of future unseen data⁴ ML involves analyzing and annotating images, with human intervention, then an algorithm classifies the input images using the available data features to deliver the desired output⁵ DL is the advanced form of ML, where machines or computers are taught to automatically, without human intervention, extract the desired image features to perform various automated tasks such as object detection, image classification, and segmentation⁶ The DL-based system can label datasets automatically using convolutional neural networks (CNN) composed of multiple layers. These layers build up from training image data inputs and supply outputs, and the learning process is repeated automatically⁷ DL has been utilized for medical purposes, especially in image interpretation and image-based radiodiagnosis⁸ In dentistry, DL has been used to detect lesions, cysts, and caries, diagnose osteoporosis, evaluate tooth identification and numbering, determine root morphology, evaluate cephalometric analysis and detect maxillary sinusitis. Numerous AI

studies in dentistry have reported that DL could be promising in the detection of many pathologies⁹⁻¹¹

The use of AI in caries detection with medical images is an active research area. Most of the previously conducted studies used CNN-based pre-trained models for medical decision support¹² CNN algorithms have been noted to achieve superior performance in caries detection compared to human examiners, particularly in identifying proximal caries on bitewing radiographs, which are often considered the gold standard for caries detection¹³ To our knowledge, limited studies have been conducted to diagnose multiple diseases on PRs using CNN-based models^{14,15} The aim of this study is to assess the accuracy of an AI-based software for the detection of caries on Panoramic radiograph. The null hypothesis is that there is no difference between the performance of the AI-based software and the expert dentists.

Materials and methods

This retrospective study was based on comparing the diagnostic performance of dental practitioners and AI-based software with several customized convolutional neural networks (WeDiagnostiX) on the detection of dental caries on Panoramic radiographic images.

We reported this study following STARD (Standards for Reporting of Diagnostic Accuracy Studies) and CLAIM (Checklist for Artificial Intelligence in medical imaging) checklists^{16,17}

Image dataset protection and sampling

This study was conducted at our Department of Oral and Maxillofacial Radiology, Faculty of Dentistry and was conducted in accordance with the code of ethics of the world medical association (Declaration of Helsinki) and approved by the Research Ethics Committee (decision no.

FDASU-RecEM102206). The sample size consisted of 325 anonymized PRs randomly acquired using Sirona D3352 Dental Imaging system (Sirona, Sirona Dental Systems GmbH, Bensheim, Germany) with sizing and resolution of 2440x1292 and 300x300 pixels, respectively. The standard exposure parameters were operating with tube voltages between 60 and 90 kV and tube currents between 1 and 10 mA. according to the manufacturer's instructions. The dataset was optimized with the exposure parameters as low as diagnostically acceptable (ALADA). PR Scans were collected during the period from January till May 2024 and were selected from dataset images acquired between 2012 – 2024 with the following inclusion criteria: Scans with permanent dentition (including missing teeth and dental treatments), scans covering at least six teeth. The selected images with the following criteria were excluded from the study: Scans with artifacts caused by patient position, motion, or superimposition of foreign objects on PRs, deciduous and mixed dentition, blurred and incomplete PRs, artifacts of earrings, glasses, and removable dentures on PRs.

Image dataset processing and reference test

The sample size calculation based upon the results of Zadrozny L et al (2022); sensitivity was (0.445), specificity was (0.982) and prevalence of caries was (200/805 = 24.8%). The desired precision was 5% and the confidence level was 95%. Based upon these data, the estimated minimum sample size was 16 records. Sample size calculation was performed according to the formula developed by Naing L for calculating sample size of accuracy studies. Sample was set to 325 to increase the robustness and reliability of the results. The selected scans were exported using Sidexis 7.52 C (Sidexis, Sirona, Bensheim, Germany) software in .jpeg

image format. Two independent oral radiologists (OMFR) with experience of 10 and 15 years were presented with 20 panoramic radiographs including all the study variables for training and calibration. The operators analyzed the cases following the diagnostic criteria set for the study. The inter-observer agreement was between 0.987 and 1.000 for each variable.

Each evaluator was given a diagnostic chart for each case with all the variables and teeth numbered and labelled with Federation Dentaire Internationale nomenclature as follows: (DC) for dental caries, (M) for missing tooth. The AI-based application was used only as viewer software without adjustments to standardize the viewing conditions between the evaluators. In case there was no agreement between the two main evaluators, a third evaluator with 20 years of experience analyzed the case to achieve the ground truth. If agreement was not accomplished, the case was excluded.

Architecture of the deep convolutional neural network

This study was conducted using a pre-trained deep learning convolutional neural network (WeDiagnostiX, LLC WeDiagnostiX, Paris, France). WeDiagnostiX Application is used in combination with standalone software WeDiagnostiX Application Programming Interface (API). WeDiagnostiX API performs the analysis of PRs, and the results are then sent back to WeDiagnostiX Application to retrieve and display the information provided by WeDiagnostiX API. The software application is still in the process of Conformité Européenne (CE) certification. Protection of patients' personal data is ensured as the data remains in the local practice and only the image to be analyzed is sent to the server in France.

The pre-trained neural network is composed of several custom neural

networks that perform the task of detecting, classifying, segmenting, and masking of dental structures and pathologies in PRs using different detection modules run by a coding system.

For the detection and classification module, first, the images are processed to establish boundaries of each tooth, Figure (1). Then the teeth numbering module classifies each cropped region according to the FDI nomenclature¹⁰ The recognition and classification of other pathologies and structures were run by a coding system based on a grey scale¹⁰ AI operates with different confidence intervals of the custom CNNs classified into three categories with respect to performance accuracy: Specific, Optimum and Sensitive.

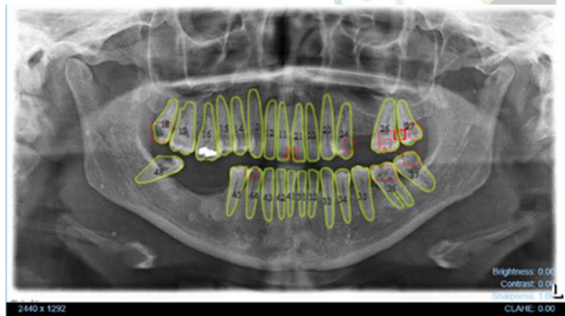


Figure 1: A case showing the detection and classification module of the software for recognition and classification of pathologies on the analyzed OPG.

The confidence interval was adjusted to the specific threshold, being the threshold of trustworthiness which the software specifies the presence of the anomalies on the OPGs. The outcomes obtained by the software were analyzed and compared to the ground truth, and a value was assigned for each outcome analyzed by the software: true positive (TP), false positive (FP), true negative (TN), false negative (FN), Figure (2). Then the results of each evaluator were copied to excel spreadsheets.

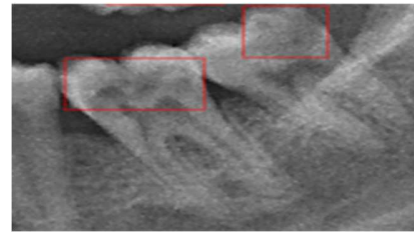


Fig 2 (A)



Fig 2 (B)

Figure 2: Selected cropped images from a case showing correct detection of caries in the correct positions of (A) teeth 36 and 37 assigned a TP, (B) tooth 17 assigned a FP.

Validation metrics and statistical analysis

Qualitative data were presented as frequencies and percentages. Friedman's test was used to compare Ground truth and the AI (Specific) threshold. Wilcoxon signed-rank test was used to compare between Ground truth and Specific threshold regarding detection of missing tooth and FDI tooth identification modules. *Kappa* statistics were used to assess inter-observer agreement. *Kappa* values ranging from 0.6 to 0.8 indicate good agreement, from 0.8 to 0.99 indicate very good agreement, a *Kappa* value = 1 indicates perfect agreement. The significance level was set at $P \leq 0.05$. Statistical analysis was performed with IBM SPSS Statistics for Windows, Version 23.0. Armonk, NY: IBM Corp. ROC (Receiver Operating Characteristic) curve was constructed to determine the diagnostic accuracy measures of AI threshold in relation to Ground truth. ROC curve analysis was performed with MedCalc® Statistical Software version 19.5.1 (MedCalc Software Ltd, Ostend, Belgium; <https://www.medcalc.org>; 2020).

Results

A descriptive analysis was done for each variable in the study. The total number of teeth detected by the ground truth was 10,725 teeth while the CNNs detected a total number of 8,999 teeth. Data were classified into (No caries) and (Caries) regardless of the number of lesions. Inter-observer agreement was very good regarding all variables; caries detection module with *Kappa* value 0.889, the missing tooth module = 0.97 and the FDI tooth identification module = 0.97.

The diagnostic accuracy for caries detection module was (85.9%), FDI tooth identification module was (74.6%) and missing tooth module was (92%). Receiver operating characteristic curve (ROC) analysis are presented in Table (2) and Figure (3).

Table 1: Descriptive statistics and results of Wilcoxon signed-rank test for comparisons between Caries, missing tooth and FDI tooth identification modules.

Variable		Ground truth (n = 10725 teeth)		Specific threshold (n = 10725 teeth)		P-value
		n	%	n	%	
Caries	No caries	8841	82.4	9011	84	<0.001*
	One lesion	1468	13.7	1531	14.3	
	Two lesions	393	3.7	173	1.6	
	Three lesions	23	0.2	10	0.1	
Missing tooth	No missing tooth	9001	83.9	8753	81.6	<0.001*
	Missing tooth	1724	16.1	1972	18.4	
FDI tooth identification	Zero	2557	23.5	3316	30.9	<0.001*
	One	8168	76.5	7409	69.1	

Values obtained by each variable were plotted representing ROC curves and their corresponding (AUCs) higher than 0.88 except for caries detection module which was (0.709) (Fig 3).

Table 2: Diagnostic accuracy.

Categories	Sensitivity (Recall) %	Specificity %	PPV (Precision)	NPV	Diagnostic accuracy %	AUC	95% CI
Caries	50	91.8	50.4	91.7	85.9	0.709	0.7- 0.718
Missing tooth	82.4	93.9	72.1	96.5	92	0.882	0.875- 0.888
FDI tooth identification	90.3	87.7	69.7	96.7	74.6	0.890	0.863- 0.913

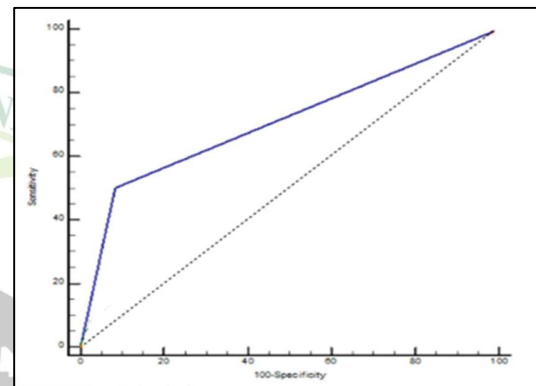


Figure 3: ROC curve of AI accuracy of detecting Caries Specific threshold of AI.

Discussion

The aim of this present study was to evaluate the clinical diagnostic accuracy of WediagnostiX artificial intelligence-based software for helping dental professionals in the automatic detection and identification of dental caries using panoramic radiographs.

Caries is considered the most prevalent disease in dentistry¹⁸ adding to the serious complications that could happen to the patient if left untreated. Periapical radiography gives detailed information about the teeth and the surrounding tissues¹⁹. Bitewing radiographs have been standardized for interproximal caries detection⁴, yet it has low sensitivity for the detection of initial interproximal caries lesions that histologically exist within the enamel²⁰. The use of CBCT in AI protocols is more promising in diagnostic accuracy studies²¹. Meanwhile caries detection is not primarily indicated by CBCT scan²². Panoramic radiography is the first radiograph to be

utilized in the evaluation of all future dental diseases as it is considered a low-dose, economically viable imaging modality that is widely employed in dental clinics to screen teeth, jaws, and the surrounding anatomic structures²³

The foreseen demand for AI in medicine and dentistry has been rapidly increasing having profound impact on populations facing shortage of radiologists or screening programs, thus relieving the overload on radiologists in large hospitals²⁴. Previous studies were conducted to determine the efficacy of AI in the field of dental radiology for the detection of each pathology seeking methods to strengthen the model after each study^{25,26}. Those studies have attempted developing AI-based systems for determining tooth numbering and detection, cephalometric analysis, periapical pathosis detection, caries detection, determination of the extent of alveolar and periodontal bone loss, and restorations detection^{9,10,14,27}.

Our software has novelty using DL CNN in the automatic detection of caries, where we propose a novel AI-based software (WeDiagnostiX). Till our time, no clinical studies have yet been conducted to verify the clinical performance of WeDiagnostiX software on the patient as far as we investigated.

Numerous studies have evaluated the clinical performance of CNN-based pre-trained models in the evaluation of 2D intraoral radiographs, such as Pearl, Overjet, or Denti.Ai. Limited studies focused on 2D OPG images such as Apox, Diagnocat and Denti.Ai^{14,28,29}. Tuzoff et al.¹⁰ and Yilmaz et al.³⁰ conducted studies for developing automatic tooth detection and numbering on OPGs by utilizing Faster R-CNN DL methods. Putra et al.³¹ evaluated the performance of YOLO V4 in automatic tooth detection and numbering. Zadrozny et al.¹⁴, assessed the reliability of Diagnocat AI-based software for the detection of caries, missing

teeth and periapical diseases on OPGs. Similarly, Szabo et al.³² and Ezhov et al.³³ utilized Diagnocat to automatically detect caries and missing teeth on periapical radiographs and CBCT. Basaran et al.¹⁵ evaluated a new DL model, CranioCatch, for diagnosing different dental conditions including caries and dental calculus on OPGs with Faster R-CNN. Mertens et al.³⁴ assessed the commercially available AI-based software DentalXrai pro for proximal caries detection on bitewing radiograph.

One of the crucial things to consider is utilizing an excellent network to investigate radiographic images during the diagnosis of dental diseases. Being aware of the successful CNNs used in previous research can boost results for future research³⁵. A recent systematic review reported that VGG16, ResNet-50, DetectNet, GoogleNet, and EfficientNet were the most frequently deployed architectures of the neural networks in dentomaxillofacial imaging studies⁸. The custom neural networks used in our study were Fast R-CNN, ResNet, and U-Net. The ResNet network, has been the most widely used CNN in previous studies. He k et al.³⁶, won the competition at the 2015 ILSVRC conference for introducing ResNet network. R-CNN, is an object detection network, and was first proposed by Girshick et al.³⁷ who innovated Fast R-CNN to increase the speed of the training and testing phases while increasing detection accuracy³⁸.

According to our results, there was a statistically significant difference between detection of carious lesions by the different methods (P -value <0.001). Regarding detection of no caries, Specific threshold showed a higher percentage of detection of no caries than Ground truth indicating an increased number of false negative cases; and a higher percentage of detection of single lesions (one carious lesion) than Ground truth indicating an increased number of false positive cases. Regarding detection of

multiple (two or three) caries lesions, Specific threshold showed a lower percentage of detection than Ground truth indicating an increased number of false negative cases. The caries detection module presented sensitivity of 50%, specificity of 91.8% and a diagnostic accuracy of 74.6%.

Regarding the missing tooth module, there was a statistically significant difference between Ground truth and Specific threshold (P -value <0.001). Specific threshold showed higher percentage of detecting missing tooth than Ground truth indicating increased number of false positive cases. The missing tooth module presented sensitivity of 82.4%, specificity of 93.9% and diagnostic accuracy of 92%.

Regarding the FDI tooth identification, there was a statistically significant difference between Ground truth and Specific threshold (P -value <0.001). Specific threshold showed lower percentage of no tooth detected and higher percentage of correctly detected than Ground truth indicating increased number of false positive cases. The FDI tooth identification module presented sensitivity of 90.3%, specificity of 87.7% and diagnostic accuracy of 74.6%.

In their studies, Putra et al.³¹ and Yilmaz et al.³⁰ compared the performance of their developed DL models to a group of 3 expert radiologists. The precision values were 87.70% and 93.67% respectively. Meanwhile the recall values were 100% and 90.79% respectively. A limitation in Putra et al. was the necessity of human intervention to minimize the error from the AI system. The computational power for developing the DL model was achieved by using cloud-based CPU³¹. Meanwhile, our AI-based software has chosen to process data on French servers that are not subject to the Cloud Act unlike all other softwares that use Amazon, Google, or Microsoft clouds for patient data processing. The developed model labeled all teeth that were present in one OPG in approximately

0.45 and 1.8 seconds, for YOLO V4 and Faster R-CNN respectively³⁰. Our AI-based software was able to detect and identify all the teeth present in one OPG in 0.3 seconds as the initial outcome prior to analyzing the remaining outcomes compared to the average time taken by the dental experts 5.06 ± 2 minutes.

In Tuzoff et al.¹⁰, Faster R-CNN achieved 99.41% recall and 99.5% precision with tooth detection and numbering on OPGs which was highly comparable to that of an expert oral radiologist. In a study conducted by Zadrozny et al.¹⁴, the performance of Diagnocat software was compared to 3 dental professionals. The software could detect the presence of caries without classification of the type or severity of the lesion. The sensitivity for caries detection was low (44.5%), while a high specificity of 98.2% was obtained. The missing tooth module presented sensitivity of 96.1% and specificity of 98.1%.

In Basaran et al.¹⁵, the new DL model (CraneoCatch) was assessed for charting a large dataset of OPGs compared to two OMFRs. The sensitivity was 30.26% and the specificity was 50.96%. The results were justified by the presence of superimpositions in OPGs which makes detection of caries a challenging process. Lee S et al.³⁹ categorized caries lesions in a huge dataset of OPGs into four categories: dental, proximal, cervical and secondary caries. The proximal caries presented the lowest precision of 26.31% highlighting the importance of using panoramic imaging modality in collaboration with another imaging tool such as bitewing radiography.

In Mertens et al.³⁴, DentalXrai Pro software was compared to AI-aided and unaided group of OMFRs. The aided group presented higher sensitivity of 81% compared to 72% of unaided group. Meanwhile the specificity was not clinically affected between groups. Li et al.⁴⁰, assessed a newly

developed DL model for caries detection on a large dataset of periapical radiographs compared to large groups of evaluators increasing robustness of the study. The model presented high sensitivity of 83.5%, specificity of 82% and precision of 82.27%; pointing out that caries could be detected more accurately on periapical radiographs with ensured reliability of the output model.

Ezhov et al.³³ achieved diagnostic consensus between two large groups of evaluators and Diagnocat software for caries detection on CBCT. The AI-aided and unaided groups of evaluators were compared to each other in a real-time clinical environment. The aided group achieved higher sensitivity of 85% and specificity of 97% compared to the unaided group 77% sensitivity and 96% specificity. The results emphasize the important role of Diagnocat in helping dental professionals achieve an accurate diagnosis of dental diseases. The missing tooth module presented high sensitivity of 98.2% on CBCT scans and a specificity of 94% demonstrating good performance of the proposed model in the detection of missing teeth.

The computer-based pattern recognition methods help dental operators to spot initial stages of caries, while for more advanced lesions, no significant support is provided to help the dentist with the diagnosis of caries. In fact, all AI-systems in all studies were trained and labelled by multiple annotators with various degrees of seniority and expertise, which then, provides multiple experts' sensitivity to an individual dentist when using the AI-system. As a result, the sensitivity of the dentist is boosted for the detection of the initial stages of caries.

The AI-based software in this study showed limitations in caries detection, in some cases the caries was detected on the gingival margin of edentulous areas. In other cases, it was incorrectly detected in the white frame of the scan image. Furthermore, the

software was unable to differentiate between darker pixels on the crowns of some teeth and identified those pixels as caries radiolucency indicating large number of false positive cases.

In this present study, while the software proceeded to detect the targeted elements, FDI tooth identification module was successful in detecting supernumerary teeth and implant supported teeth but was repeatedly unable to identify remaining roots of extracted teeth, roots of teeth with badly decayed, broken, or missing anatomical crowns, and impacted teeth. Additionally, the software couldn't detect teeth that were present in areas with artifacts or blurred areas. That has occasionally led to incorrect localization of dental caries which led to partial rejection of the null hypothesis, which was the ability of the proposed AI-based software to independently and accurately detect caries without human supervision. Meanwhile, the use of various custom neural networks with diverse automated detection tasks can boost the performance of the CNN. Hence, the results obtained have shown a faster learning phase and increasingly precise results^{10,28}

The accuracy of the FDI tooth identification module has a great impact on the overall accuracy of the software. Failure of the FDI tooth identification module to detect a tooth will result in the faulty diagnosis of that tooth by other modules.

This present study has certain limitations, such as employing two dental experts for annotating the dataset and only disagreements were evaluated by the third dental expert for setting the ground truth. Another limitation is the use of a relatively small dataset to ensure reliability of the FDI tooth identification module and the missing tooth module, adding to the importance of using a dataset with more supernumerary teeth, impacted teeth and residual roots. It should be noted that the OPGs were obtained

from a single panoramic machine, so the diagnostic capacity of the AI-based software and the operators was affected by the standardized quality of the images utilized in the study ⁴¹. Additionally, the diagnostic capability of the software was tested individually without the use of the adjusting and editing module to correct the results obtained by the software. Consequently, the software understood that what it detected was accurate while it might not be correct, so the learning capacity of the software could not be measured in this study. Another limitation was the unequal presentation of each variable in the dataset, such as presenting a larger number (10,735) of teeth to be identified by the FDI identification module and only 1884 teeth were diagnosed as carious by ground truth to be evaluated by the caries detection module. Likewise, only 1724 teeth were diagnosed as missing and evaluated by the missing tooth module. Thus, equity should be assured in future studies between the variables for a better understanding of the CNNs detection and classification capacities.

Suggestions for optimization of the AI algorithm and increasing the CNNs accuracy might include using more heterogeneous imaging dataset to avoid underrepresentation of some variables to ensure generalizability. Likewise, OPGs from diverse imaging machines should be utilized within the same study, to avoid training the software on a dataset having the same quality images. Additionally, more dental experts could be employed to set the ground truth. It is important to mention the recommendation of having an ethical board approval to follow AI-ethics related guidelines as Rokhshad et al. ⁴², stated in their study, which emphasizes the importance for dental operators and professionals to receive formal academic training on the ethical considerations in AI in dentistry. These considerations have been taken into account while conducting this present study.

Conclusions

Results of this study suggested that using this AI-based software can provide reliable evaluation for dental caries and other variables on OPGs with some limitations. The main outcomes for all the variables were higher than 74% diagnostic accuracy presented by FDI tooth identification, 85.9% for caries detection and 92% for missing tooth detection. The results obtained by the Specific threshold of the caries detection module provide a reliable performance for the early detection of caries on OPGs. Therefore, our AI-based software can help improve diagnostic quality and performance of dental clinicians with the ability of the software to improve its performance with an ascending learning curve.

Conflicts of interest: the authors declare no conflict of interest

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