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Automated diagnosis using artificial intelligence a step forward for preventive dentistry: A systematic review

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ABSTRACT

Background. Early diagnosis and monitoring the evolution of the patients is required to be able to have effective preventive attitudes. An easy and cost-effective way of diagnosis is needed for this purpose. The aim of the study was to evaluate the AI level of use in dentistry diagnosis and the fields of its applicability especially for early diagnosis purposes. A secondary objective was to point out the measured performances for automated AI diagnosis by comparison with standard diagnosis procedures.

Material and methods. A comprehensive electronic search was performed in November 2022 through PubMed, Scopus, and Web of Science databases. The following keywords were used to search the databases: ("Artificial Intelligence" OR "neural network" OR "Deep learning" OR "Machine learning") AND ("Dentistry" OR "Dental medicine") AND (" periodontal disease" OR "periodontics" OR "Carious lesions" OR "oral cancer" OR "restorative" or "early diagnosis"). The risk of bias (RoB) of the included studies was assessed using PROBAST tool.

Results. A total of 334 publications were collected after searching the databases. For 218 remaining publications the title and the abstract were assessed. The reviewers agreed to continue with 69 studies for full text assessment. Because 49 studies had not completely fulfilled the inclusion criteria only 20 publications were included in the final analysis. AI automatic data processing for diagnostic purposes was implemented in the field of dental radiology, oral pathology, restorative dentistry, pedodontics, oncology, endodontics, and periodontics.

Conclusion. AI based automatic diagnostic is a powerful and reliable tool that has a great future potential for different fields of dental medicine like periodontal disease, oral cancer, and carious lesions.

Keywords: artificial intelligence, machine learning, early diagnosis, preventive dentistry, automatic diagnosis

INTRODUCTION

Dental caries and periodontal disease are extremely widespread conditions globally [1,2]. The number of people with untreated oral conditions rose from 2.5 billion in 1990 to 3.5 billion in 2015 [3]. In 2019, there were 3.09 billion new cases of untreated dental caries in permanent teeth (48.00% increase) and there were 1.1 billion prevalent cases of severe periodontitis globally [4]. Data from the Global Cancer Observatory (GCO) shows that the annual incidence of Oral squamous cell carcinoma (OSCC) in 2020 was 377,713 cases worldwide, with the highest number recorded in Asia (248,360), followed by Europe (65,279) and North America (27,469) [5]. Early diagnosis and monitoring the evolution of the patients is required to be able to have

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effective preventive attitudes. An easy and cost-effective way of diagnosis is needed for this purpose. New specific, reliable, and valid diagnostic techniques should be developed, independent from the operator's subjective perception of variables like carries lesion color and tissue hardness, to avoid accidental invasive treatment [6] or undertreatment. This kind of technology should detect initial stages of demineralization, allowing non-invasive intervention as early as possible to prevent further damage [7]. Periodontal diagnosis is still operator dependent due to the drawbacks of manual probing. The periodontal probing and periodontal diagnosis errors can impact clinical decision-making, especially during longitudinal monitoring of the periodontal status [8]. Progress in solving this situation was made by Lee et al, demonstrating in 2020 that digital measurements of the keratinized tissue width using 3D scanned images can replace conventional clinical measurements using a periodontal probe since they are more accurate and reliable [9]. New technologies should be developed to lower the operator dependency during diagnosis processes, which can replace the lack of highly qualified personnel in the medical system, especially in developing countries and in areas with reduced accessibility to the medical services. Late diagnosis of oral cancer is probably the main reason why the prognosis of this disease—essentially referring to mortality—has not changed substantially in the last 50 years, despite advances in treatment [10].

Artificial intelligence (AI) showed in the past years a great potential to improve dental care, disease diagnosis and prognosis, treatment planning, and risk assessment. The advantages of using AI are better efficiency, accuracy, and time saving through the automatization [11,12].

The aim of the study was to evaluate the AI level of use in dentistry diagnosis and the fields of its applicability especially for early diagnosis purposes. A secondary objective was to point out the measured performances for automated AI diagnosis by comparison with standard diagnosis procedures.

MATERIAL AND METHODS

Protocol

The systematic review was conducted according to the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses Protocols (PRISMA) Statement [13]. The protocol was registered in PROSPERO database (CRD42022373286) before starting the study.

Review question: To what extent is artificial intelligence applied in automatic diagnosis in preventive dentistry and what are the performances achieved?

Search strategy

The PICO(S) strategy was considered to elaborate the research question: (P) The studies should report the performances of artificial intelligence-based software for oral-dental diagnosis (periodontal disease, dental decay, or oral cancer); (I) The AI software to suport diagnosis can be used by the patient for pre-diagnosis or by a dentist; (C) AI automated diagnosis and standard clinical diagnosis; (O) gold standard metrics and values for oral-dental diagnosis; (S) diagnostic accuracy prospective and retrospective studies, diagnostic accuracy observational studies, and diagnostic accuracy comparative studies.

A comprehensive electronic search was performed in November 2022 through PubMed, Scopus, and Web of Science databases. The following keywords were used to search the databases: (”Artificial Intelligence” OR ”neural network” OR ”Deep learning” OR ”Machine learning”) AND (”Dentistry” OR "Dental medicine") AND ("periodontal disease" OR ”periodontics” OR ”Carious lesions” OR ”oral cancer” OR ”restorative” or ”early diagnosis”)

Eligibility criteria

Inclusion criteria: Articles published in English; studies investigating the effectiveness of Artificial intelligence software diagnosis in various dental medicine fields, comparing the results with standard clinical and/or para-clinical investigation based diagnosis; Articles published in the last 10 years (up to November 2022); Exclusion criteria: studies in languages other than English; Review articles; meta-analysis studies; letter to editors and case reports; Animal studies; in vitro studies; conference abstracts; expert opinions; Full-text not available/accessible; studies related with disease risk prediction and prognostic.

Study selection

Two independent reviewers (R.C. and A.F.B.) performed the bibliographic search and selected the articles according to inclusion and exclusion criteria. The titles and abstracts were independently evaluated by the two authors. Disagreements between them were solved by discussions and the final decision was made by consulting a third author (L.M.D(R).).

Data collection

The following data from the included studies were extracted: Author, year, Study type, Country, Dataset size, Dataset training/validation/testing ratio, Dentistry field, AI model, Outcomes Clinical and/or para-clinical parameters, Conclusions. EndNote 20.4.1 Program was used for study selection and for collecting the data after searching databases. Tables 1 shows the extracted variables from the included studies.

Risk of bias assessment

The risk of bias (RoB) of the included studies was assessed using PROBAST tool [14,15]. For each study included in the research 20 questions were answered related with Participants, Predictors, Outcome and Analysis. According to the tool the answers were classified as ”Yes”, ”No”, ”Unclear” using the predefined criteria. The statistics of PROBAST percentage for the assessed studies are presented in Figure 2.

RESULTS

Study selection

After searching the PubMed, Web of Science and Scopus databases a total of 334 publications were collected (Figure 1). Using EndNote 20.4.1 Program, the duplicates were eliminated. For 218 remaining publications the title and the abstract were assessed. The reviewers agreed to continue with 69 studies for full text assessment. Because 49 studies had not completely fulfilled the inclusion criteria only 20 publications were included in the final analysis.

Studies characteristics

Twenty studies were included. Most of them, as seen in Table 1 where the collected data is presented, were retrospective studies. Three of them were carried out in China, 5 in USA, 3 in Japan, 2 in Thailand, 2 in Turkey and one in each from the following: Germany, Croatia, Austria, Saudi Arabia and New Zealand.

13 of the included studies were related with the field of radiology, analyzing CBCTs – 1 study, CECTs – 1 study, bitewing, or periapical X-Rays – 5 studies, panoramic X-Rays – 6 studies. 5 studies were related to image processing from photos, 1 study was related to image processing form videos and 1 study related to cytology-on-a-chip measurements. AI automatic data processing for diagnostic purposes was implemented in the field of dental radiology, oral pathology, restorative dentistry, pedodontics, oncology, endodontics, and periodontics.

In Kearney et al., 2022 study used the largest database for training, validation and testing the AI model. Bitewing and periapical radiographs from 12400 patients were processed to predict the clinical attachment loss according to the radiographic bone level. In all the 20 studies, 23 different AI models were used.

Risk of bias assessment

All the included studies were assessed using PROBAST tool for the risk of bias. In Figure 2 one can see the overall average score for the four types of answered questions during the evaluation process.

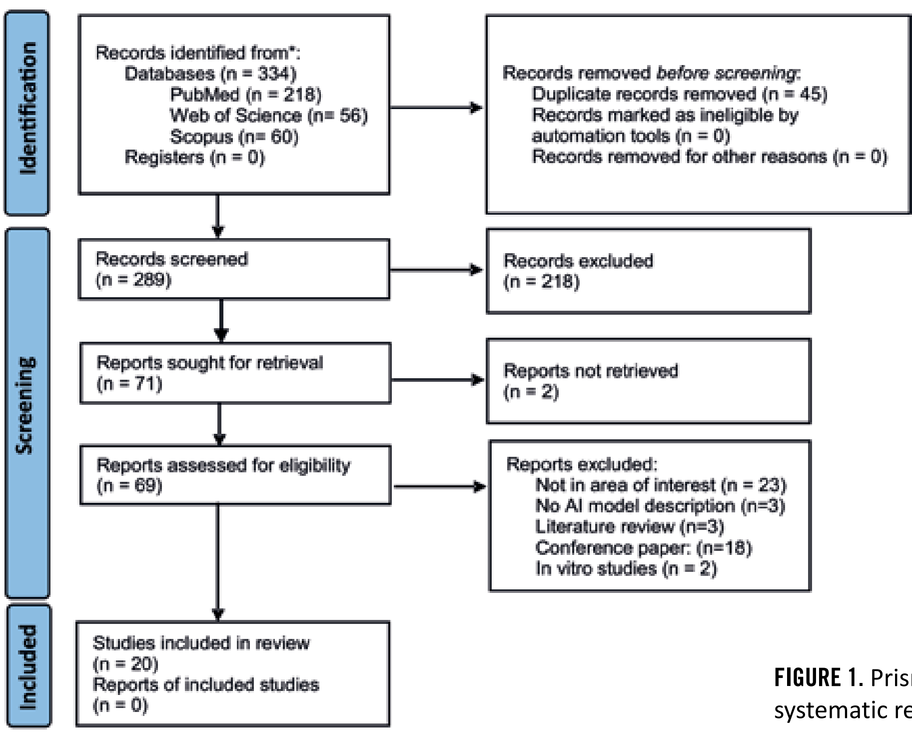

FIGURE 1. Prisma (preferred reporting items for systematic reviews and meta- analyses) flowchart

TABLE 1. Collected data from the included studies

No	Author, year	Study type	Country	Dataset characteristics and size	Dataset training/ validation/ testing ratio	Dentistry field	AI model	Outcomes, Clinical and/or para-clinical parameters, AI performance measurement parameters	Conclusions
1	Hou et al 2022 [16]	Retrospective	China	1500 panoramic X-ray	8:1:1	Radiology, panoramic images	U-Net U-Net++ SEResUNet ResUNet Own (Teeth U-Net)	Teeth manual segmentation, training and prediction Acc% Pre% Recall% Dice% Voe% Rvd%	accurate segmentation of all teeth in the dental panoramic image and clear judgment of teeth root boundary using own Teeth U-Net model
2	Setzer et al. 2022 [17]	Retrospective	USA	6 male, 14 female CBCTs, 61 roots, 29 periapical lesions	8:2:no test	Radiology, CBCT	multilabel U-Net	manual segmentation, Dice	Deep learning algorithm trained in a limited CBCT environment showed excellent results in lesion detection accuracy
3	Ariji et al. 2019]	Retrospective	Japan	24 men, 21 women, CECT, 127 metastatic lymph nodes and 314 negative lymph nodes, confirmed histopathological, data augmentation 10638 metastatic and 10724 negative lymph node images	not specified	Radiology, CECT	AlexNet	Accuracy, Sensitivity, Specificity, PPV, NPV, AUC	For identifying metastatic lymph nodes deep learning system yielded diagnostic results like those of the radiologists, which suggests that this system may be valuable for diagnostic support
4	Kearney et al. 2022 [19]	Retrospective	USA.	model was trained on 80,326 images (9264 patients) and validated on 12,901 images (1,225 patients), predictions on 1911 patients	74.6% 10% 15.4%	Radiology/ Periodontics, bitewing; periapical	Deep Lab V3+, DETR	clinical CAL as ground truth, mean absolute error between the ground truth and predicted values, comparator p-values from the Kruskal-Wallis test	Artificial intelligence developed and utilized to predict clinical attachment level found to be within the 1mm clinician-determined measurement standard
5	Warin et al. 2022 [20]	Retrospective	Thailand	300 images of Oral potentially malignant disorders OPMDs (oral leukoplakia (59 images), erythroplakia (79 images), and erythroleukoplakia (116 images), white striae (22 images) and erythematous lesions surrounded with white striae (24 images)) and 300 of normal oral mucosa	7:1:2	Oral pathology/ Image recognition	DenseNet-121, ResNet-50, Faster R-CNN	biopsy confirmation Precision, Recall, F1 score, Sensitivity, Specificity, AUC of the ROC curve	DenseNet-121, ResNet-50 and Faster R-CNN models have potential for the classification and detection of OPMDs in oral photographs

No	Author, year	Study type	Country	Dataset characteristics and size	Dataset training/ validation/ testing ratio	Dentistry field	AI model	Outcomes, Clinical and/or para-clinical parameters, AI performance measurement parameters	Conclusions
6	Abram et al. 2016 [21]	Prospective	USA	lesion samples from a total of 714 patients (348 benign, 49 mild dysplasia, 18 moderate dysplasia, 12 severe dysplasia, 2 carcinomas in situ (CIS), and 135 malignant lesions in addition to 150 healthy controls) of which 85 were previously diagnosed malignant cases. 2000 cells per patient, resulting in nearly 13 million indexed objects, each with over 200 unique measurements	2/3: blinding process:1/3	Oral pathology, cytology-on-a-chip measurements	Lasso, Random Forest	Histopathological assessment of biopsy specimens, Sens% Spec% AUC	demonstrated the utility of a new cytology-on-chip framework for extracting high-content, single-cell data composed of cellular and nuclear morphometric and molecular biomarker expression measurements that has the potential to serve as an adjunctive aid in assessing suspicious oral lesions.
7	Liu et al. 2022 [22]	Retrospective	USA	39,264 annotated image patches from 112 unique patient training and validation,44 unique patient cases (29 OED and 15 hyperplastic unremarkable oral epithelium)	not specified	Oral pathology oral epithelial dysplasia (OED)	DeepLabv3+, UNet++	Manual annotation, Sensitivity Precision Accuracy AUC-ROC (pixelwise) F1-Score Dice Index	Computer assisted detection was shown to be feasible in detecting premalignant/ precancerous oral lesions of epithelial dysplasia (OED), laying groundwork for eventual clinical implementation.
8	Fu et al. 2020 [23]	Retrospective	China	5775 randomly selected photographs for training, 401 photographs for internal validation, 420 clinical photographs for external validation, 1941 photographs of OCSCC, other diseases or disorders of oral mucosa and normal oral mucosa for clinical validation	not specified	Oral pathology, oral cavity squamous cell carcinoma OCSCC	pre-trained model ImageNet dataset	Manual annotation, AUC Sensitivity Specificity Accuracy	deep learning methods may offer opportunities for automatically identifying OCSCC patients with the performance matching or even beyond that of skilled human experts.
9	Bayraktar et al. 2021 [24]	Retrospective	Turkey	800 radiographs were consisted of 11,521 approximal surfaces of which 1,847 were decayed, augmented four times: 200 radiographs for testing and validation	8 (training):2 (testing and validation)	Restorative Dentistry/ Radiology, bitewing X-ray	YOLO-based CAA system	Manual annotation, Accuracy Sensitivity Specificity PPV NPV	The proposed CAA system achieved an accuracy of more than 90% in diagnosing approximal caries lesions without the need for a dentist.
10	Schwendicke et al 2022 [25]	Retrospective	Germany	3826 bitewing radiographs,29,011 tooth crops without caries lesions and 19,760 tooth crops with caries lesions, test data set contained 692 tooth crops without caries lesions and 401 tooth crops with caries. Resnet-18 architecture pretrained on the ImageNet data set. The number of tooth crops employed for training/validation was incrementally increased from 10% of the total data set to 25%, 50%, and 100%. 4 different models, whose classification accuracy (true and false positive or negative findings) was employed to inform the health economic model	not specified	Restorative Dentistry/ Radiology, bitewing X-ray	Resnet-18 architecture pretrained on the ImageNet data set	Manual annotation for lesions into the inner enamel half, D1: lesions into the outer third of dentin; D2–D3: lesions into the middle or inner third of dentin, true-positive (TP) and true-negative (TN) rates	With an increasing amount of data used to train the AI, both sensitivity and specificity increased. Notably, this increase was not linear; the increase was largest when increasing the data set from 10% to 25% and limited afterwards. Informed choices about the data set size may be recommended, and research toward individualized application of AI for caries detection seems warranted to optimize cost-effectiveness.

No	Author, year	Study type	Country	Dataset characteristics and size	Dataset training/ validation/ testing ratio	Dentistry field	AI model	Outcomes, Clinical and/or para-clinical parameters, AI performance measurement parameters	Conclusions
11	Zheng et al. 2021 [26]	Retrospective	China	844 periapical radiographs	85% training, 15% test	Restorative Dentistry/ Radiology, periapical X-ray	VGG19, Inception V3 and ResNet18 pre-trained models	clinical diagnosis of deep caries or pulpitis was further conducted, AUC, the area under the ROC Accuracy, Precision, Sensitivity, Specificity	The multi-modal CNN (ResNet18 + C), which took the clinical parameters into account, demonstrated significantly enhanced performance, with a promising potential for clinical diagnosis of deep-caries and pulpitis.
12	Muslin et al. (27)	Retrospective	Croatia	322 oral squamous cell carcinoma (OSCC) histology images, images have been divided into three classes: well-differentiated (grade I), moderately differentiated (grade II), and poorly differentiated (grade III) OSCC	80% model training, 20% evaluating performances	Oral cancer, image recognition	Xception, ResNet50, ResNet101, MobileNetv2, DeepLabv3+	Manual annotated masks, AUCmacro and -micro, mean intersection-over-union (mIOU), Dice coefficient (F1), accuracy (ACC), precision, sensitivity, and specificity	Obtained results reveal that the proposed AI-based system has great potential in the diagnosis of OSCC.
13	Feher et al. 2022 [28]	Retrospective	Austria	855 OPGs, test set had 384 OPGs in total, of which 240 were negative.	8:1:1	Radiology, panoramic X-Ray images	RetinaNet Random Forest classifier, U-Net++, ImageNet	cystic lesions on the OPGs confirmed histopathological diagnosis, Diagnosis of a cystic lesion, object detection model, signs of odontogenic or non-odontogenic pathogenesis, Sensitivity (Recall) Specificity PPV (Precision) NPV F1-score	A combined object detection and image segmentation approach is feasible in emulating the human clinical diagnostic reasoning process in classifying cystic lesions of the jaw.
14	Alalharith et al. 2020 [29]	Retrospective	Saudi Arabia	804 regions from 134 intraoral images of all 47 patients	training and testing with a ratio of 80:20	Periodontics, intraoral images	Faster R-CNN, ResNet-50 CNN	expert dentists labeled as either inflamed or non-inflamed using Löe and Silness gingival index, Accuracy Precision Recall mAP	This study proved the viability of deep learning models for the detection and diagnosis of gingivitis in intraoral images. Hence, this highlights its potential usability in the field of dentistry and aiding in reducing the severity of periodontal disease globally through preemptive non-invasive diagnosis.
15	Mine et al. 2022 [30]	Retrospective	Japan	220 children with supernumerary teeth Panoramic radiographs, in the region from the maxillary midline to the incisors.	validation: testing 8:2	Radiology, panoramic X-Ray images	AlexNet, VGG16-TL, InceptionV3-TL	experienced pediatric dentists diagnosed and sorted the panoramic radiographic images Accuracy (%) Sensitivity (%) Specificity (%)	The CNN-based deep learning is a promising approach for detecting supernumerary teeth during the early mixed dentition stage.

No	Author, year	Study type	Country	Dataset characteristics and size	Dataset training/ validation/ testing ratio	Dentistry field	AI model	Outcomes, Clinical and/or para-clinical parameters, AI performance measurement parameters	Conclusions
16	Kavitha et al. 2013 [31]	Retrospective	Japan	100 postmenopausal women recruited at Hiroshima University Hospital	60 were allocated for system training and 40 for testing	Radiology, panoramic X-Ray images	Histogram-based automatic clustering algorithm with a support vector machine	measurement between the upper and lower boundaries of the cortical bone on original panoramic radiographs, ROCs (AUCs), Sensitivity % Specificity % Positive predictive value % Negative predictive value % Accuracy %	proposed Histogram-based automatic clustering algorithm model with a support vector machine model combination applied on dental panoramic radiographs could be useful to assist dentists in early diagnosis and help to reduce the morbidity and mortality associated with low bone mineral density and osteoporosis.
17	Thanathornwong et al., 2020 [32]	Retrospective	Thailand	100 anonymized digital panoramic radiographs of periodontally compromised patients	7:1:2	Periodontics/ Radiology, panoramic X-Ray images	faster R-CNN model, pretrained ResNet architecture	periodontal examination chart, drawing bounding box for periodontal compromised teeth, sensitivity, specificity, F-measure	The application of a faster R-CNN to assist in the detection of periodontally compromised teeth may reduce diagnostic effort by saving assessment time and enabling automated screening documentation.
18	Kaya et al., 2022 [33]	Retrospective	Turkey	4518 anonymized panoramic radiographs of pediatric patients	3,395 images training and, 523 images were used for testing	Pedodontics/ Radiology, panoramic X-Ray images	YOLOv4 CNN model	locations of permanent tooth germs were carried out by drawing a bounding box, true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) rates, precision, recall, F1-score	The detection of permanent tooth germs on pediatric panoramic X-rays using a deep learning-based approach may facilitate the early diagnosis of tooth deficiency or supernumerary teeth and help dental practitioners find more accurate treatment options while saving time and effort.
19	Lee et al., 2021 [34]	Retrospective	USA	693 periapical radiographic images from randomly selected 37 periodontitis patients, evaluated on 644 additional periapical images (“additional dataset”) from randomly selected 46 cases to assess	7:1:2	Periodontics/ Radiology, periapical X-Ray images	U-Net, U-Net with ResNet-34, U-Net with ResNet-50 Encoder	Staging, annotate regions of the bone area, tooth shape, and CEJ line segmentations from each intra-oral radiograph, AUROC Sensitivity Specificity Accuracy	The proposed deep learning model provides reliable radiographic bone lose measurements and image-based periodontal diagnosis using periapical radiographic images.
20	Mohamed et al. 2022 [35]	Observational	New Zealand	16 females, 14 males	not specified	Restorative dentistry and orthodontics, videos	OpenFace2.2.0, automatic facial recognition software	full-face videos reviewed and coded frame-wise to identify each distinct smiling episode, (ROC) curves, Sensitivity, specificity	Individual smile episodes and their quantitative features, such as frequency, duration, genuineness, and intensity can be automatedly assessed with an acceptable level of accuracy to investigate the impact of oral conditions and their rehabilitation on smiles.

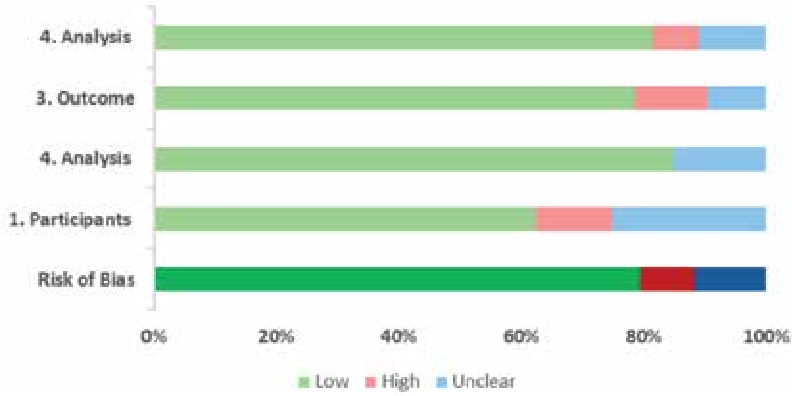

FIGURE 2. Risk of Bias assessment, PROBAST tool

DISCUSSION

Bayraktar et al., 2021 study evaluated a tool for proximal carious lesions diagnosis using AI models to process bitewing and periapical X-Rays [24]. This could be a powerful tool for monitoring the carious lesions activity of the patients, saving in the future a lot of time for the clinicians. Schwendicke et al, 2022 showed that research toward individualized application of AI for caries detection seems warranted to optimize cost-effectiveness [25].

The screening program is found to be cost-ineffective for oral precancer detection in Thailand [36]. In United Kingdom oral cancer screening program has not been implemented because had only provided evidence to satisfy five of the 20 criteria required by the UK Screening Committee [37]. Some of the unaddressed criteria were: "The program should be cost effective", and "the distribution of test values should be known (for example, sensitivity and specificity) and the criteria for a positive test should be agreed" [37]. The studies from our review showed that AI automated diagnosis tools meet both of those criteria being cost-effective due to the automated processes and their outcome is easily quantified through specific parameters. Machine learning technology used for diagnosis purposes, being developed recently, imposes a lot of future research and testing in clinical environments. Recent studies showed AI models promising results for identifying from intra-oral images precancerous or cancerous lesions. Warin et al., 2022 demonstrated good results for Oral potentially malignant disorders (OPMD) identification [20], Liu et al., 2022 showed to be a feasible technology in detecting premalignant/precancerous oral lesions of epithelial dysplasia (OED) [22] and Fu et al., 2020 used it for automatically identifying oral cavity squamous cell carcinoma (OCSCC) patients with the performance matching or even beyond that of skilled human experts [23].

Providing the field of dentistry with an enhanced non-invasive method to diagnose gingivitis using intraoral images can help to reduce the complications of untreated gingivitis [29]. Using non-invasive diagnosis methods, early signs of periodontal disease can be identified from intra-oral photos. This means reduced costs and could be a very good way to motivate and remotivate the patient to have proper oral hygiene. Assessing radiographic bone level (RBL) is important for periodontal diagnosis. The interpretation of radiographic images is subjective, and accuracy depends on a clinician's experience and knowledge [34]. Kearney et al., 2022 pointed out that well-chosen AI model and properly trained can predict clinical attachment level, found to be within the 1mm clinician-determined measurement standard, automated prediction based on periapical or bitewing radiographs [19]. The results of our study showed that good performance can be obtained, comparable with standard diagnosis methods but as previous studies showed, the AI technology it has not yet been fully introduced to dental research nor have reached technological readiness and cost-efficiency to enter the dental market [38].

We consider that the aim of this literature review was achieved by identifying multiple credible studies that show a sustained use, especially for research purposes of AI based diagnosis tools in periodontics, restorative dentistry, oral cancer, endodontics, and orthodontics. There is a real potential for extended future use, on a large scale, due to the very good results obtained compared to standard diagnostic methods. There are several limitations of our study. The most important is that the search was performed only in three databases. Future studies should extend the research to other databases and provide metanalysis to recommend the most efficient AI models according to the imaging techniques being used and to the field of dentistry where are applied.

CONCLUSION

AI based automatic diagnostic is a powerful and reliable tool that has a great future potential for different fields of dental medicine like periodontal disease, oral cancer, and carious lesions. It may help the clinician become more efficient and point out problems which could be omitted at first glance during clinical examination. It can also be an important tool for the efficiency of screening generating costs and time efficiency, helping to implement preventive methods through the early diagnosis.

Abbreviations

Artificial Intelligence (AI), Accuracy (Acc), Precision (Pre), Dice coefficient (Dice), Volumetric Overlap Error (Voe), Relative Volume Difference (Rvd), contrast enhanced computed tomography (CECT), Cone beam computed tomography (CBCT), area under the curve (AUC); negative predictive value (NPV); positive predictive value (PPV), clinical attachment levels (CAL), Oral potentially malignant disorders (OPMDs), oral cavity squamous cell carcinoma (OCSCC).

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