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Review article

Developments, application, and performance of artificial intelligence in dentistry — A systematic review

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KEYWORDS
Artificial intelligence dentistry;
Machine learning;

Abstract *Background/purpose:* Artificial intelligence (AI) has made deep inroads into dentistry in the last few years. The aim of this systematic review was to identify the development of AI applications that are widely employed in dentistry and evaluate their performance in terms of diagnosis, clinical decision-making, and predicting the prognosis of the treatment.

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Computer-aided diagnosis;
Deep learning models;
Convolutional neural networks;
Artificial neural networks

Materials and methods: The literature for this paper was identified and selected by performing a thorough search in the electronic data bases like PubMed, Medline, Embase, Cochrane, Google scholar, Scopus, Web of science, and Saudi digital library published over the past two decades (January 2000—March 15, 2020).After applying inclusion and exclusion criteria, 43 articles were read in full and critically analyzed. Quality analysis was performed using QUADAS-2.
Results: AI technologies are widely implemented in a wide range of dentistry specialties. Most of the documented work is focused on AI models that rely on convolutional neural networks (CNNs) and artificial neural networks (ANNs). These AI models have been used in detection and diagnosis of dental caries, vertical root fractures, apical lesions, salivary gland diseases, maxillary sinusitis, maxillofacial cysts, cervical lymph nodes metastasis, osteoporosis, cancerous lesions, alveolar bone loss, predicting orthodontic extractions, need for orthodontic treatments, cephalometric analysis, age and gender determination.
Conclusion: These studies indicate that the performance of an AI based automated system is excellent. They mimic the precision and accuracy of trained specialists, in some studies it was found that these systems were even able to outmatch dental specialists in terms of performance and accuracy.

Introduction

The exponential growth in science and technology has introduced different applications that are used daily, such as siri and alexa. These applications are found on the top of artificial intelligence (AI) and its components. The term AI is mostly associated with robotics. It describes how technology is used to develop a software or a machine that can easily mimic human intelligence and perform specific activities.

John McCarthy, a mathematician coined the term artificial intelligence in 1955, and widely recognized as the father of artificial intelligence. He chose this term to explain the potential of machines to perform tasks that can fall in the range of "intelligent" activities.[1]

In the year 1956, John McCarthy organized a famous Dartmouth conference, which was formally on the research project artificial intelligence, this is when this discipline originated. The conference sparked the crucial period, from 1950s to 1970s, wherein extensive research was done on AI.[2]

In 1978 Richard Bellman, an applied mathematician defined artificial intelligence as the automation of activities associated with human thinking abilities, which includes learning, decision making and problem solving.[3]

In the modern day world, artificial intelligence refers to any machine or technology that is able to mimic human cognitive skills like problem solving. To understand AI, it is important to know few of these key aspects (Fig. 1).

- *Artificial intelligence* is termed as a capability of machines that exhibits a form of its own intelligence. The aim here was to develop machines that can learn through data so that they can solve the problems.
- *Machine learning* is part of AI, which depends on algorithms to predict outcomes based on a dataset. The purpose of machine learning is to facilitate machines to learn from data so they can resolve issues without human input.
- *Neural networks* are a set of algorithms that compute signals via artificial neurons. The purpose of neural networks is to create neural networks that function like the human brain.
- *Deep learning* is a component of machine learning that utilizes the network with different computational layers in a deep neural network to analyze the input data. The purpose of deep learning is to construct a neural network that automatically identifies patterns to improve feature detection.[4]

Deep learning is also known as convolutional neural networks. They collect features from the abstracted layer of filters and are primarily used to process large and complex images.[5]

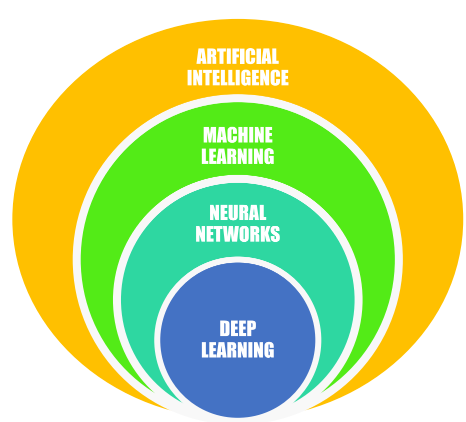


Figure 1 Key aspects of artificial intelligence.

Application of AI in dentistry

AI has been used mainly in dentistry to make the process of diagnosis more accurate and efficient, which is of atmost importance in achieving best results to the treatments provided along with superior quality patient care.

Dentists need to use all their acquired knowledge to diagnose and decide the best treatment option. They are also required to predict the prognosis where they need accurate clinical decision-making skills. However, in some cases, dentists do not have enough knowledge to make the right clinical decision in a limited period. AI applications can serve as their guide so that they can make better decisions and perform better.

Shortliffe,[6] Chae et al.,[7] Schleyer et al.,[8] reported that dentists have become dependent on computer applications to get insights for clinical decision making. The aim of this systematic review was to identify the development of AI applications that are widely employed in dentistry and to evaluate their performance in terms of diagnosis, clinical decision-making, and predicting the prognosis of the treatment.

Table 1 Description of the PICO (P= Population, I= Intervention, C= Comparison, O= Outcome) elements.

Research question	What are the developments, performance, and application of artificial intelligence in dentistry?
Population	Patients diagnostic images related to oral and maxillofacial regions [clinical images, radiographs, CBCT, confocal laser endomicroscopy (CLE) Images, intraoral fluorescence images, cephalometric radiographs, near-infrared-light transillumination (NILT) images]
Intervention	AI based models for diagnosis, treatment planning, clinical decision making, predicting the need for treatment, and predicting the prognosis.
Comparison	Expert opinions, reference standards
Outcome	Measurable or predictive outcomes such as accuracy, sensitivity, specificity, ROC = receiver operating characteristic curve, AUC = Area Under the Curve, ICC = Intraclass Correlation Coefficient, Positive/Negative Predictive Values (PPV/NPV)

Materials and methods

Data sources

This systematic review was carried after referring the guidelines for preferred reporting items for Systematic reviews and Meta-analyses extension for Diagnostic Test Accuracy (PRISMA-DTA).[9] The literature for this paper was identified and selected by performing a thorough search in the electronic data bases like Pubmed, Medline, Embase, Cochrane, Google scholar, Scopus, Web of science, and Saudi digital library published over the past two decades (January 2000—March 15, 2020) by using keywords such as artificial intelligence in dentistry, deep learning, machine learning, artificial neural networks, convolutional neural networks, and computer-aided diagnosis. This search was based on the PICO (problem/patient/population, intervention/indicator, comparison, and outcome) elements (Table 1).

Resources selection

Full-length articles were retrieved. Hand searching and electronic searching was performed to go through the journals. The required data for this review was selected in two stages. In the first stage the articles were selected based on the title and abstracts related to our research topic. The preliminary search resulted in 1268 articles that were appropriate enough to address the paper's aim. Due to duplication, 182 articles were removed. Hence, we retrieved 1086 articles for the second stage of selection. Next, the following criterion was applied.

Criteria for considering studies for this review

Inclusion criteria

1. The article must be focused on AI and its application should be related to dentistry.
2. There must be some predictive or measurable outcomes so they can be quantified.
3. There has to be a proper mention of datasets that are used to assess a model.

Exclusion criteria

1. The articles that are related to non-AI areas.
2. Uistaploaded articles that were unpublished.
3. Articles that consisted of only abstracts without the full text.
4. Articles that were not written in English.

This criteria cut down the number of articles to 46. The name of the journals and names of the authors were hidden and spread among the authors. A critical assessment was carried out for all the articles by following QUADAS-2 (Quality Assessment and Diagnostic Accuracy Tool) guidelines, a tool for quality assessment of the studies on diagnostic accuracy.[10] 3 more articles were excluded due to disagreement from the authors. Eventually, this systematic review performed qualitative synthesis on 43 articles (Fig. 2).

All the articles were read fully. The years of these articles were taken in account to study the progress of AI trends that were developed and evolved over the years in dentistry.

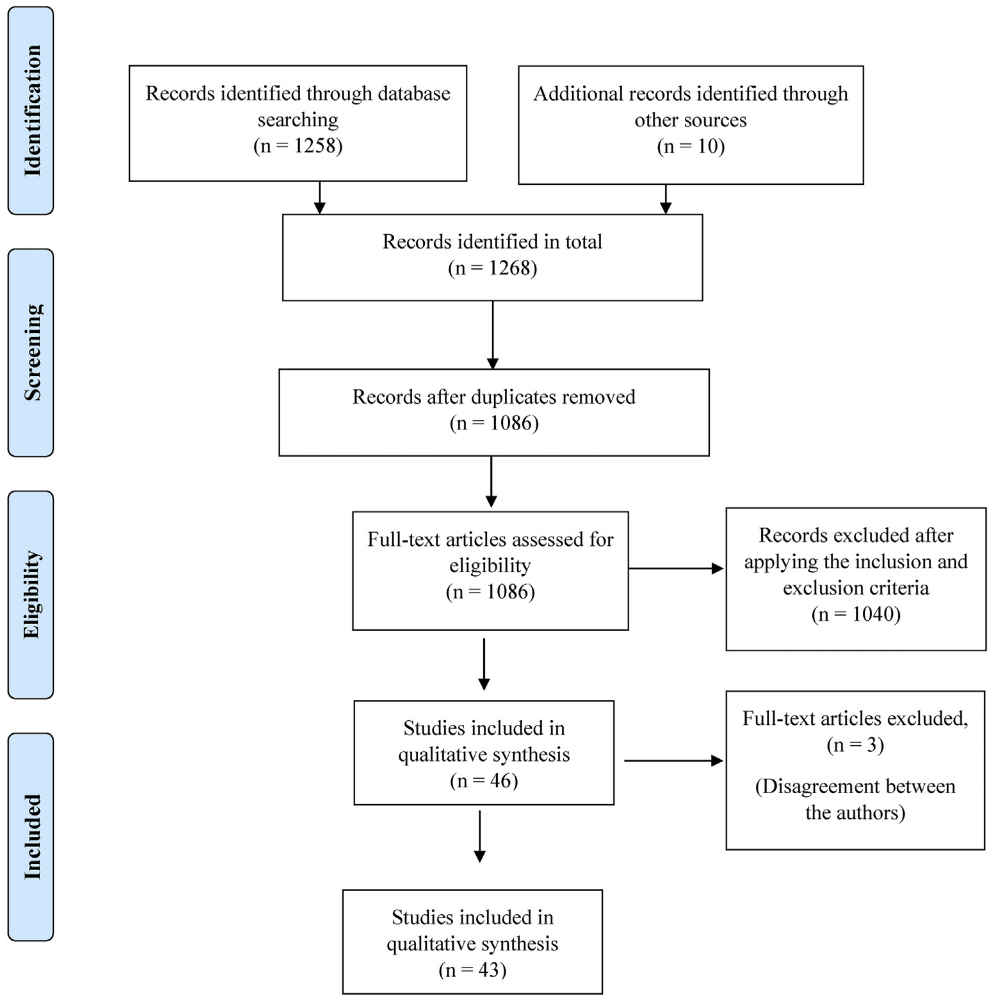
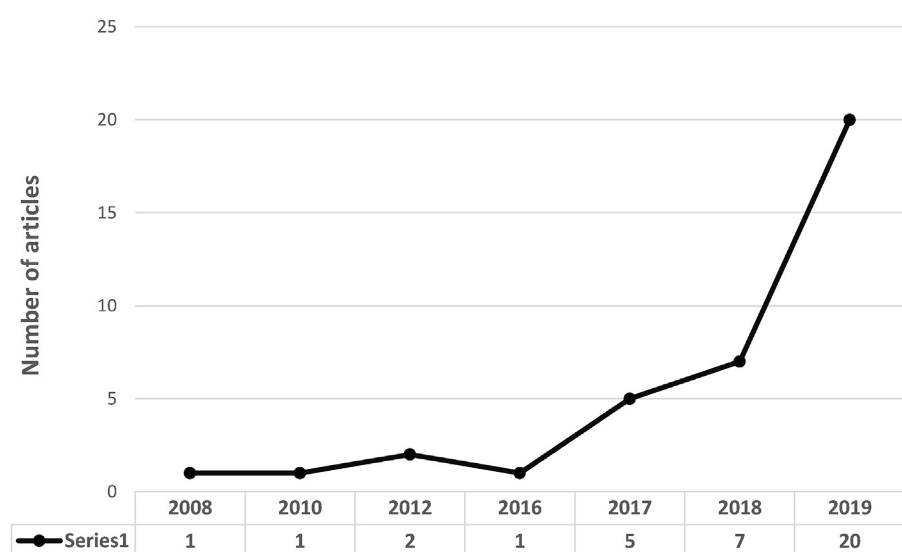


Figure 2 Flow chart for screening and selection of articles.



	2008	2010	2012	2016	2017	2018	2019
Series1	1	1	2	1	5	7	20

Figure 3 Trends of research on artificial intelligence in dentistry.

Results

This systematic review included 43 research articles that were analyzed for quantitative data. The analysis of the literature revealed that most of the studies were conducted in the past 12 years (Fig. 3). The trends showed that there is a gradual increase in the research related to artificial intelligence in dentistry.

The studies that were included in this systematic review were mainly on the application of AI for detection and diagnosis of dental caries, diagnosis of proximal dental caries, tooth detection and numbering, detection of vertical root fractures, detection of apical lesions, locating minor apical foramen, assessment of root morphology, diagnosis of salivary gland diseases, diagnosis of maxillary sinusitis, maxillofacial cysts, cervical lymph nodes metastasis, detection of osteoporosis, predicting diagnosis of orthodontic extractions, assessing need for orthodontic treatments, determining the growth and development of cervical vertebrae stages, cephalometric analysis, identifying cephalometric landmarks, diagnosis of orthognathic surgeries, assessing the impact of orthodontic treatment on the facial attractiveness, gender determination using mandibular morphometric parameters, estimating the age based on third molar development, classifying the cancerous tissues, predicting postoperative facial swelling following extractions, detection of periodontal bone loss, detecting the degree of alveolar bone loss.

Most of the studies have used convolutional neural networks (CNNs) and artificial neural networks (ANNs). Some of the studies were based on bayesian network (BN) and probabilistic neural networks (PNNS). The purpose of these neural networks is to determine computer tomography (CT) images, cone beam computed tomography (CBCT) images, lateral cephalometric radiographs, bitewing radiographs, facial photos, panoramic radiographs (OPG). (Table 2).

The studies that have been analyzed in this systematic review revealed that the AI technology has been widely used in different specialties of dentistry. AI technology has been applied in 18 studies on oral & maxillofacial radiology,[11,22,25,26,32,34,36–41,44–48,51] 11 studies on orthodontics and dentofacial orthopedics,[12,15,24,28–31,42,49,50,53] 5 studies on endodontics,[13,14,16,33,35] 4 studies on periodontics,[19,23,27,43] 2 studies from oral and maxillofacial surgery[18,21] and 3 studies from forensic odontology.[17,52,20]

Risk of bias assessment

All the studies were based on assessing the diagnostic accuracy of AI in various fields of dentistry. Hence, risk of bias assessment was assessed using QUADAS-2 assessment tool, which is frequently used tool in the literature (Supplementary Table 1). The studies conducted on human beings for determining the reference standard were rated as high risk. In the present analysis, 55.81% of studies reported high risk of bias for the reference standard. Since the data feeding in AI technology was highly standardized, AI had no effect on the flow, and time frame in the final output, hence categorized as low risk categories. In the present systematic review, low risk of bias was reported in index test (81%) and (74.41%) in flow and timings. Some studies conducted on the cadaveric samples and extracted specimens, under the applicability domain were considered as high risk for patient selection and index test domain (Supplementary Table 2). Even though, comparable results were obtained for the applicability arm of the QUADAS-2 (Figs. 4 and 5).

Discussion

AI is modernizing the traditional aspects of dentistry. AI based systems are often used for designing automated software programs that streamlines the diagnosis and data management in dentistry.[8] Mostly they are clinical decision support systems that assist and guide experts to make better decisions. These systems have been used for better diagnosis, treatment planning and also for predicting the prognosis.[54] The demand for these systems is booming due to their effectiveness in providing explanations and reasoning.[55]

AI has revolutionized in the field of dentistry and making the dentist's task easier. The clinical decision support systems that work on the AI technology are mainly designed to provide expert support to the health professionals.[56] Clinical decision support systems is defined as, any computer program that has been designed to help health professionals in making clinical decisions, and also deals with the medical data or with the knowledge of medicine necessary for interpreting such data.[6]

In this systematic review we analyzed studies on the application of AI technology in dentistry and evaluated their performance in terms of diagnosis, clinical decision-making, and predicting the prognosis of the treatment.

Application of AI technologies in the specialty of oral and maxillofacial radiology and diagnostics

Zhank et al.,[25] reported the use of AI-based CNNs and evaluated effective teeth recognition by relying on the label tree along with cascade network structure. The model demonstrated a high precision of 95.8%. A study by Tuzoff et al.,[36] showed very similar results when utilized an AI-powered CNNs model for teeth identification, which was then arranged numerically. This computer-aided diagnostic technique displayed a mean sensitivity of 0.987 and precision 0.9945. This output was similar to that of an expert.

Chen et al.,[39] applied the CNNs to detect the teeth number in intra oral periapical films and then to identify the tooth. The model demonstrated very high precision. The results indicated that AI technologies make it convenient for clinicians to do their job. They do not have to enter the details manually. Using these automated systems dentists can enter their dental charts digitally, resulting in higher efficiency.

AI technology in the detection of dental caries has demonstrated excellent results which were reflected in the study done by Lee et al.,[26] who reported applying of CNN algorithms for detection and diagnosis of dental caries on periapical radiographs. The result of the application demonstrated considerably good performance. Similar results were seen in the study done by Casalegno et al.,[32] who used deep learning model designed for the detection and

Table 2 Details of the studies that have used AI based models in various specialties of dentistry for diagnosis, treatment planning, clinical decision making, predicting the need for treatment, and predicting the prognosis.

Serial no	Authors	Year of publication	Algorithm Architecture	Objective of the study	No. of images/ photographs for testing	Study factor	Modality	Evaluation accuracy/ average accuracy	Comparison if any	Results (+)effective, (−)non effective (N) neutral	Outcomes	Authors suggestions/ recommendations
1	Devito et al.[11]	2008	ANNs	AI based model for diagnosing the proximal dental caries	160	Tooth Decay	Bite-wing Radiographs	ROC curve area of 0.884	25 examiners	(+) Effective	This neural network could improve the performance of diagnosing proximal caries.	None
2	Xie et al.[12]	2010	ANNs	ANN based AI model for deciding if extractions are necessary prior to orthodontic treatment	200	Tooth malocclusion	Lateral cephalometric radiographs	Accuracy of 80%	Not mentioned	(+)Effective	ANN was effective in determining whether extraction or non-extraction treatment was best for malocclusion patients	None
3	Saghiri et al.[13]	2012	ANNs	ANN based AI model for determining the working length	50	Tooth	Human cadavers	Accuracy of 96%	2 Endodontists	(+)Effective	The accuracy of ANN was more than the endodontists	The ANN model is accurate method for working length determination
4	Saghiri et al.[14]	2012	ANNs	ANN system for locating the minor apical foramen (AF)	50	Tooth	Human dried skull	Accuracy of 93%	Endodontists	(+)Effective	ANN can useful for secondary opinion for locating the AF on radiographs and it can be helpful in enhancing the accuracy in determining the working length	ANN can be used for decision making similar clinical scenarios
5	Jung et al.[15]	2016	ANNs	Artificial Intelligence expert system for orthodontic decision-making of required permanent tooth extraction	156	Tooth malocclusion	Lateral cephalometric radiographs	Accuracy of 92%	1 Experienced orthodontists	(+)Effective	The success rates of the models were 92% for the system's recommendations for extraction vs non extraction	AI expert systems with neural network machine learning could be useful in orthodontics
6	Johari et al.[16]	2017	PNNs	Probabilistic Neural Network (PNN) for diagnosing (VRFs) in intact and the teeth that has undergone endodontic treatment	240	Tooth	CBCT and periapical radiographs	Accuracy of 96.6, sensitivity of 93.3 and specificity of 100%	Not mentioned	(+)Effective	The designed neural network can be used as a proper model for the diagnosis of VRFs on CBCT images of endodontically treated and intact teeth; CBCT images were more effective than periapical radiographs.	None
7	Tobel et al.[17]	2017	CNNs	An automated technique for staging the development of lower third molar.	200	Tooth	Panoramic radiographs (OPG)	Mean ICC was 0.95	2 observers	(+)Effective	Deep CNN based AI system demonstrated similar results to the results demonstrated by other trained examiners.	Further optimization is required to achieve a fully automated system for estimating the dental age.
8	Aubreville et al.[18]	2017	CNNs	AI based automatic system for diagnosing (OSCC) oral squamous cell carcinoma	7894	Oral cavity	Confocal laser endomicroscopy (CLE) images	AUC of 0.96 and a mean accuracy of 88.3%, sensitivity 86.6%, specificity 90%	Not clear	(+)Effective	This approach was found to outperform the state of the art in CLE image recognition	None
9	Imangaliyev et al.[19]	2017	CNNs	CNN model for the automatic classification of red fluorescent dental plaque images.	427	Tooth	Quantitative light-induced fluorescence images	Predictive accuracy of 0.89%	Reference models	(+)Effective	CNN model prediction performance was higher than other models.	None
10	Niño-Sandoval et al.[20]	2017	ANNs	AI based model for predicting the mandibular morphology	229	Anatomical landmarks	Lateral cephalograms	Coefficients from 0.84 until 0.99	Support vector regression	(+)Effective	This model demonstrated high predictability ability	This model may be the key for facial reconstruction

(*continued on next page*)

Table 2 *(continued)*

Serial no	Authors	Year of publication	Algorithm Architecture	Objective of the study	No. of images/ photographs for testing	Study factor	Modality	Evaluation accuracy/ average accuracy	Comparison if any	Results (+)effective, (−)non effective (N) neutral	Outcomes	Authors suggestions/ recommendations
11	Zhang et al.[21]	2018	ANNs	ANN for predicting postoperative facial swelling following the extraction of impacted mandibular third molars.	100	Face	Data set	Accuracy of 98.00%	1 Oral surgeon	(+)Effective	This AI based model proved to be an accurate in predicting of the facial swelling following the extraction of impacted mandibular third molars.	None
12	Lee et al.[22]	2018	CNNs	(DCNN)-Based Computer-Assisted Diagnosis (CAD) systems. Single-Column DCNN (SC-DCNN), Single-Column with Data Augmentation DCNN (SC-DCNN Augment) and Multicolumn DCNN (MC-DCNN).	200	Face	Panoramic radiographs (OPG)	(AUC) values obtained using SC-DCNN was 0.9763, SC-DCNN (Augment) was 0.9991, MC-DCNN for 0.9987	2 Experienced oral and maxillofacial radiologists	(+)Effective	The system that was based on DCNN was effective in detecting osteoporosis and also demonstrated high agreement with the experienced oral and maxillofacial radiologists	None
13	Lee et al.[23]	2018	CNNs	Diagnosing and predicting of PCT using a computer -assisted detection system based on a deep CNN	348	Tooth	Intra oral periapical radiographs	Mean predictive accuracy of 78.9%	3 calibrated board-certified periodontists	(+)Effective	The DCNN based model was effective and efficient in diagnosing and predicting of (PCT).	Further optimization of the PCT dataset is required for improvement
14	Thanathornwong[24]	2018	Bayesian network (BNs)	Bayesian network (BN) for predicting the need for orthodontic treatment.	1000	Tooth malocclusion	Data sets	AUC (0.91)	2 Experienced orthodontists	(+)Effective	This BN based system; and demonstrated promising results with high degree of accuracy in the need for orthodontic treatment.	None
15	Zhang et al.[25]	2018	CNNs	Teeth recognition using label tree with cascade network structure.	200	Tooth	Intra oral periapical radiographs	Precision of 95.8%	Reference models	(+)Effective	This approach demonstrated a high precision of 95.8% and recall of 96.1%.	None
16	Lee et al.[26]	2018	CNNs	AI based deep learning system for detecting and diagnosing dental caries	600	Dental caries	Intraoral periapical radiographic images	Mean AUC of 0.890	4 calibrated board-certified dentists	(+)Effective	This DCNN based system algorithm performed considerably good in detection dental caries on periapical radiographs.	None
17	Yauney et al.[27]	2018	CNNs	AI based system for automated oral health screenings and cross correlations of oral-systemic health	810	Periodontium	Intraoral fluorescence images	AUC of 0.677, precision of 0.271, Recall of 0.429	Dentists	(+)Effective	This automated process was effective in correlating poor periodontal health with systemic health outcomes	Machine learning, can be used for automated diagnoses and systemic health screenings for other diseases
18	Kök et al.[28]	2019	ANNs	AI algorithms for determining the stages of the growth and development by cervical vertebrae	300	Cervical Vertebrae	Cephalometric radiographs	Mean accuracy of 77.02%	1 orthodontists	(+)Effective	ANN could be the preferred method for determining cervical vertebrae stages	None
19	Park JH et al.[29]	2019	CNNs	Comparing latest deep-CNN based systems for identifying cephalometric landmarks	283	Landmarks	Cephalometric radiographs	5% higher accuracy with (YOLOv3) than Single (SSD)	Single shot multibox detector (SSD)	(+)Effective	You-Only-Look-Once model outperformed in accuracy and computational time than the shot multibox detector	This model can be used in clinical practice for identifying the cephalometric landmarks.

20	Choi et al.[30]	2019	ANNs	ANN based model for deciding on surgery/non-surgery and determining extractions.	316	Landmarks	Lateral cephalometric radiographs	ICC 0.97–0.99	1 Experienced orthodontists	(+)Effective	This ANN based model demonstrated higher success rate in deciding on surgery/non-surgery and was also successful in deciding on the extractions.	This ANN based model will be useful in diagnosing of orthognathic surgery cases.
21	Patcas. et al.[31]	2019	CNNs	AI system for describing the impact of orthognathic treatments on facial attractiveness and age appearance	2164	Facial landmarks	Facial photographs	Not Clear	Not mentioned	(+)Effective	This CNN based AI system can be used for scoring facial attractiveness and apparent age in patients under orthognathic treatments.	None
22	Casalegno et al.[32]	2019	CNNs	AI based model for detecting and localizing dental lesions in Near-Infrared Transillumination (TI) images	217	Dental caries	Near-infrared transillumination (TI) imaging	ROC of 83.6 for occlusal and ROC of 84.6% for proximal	Dental experts with clinical experience	(+)Effective	This CNN based model demonstrated promising results with increased speed and accuracy in detecting caries.	None
23	Fukuda et al.[33]	2019	CNNs	CNN based AI system for detection of vertical root fracture (VRF)	60	Tooth	Panoramic radiographs (OPG)	Precision of 0.93 Recall was 0.75 F- Measure of 0.83.	2 radiologists and 1 endodontist	(+)Effective	The CNN based AI model is an efficient tool in detecting VRFs	None
24	Kise et al.[34]	2019	CNNs	AI system for detection of Sjögren's syndrome (SjS) on CT, and comparing its performance with radiologists	100	Salivary glands	Computed tomography (CT) images	Accuracy of 96.0, Sensitivity of 100% and specificity of 92.0%	6 radiologists	(+)Effective	The deep learning system demonstrated a higher diagnostic performance	Can be used as a diagnostic support while interpreting CT images
25	Hiraiwa et al.[35]	2019	CNNs	AI system for classifying root morphologies of mandibular first molars	760	Tooth	Cone beam computed tomography (CBCT) Images	Accuracy of 86.9%	2 radiologists	(+)Effective	The deep learning system demonstrated high accuracy in the differential diagnosis of a single or extra root in the distal roots of mandibular first molars.	None
26	Tuzoff et al.[36]	2019	CNNs	CNN based AI system for automatic teeth detection and numbering	222	Tooth	Panoramic radiographs (OPG)	Precision of 0.9945 and mean sensitivity of 0.987	Dental experts	(+)Effective	The performance of the this system was comparable to the level of performance of the experts	This system can simplify the process of filling digital dental charts.
27	Ekert et al.[37]	2019	CNNs	CNNs based AI system for detecting apical lesions (ALs)	2001	Tooth	Panoramic radiographs (OPG)	AUC of 0.85 (0.04) sensitivity 0.65 and specificity 0.87	6 Dentists	(+)Effective	This deep CNN based AI system was successful in detecting apical lesions	None
28	Murata et al.[38]	2019	CNNs	AI based system for diagnosing of maxillary sinusitis	120	Maxillary sinusitis	Panoramic radiographs (OPG)	Accuracy of 87.5%, sensitivity of 86.7%, specificity of 88.3%, AUC of 0.875	2 experienced radiologists, 2 dental residents.	(+)Effective	The AI based deep learning system demonstrated higher diagnostic performance.	The deep-learning system can provide diagnostic support for inexperienced dentists
29	Chen et al.[39]	2019	CNNs	CNN based tool package for detecting and numbering the teeth	250	Tooth	Intra oral periapical films	Precisions and recalls exceed 90%, IOU of 91%	3 Dentists	(+)Effective	The results indicate that machines performance was close to the level of a junior dentist	None
30	Vinayahalingam et al.[40]	2019	CNNs	CNN based AI system to detect and segment the approximate of inferior alveolar nerve (IAN) to the roots of lower third molars (M3) on OPGs	81	Tooth	Panoramic radiographs (OPG)	Mean dice-coefficients for M3s and IAN were 0.947 $\pm$ 0.033 and 0.847 $\pm$ 0.099	Portable network graphics (PNG) files as gold standard	(+)Effective	Deep-learning is an encouraging approach to segment anatomical structures	Further enhancement of the algorithm is advised to improve the accuracy

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Table 2 (*continued*)

Serial no	Authors	Year of publication	Algorithm Architecture	Objective of the study	No. of images/ photographs for testing	Study factor	Modality	Evaluation accuracy/ average accuracy	Comparison if any	Results (+)effective, (−)non effective (N) neutral	Outcomes	Authors suggestions/ recommendations
31	Mallishery et al.[41]	2019	ANNs	Machine learning to generate an algorithm which can help predict the difficulty level of the case and decide on referral	500	Tooth	Data Set	Sensitivity of 94.96%	2 pre-calibrated endodontists	(+)Effective	This study provides an option for automation for increasing the speed of decision-making and referrals.	An AAE endodontic case difficulty assessment form when utilized along with machine learning can assist general dentists in rapid assessment of the case difficulty
32	Patcas et al.[42]	2019	CNNs	AI system for evaluating the facial attractiveness of patients who have undergone treatment for clefts and the facial attractiveness of controls and to compare these results with panel ratings performed by laypeople, orthodontists, and oral surgeons	30	Face	Frontal and profile images	Cleft cases (all Ps $\geq$ 0.19), for control group (all Ps $\leq$ 0.02)	15 laypeople, 14 orthodontists, and 10 oral surgeons	(−)Non Effective	AI system scores were comparable with the scores of the other groups for the cleft patients, but the scores were lower for the controls	There is a need for further refinement in this AI based system
33	Krois et al.[43]	2019	CNNs	Deep- CNN based system for detecting periodontal bone loss	2001	Periodontium	Panoramic radiographs (OPG)	Predictive accuracy of 81% and were similar to the examiners	6 Experienced dentists	(N) Neutral	CNN demonstrated similar results to that of the dentists in detecting periodontal bone loss.	Machine -learning based technologies can reduce the dentists' diagnostic efforts.
34	Ariji et al.[44]	2019	CNNs	AI system for diagnosing metastasis of lymph node.	441	Cervical lymph nodes	Computed tomography (CT) images	Accuracy of 78.2%, sensitivity of 75.4%, specificity of 81.0%, positive predictive value of 79.9%, negative predictive value of 77.1%, and ROC of 0.80	Not clear	(N) Neutral	The diagnostic results of the CNN based system were similar to the results of the radiologists.	This CNN based system is a valuable for diagnostic support.
35	Ariji et al.[45]	2019	CNNs	Performance of deep learning classification in diagnosing extranodal extension of cervical lymph node metastases in CT images	703	Cervical lymph nodes	Computed tomography (CT) images	Accuracy of 84.0%	4 Radiologists	(+)Effective	The deep learning diagnostic performance in extra nodal extension was significantly higher when compared with the performance of the radiologists	This method is expected to improve diagnostic accuracy by further study with increasing sample size of patients.
36	Hung et al.[46]	2019	CNNs	AI based model for predicting root caries	5135	Root caries	Data set	Accuracy of 97.1%, precision of 95.1%, sensitivity of 99.6% and specificity of 94.3% AUC of 0.997	Trained medical personnel	(+)Effective	This model perform well and can be allowed for clinical implementation	Can be utilized by both dental and non-dental professionals
37	Kim et al.[47]	2019	CNNs	AI based (CNNs) for diagnosing maxillary sinusitis	200	Maxillary sinusitis	Waters' view radiographs	AUC of 0.93 for the temporal and 0.88 for geographic external	5 Radiologists	(+)Effective	AI based (CNNs) demonstrated statistically significantly higher AUC than radiologist in both test sets	None

38	Schwendicke et al.[48]	2020	CNNs	AI based (CNNs) to detect caries lesions in near-infrared-light transillumination (NILT) images.	226	Tooth decay	NILT images	The mean) AUC of 0.74, Sensitivity of 0.59 and specificity of 0.76 PPV was 0.63 and NPV was 0.73	2 Experienced dentists	(+)Effective	The model demonstrated satisfying discriminatory ability to detect caries lesions.	None
39	Kunz et al.[49]	2020	CNNs	An automated cephalometric X-ray analysis using a specialized (AI) algorithm	50	Landmarks	Cephalometric radiographs	Not clear	12 experienced examiners	(+)Effective	AI algorithm was able to analyze unknown cephalometric X-rays similar to the quality level of the experienced human examiners	None
40	Hwang et al.[50]	2020	CNNs	Deep -learning based automated system for detecting the patterns of 80 cephalometric landmarks	283	Landmarks	Cephalometric radiographs	Not Mentioned	Human examiners	(+)Effective	This system accuracy in identifying of cephalometric landmarks similar to the human examiners	This system might be a viable option when repeated identification of multiple cephalometric landmarks.
41	Lee et al.[51]	2020	CNNs	Deep (CNNs), on the classification of specific features of osteoporosis	136	Face	Dental panoramic radiographs (DPRs)	ROC of 0.858	Gold standard reference models	(+)Effective	This Deep (CNNs), could of use and reliable system for automated screening of osteoporosis patients.	None
42	Patil et al.[52]	2020	ANNs	ANN for gender determination	509	Mandible	Panoramic radiographs (OPG)	Accuracy of 75%	1 experienced oral and maxillofacial radiologist	(+)Effective	ANN proved as a good tool for predicting the gender and can be applied in the forensic sciences for near accurate results.	This automated application is promising for identifying gender or age with minimal errors
43	Yu et al.[53]	2020	CNNs	AI based skeletal diagnostic system	5890	Anatomical landmarks	Lateral cephalograms	Mean AUC of >95%	2 orthodontists	(+)Effective	This model demonstrated excellent performance for skeletal orthodontic diagnosis	None

ANNs = Artificial Neural Networks, CNNs = Convolutional Neural Networks, DCNNs = Deep Convolutional Neural Networks, BN = Bayesian Network, PNN = Probabilistic Neural Network, ROC = Receiver Operating Characteristic curve, AUC = Area Under the Curve, ICC = Intraclass Correlation Coefficient, F = F- measure, VRF = Vertical Root Fracture, PTC = Periodontal Compromised Teeth, Positive/Negative Predictive Values (PPV/NPV).

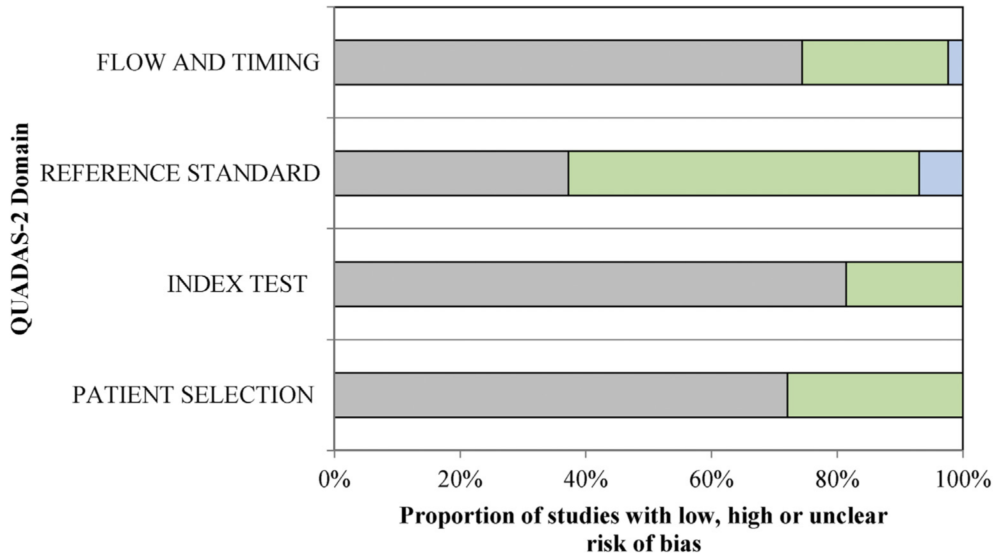

Figure 4 Assessment of individual risk of bias domains.

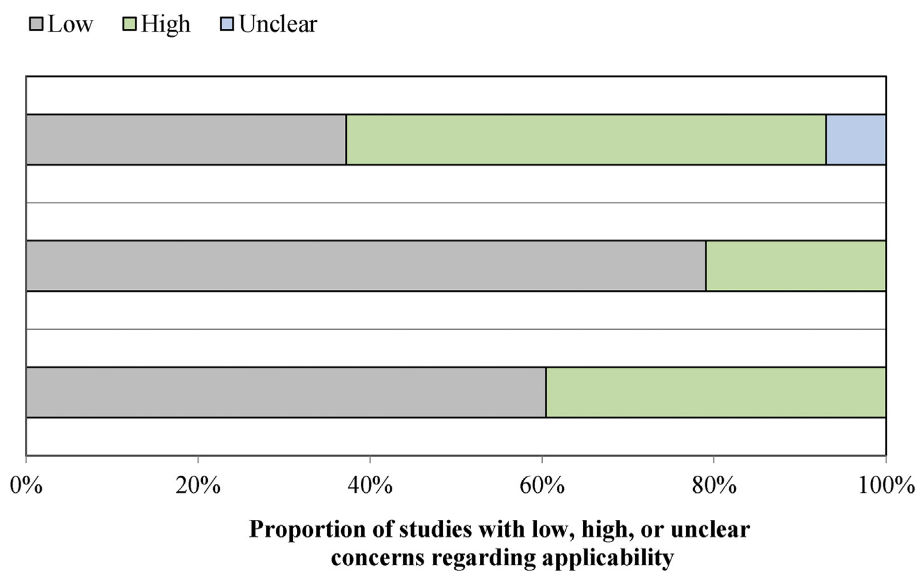

Figure 5 Concerns regarding applicability.

localization of dental lesions in near-infrared transillumination (TI) images which revealed promising results. Schwendicke et al.,[48] reported using of near-infrared-light transillumination (NILT) images for diagnosing dental caries and showed that the performance of this AI based models was satisfactory.

Devito et al.,[11] used an AI based ANN model for diagnosing proximal caries using the bitewing radiographs and found a quite encouraging results. Study by Hung et al.,[46] reported AI technology for predicting root caries and demonstrated excellent results. Ekert et al.,[37] was successful in detecting apical lesion when they applied CNNs to detect apical lesions (ALs) on panoramic dental radiographs.

Hiraiwa et al.,[34] reported of applying CNNs for detection of sjögren's syndrome (SjS) on CT images and compared the results with the performance of radiologists and showed a higher diagnostic performance. In another study by Murata et al.,[38] the authors applied the deep learning system for diagnosing maxillary sinusitis on panoramic radiography. The diagnostic performance of this system was sufficiently high. These results were similar to the study conducted by kim et al.,[47] when compared the performance with experienced radiologists.

Ariji et al.,[45] applied CNN system for deep learning image classification for diagnosing lymph node metastasis on (CT) Images and showed higher diagnosing accuracy, sensitivity, and specificity. These results were similar to the study conducted by Hung et al.,[46] who assessed the performance of deep learning classification in diagnosing extra nodal extension of cervical lymph node metastases in CT images. Both the studies showed similar performance or even higher performance when compared to professional radiologists.

Lee et al.,[22] evaluated the efficiency and performance of AI in diagnosis and detection of osteoporosis. In this study deep convolutional neural network (DCNN) based computer-assisted diagnosis (CAD) systems was applied for detection of osteoporosis, using panoramic radiographs and exhibited very promising results. This was well above in par with experienced oral and maxillofacial radiologists in detecting osteoporosis. These results were similar to the results done by Lee et al.,[51] who used deep convolutional neural networks (DCNN) for detecting osteoporosis in dental panoramic radiographs.

Application of AI technologies in the specialty of orthodontics and dentofacial orthopedics

Accurate diagnosis, treatment planning and prediction of prognosis are the key factors for successful orthodontic treatment. AI technology has been applied for deciding if extractions are necessary prior to the orthodontic treatment. In a study by Xie et al.,[12] artificial neural network (ANN) model was applied for deciding if extractions are necessary using lateral cephalometric radiographs. The results were quite promising. Jung et al.,[15] showed 92% accuracy using AI expert system for deciding on permanent tooth extraction, using lateral cephalometric radiographs. The results of both the studies are suggestive that the AI modes were effective and accurate in predicting the need for extraction. These models can be used as a tool for making decisions in clinical practice. High accuracy was seen in the study by Thanathornwong,[24] who suggested AI model based on bayesian network (BN) for assessing the need for orthodontic treatment.

Various studies have been conducted to demonstrate AI technologies and its application in identifying cephalometric landmarks. Park et al.,[29] compared the efficiency and accuracy of the updated deep-learning algorithms for automatic identification of cephalometric landmarks using cephalometric radiographs. The results revealed that the system was extremely accurate in the computation of the landmarks. Studies conducted by Kunz et al.,[49] and Hwang et al.,[50] showed excellent accuracy in identifying the landmarks similar to the trained human examiners using a specialized artificial intelligence (AI) algorithm and deep learning based automated identification system respectively. Yu et al.[53] demonstrated excellent results with automated skeletal classification with lateral cephalometry based on the AI Model. The results of the above mentioned studies indicates that, these systems prove to be a viable option for repeatedly identifying multiple cephalometric landmarks.

Establishing of accurate diagnosis and treatment planning in orthognathic surgery is the most important step for the success of the treatment.[57] Arnet et al.,[58] in his literature on facial keys to orthodontic diagnosis and treatment planning suggested that if diagnosis is incorrect, the patient esthetics may further deteriorate creating a major problem. This suggests that diagnosis is an important aspect for the dentist to analyze the problems of the patient accurately. AI technology is striving to make dentists job much accurate and precise. Choi et al.,[30] reported the use of new artificial intelligence model to decide the case for surgery/non-surgery using the lateral cephalometric radiographs. He showed that the system was very effective with 96% success rate in diagnosing the surgery/non-surgery cases. This model has shown promising results, hence can be applied for the diagnosis of orthognathic surgery cases.

Hagg et al.,[59] stated that determining the chronological age of the patient is not alone sufficient for estimating the actual growth time, hence various skeletal maturation indicators have been developed for this task. Determination of the growth and development, and estimation of the skeletal maturation stages have been used to predict the time of pubertal development, determining the growth rate and for mainly estimating the remaining growth and development potential of an individual as mentioned by Flores-mir et al.[60] These are usually determined by using hand-wrist radiographs, cephalometric analysis, and with the help of maturation stages of cervical vertebra. AI technology has also been applied for determining the growth and development by cervical vertebrae stages. Kok H et al.,[28] showed a mean accuracy of 77.02%, using artificial intelligence algorithms for determining the growth and development by cervical vertebrae stages when applied on the cephalometric radiographs.

Application of AI technologies in the specialty of endodontics

The success of root canal treatment mainly depends on accuracy of working length determination. The prognosis of the treatment can only be ensured when instrumentation terminates at the apical constriction.[61] Saghiri et al.[13] used artificial neural network (ANN) system in determining the working length and showed exceptional accuracy of 96% which is higher than the accuracy compared to professional endodontists. These results were similar to the study by Saghiri et al.,[14] where they used the ANN system for locating the minor apical foramen, with an accuracy of 93%.

In endodontics, AI is used to diagnose vertical root fractures. A study employed by Johari et al.,[16] who used probabilistic neural network (PNN) for the diagnosis of vertical root fractures. This PNN system displayed excellent performance with an accuracy of 96.6%. Similarly convolutional neural network in detecting vertical root fracture, showing a highly encouraging precision was conducted by Fukuda et al.[33] These assessments indicate that AI-based models are incredibly effective when it comes to the detection of vertical root fractures on CBCT images and panoramic radiographs.

Application of AI technologies in the specialty of periodontics

Periodontal diseases are one of the most common oral diseases affecting the mankind. It is a known fact that this is one of the main reasons for the early loss of teeth. It is well reported by Lee et al.,[62] that continuous progression of the disease will eventually lead to the loss of teeth in the adults. Various studies have been done to ascertain AI technology application to diagnose and predict periodontal diseases. Lee et al.,[23] reported use of CAD system, based on a deep convolutional neural network (CNN) algorithm for diagnosing and predicting the teeth that are compromised with periodontal health. The outcome were quite acceptable with a mean predictive accuracy of 78.9%. Yauney et al.,[27] used an AI based system based on CNNs for correlating poor periodontal health with systemic health outcomes and reported that, AI can be used for automated diagnoses and can also be useful for screenings for other diseases. Krois et al.,[43] used CNNs to detect periodontal bone loss (PBL) on panoramic dental radiographs. The results of this study were similar to that of the expert opinions. This system can still help in reducing the dentist's diagnostic efforts.

Application of AI technologies in the specialty of oral and maxillofacial surgery

It is estimated that every year there are around 657,000 new cases detected of cancers of the oral cavity and pharynx and is also a reason for 330,000 deaths as noted in the article of oral cancer by WHO.[63] AI technology has been used for detecting cancers. There is revolutionary development and refinement of convolutional neural networks that have demonstrated improved ability for automated cancer detection as seen in the study by Xu et al.[64]

Aubreville et al.,[18] showed extremely positive and promising results when employed CNNs for an automatic approach for diagnosing Oral Squamous Cell Carcinoma when used with confocal laser endomicroscopy images. The study indicated that AI model will be helpful for early diagnosis. AI technology has also been used for predicting postoperative facial swelling after extraction of teeth. Zhang et al.,[21] used an artificial intelligence model based on ANN for predicting the postoperative facial swelling following the extraction of impacted mandibular 3rd molars. The model demonstrated excellent results and will be of great importance for clinicians for predicting the prognosis of the treatment.

Application of AI technologies in the forensic odontology

Forensic odontology is relatively new, but it has made a stellar contribution to the field of dentistry. A dentist plays an important role when they have to identify people for child abuse, crime, sexual assault, mass calamities, and other legal issues. Their moral duty compels them to provide justice to the victims and their families, especially when there is no other evidence other than the dental remains. AI technology has been applied in this field and has shown excellent results.

De Tobel et al.,[17] used automated technique based on CNNs for staging lower third molar development for estimating the age of a person after applying on panoramic radiographs. The system showed remarkable results, when compared to the trained examiners. Patil et al.,[52] used ANNs to determine gender using panoramic radiographs, the results were quite promising. This system is very useful as it automates and eases the method of identifying unknown gender or age with minimal errors. Niño-Sandoval et al.,[20] reported an AI model based on ANNs for predicting the mandibular morphology and demonstrated promising results. Hence AI can be used effectively in forensic dentistry.

Uses of AI in dentistry based on the conclusions from the articles reviewed in the paper

- AI systems can assist the clinicians so they can offer high-quality dental care to their patients.
- Dentists can use AI systems as an ancillary tool for increasing the accuracy of diagnosis, treatment planning, and predicting the treatment outcomes.
- Non-specialty dentists can receive diagnostic support via the deep-learning systems.
- Automated systems can save a lot of time and increase the efficiency of the clinicians (for e.g. automatic completion of electronic dental records by identifying the tooth and numbering).
- The use of these systems for secondary opinions can improve the accuracy of diagnosis.
- These systems provide a great deal of value for forensic diagnosis.

Conclusion

AI has revolutionized dentistry in the last few years. Studies show that these AI-powered automated systems performed extremely well in various scenarios. Few authors found them to be more accurate than even dental specialists. Although these outcomes do not make them better than the dentists, they do establish that AI can be considered for clinical applications. These systems bring terrific value to the table by improving the accuracy of diagnosis, enhancing clinical decision-making, and predicting the treatment prognosis which can help the clinicians in rendering best quality care to their patients. There are also documented studies that have also reported that these automated systems are of greater value for screening the patients for osteoporosis, oral cancer, and metastasis of the lymph nodes. This is a priceless benefit because it can help professionals to diagnose cases in the early stages, which in turn can save many lives. Although AI is widely used in various fields of dentistry, some specialties such as pedodontics and oral pathology still lack the development and application of AI technology.

Conflicts of interest

The authors have no conflicts of interest relevant to this article.

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Appendix A. Supplementary data

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