Concise review

AI-Driven Dental Caries Management Strategies: From Clinical Practice to Professional Education and Public Self Care

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ABSTRACT

Dental caries is one of the most prevalent chronic diseases among both children and adults, despite being largely preventable. This condition has significant negative impacts on human health and imposes a substantial economic burden. In recent years, scientists and dentists have increasingly started to utilize artificial intelligence (AI), particularly machine learning, to improve the efficiency of dental caries management. This study aims to provide an overview of the current knowledge about the AI-enabled approaches for dental caries management within the framework of personalized patient care. Generally, AI works as a promising tool that can be used by both dental professionals and patients. For dental professionals, it predicts the risk of dental caries by analyzing dental caries risk and protective factors, enabling to formulate personalized preventive measures. AI, especially those based on machine learning and deep learning, can also analyze images to detect signs of dental caries, assist in developing treatment plans, and help to make a risk assessment for pulp exposure during treatment. AI-powered tools can also be used to train dental students through simulations and virtual case studies, allowing them to practice and refine their clinical skills in a risk-free environment. Additionally, AI tracks brushing patterns and provides feedback to improve oral hygiene practices of the patients and the general population, thereby improving their understanding and compliance. This capability of AI can inform future research and the development of new strategies for dental caries management and control.

Introduction

Dental caries remains a global public health challenge for quite a long time. The Global Burden of Disease from 1990 to 2015 showed that its prevalence in permanent dentition ranked top among 328 investigated diseases.[1] The estimated age-standardized incidence rate of dental caries in permanent teeth in 2019 was 39200.36/100,000, and 3.09 billion

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incident cases were detected in that year.[2] The high prevalence of dental caries highlights the importance of a modern dental caries management strategy that differs from the traditional "drill and fill" model. The core of modern dental caries management at the individual level is a patient-centered, dental caries risk-based philosophy that prioritizes prevention, early detection, noninvasive and micro-invasive treatments.[3,4] In accordance with this principle, good oral hygiene, precise prediction of the dental caries occurrence, timely preventive intervention, early diagnosis, and appropriate treatment are all essential for preventing dental caries. Meanwhile, dental intervention in the clinic alone is far from successful dental caries prevention, and successful dental caries management needs dentist-patient cooperation. Therefore, innovative tools that both improving dental professionalism and enhancing patients' compliance will undoubtedly help prevent dental caries.

With the development of computer science and the advent of the big data era, artificial intelligence (AI) has entered all aspects of the medical community with an extremely strong posture. In recent years, the use of artificial intelligence in various fields of dentistry has been extensively explored.[5] The present work specifically focuses on the progress of AI in aiding dental caries management to clarify its achievements and future trends. Being different from previously published reviews which concentrate on specific aspects (e.g. AI algorithms tested for dental caries detection[6] and AI in dental caries diagnosis)[7], it delves into multiple directions of AI's application, including how AI may assist dental professionals, dental students, patients, and the general population in preventing dental caries (Figure 1), considering all of them have crucial responsibilities in the "war" against this common oral disease.

Artificial intelligence

The concept of AI was first proposed by John McCarthy of Dartmouth University in 1956.[8] It is also called machine intelligence, with the aim of developing a machine mimicking the cognitive behavior of the human brain. It has evolved into a new field over the past few decades, intending to develop theories, methodologies, technologies, and application systems to simulate, enhance, and expand human intelligence.[9]

Machine learning (ML) is the main branch of AI (Figure 2). Its basic concept is that a system or machine can learn from data, identify the patterns of these data, make decisions, and perform tasks at human intelligence levels with minimal human intervention.[10] The basic elements of ML are massive data and algorithms. Algorithms learn patterns and structures in the data ("training"), and then apply the learned patterns to make predictions on unseen data. Algorithms are the virtual component of AI, and they usually present as computer codes or software. When a machine is equipped with algorithms and can autonomously perform tasks, it becomes the physical component of AI. ML can be further divided into supervised learning, self-supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning uses annotated data to train the algorithm, which is manually labeled by experts.[11] Manually annotating data is cumbersome and time-consuming, and there are also ethical risks involved. Consequently, significant efforts have been made to move forward. A special example is self-supervised learning. When fed with unlabeled data, it generates data labels automatically, and then the labels are used to train the algorithms, like supervised learning. Unsupervised learning is a type of ML where algorithms are trained on data without labeled inputs. It analyzes datasets without human

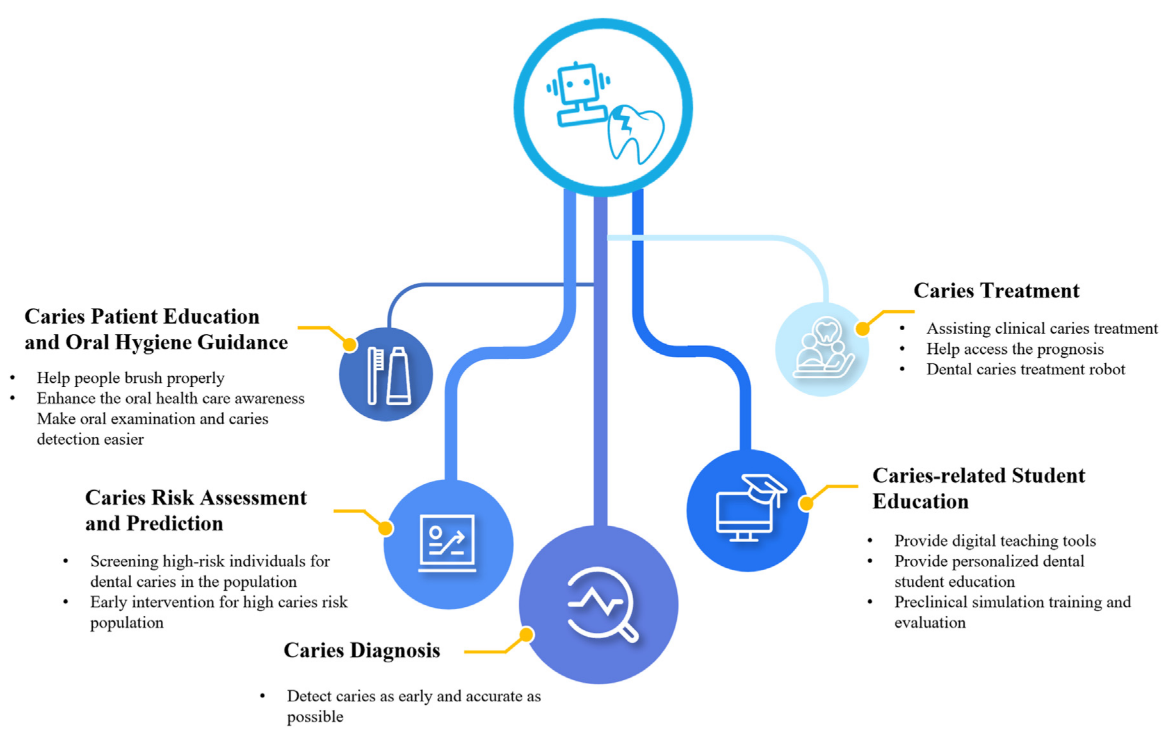

Fig. 1 – Applications of artificial intelligence in caries management.

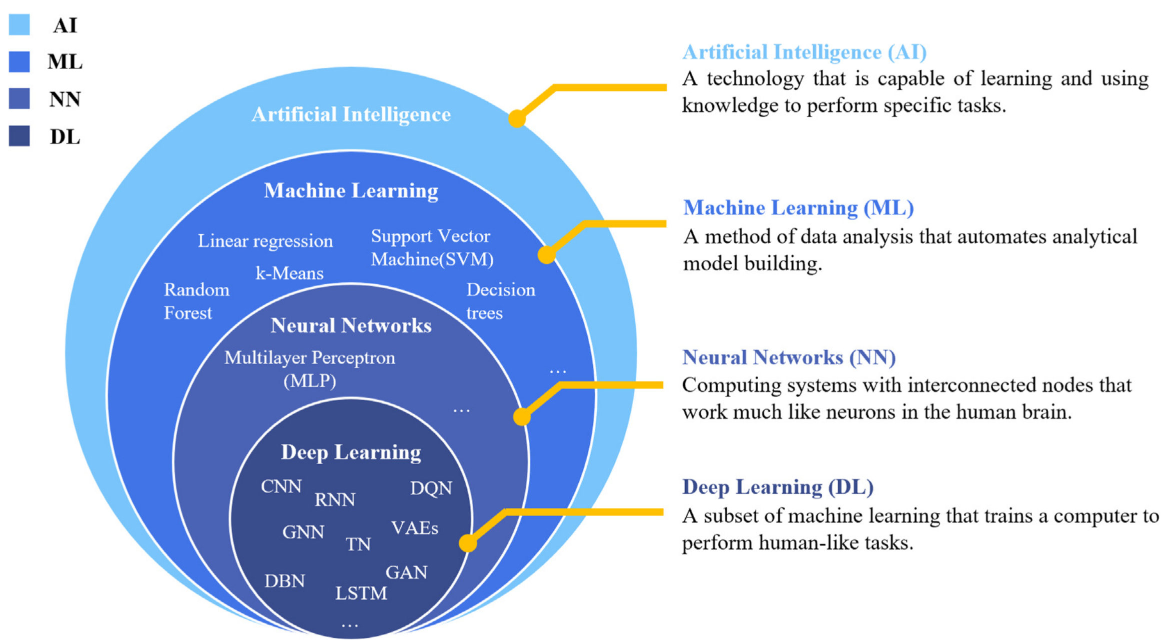

Fig. 2 – Concept set diagram of artificial intelligence, machine learning, neural networks, and deep learning. **(Abbreviations: CNN, convolutional neural networks; RNN, recurrent neural networks; LSTM, long short-term memory networks; GAN, generative adversarial networks; TN, transformer networks; DBN, deep belief networks; DQN, deep Q-networks; VAEs, variational autoencoders; GNN, graph neural networks).**

interference, and the algorithms find the internal patterns of the data themselves.[12] Self-supervised learning can be taken as a branch of unsupervised learning since there is no manual label involved.[13] Semi-supervised learning is a combination of supervised and unsupervised learning.[14,15] It utilizes both labeled and unlabeled data for algorithm training.

The algorithms used in conventional ML are mainly derived from classical statistics, such as random forest[16] and decision trees[17] (shown in Figure 2). Conventional ML algorithms have limited data requirements, making them suitable to solve simple tasks. To tackle complex tasks, algorithms must mimic the operations of the biological neural network in the human brain. The breakthrough in neuroscience and the expansion of computational power paved the way for the development of a sophisticated algorithmic structure known as an artificial neural network (ANN). Like the biological neural network, an ANN consists of multiple interconnected nodes or "neurons" that can process information and pass it among each other efficiently. The development of ANN has gone from the beginning of single-layer to 2-layer (containing a hidden layer), and then to multi-layer networks. The presence of multi-layer ANN brings ML into a new era named deep learning (DL, shown in Figure 2). The term “deep” refers to the number of layers through which the data is transformed. The more layers it has, the deeper it is. The word “learning” indicates that feature learning is the goal.

A multitude of DL algorithms have been developed and refined, including but not limited to convolutional neural networks (CNN),[18] recurrent neural networks (RNN),[19] long short-term memory (LSTM),[20] generative adversarial networks (GAN),[21] transformer networks,[22] deep belief networks (DBN),[23] deep Q-networks (DQN),[24] variational autoencoders (VAE) and graph neural networks (GNN)[25] (Figure 2). The most widely used algorithm in the medical field is CNN.[18] CNN consists of the input layer, convolutional layer, pooling layer, fully connected layer, and output layer, through which data features are extracted and classified.[26] Each layer of a CNN applies operations called convolutions to every pixel of an image, enabling the extraction of important features.[27] Typical CNN architectures include GoogLeNet Inception, Xception, ResNet, DenseNet, U-Net, VGG16, etc.[28]

AI in dental caries management

AI in dental caries risk assessment and prediction

Dental caries risk assessment predicts the likelihood of developing new cavities or incipient lesions within a specified time frame, as well as the probability of changes in the size or activity of existing lesions.[29] It helps to tailor specific preventive measures to the highest-risk persons, identifying low-risk patients to delay restorations and preventing unnecessary surgical intervention.[30] Different systems have been suggested for dental caries risk assessment, including CAMBRA, Cariogram, and CAT. These systems predict future dental caries development by selectively analyzing combinations of dental caries risk and protective factors, while their predictive performance is still under debate.[31] Dental caries is a multi-factorial disease. Logically, the more risk/protector factors that are considered, the more accurate risk assessment and prediction can be generated. At the same time, the more factors are considered, the more powerful tools are needed to find patterns of these factors for downstream risk prediction.

In recent years, AI has shown its power in developing dental caries risk assessment and prediction systems.[32] AI-based dental caries risk assessment could be divided into oral microbiota-independent, -related, and -based systems. Oral microbiota -independent system emphasizes the importance of demographic and environmental factors without considering oral microbiota.[33-35] Among these systems is the 1 introduced by Qu et al.[33] It was developed on the child's age, height, weight, family dental caries status, duration of brushing per session, fluoride toothpaste usage, frequency of brushing, parental supervision of brushing, mother's mode of delivery, daily brushing routine, number of children, and frequency of nocturnal feeding in the last month. Systems that consider oral microbe as an indicator for dental caries risk assessment, among other non-bacterial factors, are oral microbiota-related. For example, Pang et al. generated a system by using variants in gene loci, cario-state score, plaque index, and past dental caries experience.[35] Efforts have also been made to predict the risk of dental caries by analyzing the features of the oral microbiome via AI. The first attempt was made by Teng et al.[36] Through evaluating the oral microbial shift before, during, and after the occurrence of dental caries, a prediction algorithm named MiC (i.e., Microbial Indicators of Caries) was built with random forest method, and MiC predicts future new dental caries among kids with 81% accuracy.

The AI-driven dental caries risk assessment systems are mainly constructed by conventional ML algorithms to date. There are few systems really driven by DL. Future advances in this field may provide more precise assessments through "deep learning" of oral microbiome, demographic characteristics, lifestyle habits, genetic information, medical history, radiographic images, intra-oral images, as well as other data simultaneously.

AI in dental caries detection and diagnosis

AI-powered dental caries detection from radiographic images

Early detection and diagnosis enable the avoidance of invasive treatment and reduce healthcare costs. Radiographic images, including bitewing, periapical, panoramic X-rays, and CBCT, are among the major tools for dental caries detection. However, detecting dental caries from radiographic images is dentist-dependent, with limitations of subjectivity and instability. Hence, the urgent need arises for novel techniques that can help make precise and objective diagnoses.

At the early stage, engineers attempted to construct AI themselves, followed by testing the effectiveness of these algorithms in detecting dental caries.[37,38] As DL advances, various algorithms were developed, and efforts concentrate on how these algorithms could be applied with or without modifications to diagnose dental caries. The most intensively tested DL algorithm is CNN[7] because it is good at processing grid-like matrix datasets[18]. Supervised learning is predominant for AI-driven automatic dental caries detection. It requires large amounts of high-quality training data with labels during training.[39] To tackle the annotation difficulty, certain groups tried semi-supervised and self-supervised learning methods, aiming to minimize the dependency on labeled datasets and clinicians' support. In this area, Qayyum et al. proposed a semi-supervised learning system, and it exhibited significant computational and performance improvements over the supervised and self-supervised learning models.[40] Hopefully, innovative and effective algorithms belonging to semi-supervised and self-supervised learning would provide novel directions to improve the effectiveness of AI-assisted dental caries diagnosis in the future.

AI algorithms that have been trained and tested for dental caries detection include but are not limited to ResNet,[41-43] RetinaNet, As You Only Look Once (YOLO) v5, EfficientDet,[44] EfficientNet-B0, DenseNet, ResNet-50,[45] DeeplabV3 and visual geometry group (VGG)16,[46] YOLOv3,[47,48] U-Net,[49-52] and GoogLeNet Inception[43,53] (Table 1). Zhu et al. constructed CariesNet, a model specifically designed to detect dental caries.[54] Metrics used to assess the accuracy and reliability of their performance, including sensitivity, specificity, precision, F1 scores, receiver operating characteristic curve analysis, and intersection-over-union (IoU) scores. AI has shown great potential in detecting dental caries from radiographs. However, the performance of different algorithms varies. Taking the accuracy as an example, it ranges from 82% to 99% on periapical and panoramic radiographs, and from 68.7% to 94.59% on bitewing radiographs (Table 1). A key constraint inherent in these investigations stems from the limited sample sizes and substantial heterogeneity of the datasets. Future studies should prioritize the utilization of standardized, population-diverse cohorts with robust clinical annotations to accurately represent the true performance of AI.[6]

The management of a dental caries lesion depends primarily on its depth or severity. Therefore, some studies go further by using AI to delineate the severity of dental caries lesions.[47,51,54] DenseNet121 showed an overall detection accuracy of 0.957, 0.832, and 0.863 from panoramic radiographs for lesions affecting the outer, middle, and inner third dentin, respectively.[51] The International Dental Caries Classification and Management System™ (ICCMS™) provides a standard for defining the severity of carious lesions. Although YOLOv3 was unable to classify all dental caries lesion types included in ICCMS™, it accurately classified the enamel caries and initial dentin caries.[47] There was significant variability in the accuracy of AI in classifying caries depth. Ahmed et al. found that, the IoU scores of the AI performance gradually improved with increasing lesion depth: 21% for lesions within the outer half of the enamel, 23% for lesions within the inner half of the enamel, 35% for lesions within the inner half of the dentin, and 41% for lesions within the inner half of the dentin,[55] suggesting that deeper caries lesions are, the more accurate the AI assessment.

When faced with so many kinds of algorithms, a question arises as to the optimal choice for dental caries detection. Studies have been carried out to answer it. One of these studies was conducted to compare the performance of EfficientNet-B0, DenseNet-121, and ResNet-50, with results suggesting that ResNet-50 exhibited the best performance with high accuracy and reliability.[45] However, when Pérez de Frutos et al. evaluated the performance of RetinaNet (ResNet-50), YOLOv5 (M size), and EfficientDet (D0 and D1 sizes), they found that YOLOv5 excelled ResNet-50 and EfficientDet in detection accuracy.[44] Interestingly, Zhu et al. proposed an AI model based on Faster-RCNN and compared its performance

Table 1 – Performance of different AI algorithms in dental caries diagnosis.

Refs	Algorithms	Dataset size	Radiography images	Aim	Results
41	ResNet + SAM	4278	periapical	develop models for caries detection	Accuracy = 0.885, Sensitivity = 0.894, Specificity = 0.887
44	RetinaNet, YOLOv5, and EfficientDet	197	bitewing	compare 3 models for caries detection	YOLOv5: mean average precision = 0.647, mean F1-score (mF1) = 0.548, mean false negative rate(mFNR) = 0.149 RetinaNet: mAP = 0407, mF1 = 0.177, mFNR = 0.210 EfficientDet D0: mFNR = 0.592 ± 0.025 EfficientDet D1:mF1 = 0.534 ± 0.019, mFNR = 0.487 ± 0.011
45	EfficientNet-B0, DenseNet-121 ResNet-50	13870 images from 562 participants	Panoramic	Caries detection	EfficientNet-B0: Accuracy = 90.00%, Sensitivity = 83.00%, Specificity = 97.00% DenseNet-12: Accuracy = 91.83%, Sensitivity = 87.33%, Specificity = 96.33% ResNet-50: Accuracy = 92.00%, Sensitivity = 87.33%, Specificity = 96.67%
46	DeeplabV3 and VGG16	2075	Panoramic	Caries detection and severity classification	Accuracy = 0.9401
54	Caries-Net	1159	Panoramic	Develop a model to delineate different caries degrees including shallow, moderate, and deep caries	Accuracy = 0.9361
47	YOLOv3	994	Bitewing	assessment of the performance of YOLOv3 in carious detection and classification based on (ICCMS^{TM}) radiographic scoring system (RSS)	Detect and classify enamel caries and initial dentin caries (IoU_{50}): precision = 0.75 Detect and classify caries with pulpal exposure (IoU_{50}): precision = 0.77 Predict the outer half of enamel caries (IoU_{50}): precision = 0.35 IoU = Intersection over Union
49	U-Net	500	Bitewing	Caries detection and other purposes	Accuracy = 0.9491, Sensitivity = 0.8235
59	a modified U-shaped deep network	Not mentioned	Not mentioned	build a model for caries detection	Accuracy = 0.7443
50	VGG-16 for detection; U-Net for segmentation	613	Bitewing	caries detection and segmentation	Detection: Accuracy = 0.84, Sensitivity = 0.84 Segmentation: Accuracy = 0.86, Sensitivity = 0.81
48	YOLO V3	1000	Bitewing	Caries detection and labeling the location of caries lesion.	Accuracy = 94.59%, Sensitivity = 2.26%, Specificity = 98.19%
60	Denti.Ai (Deep Convolutional Neural Network-Based Software)	300	Panoramic	evaluate the diagnostic reliability of Denti.Ai	Accuracy = 0.82, Sensitivity = 0.698, Specificity = 0.854
42	Faster R-CNN ResNet v2	2468	Bitewing	Caries detection	Accuracy = 0.87, Sensitivity = 0.86, Specificity = 0.86
61	multi-input deep convolutional neural network ensemble (MI-DCNNE) model	340	Periapical	Establish a model for caries detection	Accuracy = 99.13%
51	U-Net for segmentation; DenseNet121 for caries severity classification	1160	Panoramic	To detect caries and to classify the depth of caries lesions (dentin lesions in the outer, middle, or inner third D1/2/3 of dentin)	Caries Detection: Accuracy = 0.986, Sensitivity = 0.821, Specificity = 1.00 Caries in enamel or the outer third of dentin: Accuracy = 0.957, Sensitivity = 0.765, Specificity = 0.812 Caries in the middle third of dentin: Accuracy = 0.832, Sensitivity = 0.652, Specificity = 0.732 Caries in the inner third: Accuracy = 0.863, Sensitivity = 0.918, Specificity = 0.865

(continued)

Table 1. (*Continued*)

Refs	Algorithms	Dataset size	Radiography images	Aim	Results
62	A commercially available CNN based software (dentalXrai Pro, dentalXrai Ltd.)	140	Bitewing	compare the accuracy and decision-making impact of an AI for proximal caries detection by dentists	Caries detection without AI Accuracy = 0.93, Sensitivity = 0.72, Specificity = 0.97 Caries detection with AI Accuracy = 0.94, Sensitivity = 0.81, Specificity = 0.97
43	ResNet and Inception belonging to CNN	112	Bitewing	Build and evaluate the performance of different AI models in detecting caries with distinct lesion severity	The best 1 is Inception trained with the 0.001 learning rate Accuracy = 0.687~0.818, Sensitivity = 0.833-0.933 (depending on the severity)
63	optimal CNN-LSTM classifier	1500	Periapical image	developing AI models to detect dental caries and classify them into various classes of G.V Black Classification	Accuracy = 0.96, Sensitivity = 0.96, Specificity = 0.93
64	artificial neural network classifier	420	Panoramic	to detect and predict radiation-related caries	Detection: Accuracy = 98.8% Prediction: Accuracy = 99.2%
52	U-net	Not mentioned	bitewing images	compared performance of dentists and AI in caries detection	U-Net: Accuracy = 0.80, Sensitivity = 0.75, Specificity = 0.36 Dentist: Accuracy = 0.83, Sensitivity = 0.96, Specificity = 0.91
65	Back propagation Neural Network	105	dental X-ray images	build a system to detect caries	Accuracy = 0.971
53	GoogLeNet Inception v3 CNN network	3000	Periapical	Caries detection and diagnosis	Accuracy = 0.82~0.89, Sensitivity = 0.81~0.923, Specificity = 0.81~0.94 (depending on the types of the posterior teeth)
38	Back propagation Neural Network	120	Periapical images	Caries detection	Accuracy = 99%
37	stacked sparse auto-encoder and a softmax classifier	Not mentioned	Not mentioned	build a system to detect caries	Accuracy = 97%

with that of YOLOv5. Faster-RCNN showed higher detection accuracy, although YOLOv5 outperforms in terms of speed.[56] Due to the use of different image datasets, unstandardized comparison procedures, and comparison being conducted on only few algorithms, no consensus has been reached so far on the best algorithm for dental caries diagnosis. Generally, each AI algorithm comes with its own strengths and weaknesses; probably the selection of an algorithm for dental caries detection should depend on the specific task goals and requirements.[6] For instance, ResNet and DenseNet are renowned for their high accuracy and stability, making them well-suited for handling complex features in high-resolution images. However, their computational costs are relatively high, which may limit their use in resource-constrained environments.[57] EfficientNet strikes a balance between accuracy and efficiency through its compound scaling method, making it an ideal choice for scenarios with limited computational resources.[58] Although the detection time of Faster-RCNN is 0.13 seconds slower than that of YOLOv5 when processing a single sample,[56] considering the significance of detection accuracy in clinical applications, this time difference is acceptable when dealing with non-big data volumes.

Although AI has shown its capabilities in dental caries detection and severity assessment, its clinical application ultimately depends on a key determinant: whether AI can outperform or at least match the diagnostic performance of human experts. Studies have shown that AI can detect caries lesions as well as or better than professionals.[50] Lian et al observed that nnU-Net and DenseNet121 performed at a level similar to expert dentists,[51] while a study carried out by Moran et al. showed the CNN-based models exhibited significantly higher sensitivity and accuracy in dental caries detection compared to the reference test.[43] Cantu et al. reported that CNN outperformed dentists with 3 to 14 years of experience in diagnosing initial carious lesions.[52]

AI-powered dental caries detection from optical images

In addition to radiographic examination, optical-based techniques have been used to aid the dental caries detection. These techniques include Quantitative Light-Induced Fluorescence (QLF), Near-Infrared Light Transillumination (NILT), Laser-Induced Fluorescence, Optical Coherence Tomography, and Fiber Optic Transillumination.[66] Efforts have been made to develop AI-based automatic dental caries detection systems by analyzing images captured using these techniques. AI had a good performance in detecting dental caries from QLF images, with 83.2% of accuracy, 85.6% of precision, and 86.9% of sensitivity.[67] A cascade region-based CNN also showed its applicability in detecting dental caries from full intraoral NILT images.[68]

Intra-oral images taken by digital cameras or smartphones could also serve as resources for AI-powered dental caries detection. Studies have been conducted on the use of red, green, and blue (RGB)-based images in AI-powered dental caries diagnosis.[69-72] A prospective clinical trial used an AI algorithm integrating MobileNet-v3 with U-net to detect dental caries in digital intraoral images. This system showed remarkable diagnostic performance, achieving an overall accuracy of 93.40% in dental caries identification.[73] Notably, the sensitivity of the AI diagnostic system using intraoral RGB images varied greatly depending on the type of affected tooth and the severity of caries lesions, indicating the need for further improvement.[73,74]

AI-powered dental caries detection systems: more than codes

AI algorithms have been integrated into the software. Up to now, many software programs have been approved by authorities, including the US FDA, and are prepared to be used routinely in clinical diagnosis. Commercially available software and services include Overjet, Pearl, Dentrix, VideaHealth, Carestream, etc. Small-scale randomized controlled trials have been conducted to validate the effectiveness of these AI software tools in assisting dentists. A recent publication evaluated the roles of dentalXrai Pro 1.0.4 in aiding dentists in proximal dental caries detection, and the results showed that it increased dentists' diagnostic accuracy for enamel caries.[62] Another randomized controlled study found that the use of AssistDent AI software resulted in a 71% increase in the ability to detect enamel-only proximal caries with an 11% decrease in specificity.[75] AI-enabled smartphone applications for real-time dental caries detection from bitewing radiographs are also available.[76] Mobile applications that utilize AI to analyze intraoral digital photos have been developed to offer tele-consultation, simple examination, assessment, and appointment booking for dental caries patients.[77,78] More recently, AICaries was developed by Xiao et al to detect dental caries from photos taken by smartphones.[78] Hopefully, it will simplify dental caries screening for patients, leading to early detection and treatment, and improved patient engagement. AI-equipped machines that can autonomously detect dental caries are also commercially available at present. Optical dental caries detection tools and AI-based scoring systems have been implemented in modern 3D intraoral scanners, enabling automated dental caries assessment and detection.[79-81]

Cost-effectiveness of AI-powered dental caries detection

AI enhances dentists' diagnostic capabilities and influences their treatment decisions.[62] Therefore, the cost-benefit of applying AI in dental caries diagnosis needs to be carefully evaluated. Current evidence shows that higher accuracy of AI does not lead to higher cost,[82,83] and AI-assisted diagnosis results in better retention of the affected teeth compared to conventional assessment by dentists.[84] A potential reason for the cost-effectiveness of applying AI for caries diagnosis might be due to fewer lesions remaining undetected, and this cost-effectiveness requires dentists to perform non-restorative treatment for early lesions that are detected.[84]

AI in dental caries treatment

Studies exploring AI's application in dental caries treatment are quite few. The limited studies focus on utilizing AI to predict pulp exposure risk during deep dental caries treatment. Dentists rely heavily on preoperative radiographs to get pulp exposure clues currently. However, the image acquisition angle, as well as the experience and expertise of the dentists, affect their assessments. AI can extract more information than human eyes, allowing it to make more accurate predictions. A pioneer study suggested that AI holds the potential of predicting pulp exposure.[85] Another group further compared the effectiveness of different AI algorithms in predicting pulp exposure risk.[86] Among the 3 CNN models tested, DenseNet emerged as the most effective, and its predictive effect was comparable to that of senior experts.[86] Although the published results are exciting, the clinical efficacy validation studies are still absent. Furthermore, the cost-effectiveness of AI-powered pulp exposure prediction also needs to be evaluated, as a predicted outcome without pulp exposure risk may place the involved tooth at higher risk due to reduced vigilance by dentists.

AI-enabled robotics has started to perform surgery without human input. At present, dental robotics is mainly used in orthodontics and implantology.[87] AI-enabled robotics for dental caries treatment is not yet available. In 2011, Ortiz Simon et al. took an initial step in this direction.[88] The mechatronic assistant system they developed can hold a dental drill, perform precise positioning, and drill under the guidance of a dentist.[88]

Generally, the application of AI in dental caries treatment is still underdeveloped. In the future, AI is likely to automatically formulate treatment plans for patients. AI could also streamline the assessment of treatment difficulty when factors influencing treatment difficulty are provided. Future directions for AI in dental caries treatment may also encompass the advancement of AI-enabled robots, as they have the potential to augment the efficiency, precision, and cost-effectiveness.

AI in oral hygiene guidance

Effective prevention and control of dental caries requires the participation of patients and the general public. The adoption of AI may increase their confidence in the diagnosis and foster their understanding of dentists' decisions.[89] In addition, expanding oral health care beyond the clinical setting can help patients maintain long-term oral health, reduce the likelihood of developing dental diseases, and increase satisfaction with the dental visit.

AI-enabled health applications are becoming more integrated with family oral health care. Dentists can leverage AI to monitor and provide feedback to patients and the general population, aiding in the maintenance of good oral health habits. Tooth brushing is the most effective way to prevent dental caries. Dentists' inability to oversee patients' brushing habits exacerbates the disparity between ideal oral hygiene and individuals' actual practices.[90] By combining front-end oral healthcare devices like electronic toothbrushes and smartphones with back-end risk prediction and personalized intervention algorithms, oral health can be effectively measured and managed. Smart toothbrushes equipped with sensors can collect data about brushing habits, then transmit to a cloud server for AI-based analysis, and then provide real-time feedback to continually optimize their brushing technique.[91]. In this area, Chen et al.[92] used a Recurrent Probabilistic Neural Network to recognize toothbrush posture and brushing position and to monitor the correctness and integrity of the volunteers' Bass brushing technique. Another system developed by Kim et al.[93] consists of a device identifying plaque through light-induced fluorescence technology and a mobile app displaying the location of dental plaque over time. By employing a deep learning-based algorithm, the app can automatically predict plaque distribution and present the results as time series data. Smartphone app WhiteTeeth has been developed and tested for its effectiveness in improving oral hygiene.[94,95] With the help of WhiteTeeth, adolescents wearing fixed orthodontic appliances improved their oral hygiene, demonstrating the positive influence of intelligent software in oral hygiene management.

AI in dental caries-related education

The incorporation of AI into dental caries-related education might become commonplace in the future, considering the alarming development speed of AI. Dental education helps students learn scientific knowledge and clinical skills, and then apply them in clinical situations, including the management of dental caries. Mapping dental students' preferred learning styles to suitable instructional strategies by educators enhances their academic performance. AI-powered tools can tailor instructional strategies to students' specific needs.[96] They provide paths to plan student-centered lessons and to improve the learning experience of the students.

Pre-clinic training prepares students to become qualified dental practitioners. In recent years, virtual reality and augmented reality simulators have been extensively applied to reproduce the physiological responses of real patients. However, assessing students' performance automatically on a simulator remains challenging. ML may offer potential solutions.[97] A virtual patient called Julia (which is a conversational AI chatbot as a fact) was created to develop dental students' diagnostic skills.[98] Through meticulous design, Julia effectively addressed the students' inquiry about dental issues, guiding them towards a precise diagnosis. This interaction helps students to enhance their diagnostic skills.

AI can assist in forecasting the prognosis for interns through the Case-based reasoning (CBR) system. This AI-enabled tool integrates various ML methodologies to realize its functions. CBR can predict the likelihood of restoration failure performed by dental students.[99] Notably, a significant correlation was found between the predicted failure and the grades assigned by the supervisor, suggesting this system is also a useful teaching tool able to adequately assess the competencies of dental students.[99]

Concerns and prospects

Despite the exciting progress to date, the application of AI in dental caries management is still in its early stages and has not yet been fully integrated into standard dental practice. Large-scale clinical trials validating its efficacy and reliability remain absent, and most existing studies are small-scale and conducted in controlled settings with relatively limited sample sizes. These studies have mainly focused on the diagnostic performance of AI in detecting carious lesions from radiographic images, often comparing AI to human dentists in retrospective datasets rather than in real-world clinical settings. Future research should prioritize multi-institutional collaborations to validate the effectiveness of AI-driven tools across diverse demographic and geographical settings, complemented by longitudinal studies to assess long-term impacts on prevention and treatment outcomes.

Besides, numerous obstacles need to be addressed before AI can be seamlessly incorporated into dental caries management. One major challenge is the reliance on patient data to train AI. It is important to recognize that these data may reflect biases and inequalities present in society. If the training data contains racial discrimination or prejudice, AI is likely to learn and perpetuate these undesirable traits in its decision-making process.[100] Interpretability is another crucial aspect. Dental professionals require a clear understanding of how AI arrives at its decisions to facilitate accurate diagnostic and treatment options. However, AI frequently lacks the ability to articulate the rationale behind its conclusions. Third, the integration of AI in dentistry elicits ethical and legal considerations. Issues such as patient privacy, confidentiality, and informed consent must be meticulously managed when using patient data for AI purposes. It is also important to understand that poorly designed algorithms can lead to misinterpretations by healthcare providers. Therefore, the cooperation between experienced dentists and computer engineers is critical to reduce potential risks. Last but not least, AI is not a 1-size-fits-all technology, and infrastructure, economic, and ethical barriers that vary across regions and countries may hinder the general applicability of AI for dental caries management. However, targeted efforts can make AI a cornerstone of equitable global caries management, such as developing context-specific solutions tailored to regional needs, investing in infrastructure and affordable AI tools for resource-poor settings, ensuring diverse training data to minimize bias, and prioritizing ethical frameworks for data use and accountability.

Conclusions

AI has shown great potential in dental caries management, including risk assessment, diagnosis, treatment planning, home-based oral health monitoring, and dental education. Through interdisciplinary collaboration and continued technological advancements, it is expected to transform dental caries management, making dental care more efficient, precise, and accessible.

Author contributions

L.C. and J.H. conceived of the presented idea, Y.L., D.L., L.C., and J.H. collected the data and drafted the manuscript. All authors discussed, commented, and revised the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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