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A review of advancements of artificial intelligence in dentistry

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ABSTRACT

Artificial intelligence (AI) has been used in healthcare for decades and has the potential to revolutionize dentistry by solving multiple clinical problems and making the work of clinicians easier. In particular, the study of AI applications in periodontal disease and cariology is important because these are two major areas of concern in dental health. Periodontal disease, which affects the gums and bone surrounding the teeth, is a major cause of tooth loss in adults. Cariology, the study of dental decay, is also an important area of focus for AI research. AI algorithms can be used to analyze dental images and detect early signs of decay that may be missed by human dentists. The review first discusses the history of AI in healthcare and then highlights some of the ways technology has improved dentistry and then describe some basic AI models such as artificial neural networks (ANNs), convolutional neural networks (CNNs), and random forest. The article then delves into how AI is involved in periodontal disease, cariology, endodontics, prosthodontics, and orthodontics including classifying different types of periodontal disease, identifying areas of bone loss, determining the severity of the disease, analyzing dental images, and detecting early signs of diseases. On the other hand, the application of AI in dentistry is relatively uncommon because implementing AI technologies in dentistry presents several challenges that need to be addressed for successful implementation of AI technologies in dentistry.

Introduction

Artificial intelligence (AI) is the simulation of intelligence exhibited by animals and humans that processed by machines. AI includes various subfields, including machine learning (ML), natural language processing (NLP), computer vision, robotics, and more. Each category has different applications and associated algorithms that provide different results. With proper training, AI can perform tasks with greater precision and accuracy than humans. AI has a long history in health care, with early efforts dating back to the 1950s. The first AI systems in medicine were developed in the 1950s when researchers at Jack Whitehead's Technicon Corporation built a computer program called the "MIT Programmed Autoanalyzer" to analyze blood and urine samples [1]. MYCIN system developed in the 1970s was an early expert system that used AI to diagnose and treat infectious diseases [2]. In the 1980s machine learning algorithms have been used in medical image analysis and drug discovery. "IntelliCare" system, which was used to diagnose and treat mental health disorders, and the "CardioCom" system, which was used to diagnose and treat patients with heart disease were developed in the 1990s [3]. The 2000s and following years showed advances in NLP and ML allowing AI in a wide range of medical applications, including diagnosis, treatment planning, drug discovery, and patient monitoring [4]. Despite being a relatively new technology, AI is increasingly being used in various medical specialties to diagnose diseases, interpret results, and help healthcare providers achieve positive patient outcomes. AI search in health care can be divided into two types virtual and robotic (Fig. 1). The virtual type deals with mathematical algorithms and the robotic type supports the physical part of healthcare systems. Table 1 listed some examples of how AI is being used in virtual type of AI.

William Ecenbarger in the 90 s came to the conclusion that 'Going to the dentist is nothing to smile about. Dentistry is a stunningly inexact' [5]. Since then, dentistry has seen tremendous changes. The increasing use of advanced technology in clinical practice makes dentistry more precise, efficient, and comfortable for patients. Some of the ways technology has improved dentistry are Intraoral scanner, 3D printers to create dentures, robotic surgery, regenerative dentistry, virtual reality, and AI. The application of AI in dentistry is gaining popularity in imaging and pathology, dental radiology, caries detection, electronic record keeping, and robotic assistance. This review aims to provide a comprehensive overview of the role of AI in dentistry, exploring its

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potential to revolutionize the field and address clinical challenges. The review encompasses different types of AI, including supervised, unsupervised, and deep learning, and outlines specific examples of AI applications in dentistry. Additionally, the current challenges regarding the applicability, cost-effectiveness, and patient privacy associated with AI in dentistry are included.

Metrics evaluation

Various metrics can be used to evaluate the performance of AI systems in healthcare. These metrics are not mutually exclusive, and the right metric to use depends on the specific application and goals of the AI system. Metrics and their brief descriptions used in the manuscript are listed in Table 2.

Basic operation of AI models

AI is a broad field that includes a wide variety of techniques and technologies that can be used to solve various tasks (classification, detection, segmentation, prediction). Nguyen [6] suggested to classifying the AI-based methods into four groups: statistical learning, artificial neural networks based, genetic algorithms based, and hybrid AI methods.

Statistical learning methods utilize statistical principles and concepts to make predictions or decisions based on data. These techniques typically involve fitting mathematical models to data and utilizing statistical techniques for inference. Some common statistical learning methods include linear regression, logistic regression, decision trees, random forest (RF), and support vector machines (SVM). These methods can help analyze and model dental data, such as patient demographics, clinical measurements, or treatment outcomes. Statistical learning techniques can assist in predicting the risk of dental diseases, understanding factors affecting oral health, analyzing treatment effectiveness, and identifying patterns or associations in dental datasets [6]. In Fig. 2, the fundamentals of two of the most commonly used algorithms – RF and SVM- were explained.

Artificial neural networks (ANNs) are a type of machine learning algorithm that takes inspiration from the structure and functioning of the human brain. These algorithms utilize interconnected layers of artificial neurons (nodes) to process and transmit information. Neural networks can learn complex patterns and relationships in data by adjusting the strengths of connections (weights) between neurons. They have been proven successful in various tasks such as image recognition, natural language processing, and time series analysis. Examples of neural network-based methods include feedforward neural network, convolutional neural network (CNN), and recurrent neural network (RNN). In dental imaging, CNN can be employed for tasks like tooth

Table 1
Examples of how AI is being used in virtual applications.

Application	Description
Diagnosis	AI algorithms can analyze medical images such as X-rays and 3D scans to detect abnormalities and make diagnoses
Predictive analytics	AI can analyze large amounts of data such as electronic medical records and genetic information to predict the prospect of certain diseases and patient outcomes.
Personalized medicine	By analyzing a patient's medical history and genetic makeup, AI can help create a personalized treatment plan
Drug discovery	AI can analyze compounds, predict their potential efficacy as drugs, and accelerate the drug discovery process
Clinical decision support	AI can provide doctors with real-time recommendations based on the latest medical evidence and guidelines

Table 2
List of key metrics that are used to monitor and measure the performance of a model.

Metric	Description	Formulation
Accuracy	Measures the overall correctness of the model's predictions	$(TP + TN) / (TP + TN + FP + FN)$
Precision	Proportion of true positives among positive predictions	$TP / (TP + FP)$
Recall (Sensitivity)	Proportion of true positives correctly identified	$TP / (TP + FN)$
Specificity	Proportion of true negatives correctly identified	$TN / (TN + FP)$
F1 Score	Harmonic mean of precision and recall	$2 * (Precision * Recall) / (Precision + Recall)$
Area Under ROC Curve (AUC-ROC)	Measures the model's ability to rank predicted probabilities	ROC curve represents the TPR plotted against the FPR
Mean Absolute Error (MAE)	Average absolute difference between predicted and actual	$(1 / N) * \Sigma$
Mean Squared Error (MSE)	Average squared difference between predicted and actual	$(1 / N) * \Sigma (y - \hat{y})^2$
Root Mean Squared Error (RMSE)	Square root of the MSE	$\sqrt{(1 / N) * \Sigma (y - \hat{y})^2}$
R-squared	Proportion of the variance in the dependent variable	1 - (SSE / SST)
Confusion Matrix	Summarizes the performance of a classification algorithm	–

TP: True Positives, TN: True Negatives, FP, FN: False Negatives, TPR: True positive rate, FPR: False positive rate, N: The total number of instances, y: The actual (true) values, $\hat{y}$: The predicted values, SSE: Sum of Squared Errors, SST: Total Sum of Squares.

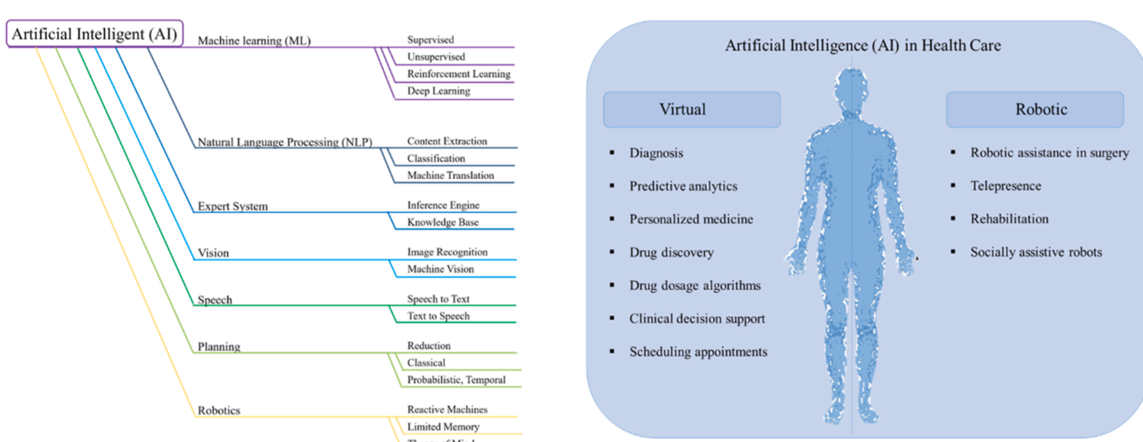

Fig. 1. Taxonomy of Artificial intelligence techniques and their applications in health care.

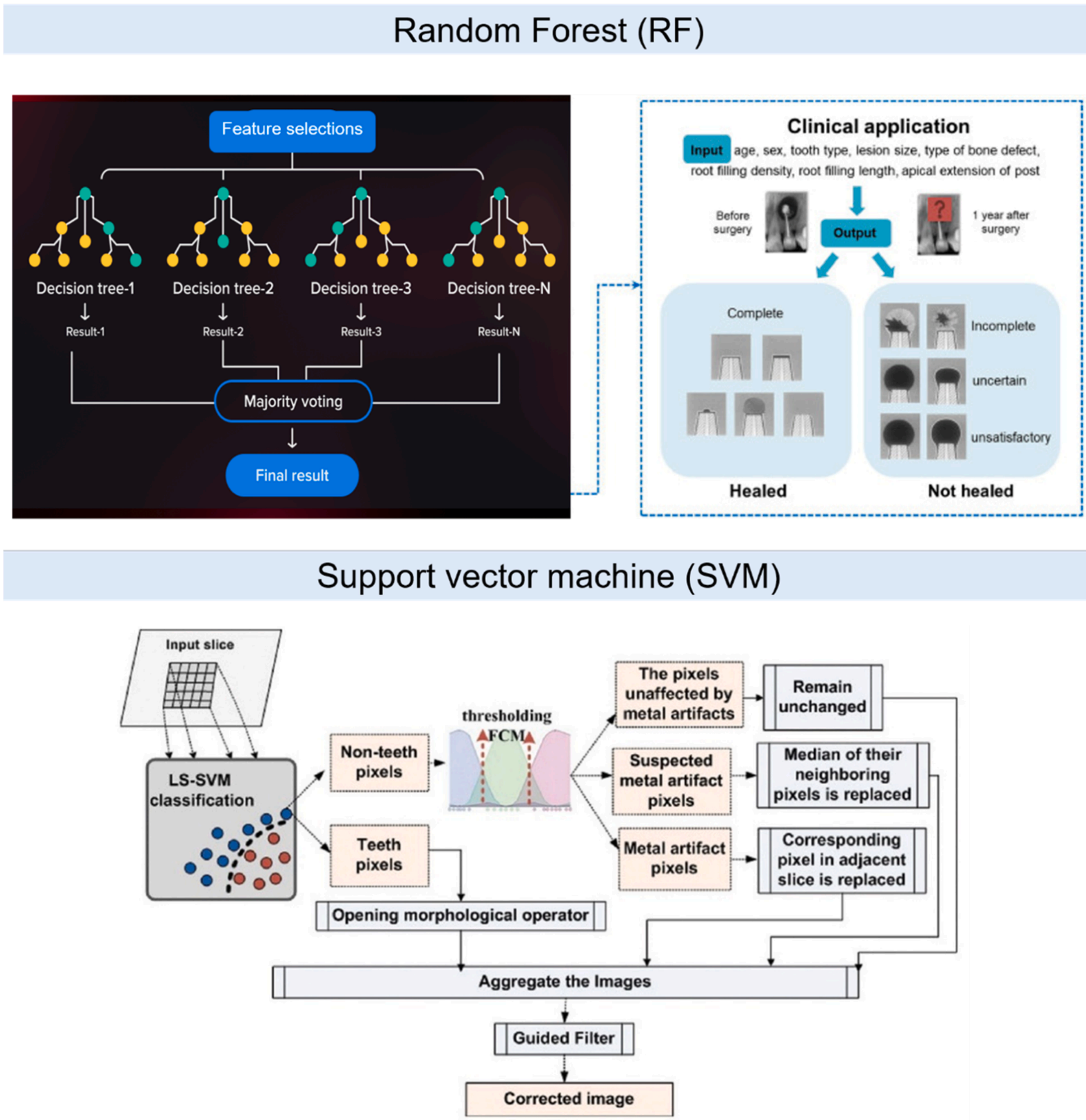

Fig. 2. The RF and SVM algorithms are machine learning techniques used in clinical studies. The RF algorithm employs ensemble learning with decision trees, while SVM focuses on finding optimal boundaries to separate classes in datasets. RF utilizes bootstrap sampling to train multiple trees, each considering a random subset of features to prevent overfitting. On the other hand, SVM maps input data into a high-dimensional space to identify a hyperplane that maximizes the margin between classes, facilitating accurate classification of new data points. Figures were adapted and modified from [7–9].

segmentation, dental anomaly detection, or image-based diagnosis. RNN can be used in dental time series analysis, such as predicting orthodontic treatment progress or modeling temporomandibular joint disorders (TMJ) [10]. In Fig. 3, the fundamentals of two of the most commonly used algorithms - ANN and CNN - were explained.

Genetic algorithms are a type of optimization technique that is inspired by the process of natural selection and genetics. They are used to search and optimize solutions to complex problems. Genetic algorithms involve a population of potential solutions that undergo evolutionary processes such as selection, crossover, and mutation to produce improved solutions over generations. These methods are particularly useful when dealing with large solution spaces and complex constraints. Genetic algorithms can be applied to various problem domains, including optimization problems, feature selection, and parameter tuning. Genetic algorithms can be applied to various dental problems, such as treatment planning, optimization of dental prosthetics, or orthodontic treatment design. These methods can help in finding optimal configurations or solutions considering multiple factors, constraints, and objectives. Genetic algorithms can be utilized for optimizing parameters in dental implant placement, designing optimal dental appliance

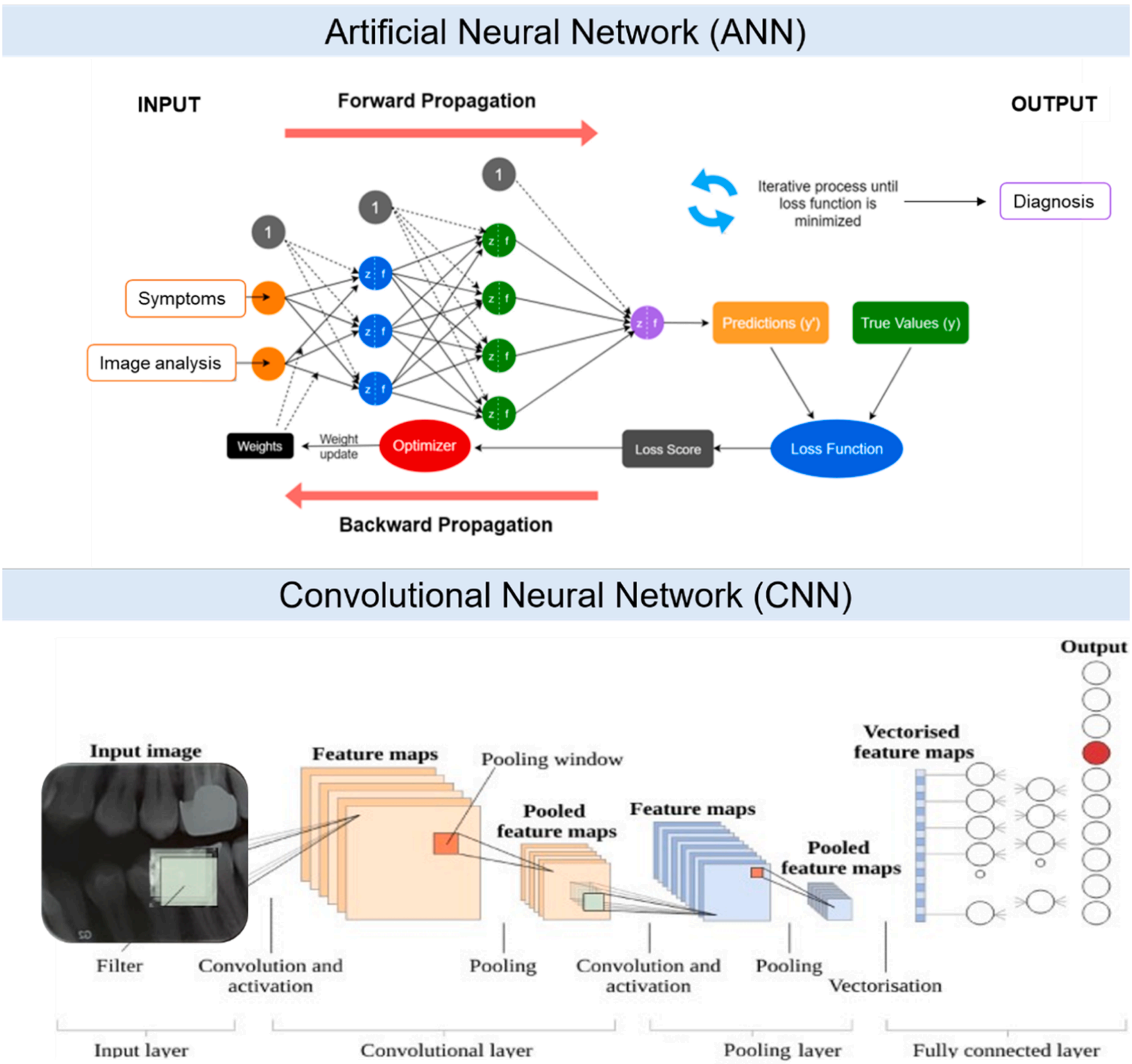

Fig. 3. The ANN and CNN algorithms play vital roles in clinical studies, particularly in image analysis. ANN comprises interconnected artificial neurons arranged in layers: input, hidden, and output. During training, weights representing neuron connections are adjusted to enhance performance, typically using backpropagation. CNN, specialized for image analysis, features layers extracting crucial image features. Convolutional layers capture edges and textures, followed by pooling layers reducing data dimensionality. Fully connected layers then analyze features to generate output probabilities for different classes. Both ANN and CNN employ backpropagation to refine model performance. Figures were adapted and modified from [11,12].

structures, or determining personalized treatment plans [13].

Hybrid AI methods refer to approaches that combine multiple AI techniques or models to solve complex problems. These methods leverage the strengths of different algorithms or methodologies to improve performance and overcome limitations. A hybrid AI method might combine statistical learning methods with neural networks or incorporate genetic algorithms for feature selection in a neural network model. Hybrid AI approaches are often used in domains where a single technique may not be sufficient or where a combination of techniques can provide better results. These methods require careful integration and coordination of different components to achieve the desired outcome. Combining statistical learning methods with neural networks can provide more accurate prediction models for dental disease risk assessment [14]. These combinations allow for leveraging the strengths of different methods and providing more comprehensive solutions to dental problems.

AI applications in periodontal disease

Chronic oral inflammatory diseases are conditions that cause long-term inflammation of the tissues in the mouth. They can be caused by a variety of factors, including infections, autoimmune disorders, and environmental exposures. Gingivitis and periodontitis are widespread chronic oral inflammatory diseases. Early detection can improve treatment outcomes, prevent disease from spreading to surrounding tissues, and reduce the number and impact of complications. Detecting periodontal disease is complex and requires advanced skills. Detection of periodontal conditions relies on clinical examination, periodontal probing, radiographic assessment, quantitative light-induced fluorescence (QLF), and oral bacteria DNA testing. Clinical examination is an effective way to detect periodontal disease, but it is subjective and relies on the skill and experience of the dentist or dental hygienist. It may also be limited by the amount of time available for the exam. Difficulty in obtaining and interpreting radiographic assessment can pose a problem in periodontal and endodontic diseases. Accurate diagnostic images, such as radiographs are important for planning and carrying out treatments. In addition, radiographic assessment does not indicate the early stages of periodontal disease. QLF method is not as accurate as other methods and oral bacteria DNA testing is relatively new, expensive, and is not widely available [15]. Applying AI systems to detect periodontal conditions might improve reliability and enable clinicians to achieve detection accuracy equal to or better than experienced professionals. Revilla-León et al. [16] in a systematic review evaluated the performance of the AI models for diagnosing gingivitis and periodontitis. The studies reported 47 % and 99 % accuracy in detecting dental plaque, diagnosing gingivitis, and quantifying alveolar bone loss. They concluded that AI models developed for periodontal applications still need development and they have the potential to be powerful clinical assistance or diagnostic tools. Table 3 summarizes the selected articles using AI for periodontal applications.

AI applications in oral mucosal disease

Lichen planus is another chronic inflammatory disease that affects the skin and mucous membranes, including those in the mouth. It is characterized by the development of flat, purple lesions on the gums and other oral tissues. The diagnosis of oral lichen planus is usually based on a combination of clinical examination, laboratory testing and imaging studies. Keser et al. [30] used the Inception v3 algorithm, a convolutional neural network for assisting in image analysis, to classify oral lichen planus lesions using intraoral photographs. Their finding showed that deep learning provided 100 % classification success rate.

AI applications in cariology

Cariology deals with the prevention, diagnosis, and treatment of dental caries. Dental caries is a multifactorial disease and one of the most common chronic diseases worldwide [31]. Visual examination, dental radiography, dental cavities detection devices (such as the DIAGNOdent, Caries Detector, and the Spectra) and saliva tests are diagnostic tools that are commonly used in cariology to identify areas of caries lesion. Detection of carious lesions, particularly in the early stages can be subjective as they have different forms of clinical presentation during the disease process. As noted in the previous section, lack of consistency in dental radiographic interpretations have led to increased interest in using deep learning to process images. Lee et al. [32] proposed machine learning for early detection of initial dental caries. In their study bitewing radiographic were used to train the U-shaped deep CNN (U-Net) model. Example of the analysis of dental structures and caries tagging with observers and deep learning model were shown in Fig. 4. Clinicians had significantly improved sensitivity to easily missed early and moderate caries following deep learning. However, the CNN model also showed more false-positive errors in detecting caries in overlapping proximal surfaces. A faster R-CNN algorithm was studied by Chen et al.[33] for caries detection in the proximal region. Faster R-CNN is a deep learning-based object detection method in medical imaging. After model training the evaluation metrics showed the accuracies of the model, and the students were similar (0.87 vs. 0.82) and the model exhibited a sensitivity and specificity of 0.72 and 0.93, respectively while students showed sensitivities below 0.40. Mohammad-Rahimi et al. [34] in a systematic review of 42 studies using deep learning for caries detection reported that the accuracy of caries classification models was 71 % to 96 % on Intraoral images, 82 % to 99.2 % on periapical radiographs, 87.6 % to 95.4 % on bitewing radiographs, 68.0 % to 78.0 % on near-infrared transillumination images, 88.7 % to 95.2 % on optical coherence tomography images, and 86.1 % to 96.1 % on panoramic radiographs. The differences in coverage area, image quality, lesion characteristics, and dataset quantity may contribute to the observed variation in accuracy for caries detection between the imaging modalities.

Another aspect of cariology is to minimize the experience and impact of caries on an individual's general health and quality of life. In this regard, Hung et al. [35] studied the SVMs method to develop models for the identification of dental caries risk. This prediction guides treatment decisions and leads to better oral health outcomes. This model used data from the National Health and Nutrition Examination Survey. The model

Table 3
Applications of AI in chronic oral inflammatory diseases.

Diagnostic	Diagnostic tool	Input data	Framework	Results	Ref
Gingivitis	Supragingival dental plaque	Oral endoscope images	CNNs	No significant differences between the AI model and the human specialist (P > .05)	[17–19]
	Supragingival dental plaque (Biofilm)	QLF images	GMRF	No significant differences between the AI model and the human specialist (P > .05)	[20]
Periodontitis	Pocket depth of teeth	oral images	CNNs	Accuracy: 0.76	[21]
	Clinical examination	Periapical radiographic	CNNs	Premolars diagnostic accuracy: 0.81 Molars diagnostic accuracy: 0.76	[22]
	Alveolar bone loss	Periapical radiographic	Bayesian classifier	True positive fraction: 92.5 % False positive fraction: 14.0 %	[23]
	Alveolar bone loss	Panoramic radiograph	CNNs	Mean (SD) accuracy: 0.81 Mean (SD) sensitivity: 0.81 Mean (SD) specificity: 0.81	[24]
	Alveolar bone loss	Panoramic radiograph	CNNs	The Pearson correlation coefficient of the automatic method with the diagnoses by radiologists was 0.73 overall for the whole jaw	[14]
	Alveolar bone loss	Panoramic radiograph & clinical examination	DeNTNet	F1 score of 0.75	[25]
	Abnormalities in the periapical region	CBCT	CNNs	Accuracy: 0.93 Specificity: 0.88	[26]
	Pathogenic microflora	Proinflammatory component	Random forest	The importance of proinflammatory cytokines, monocytes, T-lymphocytes, and memory B-cells in the development of osteodestructive inflammatory process	[27]
Lichen planus	Counting inflammatory cells	Digitized H&E-stained microscopic slides	ANNs	Accuracy: 0.95 Sensitivity: 1 Specificity: 0.91	[28]
	Cytology slides	Positively stained protein expression	Regression models	Accuracy: 0.95 Sensitivity: 1 Specificity: 0.9	[29]

GMRF: Gaussian Markov Random Fields, LVQ3: Learning Vector Quantization, DeNTNet: Deep Neural Transfer Network.

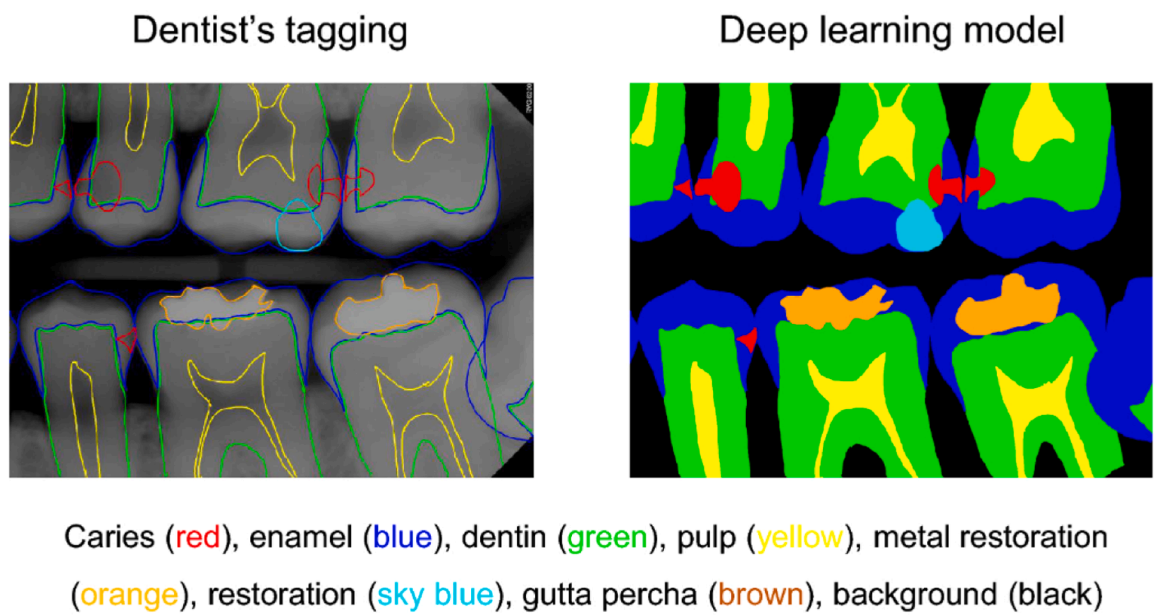

Fig. 4. Analysis example of tooth structure and caries marking. On the bitewing radiographs, the observer drew lines for segmentation of tooth structure (enamel, dentin, pulp, metal restorations, tooth-colored restorations, gutta-percha) and caries. Reprinted with permission from [32].

predicted the most relevant variables from demographic and lifestyle factors with an accuracy of 97.1 %, precision of 95.1 %, sensitivity of 99.6 %, and specificity of 94.3 % for identifying dental caries. A recent systematic review evaluated the success of machine learning algorithms in caries diagnosis and prognosis prediction [36]. Most models were developed outside of a real clinical setting and were at unclear/high risk of bias, limiting the general applicability of the evidence. They concluded that the use of machine learning for caries diagnosis and prognosis is promising, but still in its early stages [36]. Table 4 enlists some recent studies on deep learning methods in cariology disease detection.

AI application in endodontic disease

Endodontics is a branch and specialty of dentistry that focuses on the morphology, physiology, and pathology of the dental pulp and periradicular tissues. Endodontic disease refers to the development and progression of disease or damage in the dental pulp and periradicular tissues that can be caused by a variety of factors, including caries, trauma, and infection. Early detection of endodontic disease is important as it allows for timely treatment, saves the affected tooth, and helps prevent the infection from spreading. Improved diagnosis of inflamed pulp leads to vital pulp therapies (VPT) that helps to maintain pulpal vitality [45].

Detecting endodontics diseases in periapical radiographs is an image classification task that can be automated using deep learning. Most studies used machine learning to assist dentists in the detection and diagnosis of a single disease. However, recent studies have focused on multi-disease detection methods which is more common in clinical practice. Li et al. [46] used periapical radiographs to propose an automated deep learning method to detect both caries and periapical lesions. The model demonstrated a strong ability to learn features from manually

Table 4
Applications of AI in cariology.

Diagnostic	Diagnostic tool	Input data	Framework	Results	Ref
Dental caries	labeling images by dentists	Intraoral images	CNNs	Accuracy: 0.92 Sensitivity: 0.89 Specificity: 0.94	[37]
	ICDAS cods	Smartphone images	SVM	Accuracy: 0.92 Sensitivity: 0.88 Specificity: 0.96	[38]
	labeling images by dentists	Bitewing radiographs	F-CNNs	Accuracy 0.87 Recall 0.89 Precision 0.86 Specificity 0.86 F1 scores 0.87	[39]
Screening for dental caries	Survey data	182 parents and their children 2–7 years of age	Random forest	Accuracy 0.71 Sensitivity 0.94 Specificity 0.68	[40]
	Survey data	4195 children aged 1–5 years	logistic regression and ML-based models[a]	AUROC > 0.7	[41]
	Genetic and environmental risk factors	1055 teenagers aged 13 years	Random forest	AUC: 0.78	[42]
Relationship between dental caries and diabetes	Medical records	193 dental records	K-means	Corroborate the relationship between diabetes and dental caries	[43]
Caries microbiome	Meta-analytic microbiome research	22 literatures	Random forest	Identify Selenomonas spp HMT-146., Aggregatibacter actinomycetemcomitans, Actinomyces spp HMT-896, and Treponema spp HMT-257 as prevalent within the cohort data as markers of caries.	[44]

ICDAS: International Caries Detection and Assessment System, F-CNNs: Faster region-based CNN.
[a] ML-based models: XGBoost, random forest, and LightGBM.

annotated periapical radiographs. Compared to expert detection, their model showed good performance (F1-scores of 0.8288) and high accuracy (86 %) for detecting dental caries and periapical lesions. Table 5 enlists some recent studies on deep learning methods in Endodontics disease detection.

During endodontic treatment, two major challenges are correct working length determination and complexity of the root canal anatomy. Some teeth have complex root canal anatomy, with multiple canals or unusual shapes, which can make treatment more difficult. Various methods used to determine working length include radiographic examination, electronic apex locator (EAL)+ and measuring the tooth in radiographs with a ruler. Incorrect working length can lead to incomplete treatment and increased risk of failure. Radiographic examination is the most common method of determining the working length in root canal treatment. However, it has several limitations. A two-dimensional image, dense bone and other structure in the area, and position of the tooth make it difficult to accurately determine the length of the root. Cone-beam computed tomographic (CBCT) imaging is demonstrated to be more accurate in assessing root and root canal composition compared to radiography [47]. However, due to radiation concerns, it is not recommended in routine clinical practice and the system is not readily available to many clinicians. Machine learning showed the potential to improve the accuracy and efficiency of determining the working length in root canal treatment in different ways. According to Saghiri et al. [48], using an ANNs improved the accuracy of locating apical foramen from radiographs by 93 %. They reported that their model was more accurate than endodontists' determinations when compared with the real length of the root measurements by using the stereomicroscope as the gold standard after tooth extraction. AI algorithms could also be trained on large datasets of root canal treatment cases to predict the technical treatment outcome for a given tooth based on various factors, such as tooth anatomy and position. Herbst et al. [49] collected 555 complete root canal treatment datasets to yield insights to predict treatment outcomes with the help of machine learning. Root-filling length was considered a simple and suitable parameter to assess treatment quality. Six ML models (logistic regression (logR), support vector machine (SVM), random forest (RF), decision tree (DT), gradient boosting machine (GBM), and extreme gradient boosting (XGB)) were performed to predict outcomes. They concluded that the most influential risk factor across the dataset was root canal visibility. Because of some limitations in their study the predictive performance of the technical outcome of root canal treatment using the ML was poor. EAL is another common method of determining the working length of root canal treatment. However, its accuracy is questionable, particularly in cases where the root canal anatomy is complex or there is significant root resorption. Qiao et al. [50] performed EAL based on neural network for root canal length measurement. The dataset was collected from numerous measurements of 21 teeth with multifrequency signals combinations. The optimal neural network model increased the measurement accuracy. This method may eliminate the influence of human and environmental factors on root canal length measurement, thus improving the performance of EAL.

The failure rate of root canal treatment is higher in teeth with more complex root morphology like C-shaped canals. Jeon et al. [51] used the CNN model to distinguish C-shaped root canals of second molars from panoramic images. A comparison of diagnostic performance between CNN models and specialists showed that the AUCs of CNN models, radiologists, and endodontists were 0.982, 0.872, and 0.885, respectively. The AUC for the CNN model was significantly higher than the dentist's AUC.

Prosthodontics

Prosthetics is a branch of dentistry focused on replacing or restoring missing or damaged teeth and jaws using prosthetic appliances such as dentures, bridges, and crowns. It also includes treatment of jaw and facial conditions such as cleft lip and palate, temporomandibular join (TMJ) disorders, and other complex craniofacial problems. AI can be quite beneficial for various prosthodontics treatments and its applications are expanding exponentially. Reducing human error in denture and maxillofacial prosthesis classification, margin line extraction, and implant cementation [64].

Computer-Aided design and computer-aided manufacturing (CAD/CAM)

In prosthodontics, CAD/CAM manufacturing is used to design and fabricate various types of dental restorations, such as crowns, bridges, inlays, onlays, and implant-supported restorations. One of the main uses of CAD/CAM in prosthodontics is the creation of digital impressions. Instead of using traditional dental impressions, which uses a physical mold of the patient's teeth and gums, a digital impression can be made using a special camera or scanner. This digital impression is then used to create a 3D model of the patient's teeth and gums, which can be used to design and fabricate the restoration with CAD/CAM technology. This typically involves using a milling machine or a 3D printer to create the restoration from materials such as ceramics, zirconia, or metals. CAD/

Table 5
Applications of AI in Endodontics.

Diagnostic	Diagnostic tool	Input data	Framework	Results	Ref
Pulpitis	Depth of carious lesions	Periapical radiographs, Clinical parameters	CNN of ResNet18	Accuracy: 0.86 Precision: 0.85 Sensitivity: 0.89 Specificity: 0.86	[52]
	Depth of carious lesions	Periapical radiographs	CNN-fuzzy-based	Accuracy: 0.94	[53]
	GLCM* and Watershed image segmentation methods	Periapical radiographs	K-NN	The best dimension to extract periapical radiograph is 256 × 256 which achieve 83.3 % accuracy	[54]
	Symptoms	Symptoms	LVQ3	Accuracy in training set: 0.97	[55]
Periapical lesions	Manual segmentation	CBCT images	U-Net	Recall: 0.89 Precision: 0.95 F-Score: 0.93	[56]
	Three evaluators	Panoramic radiographs	CNN	Specificity: 0.9	[57]
	Manually label	Periapical film	SIFT-SVM, CNN (VGG16)	Accuracy > 95 %	[58]
	Manually label	CBCT images	U-Net	Sensitivity: 0.97 Specificity: 0.88	[59]
Post-Streptococcus mutans in root	Clinical trial results	Caries excavation methods, pre-Streptococcus mutans	ANN	Efficiency: 0.99033	[60]
Pulpal calcification	labeling images by oral radiologists	Bite-wing radiographs	YOLOv4	Accuracy: 0.96 Precision: 0.85 Specificity: 0.97	[61]
Inflammatory toothache	Panoramic radiographic and clinical examinations	Infrared thermography	CNN of MobileNetV2	The best performance was possible only by the frontal view (accuracy 96.63 %)	[62]
Physical properties of dentin	Root fracture resistance, Surface microhardness, Tubular density	Magnesium, strontium zinc	ANN	There were no significant differences between evaluations by manual or ANN methods	[63]

K-NN: K-Nearest Neighbor.
* GLCM: Gray Level Co-occurrence Method.

CAM technology in prosthodontics offers several advantages such as reduced chair-side time, increased precision and accuracy in the final restoration, reduced number of adjustments needed, and provide a precise fit and occlusion [65]. CAD/CAM also can be integrated with other technologies such as CBCT and AI to increase the precision of implant placement and to design implant-supported restorations. This integration could enhance patient outcomes like improved functionality and aesthetics. Its precision and accuracy ensure optimal fit and function, reducing chair-side time and the need for post-placement adjustments. Moreover, CAD/CAM facilitates the correlation with different occlusal schemes, tailored to the patient's specific needs and occlusal anatomy. In terms of aesthetics, CAD/CAM plays a dual role: firstly, by capturing detailed aesthetic data during the initial digital impressions secondly, by enabling precise manipulation of digital models to achieve optimal aesthetics, including tooth shape, size, color, and alignment. [66]. AI-powered CAD/CAM systems use machine learning to automatically optimize prosthesis designs based on data from previous patients or to predict how materials behave during the manufacturing process [67]. These AI-powered features can add more value to the CAD/CAM system than traditional versions.

Tooth-supported fixed and removable prosthodontics

Dental prostheses are dental appliances for replacing one or more teeth and associated alveolar structures. To restore esthetics, oral function, and occlusal integrity, dental prostheses must be adapted to the remaining dentition and oral environment for each patients [68]. Tooth-fixed and removable prostheses have different aspects that AI models could help to improve it. Facial changes prediction after prosthesis, tooth shade selection, optimizing the manufacturing casting procedures are area of several recent interests [69]. 3D Generative Adversarial Network (GAN) is a recent neural network used in prosthodontics to learn the features of teeth and to generate AI-designed tooth. Chau et al. [70,71] described the protocol of a prospective experimental study aimed at training and validating a GAN system for the design of single molar prostheses. Maxillary and mandibular tooth models were collected and digitized. Use various GAN algorithms and the need for antagonistic mandibular tooth models were explored. GAN are system could automate the biomimetic design of crowns with acceptable performance in terms of accuracy.

Implantology

Implantology is a branch of dentistry that deals with the surgical placement and restoration of dental implants. Dental implants are a popular and effective treatment option for people who have lost one or more teeth due to injury, disease, or decay. They are made of biocompatible materials such as titanium, zirconia or ceramics, which allows the implant to fuse with the patient's alveolar bone over time, creating a strong, stable base for the replacement teeth. The process of placing dental implants typically involves several stages, including preoperative evaluation, implant placement, abutment placement, prosthetic placement. With integration of technologies like CAD/CAM, CBCT and AI, implant placement has become high accurate, efficient and predictable outcomes. AI provided dentists with more detailed information about the patient's mouth with 3D models of the jaw and teeth [72] automated tooth segmentation, and guided implant placement [73,74], predict the outcomes of the implant placement [75], and design the final restoration, such as a crown, bridge or denture [76]. AI also can be helpful in predicting the failure rate of implants and monitoring the status of the implant over time and to predict when it may need to be serviced or replaced [77].

Maxillofacial prostheses

Maxillofacial prostheses, also known as craniofacial prostheses, are specialized prostheses used to replace or repair missing or damaged facial structures like ear, eye, nose, lip and facial bones. These devices are used to treat a variety of conditions, including birth defects, facial injuries, cancer, and major facial surgery or reconstruction. These maxillofacial prostheses are often designed and fabricated using CAD/CAM technology, which allows for the creation of highly customized and precise devices that can be tailored to the specific needs of individual patients. They are also designed with the patient's input and feedback to make the prostheses as aesthetically pleasing as possible [78]. AI can be used to improve the design, manufacturing, and fit of custom-fit maxillofacial prostheses in several ways like facial recognition and analyze a patient's face and create a 3D model of their remaining facial structure [79]. AI algorithms can also optimize prosthetic design based on factors such as weight, strength, and aesthetic appearance. The algorithm trained to predict how the prosthesis will perform in different situations, allowing for faster design iterations, and better results. Real-time monitoring without physical space limitations is one of the surgeon's requirements during a maxillofacial surgery. Wang et al. [80] worked on a see-through augmented reality (AR) that integrated into the current surgical workflow. The patient's CT and video camera data were used to prepare a 3D model. Iterative Closest Point (ICP) algorithm, an algorithm for aligning two-point clouds, were used to provide image guidance techniques, and showed promising potential with satisfactory response time and accuracy. With the help of AI prosthesis designers can select the best materials and optimize their use, and also to identify the best manufacturing methods to use in order to make the prosthesis as lightweight, durable and functional as possible [81,82].

AI application in orthodontics and dentofacial orthopedics

Orthodontics and dentofacial orthopedics are closely related branches and specialties of dentistry that concerned with monitoring, guiding, and correcting of the growing or mature dentofacial structures and diagnosing, preventing, and treating abnormalities associated with these structures. The use of AI in orthodontics is relatively recent, with initial research and applications in the diagnosis and treatment of patients [83]. Researchers began using AI to analyze dentofacial images and patient data to help orthodontists make more accurate diagnoses and treatment plans. Classification and archiving of orthodontic images are one of the main requirements for orthodontic treatment. Deep convolutional network (DCN) is a deeper version of CNN, which means it has more layers than traditional CNN, has been proposed to use in orthodontic continuous image acquisition. Li et al. [84] proposed an automated deep learning method for the classification and archiving of orthodontic images based on the leveraged DCN method. Their results showed deep learning model can classify and monitor orthodontic images quickly and effectively with very high accuracy (99.4 %). However, the performance of their deep learning models relied primarily on large, manually annotated training sets. Future work should investigate automatic quality assessment of images before classification. This is especially important when dealing with very large datasets. Kunz et al. [85] investigated to create automated cephalometric X-ray analysis for orthodontic application. Customized CNN model and the current gold standard (human expert analyses) showed no bias in determining orthodontic parameters, except for mandibular tilt.

Predicting the outcome of orthodontic treatment like the final tooth position or the duration of treatment is important as it allows for more accurate treatment planning and better communication with the patient, which can result in improved treatment outcomes, shorter treatment time and increased patient satisfaction. AI is being used to predict the likely outcome of different treatment options, helping orthodontists make more informed decisions. In a study, landmark-based geometric morphometric methods (GMMs) and deep learning were used to predict the 3-D facial topography after orthognathic surgery and fixed edgewise orthodontic treatment. [86]. AI can be used to create 3D models of teeth and jaws, which can be used for planning and simulating treatment outcomes [87]. More recently, the use of AI in orthodontics has expanded to include digital impressions that can be used for diagnosis, treatment planning, fabricate appliances and monitoring treatment progress [88,89]. Furthermore, chatbots have been developed to communicate with patients, answer questions, and schedule appointments [90].

AI application in oral medicine and pathology

Most oral cancer patients present to the hospital network with advanced stage disease, resulting in a high morbidity and mortality rate. Oral cancer prognosis depends on early diagnosis, high accuracy of oral cancer classification, reduction of human error in detection and treatment, individualized treatment planning, and cost effectiveness. AI can assist in oral cancer to improve the prognosis in different ways. One of the earliest studies using AI to diagnose oral cancer was published in the late 1990s. This study used a neural network to classify oral lesions as benign or malignant based on clinical and histologic features [91]. The use of AI as a tool to aid oral cancer diagnosis is becoming increasingly popular. The main goal is to automate early detection of oral cancer lesions with performance comparable to experienced specialists (Fig. 5). A recent systematic review on 36 studies that were using different machine learning techniques as an adjunct to the early diagnosis of cancer showed that AI has the potential to significantly improve the accuracy and speed of oral cancer diagnosis; although the available evidence is not enough to validate any of the algorithms in the diagnosis of certain precancerous lesions [92]. Baniulyte et al. [93] reported the average sensitivity of AI for oral cancer diagnosis was 83 %. The average specificity of AI in studies was 87 % that is an indication of a test to correctly identify patients without the disease. AI algorithms have also used in several studies with the aim of developing prognostic prediction models. The purpose of this type of studies is to identify the patterns, analyze the past data, and automatically reaches a conclusion based on AI model to predict the likelihood of an individual having a malignant or potentially malignant oral lesion. The past data might include knowledge of individuals' risk factors, systemic medical conditions, and clinic-pathological data [94–96]. Moreover, AI can be used to develop predictive models that can help to identify individuals who are at high risk for a cancer, or on people who have no symptoms but are considered to be at average risk for certain types of cancer based on demographic profiles, lifestyle, and other factors [97]. Table 6 enlists some recent studies on deep learning methods in oral cancer applications.

AI in current dentistry market

The dental AI market refers to the application of AI technology in dentistry. It entails the use of AI algorithms and models to assist dental practitioners in tasks such as diagnosis, treatment planning, and patient care. There are a variety of different AI-powered solutions available in the dental market, including systems for image analysis, diagnostic aids, and treatment planning. The market for dental AI is growing rapidly, driven by factors such as increased digital technology usage in dentistry, increased demand for more accurate and efficient diagnostic tools, and the need to improve patient treatment outcome. The dental AI market is estimated to reach $1.3 billion by 2028, expanding at a compound annual growth rate (CAGR) of 27.4 % from 2023 to 2028 [117]. The CAGR is often used to estimate the future growth of a market, and it is calculated by taking the ratio of the final value to the initial value, raised to the power of 1/n, where n is the number of years in the period being considered. The market can be segmented by application, including diagnosis, treatment planning, and patient management. The diagnosis segment is expected to hold the largest share of the market. The treatment planning segment is projected to grow at the highest CAGR during the forecast period. On the other hand, the market can be segmented by end-user, including dental clinics, dental schools, and dental research institutions. Dental clinics are expected to hold the largest share of the market. From a regional perspective, North America is expected to dominate the market due to the presence of many dental AI companies, and the high adoption of advanced technologies in the region. Europe is expected to be the second-largest market due to the presence of many dental clinics and the growing adoption of advanced technologies in the region.

One of the most well-known AI-powered platforms in dentistry is Overjet (https://www.overjet.ai/) that received FDA clearance in 2020.

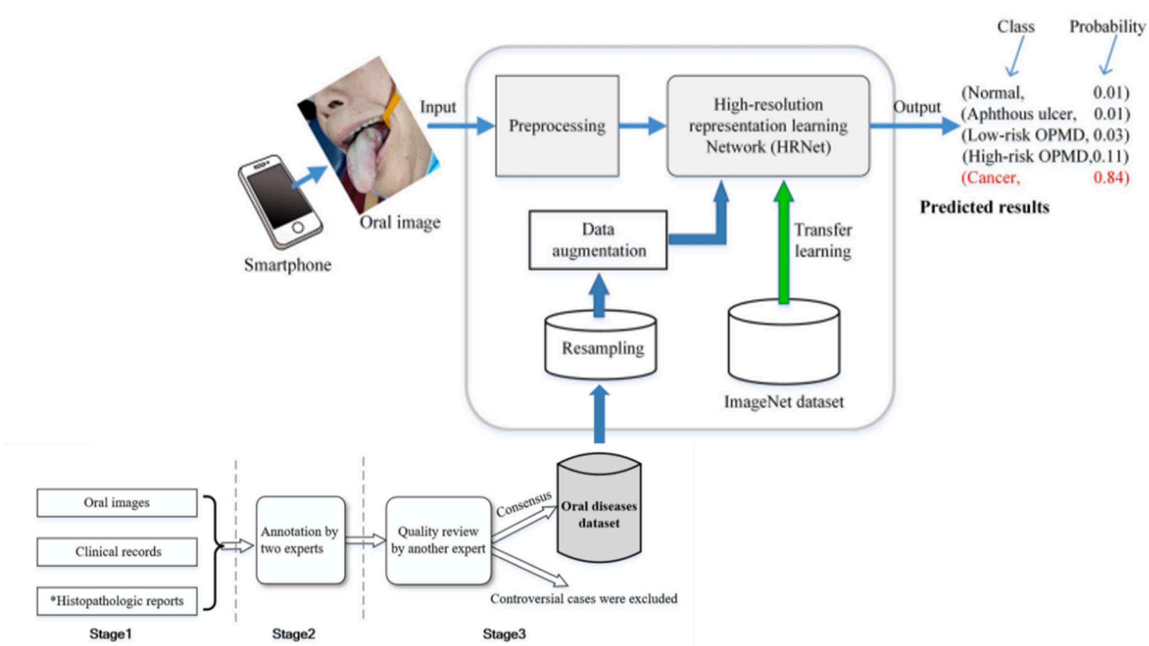

Fig. 5. Schematic illustration of smartphone-based oral cancer detection using deep learning for early diagnosis. Initial dataset preparation involved collecting lesion images and clinical records, annotated by senior experts and reviewed by a specialist. Utilizing a CNN-based system involves three steps: capturing the lesion with a smartphone, preprocessing to extract relevant information, and image classification using CNN technology. Reprinted from [100] with permission.

Table 6
Applications of AI in oral cancer.

Application	Diagnostic tool	Input data	Framework	Results	Ref
Cancer detection	Visual examination	Photographic images	CNN-ResNet	Accuracy 78 % Sensitivity78.5 % Precision 77.1 % F1 score 77 %	[98]
		Optical coherence tomography	ANN-SVM	Sensitivity 93–96 % Specificity 49–74 %	[99]
		Smartphone-based imaging	HRNet	Sensitivity 83 % Specificity 96.6 % Precision 84.3 % F1 score 83.6 %	[100]
		Autofluorescence imaging	ANN	Sensitivity 86 % Specificity 100 %	[91]
		Fluorescence visualization	ANN	Sensitivity 96.5 % Specificity 100 %	[101]
		MRI	CNN	Accuracy 96.5 %	[102]
		Hyperspectral imaging	CNN	Accuracy 91.4 % Sensitivity 94 % Specificity 91 %	[4]
		Confocal laser endomicroscopy	SVM	Accuracy 74 % Specificity 85 % Sensitivity 72 %	[104]
	Saliva	Metatranscriptomics Microbiome	Logistic regression	Specificity 94 % Sensitivity 90 %	[105]
		DNA methylation	SVM	Recall 0.94 Specificity 93 % Precision 94 %	[106]
		Impedance spectroscopy	SVM	Accuracy 80 %	[107]
	Oral smear	Cytology assay	k-Nearest Neighbor	Early disease with AUCs of 0.82 Late disease with AUCs of 0.93	[108]
		Papanicolaou stained cytology sample	R-CNN, ResNet 34	F1 score: 0.86	[109]
	Tissue biopsy	FTIR[a]	SVM	Sensitivity 81.3 % Specificity 95.7 % Accuracy 89.7 %	[110]
		PESI-MS[b]	PLS-LR	Accuracy 90.48 % and 95.35 % in positive- and negative-ion modes	[111]
		^{1}H HRMAS NMR[c]	Statistical model	Accuracy 90 %	[112]
Prognostic prediction	Medical records	Clinical characteristics	Deep learning	higher performance compared to the classic statistical method	[113]
		Gene expression profiling	SVM, DNN	Accuracy 96.5 % Sensitivity 98.1 % Specificity 94.2 %	[114]
		comprehensive, feature selection, nomogram	logistic regression, decision tree, SVM, ANN	Accuracy 80.08 %	[115]
Risk determination	Blood sample	Serum total malondialdehyde, serum proton donor capacity	Fuzzy logic	The risk was estimated as a concrete numerical value on a scale from 1 to 10	[116]

PLS-LR: Partial least squares-logistic regression.
[a] Fourier-transform-infrared-spectroscopy.
[b] Probe electrospray ionization mass spectrometry.
[c] Magnetic resonance imaging.

The system uses AI to analyze digital radiographs of teeth for decay detection and bone loss quantification. It is designed to assist dentists in making more accurate and consistent diagnostic decisions, which can lead to more effective treatment planning and improved patient outcomes. Another famous AI-powered system in dentistry is VideaHealth (https://www.videa.ai/). The system uses AI to analyze extensive database of dental X-rays, and help dentists identify potential issues such as cavities, cysts, and tumors. According to clinical trial results, VideaHealth platform helped reduce the number of caries lesions dentists missed by 43 %. It also cut back on their incorrect diagnoses by about 15 %. Diagnocat (https://eu.diagnocat. com/) is another AI analysis of dental X-rays, which can be used to create the STL—creation of 3D models from CBCT data. The same CBCT data were used to create the 3D model of maxilla and mandible including teeth in STL file format and then segmented of the maxillary and mandibular using AI powered Diagnocat software. Automated dental radiography assistance systems help provide reliable and stable diagnostic results, especially for inexperienced examiners. Also, this system can reduce diagnosis time and improve treatment efficiency. The dental AI market is expected to see significant growth in the coming years due to the increasing adoption of digital technologies in dentistry, the growing demand for more accurate and efficient diagnostic tools, and the need to improve patient outcomes.

Discussion

The extensive examination of AI use in various dental fields has uncovered vast potential and promising developments in the industry. By employing a variety of AI systems, such as supervised, unsupervised, and deep learning, significant advancements have been made in the identification and planning of treatment for chronic oral inflammatory diseases, cariology, endodontics, prosthodontics, orthodontics, and oral pathology. The integration of AI technology in these fields has demonstrated remarkable improvements in precision, productivity, and customized patient care. Unfortunately, there are several challenges that impede the seamless integration of AI technologies in the field. In this section, we will delve into some of the primary obstacles facing the adoption of AI in the dental industry. One major hurdle is the limited availability of comprehensive and standardized data. To train and enhance their performance, AI algorithms depend on extensive datasets. Unfortunately, dental datasets are frequently incomplete and insufficient in size and diversity, making it difficult to construct strong AI models. Accessing medical and dental data poses significant challenges due to concerns surrounding data protection and the presence of organizational hurdles. These issues make it difficult for researchers and healthcare professionals to readily obtain and utilize such data. Additionally, the datasets themselves often lack structure and are relatively small compared to other datasets used in AI research. This limited availability of comprehensive data contributes to the problem of data completeness, with systematic gaps and missing information introducing selection bias. As a result, validating and triangulating complex and sensitive patient data becomes a challenging task, further limiting the options available to address these concerns effectively. Consequently, acquiring dependable datasets that cover a broad range of dental problems and patient demographics is essential for effectively integrating AI technologies. Interoperability and integration pose another significant challenge. Numerous dental practices use varying software and imaging systems that may not have interoperability with AI platforms. This lack of integration may hinder the smooth flow of data and impede the adoption of AI technologies. It is crucial to develop standardized interfaces and protocols that enable the compatibility of AI systems with existing dental software to overcome this challenge [118]. Ethical and legal considerations must also be addressed particularly in relation to patient privacy, data security, and liability. To implement AI systems, strict regulations like HIPAA (Health Insurance Portability and

Accountability Act) must be followed. It is crucial to maintain the privacy of patient data and safeguard sensitive information in order to build trust and confidence among patients and dental professionals. To address these ethical and legal concerns, it is essential to establish strong data governance frameworks and implement rigorous security measures [119]. In addition, data encryption can indeed be a viable solution to address privacy concerns in using patient data within AI systems for dentistry. Data encryption involves converting sensitive information into a coded format that can only be accessed with a decryption key, thus providing an additional layer of security against unauthorized access [120]. Cost and resource constraints hinder the widespread adoption of AI in dentistry. Particularly for smaller dental practices, acquiring AI systems, hardware, and software licenses can be challenging due to limited resources. Furthermore, the training of dental professionals to proficiently operate AI technologies and integrating them into existing workflows can be a time-consuming and costly endeavor. It is crucial to overcome these financial and resource barriers to enable the widespread use of AI in dentistry. Resistance to change is a common challenge when introducing new technologies, including AI. This is particularly true in professions like dentistry, which is rooted in long-standing traditions. Dental professionals may have concerns about the reliability and accuracy of AI systems, as well as changes to their roles and responsibilities. To overcome these challenges, it is essential to educate and create awareness about the potential benefits of AI, provide training programs, and showcase successful case studies. This approach can help foster a culture of acceptance and encourage the integration of AI in dentistry. Furthermore, there is a limited availability of AI expertise within the dental community. Factually, the dental industry has not prioritized research and development in the realm of AI. As a result, there is a lack of AI expertise within the dental community. To successfully integrate AI technologies, it is necessary to bridge the gap between AI research and dentistry. By fostering collaboration between dental professionals and AI experts, and incorporating AI-focused education and training into dental curricula, we can cultivate a workforce that is proficient in utilizing AI to enhance oral healthcare [121]. Overcoming these hurdles is crucial for the dental industry to fully leverage AI's potential to enhance patient care, improve diagnosis accuracy, and enhance treatment outcomes.

Conclusion

AI has the potential to improve patient care and reduce the strain on healthcare systems by automating routine tasks and enabling clinicians to focus on more complicated and demanding cases. However, it is important to note that AI is not a replacement for human expertise, and its use in medicine should always be guided by ethical principles. AI can only assist clinicians in performing their tasks professionally. It cannot replace human knowledge, skill, or treatment planning. Despite the challenges of data collection, interpretation, computational power, and ethical concerns that must be addressed, AI is widely recognized as a valuable tool for dentists. Careful design and long-term clinical validation make AI unbiased, reproducible, user-friendly, and transparent. Future AI development must continue to prioritize human interests while improving our ability to process big data. Although AI can help in many ways, dentistry is a multidisciplinary field in which the final decision must be made by the dentist. This review showed that AI has progressed rapidly in recent years and has the potential to become a standard tool in modern dentistry in the near future.

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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