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Review article

Artificial intelligence in dentistry — A scoping review

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A R T I C L E I N F O

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A B S T R A C T

Introduction: In dentistry, AI technologies are revolutionizing diagnosis, treatment planning, and patient care. From image analysis for detecting cavities and fractures to personalized treatment recommendations based on patient data, AI is enhancing efficiency and accuracy in dental practices, leading to improved outcomes and patient satisfaction.

Objectives: This scoping review was done to assess the use of artificial intelligence in various fields of dentistry.

Methods: The electronic databases were searched for scientific research articles in electronic search engines like PubMed, Scopus, Web of science etc. and 87 articles fulfilled the eligibility criteria. Various artificial intelligence, machine learning and deep learning tools and techniques used in various fields of dentistry were studied and their accuracy and precision were noted.

Results: We have various artificial intelligence models being used in various fields of dentistry with high accuracy, sensitivity and specificity.

Conclusion: This data would be helpful for dental practitioners in reducing their workload and improve precision and accuracy in various treatments.

1. Introduction

The capability of a platform to obtain, process, use skills and knowledge which it gains through education or experience and which is a result of human intelligence is defined as artificial intelligence [1]. Alan Turing [1950] first developed modern computer system and artificial intelligence. The premise of the "Turing test" is that a computer can behave intelligently and is capable of performing tasks related to cognition at a level that is comparable to that of a person [2]. The "fourth industrial revolution," which is artificial intelligence, makes use of the computer technology to imitate wise behavior, develops capacity to think critically, and makes intelligent decisions which are very similar to that of humans [3].

The development of biomedical research, which includes genetics, digital medicine, artificial intelligence, and its sub branch, machine learning, is transforming healthcare. These innovative emerging technologies serve as the backdrop to this change, which also calls for the need of new kind of labor force and set of practices. Images and diagnostics used in medical field, virtual patient care, research in medical field and drug discovery, engagement and compliance of patients, rehabilitation, and other applications related to administration are just a few of the areas where artificial intelligence has found extensive use [4]. It has been demonstrated that artificial intelligence can work similarly to medical experts and improve human intelligence and the capacity to accomplish particular tasks and duties in time ensuring cost-effectiveness [5].

Artificial intelligence is a newer and recent technology that provides wide applications in dentistry. Artificial intelligence technology has mostly been made use by dental practitioners to diagnose problems, plan treatments, make clinical judgments, and forecast outcomes [6]. It is used to recognize and spot different details in radiographs, like tooth decay and implant placement [7]. AI-based predictive analytics tools are being developed to assess patients' risk of developing oral health problems such as tooth decay, gum disease, and oral cancer. By analyzing factors such as lifestyle habits, medical history, and genetic predispositions, these systems can help dentists identify patients who

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may benefit from preventive interventions. AI-driven robotics are being explored. AI algorithms have been developed to analyze dental images such as X-rays, CBCT scans, and intraoral photographs with high accuracy. With the COVID-19 pandemic prompting a shift towards telehealth, AI-powered virtual consultation platforms such as AI-driven chatbots or virtual assistants have emerged in dentistry. AI algorithms can generate personalized treatment plans for procedures such as orthodontic treatment, dental implant placement, and smile design. Even before artificial intelligence was applied to medicine and dentistry, it seems to have greatly aided in modifying the healthcare industry and improving patient care. In dentistry, among other things, it is able to distinguish between normal and diseased traits, identify infections, and forecast treatment outcomes. It is widely used in dental laboratories, and dentistry education is starting to use it more frequently [8]. Nearly all areas of dentistry, including periodontics, oral and maxillofacial surgery, pediatric dentistry, orthodontics, and prosthodontics, may be significantly impacted by artificial intelligence in the near future. The artificial intelligence and its subgroups – Machine learning and deep learning [Fig. 1] are increasingly used in the field of dentistry.

The implementation of artificial intelligence in the dental and other medical disciplines can considerably enhanced and enriched the clinical work of aspiring medical and dental professionals. Both dental professionals and patients now hold both hopeful and negative perspectives on artificial intelligence and its potential benefits. A conceptual framework has recently been used to integrate artificial intelligence into dental and medical education, teaching graduates the fundamentals of artificial intelligence [11,12]. Recent research from a small cohort in Germany shown that medical students are supportive of using artificial intelligence in medical procedures [13]. The future generations of doctors and dentists will be most affected by artificial intelligence because these fields have not yet completely embraced it.

2. Methodology

The transparency and reliability of the research is made sure by following PRISMA [Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews] principles. The Joanna Briggs Institute and Cochrane strongly endorsed PRISMA-ScR recommendations for scoping reviews [14]. The question proposed was as follows: What is future of AI in dentistry?

Studies on artificial intelligence methods applied in dentistry were included in this review. We concentrated on artificial intelligence models employed for any function associated with prognosis, treatment, or diagnosis. However, this evaluation did not include papers that were only based on clinical trials and experimental studies, as well as articles that gave an overview of artificial intelligence techniques for dentistry [e.g., literature reviews]. Although we did not impose any limitations on the publication month, study setting, study design, or study outcome, this review included studies that were exclusively published in English.

Before focusing our search, we conducted a thorough analysis of the available information. Dental researchers and the authors of the current review have a cause to think that artificial intelligence will have a substantial impact on dentistry in the years to come based on both their own experiences and published material. For the review to be guided and to decide how to find and choose the pertinent studies research questions had to be established and then the pertinent studies were found.

Search terms were as follows: ["Artificial intelligence" OR AI] for AI, [dentistry OR dentist OR dental] for dentistry. An "and" term was used between each of the search terms while entering them into the database. The inclusion criteria were peer-reviewed and were for English language.2 databases were utilized in this review – PubMed and Scopus. 4801 articles appeared by the above search terms and databases. These studies were managed using Zotero software. Titles which were duplicate between the two databases were removed [145]. 4656 articles were extensively screened [Fig. 2]. This process was carried out independently by two reviewers, and any differences between them were settled through discussions. 87 articles were included in the study. Out of these 87 articles,four studies dealt with general aspects of use of AI in dentistry without mentioning the use of any specific AI based model in their studies. Thus, the characteristics summary of 83 selected studies for a scoping review of the use of AI in dentistry is depicted in Table 1.

3. Role of artificial intelligence in dentistry

The field of oral care has likewise made substantial use of deep learning and AI, for example, in caries diagnosis [15], identification of cystic lesion [16], dental color selection [17], diagnoses of temporomandibular disorder [18], orthognathic treatment [19] and much more. We will discuss the role of AI in each field comprehensively.

The concept of ANNs, CNNs and GANs is also widely used in dentistry as an application of artificial intelligence. The concepts of deep learning and neural networks came into existence by simulating the neurons in the human nervous system. These artificial neural networks swiftly process inputs using a sophisticated network of neurons [hidden layers]. The input nodes take in inputs and look for nonlinear input-output

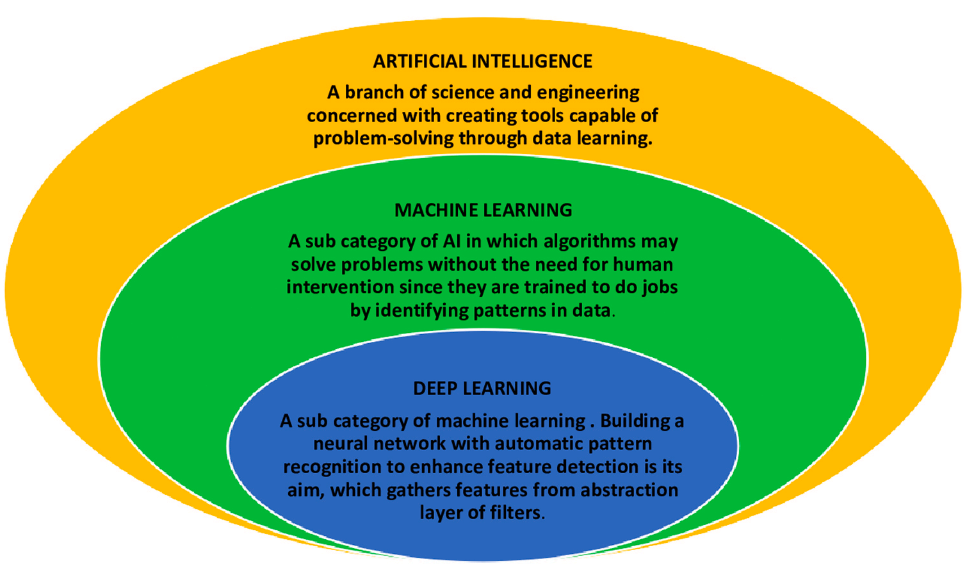

Fig. 1. Artificial intelligence, Machine learning and Deep learning –Definitions [Source – Authors have adapted from [1,9,10]].

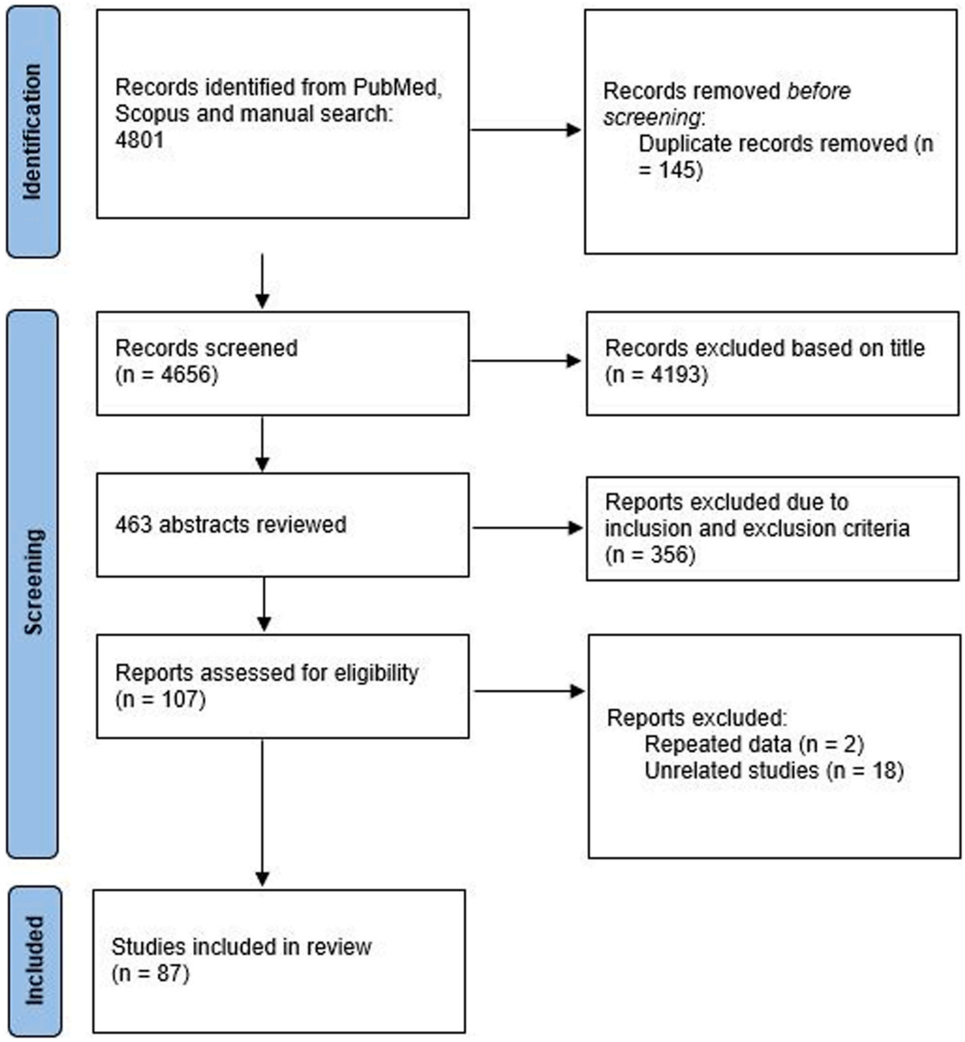

Fig. 2. PRISMA flowchart [Source – Author].

relationships to determine the best possible solution to the problem at hand [20]. Each node in Convolutional Neural Network, a subset of artificial neural networks, extracts local features from the input vector, followed by sampling of the parameters, and finally integrating those features into a fully connected layer in the succeeding layers [21].

Convolutional Neural Network finds its application as a main component of networks in oral and maxillofacial radiology [22]. The radiographic images are put through upgraded GAN models that make use of Convolutional Neural Network. Two networks, a generator and a discriminator, make up GAN models. These networks are trained by playing a game in which they compete against one another and produce new data that closely resembles the original data [23].

3.1. Oral medicine and radiology

3.1.1. Diagnosis

120 OPGs were acquired and analyzed using Apox. Apox is offered through an application programming interface (API) and integrates easily into existing dental software systems. Apox takes a panoramic X-ray and turns it into clinical insights and identify most dental structures with the same accuracy as a dentist. The overall sensitivity and specificity were 0.89 and 0.98 respectively [24]. When utilized by dentists in a clinical context, the Convolutional Neural Network model is also used to diagnose anatomical landmarks, diseases, clinical effectiveness, and safety [25]. 4 models of artificial neural network [MobileNetV2, InceptionV3, ResNet101V2, and ResNet50V2] were used in thermographic Toothache Screening and MobileNetV2 performed better in both front and lateral views [26].

3.1.2. Patient data

Artificial intelligence can be used to schedule visits and notify patients of their full medical and dental histories, oral hygiene habits, dietary restrictions, and harmful behavior [27].

3.1.3. Classification, detection, and segmentation

The Sensitivity and Specificity of You Only Look Once, YOLO V4 model which was used for detecting tooth on Panoramic Radiographs was 99.42% and 87.06%, respectively. [28].

CNNs are used in this aspect. Identifying the type of malignancy to detecting if a disease is present or absent are all examples of classification tasks. To find lesions or specific anatomical features, detection is carried out in radiographic image analysis. Pictures collected utilizing a range of modalities, such as conventional radiography, CT, MR, and ultrasound imaging, are divided into different anatomical characteristics or lesions [29–31].

In a study by Abesi et al. [32], the recall and precision of artificial intelligence for detection and segmentation was measured by cone-beam computed tomography images of the oral and maxillofacial region. The detection and segmentation performance of artificial intelligence (AI) using Cone Beam Computed Tomography (CBCT) refers to the ability of

Table 1
Characteristics summary of the 87 selected studies for a scoping review of the use of AI in dentistry.

S. NO	Author	Year	Country	Branch	Subbranch	Best model identified/Algorithm used	Accuracy/ Precision	Sensativity	Specificity
1	angelis_et_al.,2022	2022	Italy	OMR	Diagnosis	Apox software	96 %	89 %	98 %
2	haddad_et_al.,2022	2022	brazil	OMR	Detection of inflammatory toothache	ANN MobileNetV2			
3	ezhov_et_al.,2021	2021	cyprus	OMR	CBCT imaging diagnosis of anatomical landmarks, pathologies, clinical effectiveness, & safety	CNN		92 %	98 %
5	astuti_et_al.,2023	2023	indonesia	OMR	Detecting tooth on radiographs	YOLO V4		99.4 %	87.06 %
6	hesamian_et_al.,2019	2019	australia	OMR	Classification, detection & segmentation	CNN			
9	abesi_et_al.,2023	2023	korea	OMR	Detection	CBCT imaging, a 3d imaging method	90 %		
9	abesi_et_al.,2023	2023	korea	OMR	Segmentation	CBCT imaging, a 3d imaging method	94 %		
10	adeoye_et_al.,2023	2023	hong kong	OMR	Classification, detection, and segmentation	15-parameter gradient boosting mode			
11	adeoye_et_al.,2021	2021	hong kong	OMR	Oral cancer screening program	11 supervised learning algorithms			
12	alhazmi_et_al.,2023	2023	hong kong	OMR	Oral cancer prediction	ANN	78.95 %	85.71 %	60 %
13	alam_et_al.,2023	2023	saudi arabia	OMR	Dental diagnosis	VGG-16 deep learning	89.80 %		
13	alam_et_al.,2023	2023	saudi arabia	OMR	Tooth numbering	VGG-16 deep learning	86.50 %		
14	sukegawa_et_al.,2020	2020	Japan	OMR	Categorization of dental implants	VGG16			
15	farhadian_et_al.,2019	2019	iran	OMR	Automated age estimation based on dental parameters	ANN			
16	aljameel_et_al.,2023	2023	saudi arabia	OMR	Automated age estimation	Xception model			
17	barayan_et_al.,2022	2022	saudi arabia	OMR	Assessing the Diagnostic Quality of Radiographs, Overlap within Enamel	Model Efficientdet-d0 precision	89.30 %		
18	basaran_et_al.,2022	2022	Japan	OMR	Assessing the Diagnostic Quality of Radiographs for detecting dental conditions in crown	R-CNN Inception v2 (COCO) model		96 %	
19	bermudez_et_al.,2020	2020	UK	OMR	Quality Assessment of Dental Photostimulable Phosphor Plates	InceptionV3 and Resnet50	> 80 %		
20	bilgir_et_al.,2021	2021	turkey	OMR	Automatic tooth detection and numbering	Faster R-CNN Inception v2 precision	96 %	95 %	
21	gulum_et_al.,2023	2023	japan	OMR	Automatic tooth detection and numbering	YOLOv4 algorithm (2500 data precision)	62 %	88 %	
22	jaiswal_et_al.,2022	2022	india	OMR	Multi oral disease classification	EfficientNetB0	93.20 %		
23	kim_et_al.,2020	2020	south korea	OMR	Mandibular Condyle Detection and Osteoarthritis Classificationin Panoramic Imaging	Visual Geometry Group-16 (VGG16) model	84 %	54 %	94 %
29	schwendicke_et_al.,2021	2021	Germany	Orthodontics	Recognition of facial landmarks	Deep learning systems			
31	jung_et_al.,2016	2016	Korea	Orthodontics	Order of extraction	ANN	84 %		
32	akdeniz_et_al.,2021	2021	Turkey	Orthodontics	Bone age assessment	an ImageNet pretrained - male cohort	61.40 %		
34	lee_et_al.,2020	2020	USA	Prosthodontics	Classifying implants	CNN			
35	lerner_et_al.,2020	2020	Germany	Prosthodontics	assisting in creation of fixed implant prostheses, find the abutment's subgingival margins				
36	sarem_et_al.,2022	2022	Saudi arabia	Prosthodontics	detects missing teeth's position	DenseNet169	89 %		
37	alharbi_et_al.,2022	2022	Saudi arabia	Prosthodontics	when a patient might need dental implants	AdaBoost algorithm	91.70 %		
38	chen_et_al.,2023	2023	Taiwan	Prosthodontics	accurately detect the location of the implant	AlexNet damage detection model	90.40 %		
39	ding_et_al.,2023	2023	Korea	Prosthodontics	Designing dental crown	3D-DCGAN			

(continued on next page)

Table 1 (*continued*)

S. NO	Author	Year	Country	Branch	Subbranch	Best model identified/Algorithm used	Accuracy/ Precision	Sensativity	Specificity
40	afrashtehfar_et_al.,2021	2021	UAE	Dental education	virtual technologies				
41	thurzo_et_al.,2022	2022	Slovakia	Dental education	Metaverse for consultations	metaverse			
	afrashtehfar_et_al.,2022	2022	UAE	Dental education	Metaverse for consultations	metaverse			
	schwendicke_et_al.,2023	2023	Germany	Dental education	Dental education				
	thurzo_et_al.,2023	2023	Slovakia	Dental education	Record maintenance				
43	bombard_et_al.,2018	2018	Canada	Periodontics	Diagnosis and treatment plan				
44	plessas_et_al.,2019	2019	UK	Periodontics	Diagnosis and treatment plan				
45	aberin_et_al.,2019	2019	Phillipines	Periodontics	detect periodontal disease	Tensorflow framework	75.50 %		
46	aminoshariea_et_al.,2022	2021	USA	Periodontics	periapical lesions	CBCT imaging, a 3d imaging method			
47	balaban_et_al.,2021	2021	UK	Periodontics	measure from the CEJ to the crestal bone				
48	patil_et_al.,2022	2022	Saudi arabia	Periodontics	quick clinical choices				
49	nakano_et_al.,2018	2018	Japan	Periodontics	Detect oral malodor		97 %		
50	danks_et_al.,2021	2021	UK	Periodontics	periodontal bone loss	single hourglass network - severity stage classification accuracy	58 %		
51	alotaibi_et_al.,2022	2022	Saudi arabia	Periodontics	classification of the levels of severity of the bone loss	VGG-16	59 %		
51	alotaibi_et_al.,2022	2022	Saudi arabia	Periodontics	classifying normal versus disease	VGG-16	73 %		
52	chang_et_al.,2022	2022	USA	Periodontics	Calculating amount of radiographic bone loss	InceptionV3	0.87 $\pm$ 0.01		
53	cha_et_al.,2021	2021	Korea	Periodontics	Peri-Implant Bone Loss	R-CNN model	NS		
54	lakshmi_et_al.,2023	2023	India	Periodontics	Classification & Segmentation of Periodontal Cyst	transfer learning with VGG16	98.48%		
55	wang_et_al.,2020	2020	LA	Pedodontics	Oral health assessment toolkits to predict COHS score & RFTN			93 %	49 %
56	park_et_al.,2021	2021	Korea	Pedodontics	Predict early childhood caries	ML-based models			
57	you_et_al.,2020	2020	China	Pedodontics	Detecting plaque	CNN	72 %		
58	ahn_et_al.,2021	2021	Korea	Pedodontics	Mesiodens in primary or mixed dentition	ResNet-101	92.70 %		
59	mine_et_al.,2022	2022	Japan	Pedodontics	Identifying presence of supernumerary	CNN VGG16-TL model	84.0 $\pm$ 8.2	85.0 $\pm$ 7.9	83.0 $\pm$ 9.1
60	ALBAYRAK_et_al.,2021	2021	Turkey	Oral surgery	estimated amount of swelling after extraction	ANN			
61	amodeo_et_al.,2021	2021	Italy	Oral surgery	detect traumatic fractures	CNN MFDS	80 %		
62	chen_et_al.,2021	2021	Taiwan	Public health dentistry	Brushing Monitoring	RPNN	99.08 %		
63	lee_et_al.,2022	2022	USA	General	Diagnosis of Tooth Prognosis	decision tree classifier	84 %		
64	altukroni_et_al.,2023	2023	Saudi arabia	Conservative dentistry & Endodontics (CDE)	Detection of the pathological exposure of pulp	Yolov5-x model	> 90 %		
65	zheng_et_al.,2021	2021	China	CDE	deep caries and pulpitis	CNN ResNet18	82 %		
66	navarro_et_al.,2021	2021	China	CDE	Locate smooth surface caries	support vector machine MATLAB R2018a Classification Learner	78 %		
66	navarro_et_al.,2021	2021	China	CDE	Locate smooth surface caries	Decision Tree in MATLAB R2018a Classification Learner	84 %		
67	garcia_et_al.,2023	2023	Spain	CDE	Interproximal Caries Lesions	CNN	86.10 %		
68	kang_et_al.,2022	2022	Korea	CDE	Prediction of Dental Caries	RF	92 %		
69	khan_et_al.,2022	2022	UAE	CDE	Automatic dental cavity detection	ResNetlS	94.25 %		
69	khan_et_al.,2022	2022	UAE	CDE	Automatic dental cavity detection	Dental-Net model	91.09 %		
71	saghiri_et_al.,2012	2012	Iran	CDE	Locating apical foramen	ANN	93 %		

(*continued on next page*)

Table 1 (*continued*)

S. NO	Author	Year	Country	Branch	Subbranch	Best model identified/Algorithm used	Accuracy/ Precision	Sensativity	Specificity
72	hiraiwa_et_al.,2019	2019	Japan	CDE	differential diagnosis of a single or multiple roots in the distal roots of mandibular first molars	Deep learning systems	86.9 %		
73	albitar_et_al.,2022	2022	USA	CDE	Assess root canal configuration	CNN, U-Net	90 %	0.8	1
74	bruellmann_et_al.,2013	2013	germany	CDE	Assess root canal configuration - Molars	augmented reality system	65.0 - 81.2 %	94 %	
74	bruellmann_et_al.,2013	2013	germany	CDE	Assess root canal configuration - Premolar	augmented reality system	85.7 - 96.7 %	94 %	
77	campo_et_al.,2016	2016	Israel	CDE	predict nonsurgical endodontic retreatment outcomes	case-based reasoning (CBR) paradigm			
78	abdalla_et_al.,2020	2020	Israel	CDE	multiclass Classification of restorations	Cubic Support Vector Machine algorithm with Error-Correcting Output Codes	94.60 %		
79	engels_et_al.,2022	2022	Germany	CDE	Classifying posterior restorations in permanent teeth		> 90 %		
80	almalki_et_al.,2022	2022	saudi arabia	CDE	Studying X-ray	YOLOv7 deep learning model	99.33 %		
81	chen_et_al.,2023	2023	Taiwan	CDE	Studying X-ray	YOLOv3 deep learning model	97.10 %		
82	buyuk_et_al.,2023	2023	Turkey	CDE	Detection of the separated root canal instrument on panoramic radiograph	Gabor filtered-CNN model	84.37 ± 2.79	81.26 ± 4.79	
83	czajkowska_et_al.,2022	2022	Poland	CDE	Modeling & simulation of composite materials used for permanent dental fillings	complex algorithms and simulation			

AI algorithms to accurately identify and delineate anatomical structures or abnormalities in CBCT images. The precision value for detection was 0.90 [95% CI: 0.77–0.96]. The precision value for segmentation was 0.94 [95% CI: 0.89–0.97].

In a study by Adeoye et al.[9], it was discovered that oral leukoplakia and oral lichenoid mucositis affected individuals who could possibly undergo a cancerous change can be identified with adequate sensitivity and accuracy using machine learning-based models.2 tree-based algorithms, gradient boosting and random forest, which are considered high in terms of effectiveness were employed to create two promising models with 15 and 26 features.15- parameter gradient boosting model was more sensitive to binary epithelial dysplasia grading system, although this difference was not statistically significant. He also found in other study that machine learning algorithms can accurately predict three of the four outcomes of cancer of oral cavity, including, malignancy, metastasis in lymph nodes, and prognosis of the disease [33].

11 learning algorithms under supervision acted as base learners and gave predicted probabilities that were weighted and aggregated by the meta-classifier using comprehensive risk factor data from a retrospective dataset from the oral cancer screening program as input features. SMOTE- ENN was used to supplement the training dataset. To demonstrate the key risk indicators and implement the model's explainability, Shapley additive explanations values were created.

Internal validation recall, specificity, and AUROC of the meta-classifier were respectively 0.83, 0.86, and 0.85 for predicting the risk of oral cancer and 0.92, 0.60, and 0.76 for predicting the presence of a suspicious oral mucosal illness. After being externally validated, the meta-classifier greatly outperformed the outdated/rough technique for estimating the risk of oral cancer [0.78 vs. 0.46; $p = 0.001$] in terms of AUROC. Additionally, for estimating the likelihood of suspect oral mucosal disorders, meta-classifier demonstrated higher recall than the simple technique [0.78 vs. 0.47] [34]. Alhazmi et al. [35] analyzed the use of artificial neural network for oral cancer prediction and the average sensitivity and specificity based on the 10-fold cross-validation analysis was 85.71 % and 60.00 % respectively. The artificial neural network prediction accuracy for oral cancer was 78.95 %.

Alam et al. [36] said that teeth segmentation by optical radiographic images using VGG-16 deep learning convolution architecture with R-CNN network approach yielded a result of 89.8 % in dental diagnosis and 86.5 % in the tooth numbering.

3.1.4. Categorization of dental implants

A deep neural network study for categorization of dental implants was conducted by Sukegawa et al. The evaluation of five deep CNN modes, led researchers to the conclusion that the well calibrated VGG16 produced the best classification outcomes for dental implant system [37].

3.1.5. Automated age estimation

Teeth or other supporting tissues associated with teeth in the oral cavity undergo developmental and degenerative changes over time, which can be used to estimate age. To investigate the anatomy of teeth without sectioning or extracting them, dental radiology-based technologies are advantageous because they are precise, non-invasive, and can be applied to both living and dead people. Automatic age estimate often entails a number of steps, such as image preprocessing, segmentation, feature extraction, and classification, although the results might be influenced by observers. Deep learning algorithms, however, do not need these phases [21]. In a study on Artificial neural network for dental age prediction using the.

Pulp-to-tooth ratio in canines, Farhadian et al. made the case for the potential creation of a new tool that would use neural networks to predict age based on dental results [38]. Aljameel et al. [39] used a variety of deep learning techniques, including Xception, VGG16, DenseNet121, and ResNet50, to identify the dental age of panoramic radiograph pictures. The findings showed that the Xception model performed the best, with an error rate for the 6–11 age range of 1.417.

3.1.6. Assessing the diagnostic quality of radiographs

To evaluate the quality of a bitewing radiograph, Efficientdet-d0 using Tensor Flow was utilized. A log loss value of 0.15 indicated a very accurate model [40]. A deep CNN method-based AI model called CranioCatch, created in Eskişehir, Turkey, was suggested to assess diagnostic charting in panoramic radiography. Model development utilized the Tensor Flow framework and a Faster R-CNN Inception v2 [COCO] model. With the exception of caries and dental calculus, it demonstrated promising results in the detection of dental problems in panoramic radiography [41].

3.1.7. Quality assessment of dental photostimulable phosphor plates

Fivefold cross validation was used to test State-of-the-art deep convolutional networks, and the results showed classification accuracies ranging from 87% to roughly 89 %. InceptionV3 and Resnet50 showed the best results [42].

3.1.8. Automatic tooth detection and numbering

An AI program was created using a Faster R- CNN Inception v2 model, and it was successful at identifying and counting teeth [43]. However, it was discovered that as the number of data used to train the model increased, the model's performance improved while examining the impact of data size on tooth numbering performance using the YOLOv4 algorithm and panoramic radiographs [44].

3.1.9. Multi oral disease classification

Transfer learning was used to detect the suggested model using a variety of pre-trained networks, including ResNet50V2, ResNet101V2, MobileNetV3Large, MobileNetV3Small, MobileNet, EfficientNetB0, EfficientNetB1 and EfficientNetB2. With corresponding accuracy of 91.8 %, 92.2 %, 92.4 %, 93.2 %, 91.6 %, and 90.8 %, tooth wear, periapical, periodontitis, tooth decay, missing tooth, and impacted tooth were all correctly identified [45].

3.1.10. Detection of mandibular condyle and classification of osteoarthritis in panoramic imaging

For learning and condyle discrimination, R-CNN model and a Visual Geometry Group-16 [VGG16] model were employed. The temporomandibular osteoarthritis classification approach utilizing a convolutional Neural Network has sensitivity, specificity, and accuracy of 0.54, 0.94, and 0.84[46].

3.2. Orthodontics

Robotics find use in orthodontics in TMD rehabilitation, as dental assistants, wire bending, remote monitoring and telecommunication, maxillofacial surgeries and implant placement, automatic aligner production [47].

3.2.1. Diagnosis

Artificial intelligence has been useful in analysis photographs by intraoral scanners and cameras thus enhancing the diagnosis and treatment planning [48].

3.2.2. Recognition of facial landmarks

Facial landmarks are recognized using cephalometric pictures. These landmarks allow for geometric evaluations to be made in terms of angles, lengths, and ratios, allowing for an examination of the facial skull, both sagittal and vertical [49]. Geometric measurements and structures were previously only made possible by software, but the practitioner had to manually identify the landmarks themselves before the advent of AI [50].

Several people in research have lately been able to make this time-consuming process automatic with the use of artificial intelligence algorithms. The majority of research papers on the use of artificial intelligence in automated cephalometric X-ray analysis gauge the accuracy of their artificial intelligence by comparing the metric divergence between landmarks specified by the artificial intelligence and the human gold standard. Schwendicke et al. performed a meta- analysis in this case to evaluate the accuracy of the automatic landmark detection used by various investigations. Most studies that were considered were able to locate landmarks using an error-prone approach with a metric tolerance of 2 mm [49,51,52]. It is generally agreed that this 2 mm tolerance is enough for clinical purposes in this regard [49,50].

Evaluation of facial proportions includes measuring ratios and the linear spacing between facial components. To comprehend the standards of beauty and duplicate an aesthetically beautiful proportion, surgeons and orthodontists currently use measurement of perfect face proportions [53]. At the moment, artificial intelligence applications execute optical facial recognition while simulating more complicated cognitive functions, such as the analysis and interpretation of facial data. Studies in this area suggested that artificial intelligence systems could be useful tools for creating a formula that accurately captures how people perceive face attractiveness [19].

3.2.3. Order of extraction

If we talk about the tooth extraction in orthodontics, it is mainly done for the following reasons.

1. When there is extreme crowding, there is a need for space to align the teeth.
2. To remedy the protrusion or hide the Class II or Class III skeletal abnormalities, the teeth may be relocated or repositioned [typically to retract the incisors].

Jung et al. employed the artificial neural network technique to anticipate the precise sequence in which extraction may be performed, and they achieved an accuracy of 84 % [54].

3.2.4. Bone age assessment

On our held-out test images, the study used an Image Net pretrained, fine-tuned convolutional neural network to achieve accuracy of 57.32% for male cohort and 61.40 % for the female cohorts for assessing the bone age [55].

3.3. Prosthodontics

AI can be used in conjunction with design software to create the finest possible prosthesis [48].

3.3.1. Classifying implants

Implants are a common method of replacing lost teeth today. It is important for a dentist to correctly identify and classify the implants in order to lower the risk of replantation and repair which is caused due to certain biological as well as mechanical challenges. The two primary methods for classifying the implant structure are CAD-CAM and panoramic radiography [56]. Convolutional neural networks from deep learning were used in a study by Hong et al. to test their effectiveness in classifying implants using panoramic and periapical radiographs. Based on the study's findings, it can be said that the deep convolutional neural networks model can classify implant systems with nearly equal or greater accuracy than humans [57].

3.3.2. Error free cementing of implants

Cementing implantable prosthesis in the mouth with conventional CAD-CAM techniques may result in a number of problems. Among the possible causes of errors include positioning errors, cementation errors, and occlusal or interproximal rectification using an abutment. An AI model was prepared by Henriette Lerner et al. to eliminate these kinds of errors. This AI model was intended to assist in the development of fixed implant prostheses using monolithic zirconia crowns. Additionally, an AI model helped to locate the sub gingival borders of the abutment. The above model was also used by dentist to concentrate more intently on maintaining interproximal and occlusal contacts and teeth preparation. The usage of AI was intended to reduce time and mistake [58].

In a study by Sarem et al., a model that recognizes missing teeth positions on a dataset split from cone beam computed tomography images was developed using a total of six pretrained convolutional neural networks models, including VGG16, VGG19, Alex Net, DenseNet169, ResNet50 and MobileNetV3. The proposed pretrained DL models performed well in terms of precision, scoring above 0.90. Additionally, the experimental findings demonstrated DenseNet169's superiority with a precision of 0.98. A precision of 0.95 was obtained for MobileNetV3, 0.94 for VGG19, 0.94 for ResNet50, 0.93 for VGG16 and 0.92 for Alex Net.

DenseNet169 model performed well at the various CBCT-based detection and classification phases, classifying missing tooth regions with an accuracy of 89 % and segmentation accuracy of 93.3 % respectively [59].

Using a collection of four machine learning algorithms [Bayesian network, random forest, and AdaBoost], an enhanced AdaBoost algorithm demonstrated an accuracy of 91.7 % in predicting when a patient could require dental implants [60].

3.3.3. Improving dental implants outcome

The technology uses two convolutional Neural Networks models to precisely locate implant and determine the degree of damage caused by peri- implantitis. YOLOv2 model's accuracy in determining the implant position was 89.3 %, whereas the accuracy of the Alex Net damage detection model was 90.4 % [61].

3.3.4. Designing dental crown

When compared to the other groups, the crown with the 3D-Deep Convolutional Generative Adversarial Network [3D-DCGAN] design exhibited the lowest morphological discrepancy [62].

3.4. Dental education system

Corona virus outbreak has increased the use of virtual technology in dental teaching [63].

3.4.1. Simulation

AI is used for creating a virtual reality that enables simulation of the practical procedures in three dimensions [48].

Although research and development are still underway, dental practices currently frequently integrate 3 dimensional scans from smart phones and applications to improve artificial intelligence-based patient diagnosis and treatment.

3.4.2. Metaverse for consultations

Metaverse have the potential to be used in dental field. Metaverse is a virtual environment that resembles the actual world and could be used for dental education and telemedicine consultations. Businesses in the dental industry may find it simpler to employ block chain and smart contracts thanks to the metaverse [64,65].

Recent study by Schwendicke et al. [66] on dental education curricula and AI identified four sectors of learning outcomes, with most outcomes at the knowledge level. These four domains are as follows.

1. It is important to understand fundamental terminologies, the rationale behind artificial intelligence [AI] and the principle of machine learning, the concept of building, validating, and testing models, the meaning of reference tests, the distinction between dynamic and static AI, and the issue that AI is a "black box" that requires explanation.
2. Use of case: It is important to teach the kinds of AI that are needed for them.
3. Assessment metrics, their interpretation, the relevant effects of AI on patient or community health, and related instances should all be taken into account.
4. The importance of governance is highlighted, as well as the issues of generalizability and representativeness, explainability, autonomy, and accountability.[66]

The curriculum for dental education can use AI in a number of ways. The use of AI-powered simulation tools to give students practical experience in the diagnosis and treatment of dental disease, the incorporation of AI-powered decision support systems into clinical education to support students in learning to make well-informed treatment decisions, and the use of AI-powered image analysis and interpretation technologies to enhance students' comprehension of radiographic images are a few examples that come to mind.

3.4.3. Effectiveness and precision

AI may also increase the effectiveness and precision of administrative and paperwork activities, like appointment scheduling and patient record management. Here are a few examples of how artificial intelligence might be included into dental school programs [67].

3.5. Periodontics

The most prevalent inflammatory condition affecting adults is periodontitis, whose incidence is positively connected with age [68].

3.5.1. Diagnosis and treatment plan

A patient's radiographs, a soft-tissue periodontal assessment, and a clinical examination are used to diagnose periodontitis. Dental hygienists and dentists rely on their academic knowledge, training sessions, and expertise to identify disease symptoms including erythema, inflammation, bone loss, etc. in order to create a treatment plan. However, some health characteristics of high-risk groups, such as inadequate health literacy, constrained access to care, and low socioeconomic status, have an impact on the treatment method. Patients are less likely to detect the seriousness of their disease or infection and are consequently less able to make informed treatment decisions if they are not actively involved in their care or are rushed during appointments [69,70].

In a study done by Aberin et al. [71], Tensor flow framework developed by google for machine learning, using Python language was used to detect periodontal disease using convoluted neural network. Also, the model was run on a GTX 1060 GPU. An accuracy of 75.5% was obtained.

The most often used 2d diagnostic techniques in routine clinical practice to diagnose apical periodontitis for the early detection and treatment of the condition, which is relatively common, are intraoral periapical and panoramic radiographs. Periapical lesions are often seen as radiolucency on radiographs. However, the information obtained from periapical radiographs is incorrect since the true 3d anatomy is converted to a 2d picture. Cone-beam computed tomographic imaging, a 3d imaging technique, was developed to precisely detect periapical lesions and assess their size and location [72].

3.5.2. Treatment effectiveness

The addition of AI technology to dental office software can enhance patient education strategies and tools, increase clinical efficacy, raise provider uniformity, simplify clinical judgment, and promote collaboration amongst professionals. Some AI-powered radiograph analysis methods may measure from the cementoenamel junction [CEJ] to the crestal bone, providing objective information to enhance dentists' clinical judgment and diagnostic consistency [73]. The application of AI can also enhance patient participation, which can promote the best possible health outcomes and the efficient use of healthcare services [69]. AI may be able to relieve dental professionals' stress by assisting dentists in making quick clinical decisions, reducing the possibility of human error, and providing standardized care [74].

3.5.3. Detect oral malodor

Deep learning was utilized by Nakano et al. to identify oral malodor from microbiota, and they discovered that it had 97 % prediction accuracy [10]. By examining periapical radiographs, Danks et al. developed a deep neural network to quantify periodontal bone loss [75].

3.5.4. Detection of alveolar bone loss

In a study, deep CNN algorithm [VGG-16] was employed, and the diagnosis accuracy for differentiating between normal and illness was 73.0 %, as well as 59 % for differentiating between the severity degrees of bone loss [76].

Another study used the InceptionV3 model, which had an average accuracy of 0.87 0.01, to calculate the amount of bone loss due to radiography in the diagnosis and treatment planning of periodontitis [77].

In research assessing peri-implant bone loss, however, no statistically significant difference was found between the modified R-CNN model and dental clinician for detecting landmarks around dental implants [78].

3.5.5. Classification and segmentation of periodontal cyst

It made use of convoluted neural network, U-Net and VGG16. By utilizing CNN, accuracy of 77.78 % is achieved, while improved accuracy of 98.48 % is attained utilizing transfer learning and VGG16. Additionally, the U-Net approach yields positive outcomes [79].

3.6. Pedodontics

3.6.1. Predict oral health needs

In a study by Wang, Y. et al., utilizing artificial neural networks to develop oral health assessment toolkits to predict children's oral health status index [COHSI] score and RFTN, the sensitivity and specificity for predicting referral for treatment needs of oral health [RFTN] were 93 % and 49 %, respectively. The COHSI toolbox has COHSI RMSEs of 4.2 [80].

In order to predict early childhood caries, Park, Y.H. et al. employed machine learning based AI models [Random Forest, Light GBM techniques, XG Boost and Final model]. The study found that ML-based models did well in predicting dental caries, with a respectable AUC value and no appreciable differences between the four models' AUROC [area under the receiver operating characteristic curve] values [81].

3.6.2. Detecting plaque

In a different study, CNN examined an artificial intelligence-based algorithm for identifying plaque on teeth of primary dentition done by You, W. et al. Significant differences between the artificial intelligence model and the specialist were not found.

Comparing a CNN-based model to a pediatric dentist, CNN model showed great accuracy in detecting plaque [82].

3.6.3. Classifying teeth

Additionally, the classification of mesiodens in primary or mixed dentition was based on a study by Ahn, Y. et al. Greater accuracy was shown when using AI models to categorize the presence of mesiodens in panoramic radiographs with mixed dentition [83].

For detecting the existence of supernumerary teeth in the early stages of mixed dentition, CNN- based deep learning has good accuracy [84].

3.6.4. Prediction of early childhood caries

Neural networks was used to analyze 22 single nucleotide polymorphisms in a cohort of 95 Polish children between the ages of 2–3. The best predictors [with an overall accuracy of 93 %] were AMELX_rs17878486 and TUFT1_rs2337360 [both in LogReg and NN], MMP16_rs1042937 [in NN], and ENAM_rs12640848 [in LogReg] [85].

3.7. Oral surgery

The quantity of swelling that will develop in patients after having their mandibular third molars extracted was accurately predicted by Albayrak et al. using artificial neural network operating on the conjugate gradient back-propagation algorithm [86].

To identify traumatic fractures in patients, a novel maxillofacial fracture detection system based on transfer learning and convolutional neural networks was proposed. The model's classification of the maxillofacial fractures was 80% accurate [87].

3.8. Public health dentistry

3.8.1. Brushing monitoring

Comparing the RPNN to other classic deep learning models, its recognition accuracy was 99.08%, 16.2% greater than the Convolutional Neural Network and 21.21% higher than the Long Short-Term Memory [LSTM] model [88].

3.9. General

3.9.1. Diagnosis of tooth prognosis

The program was created using three AI machine-learning techniques: decision tree classifier, gradient boosting classifier and random forest classifier. The decision tree classifier showed the highest accuracy [89].

3.10. Conservative dentistry and endodontics (Fig. 3)

By identifying answers to a variety of clinical issues and simplifying the work of physicians, AI systems have the potential to change medicine and dentistry. Research in endodontics has expanded in tandem with other dental specializations [72].

3.10.1. Detection of the pathological exposure of pulp

Altukroni et al. [90] evaluated the performance of the Yolov5-x model-based Make Sure Caries Detector and Classifier [MSc], an AI tool for identifying exposed and unexposed pulp. It performed better than 90% across all parameters looked at.

3.10.2. Diagnose caries

Deep caries - For the diagnosis of pulpitis and deep caries, convolutional neural networks [VGG19, Inception V3, and ResNet18] were utilized in a study by Zheng et al. [2021]. The ResNet18 CNN performed the best, with an accuracy of 0.82 and a 95% confidence interval [CI] of 0.80 to 0.84[91].

Smooth surface caries – Classification Using Support Vector Machine and Decision Tree in MATLAB R2018a, the learner was used to find cavities in smooth surfaces. The research yielded noteworthy findings, with accuracy rates of 78% and 84%, respectively [92].

Interproximal Caries Lesions - A CNN was used in Bitewing Radiographs for the diagnosis [93].

Traditional machine learning techniques like RF, GBDT, LR, SVM, and DL techniques like ANN, CNN, and LSTM were utilized to predict dental caries, and RF performed better than any other used ML techniques or neural network-based techniques [94]. Four pre-trained models, including VGG16, MobileNetV2, InceptionV3, ResNetlS, and Dental-Net, were used to attempt automatic dental cavity identification from oral photos. These models' accuracy on the training and validation sets, respectively, was 94.25% and 91.09% [95].

3.10.3. Locating apical foramen

AI is also used to located the apical foramen. The idea of mimicking

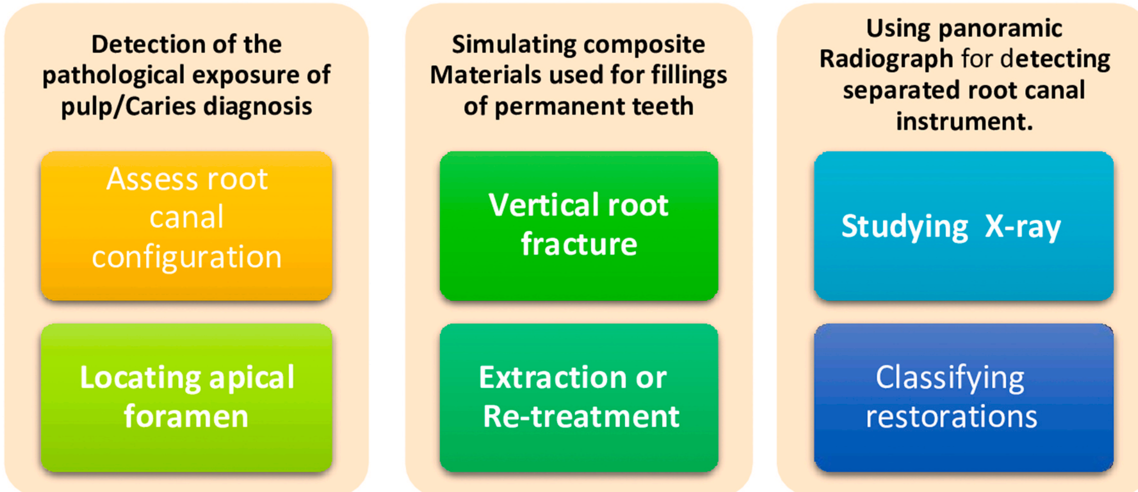

Fig. 3. Summary of use of AI in endodontics [Source – Author].

the human brain gave rise to the neural network which is a technique of machine learning [96].

Artificial neural network can be used as a second opinion in radiographs to locate the apical foramen, which will ultimately boost working length assessment accuracy because faulty radiographic interpretations could result in an incorrect diagnosis [97].

3.10.4. Assess root canal configuration

The root and root canal configurations are evaluated using CBCT imaging and periapical radiography. Due to radiation concerns, CBCT is not utilized clinically even though it is thought to be more accurate than a periapical radiograph. Hiraiwa et al. [98] by employing a deep learning algorithm on panoramic radiographs found that the differential identification of whether a single or multiple roots in the distal roots of mandibular first molars was present was remarkably accurate. By importing image patches taken from panoramic radiographs, deep learning systems were employed to create learning models. The root canal curvature and its subsequent 3-dimensional alteration could be measured using a computer developed using information analysis and artificial intelligence.

In a study by Albitar et al. [69,99] ITK-SNAP was used to segment 102 maxillary molar roots, including those with and without unobturated MB2 canals. The convolutional neural network [CNN], U-Net, was trained using the training samples, and its performance was assessed using the testing samples. The detection performance showed an accuracy of 0.9, sensitivity of 0.8, specificity of 1, high PPV of 1, and NPV of 0.83 for the testing set.

An augmented reality system that uses a geometric tooth criterion and k-nearest neighbor color classification to accurately identify root canals in video sequences. For automatic classification of the teeth in video pictures, the software recognizes root canal orifices and records the size and location of the discovered structures. Overall, 305 root canals out of 287 were successfully identified. Around 94% was the total sensitivity [100].

3.10.5. Vertical root fracture

To detect vertical root fractures, AI tools including machine learning, CNN, and PNN [probabilistic neural network] are used [72] probabilistic neural networks are three-layer networks where the second layer generates a vector of probabilities and the input layer displays training patterns [101].

Vertical root fracture was initially found using radiography and CBCT imaging. Although radiographs performed slightly better in teeth with restored teeth, CBCT imaging proved successful in finding VRFs in teeth without restorations as compared to conventional radiographs. Different innovative methods have been suggested for improving the diagnosis of vertical root fracture because to the shortcomings of current processes for reliably diagnosing Vertical root fracture [102].

3.10.6. Extraction or retreatment

Extraction or retreatment is predicted using CBR technique. Campo et al. [103] used CBR case-based reasoning to forecast the results and dangers of nonsurgical endodontic retreatment. Finally, the system determined whether retreatment was necessary. The method considers information from domains like accomplishment, memory, and analytical probability. The system's ability to anticipate retreatment's outcome realistically is one of its strongest points. The system would only have been as useful as the knowledge extrapolated from the data thus that was a limitation.

3.10.7. Classifying restorations

In a study done by Abdalla et al. [104], For the multiclass categorization of the restorations, a Cubic Support Vector Machine algorithm which has Error- Correcting Output Codes was utilized using a cross-validation strategy, and 94.6% of the restorations were detected by algorithm. Engels et al. used artificial intelligence to detect posterior restorations in permanent teeth on intraoral pictures, and convoluted neural networks was able to accurately classify restorations with the accuracy values of diagnosis in which: Unrestored teeth scored 94.9%, composites scored 92.9%, cements scored 98.3%, amalgam scores 99.2%, gold scores 99.4%, and ceramic scores 97.8% [105].

3.10.8. ***3.10.8***

To create an automatic tool for identifying and categorizing dental problems, such as in dental panoramic X-ray images [OPG], a YOLOv3 deep learning model was presented. The proposed model obtained 99.33% accuracy [106]. Another investigation found that YOLOv7's average precision for tooth detection was 97.1% [107].

3.10.9. Using panoramic radiograph for detecting separated root canal instrument

In a study by Buyuk et al. [108] Six deep learning models in all were trained: two LSTM models [Raw-LSTM and Augmented-LSTM] and four CNN models [Augmented-CNN, Gabor filtered-CNN, Raw- CNN and Gabor filtered-augmented-CNN] to detect the separated root canal instrument. The model with the highest accuracy was the Gabor filtered-CNN model.

3.10.10. Modeling and simulating composite materials used for dental fillings in permanent dentition

Czajkowska et al. [109] did a study where using sophisticated artificial intelligence- based algorithms, common composite materials used for direct dental restorations were tested for their Vickers hardness and roughness. The samples' surfaces were tested after being polished with conventional silicone polishing rubbers and discs used by dentists. To simulate the composite in conditions that are as close to real-world as possible, a model and process were also developed.

4. Strengths and weaknesses

4.1. Strength

This scoping review highlights the output as well as the models used of Artificial intelligence in dentistry. This provides information about the correctness of various Artificial intelligence technology models used in dentistry and its problematic branches that is useful for researchers, computer scientists, policy makers, and executives in the healthcare industry. In addition, we reduced selection bias by doing the selection of studies and extracting data separately by 2 different reviewers, with 100% agreement in all phases.

4.2. Weakness

The following are the study's limitations. Thesis, conference abstracts, review articles and review reports were not included; only preprints and journal articles were. Articles written in languages other than English, such as Chinese and French, were also disregarded. Only 2 databases were considered.

5. Discussion

5.1. Empowering oral health equity: leveraging AI for accessibility, education, and ethical advancements

Unmet oral health needs are nevertheless common among the most vulnerable communities, have an impact on systemic health [110]. Higher rates of oral illness and lower health outcomes are caused by disparities including low health literacy and limited access to care. This can also make systemic chronic diseases like diabetes, cancer, and cardiovascular disease worse or increase the chance of developing them [111]. By standardizing the medical process and making health information more accessible, AI can empower people. [112].

AI has the ability to dramatically increase dentistry education's effectiveness and efficiency. Vigilance and knowledge are required to ensure responsible and ethical use, prevent biased training data sets, and other goals. Different AI detectors that have evolved as new, crucial elements of anti-plagiarism systems demonstrate that AI plagiarism already exists. The discovery that AI can successfully perform some human tasks may lead to attempts to ban students from utilizing AI in universities in a backward manner rather than modifying student evaluation in more modern ways appropriate to the age of Artificial intelligence [67].

5.2. Unlocking the potential: advancing dentistry with AI integration and education

Studies show that most dentists do know that AI has various uses in the field of dentistry and believed that the future of dentistry could be improved by using more AI. Enhanced technical resources in dental clinics and professional education at the undergraduate and graduate levels could potentially mitigate future obstacles in the application of AI in dentistry. The best uses for Artificial intelligence would be in the planning of diagnostics and therapies. To probe deeper into these issues, follow-up surveys and multicenter research should be carried out. Lectures and seminars must be prepared to assist dental students comprehend Artificial intelligence better and ultimately enable them to participate fully consciously and actively in the development, acceptance, and usage of Artificial intelligence tools in dentistry [113,114].

5.3. Advancements in artificial intelligence applications for oral medicine and radiology: enhancing diagnosis, treatment, and patient care

The integration of artificial intelligence (AI) into oral medicine and radiology has brought about significant advancements, revolutionizing various aspects of dental practice. Through the utilization of AI tools such as convolutional neural networks and deep learning algorithms, clinicians have gained access to powerful diagnostic aids and treatment planning resources. These technologies have demonstrated remarkable capabilities in accurately detecting dental structures, identifying pathologies, and even predicting disease outcomes with high sensitivity and specificity. Furthermore, AI has facilitated the management of patient data, improved the quality assessment of radiographs, and automated tedious tasks like tooth detection and numbering. The potential of AI in oral medicine and radiology extends beyond diagnosis and treatment, encompassing areas such as age estimation, dental implant categorization, and multi-disease classification. As these technologies continue to evolve, it is imperative for dental professionals to remain vigilant and ensure the responsible and ethical use of AI to maximize its benefits while addressing potential challenges and limitations. By embracing AI advancements and fostering interdisciplinary collaboration, the future of oral medicine and radiology holds promise for further enhancements in diagnosis, treatment efficacy, and overall patient care.

5.4. AI innovations in orthodontics: transforming diagnosis, treatment, and facial analysis

The integration of artificial intelligence (AI) into orthodontics has ushered in a new era of innovation and precision in diagnosis, treatment planning, and facial analysis. From the utilization of robotics in temporomandibular joint rehabilitation to the automation of cephalometric X-ray analysis, analysis of photographs obtained from intraoral scanners and cameras, Use of AI algorithms in recognition of facial landmarks, allowing for geometric evaluations that were previously time-consuming and manual, AI technologies have demonstrated remarkable capabilities in enhancing orthodontic practice. As AI technologies continue to evolve, it is crucial for orthodontic professionals to stay abreast of these advancements and leverage them responsibly to optimize patient care. By embracing AI tools and methodologies, orthodontists can enhance treatment efficacy, streamline workflow efficiency, and ultimately improve patient satisfaction and outcomes in orthodontic practice.

5.5. Revolutionizing prosthodontics: AI's impact on precision design and implant classification

In prosthodontics, AI technologies are revolutionizing various aspects of treatment, from precision design to implant classification and outcome improvement. Convolutional neural networks (CNNs) are being employed to classify implants with accuracy comparable to or greater than humans, reducing risks associated with replantation and repair. AI models assist in error-free cementing of implants, eliminating positioning errors and reducing time and mistakes. Additionally, pretrained deep learning models demonstrate high precision in recognizing missing teeth positions on cone beam computed tomography (CBCT) images, aiding in treatment planning. Machine learning algorithms accurately predict when patients may require dental implants, while convolutional neural networks precisely locate implants and assess periimplantitis damage. Furthermore, AI-driven design techniques, such as 3D-Deep Convolutional Generative Adversarial Network (3D-DCGAN), enhance the precision of dental crown design, ensuring optimal treatment outcomes.

5.6: AI smiles bright: revolutionizing periodontics for better diagnosis and treatment: In periodontics, AI technologies are reshaping diagnostic approaches, treatment planning, and patient engagement strategies. From machine learning algorithms detecting periodontal diseases with high accuracy to deep learning models identifying oral malodor and quantifying bone loss, AI offers promising solutions for improving clinical outcomes. Moreover, AI integration into dental office software enhances patient education, clinical efficacy, and diagnostic consistency, while alleviating stress for dental professionals by aiding in quick clinical decision-making and reducing human error. Cone-beam computed tomography imaging provides precise detection of periapical lesions, while AI-powered radiograph analysis methods offer objective information for enhancing dentists' clinical judgment. Despite challenges in differentiating normal from abnormal findings, AI holds potential for improving periodontal diagnosis and treatment planning. Collaboration between AI technologies and dental professionals can lead to more standardized care, improved patient outcomes, and efficient healthcare service utilization in periodontics.

5.6. AI innovations in conservative dentistry and endodontics: transforming diagnosis and treatment

AI technologies are revolutionizing conservative dentistry and endodontics, offering solutions for precise diagnosis and treatment planning. From detecting pathological exposure of pulp to diagnosing caries and assessing root canal configurations, AI tools demonstrate high accuracy and efficiency. Machine learning algorithms and deep learning models enable the identification of vertical root fractures, extraction or retreatment predictions, and classification of restorations with remarkable precision. Additionally, AI-powered systems aid in studying X-rays, detecting separated root canal instruments, and modeling composite materials for dental fillings. These advancements not only streamline clinical processes but also enhance patient outcomes in conservative dentistry and endodontics.

5.7. Dentistry in diverse domains: leveraging AI for advanced diagnosis and treatment prediction

In conclusion, the integration of artificial intelligence (AI) into various domains of dentistry, including oral surgery, general dentistry, and pediatric dentistry, has shown promising results in enhancing diagnosis, treatment prediction, and patient care. From predicting post-operative swelling after mandibular third molar extractions to identifying traumatic fractures and monitoring brushing habits, AI-powered tools are revolutionizing the field. Additionally, AI is aiding in the diagnosis of tooth prognosis and oral health needs prediction, demonstrating its potential to optimize dental care across different areas of specialization. As research and development in AI continue to advance, the future of dentistry holds immense potential for improved patient outcomes and streamlined clinical workflows.

5.8. Balancing act: ethical considerations in integrating artificial intelligence into dentistry

Although the fact cannot be ignored that we need to be careful while including Artificial intelligence in dentistry. Despite the fact that LLMs like ChatGPT may have a range of useful applications in dental medicine, they have significant downsides, such as the potential for malicious use and misrepresentation [115].

6. Conclusion

Future dentistry will be significantly impacted by artificial intelligence. It will be the most promising instrument in the future for the detection and treatment of dental issues due to its expanding applicability in recent years. Since dental practice entails more than merely diagnosing illnesses, one cannot assume that technology will completely replace dentists in their role of providing patients with the necessary care.

To fully take use of Artificial intelligence, however, a strong understanding of its principles and models is required. In order for the models to produce reliable findings, dentists and physicians must also make sure that authentic data is collected and supplied to their database. For the models to be successfully used in dentistry and to have long-term dependability, the problems that must be overcome must also be addressed [116].

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Ethical Statement

Hereby, I, Dr. Tanvi Kiran consciously assure that for the manuscript "Artificial intelligence in dentistry- a scoping review" the following is fulfilled:

2) This material is the authors' own original work, which has not been previously published elsewhere.
3) The paper is not currently being considered for publication elsewhere.
4) The paper reflects the authors' own research and analysis in a truthful and complete manner.
5) The paper properly credits the meaningful contributions of co-authors and co-researchers.
6) The results are appropriately placed in the context of prior and existing research.
7) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
8) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

I agree with the above statements and declare that this submission follows the policies of Solid State Ionics as outlined in the Guide for Authors and in the Ethical Statement.

Declaration of Competing Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Authors contributions

Designing the review: RV and TK, Data search and extraction: AS, JVP and RV, Data analysis: AS, TK and RV, Data interpretation: AS, TK and RV, Wrote the paper: AS, RV, Critical evaluation of manuscript: TK, RV, SJ, PK.

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