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Artificial Intelligence in Endodontics: A Scoping Review

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Artificial intelligence (AI) is transforming the diagnostic methods and treatment approaches in the constantly evolving field of endodontics. The current review discusses the recent advancements in AI; with a specific focus on convolutional and artificial neural networks. Apparently, AI models have proved to be highly beneficial in the analysis of root canal anatomy, detecting periapical lesions in early stages as well as providing accurate working-length determination. Moreover, they seem to be effective in predicting the treatment success next to identifying various conditions e.g., dental caries, pulpal inflammation, vertical root fractures, and expression of second opinions for non-surgical root canal treatments. Furthermore, AI has demonstrated an exceptional ability to recognize landmarks and lesions in cone-beam computed tomography scans with consistently high precision rates. While AI has significantly promoted the accuracy and efficiency of endodontic procedures, it is of high importance to continue validating the reliability and practicality of AI for possible widespread integration into daily clinical practice. Additionally, ethical considerations related to patient privacy, data security, and potential bias should be carefully examined to ensure the ethical and responsible implementation of AI in endodontics.

Keywords: Artificial Intelligence; Artificial Neural Networks; Deep Learning; Diagnostic Precision; Endodontics; Convolutional Neural Networks

Introduction

Artificial Intelligence (AI) is transforming healthcare by bridging the gap between computers and humans. It exhibits intelligent behavior to achieve specific goals. AI was formally established in the 1950s and has since evolved into a cornerstone of healthcare. It promises to bring a paradigm shift in diagnostic accuracy, treatment planning, and clinical decision-making [1]. The applications of classical machine learning (ML) have garnered attention, particularly in precision medicine. They can predict treatment success based on patient traits. Deep neural networks (DNN) have also revolutionized medical image analysis. They demonstrate superior outcomes in tasks such as detecting cancer through lymph nodes. Implementing AI can improve diagnostic accuracy, reduce healthcare costs, and enhance overall patient care [2]. Robotic process automation, a facet of AI, can perform administrative procedures and alleviate physician burnout by automating repetitive tasks. AI's ability to extract medical insights enhances decision-making in patient healthcare. It contributes to anticipatory decision-making and targeted treatment. ML algorithms contribute to radiological analysis, early disease detection, and diagnosis. Digitization of provider-patient interactions through AI-driven technologies enhances user experience and personalization in healthcare services. AI has the potential to provide up-to-date guidelines, foster economic growth, and contribute to innovation. However, misconceptions surrounding AI contribute to sensationalism and unrealistic expectations, emphasizing the need for accurate understanding and awareness in healthcare. The integration of AI represents a transformative era in healthcare, promising improved patient care, efficiency, and overall advancement in the medical field.

AI in dentistry

AI technology has brought about a significant transformation in the field of dentistry [3, 4]. AI applications leverage models such as convolutional neural networks (CNN) and artificial neural networks (ANN) to perform a wide range of functions within dental practice. Virtual dental assistants powered by AI ensure precision and efficiency in dental offices, performing tasks with reduced manpower and high accuracy. AI's diagnostic capabilities are particularly useful in oral and maxillofacial surgery, aiding in procedures such as dental implants and tumor removal. Design assistants such as RaPiD contribute to prosthetic dentistry by ensuring optimal aesthetic prostheses through anthropological calculations and patient preferences. Moreover, AI facilitates personalized care in orthodontics by analyzing radiographs, predicting malocclusion, identifying cephalometric landmarks, eliminating the need for multiple laboratory procedures and offering more precise diagnostics than human perception alone. Forensic odontology benefits from AI applications that can determine biological age and gender and analyze bite marks. Dental radiology harnesses AI's ability to recognize teeth, diagnose conditions such as caries, and predict issues like root caries and TMJ osteoarthritis. Also, periodontics and endodontics benefit from AI algorithms that enhance the diagnosis of compromised teeth [3, 4].

Rapid evolution of AI in endodontics

The rapid progress of AI in endodontics illustrates its potential to revolutionize patient care in this specialized field. Specifically, the emergence of CNN has led to remarkable advancements in diagnostic accuracy and treatment planning [5]. For instance, CNNs have demonstrated exceptional capabilities in tasks such as identifying intricate root canal morphology, determining working length (WL), detecting vertical root fractures (VRF), predicting thrust force and torque in canal preparation and detecting subtle signs of pathology in radiographic images [6]. These advances enable endodontists to make more precise diagnoses and develop tailored treatment plans, ultimately improving patient outcomes.

In addition to enhancing precision/efficiency, AI offers a range of other benefits in endodontics. For example, AI-powered algorithms can aid in treatment planning by analyzing patient data and predicting the optimal course of action based on individual characteristics and treatment objectives. Furthermore, AI can help reduce errors by providing real-time feedback during procedures and alerting clinicians to potential complications or deviations from optimal treatment protocols. Moreover, AI-driven technologies enable earlier detection of endodontic issues, allowing for timely intervention and prevention of disease progress.

The integration of AI into endodontic practice is supported by thorough research methodologies aimed at evaluating the reliability/accuracy of AI-driven diagnostic tools and treatment algorithms. Studies utilizing large datasets of clinical cases and employing rigorous validation techniques, such as cross-validation and external validation, provide compelling evidence for the efficacy of AI in endodontics. Moreover, the seamless integration of AI into clinical workflows is facilitated by user-friendly interfaces and interoperability with existing dental software systems.

Despite its transformative potential, the integration of AI into endodontic practice is not without challenges and limitations. For example, concerns related to data privacy and security must be addressed to ensure the ethical and responsible use of patient data in AI-driven applications. Additionally, the reliance on AI algorithms may pose challenges in cases where clinical judgment and expertise are required to interpret complex clinical scenarios or make treatment decisions.

Role of CNN and ANN

The combination of CNNs and ANNs has led to significant progress in endodontics, especially in tasks related to image recognition. Endodontists frequently use CNNs, which are a type of neural network (NN), to determine the working length (WL), detect vertical root fractures (VRFs), and evaluate root morphology. These networks comprise convolutional and pooling layers, which relevant features from input images, enabling accurate predictions [7]. Training CNNs involves exposing them to labeled datasets, allowing the network to learn associations between extracted features and correct labels through back propagation and optimization. Each layer in CNNs, including convolutional, pooling, activation, batch normalization, dropout, and fully connected layers, contributes to the network's ability to extract intricate features and make precise predictions. Understanding the role of each layer assists researchers and practitioners in designing effective CNN architectures for various computer vision tasks.

Moreover, the advancement of ANNs has been instrumental in the development of AI in endodontics. The first generation of ANNs, characterized by linear logic networks, treated neural events using propositional logic. The second generation, known as connectionist networks, emerged in the mid-1980s and experienced a resurgence driven by the demand for AI development and debugging. This period saw the creation of various neural models and learning algorithms, contributing to the revival of ANNs. The third generation, represented by spiking neural networks (SNNs), incorporates neurobiological findings related to synaptic transmission, ion channel conductance, and spike-timing-dependent plasticity [8]. SNNs, with categories like rate encoding, paired-pulse ratio (PPR) encoding, and spike-time encoding, demonstrate enhanced capabilities in temporal coincidence and noise considerations, aligning with the intricacies of endodontic diagnoses and predictions.

Objectives of the review

The purpose of this review is to analyze the recent advances and performances of AI models in endodontics, and to examine how they can enhance prognosis predictions and improve treatment outcomes. The review will cover various applications of AI in endodontics, including determining critical parameters such as WL, VRFs, root canal failures, root morphology, and diagnostic aspects like pulpal diseases and periapical lesions. By synthesizing findings from various sources, this review aims to provide a contemporary understanding of AI's potential to increase the accuracy, efficiency, and accessibility of endodontic services. The ultimate goal is to be a valuable resource for practitioners and researchers in endodontics, guiding the development of precise AI models tailored to the field's unique challenges and informing future research directions.

Materials and Methods

A systematic search was conducted to find relevant articles about AI in endodontics, covering studies published up to October 15, 2023. The search protocol involved the next steps:

1. Database selection and search strategy: PubMed and Scopus were chosen as primary sources for the systematic search because they extensively cover medical/dental literature. The search strategy involved the use of carefully selected search terms and Boolean operators, including ("artificial intelligence," OR "machine learning," OR "deep learning," OR "neural network*," OR "dental diagnosis," OR "prognosis prediction" AND "endodontic*"). These search terms were combined using Boolean operators to ensure comprehensive retrieval of relevant articles. Filters/limitations were applied to narrow the search results to articles published prior to the specified cutoff date, increasing their relevance and specificity.

2. Adherence to guidelines: Although no official guidelines were followed, best practices were adhered to ensure reproducibility and rigor throughout the search/review process.

3. Inclusion and exclusion criteria: Inclusion criteria were established to select articles relevant to the topic of AI applications in endodontics. Articles were included if they addressed AI technologies, machine learning algorithms, or deep learning models in the context of endodontic diagnosis, treatment planning, or clinical decision-making. Studies published in peer-reviewed journals up to the specified cutoff date were considered. Exclusion criteria included non-English articles, studies unrelated to endodontics or AI, and articles not relevant to the research focus.

Each selected article underwent complete data extraction, including author identification, title, year of publication, and extraction of key findings and conclusions. Articles were systematically categorized based on their research focus and specific topics related to AI applications in endodontics to facilitate subsequent data analysis and synthesis.

Results

The systematic search yielded a significant number of articles from two major databases. PubMed provided 131 results, while Scopus contributed 103 relevant documents. Additionally, a thorough manual search uncovered 18 pertinent articles that may have been initially overlooked. After meticulously removing duplicate publications and those deemed unrelated, the research team identified and selected 58 unique articles for detailed scrutiny/synthesis (Table 1). Our meticulous curation process ensures a comprehensive review of AI in endodontics.

Discussion

This review is focused solely on original research contributions in AI applications in endodontics, setting it apart from other scholarly discussions. The review process only included original studies, which provide new insights and methodologies directly from primary research. While acknowledging previous review articles [9-12], this compilation prioritizes original research, offering an authentic snapshot of the latest advancements in integrating AI technologies into endodontic practice. This approach enhances the reliability and credibility of the included studies, reinforcing the scholarly rigor of this comprehensive exploration.

Furthermore, it is important to recognize the diversity in diagnostic accuracy among different imaging modalities employed across these studies. Variations in diagnostic accuracy among panoramic radiographs/orthopantomographs (OPGs), periapical radiographs (PRs), cone-beam computed tomography (CBCT) scans, and micro-CT scans should be considered when interpreting the results. Each modality has its strengths and limitations, which can significantly influence diagnostic outcomes. Therefore, discussions should account for these differences to ensure accurate assessments and informed decision-making in clinical practice.

Automated canal/root/tooth morphology detection systems

Over the years, several studies have explored the potential of using AI to improve endodontic diagnostics. Automated systems have been developed to detect canal, root, and tooth morphology in endodontics, using advanced algorithms to analyze dental images. These systems provide endodontists with precise assessments of root canal configurations and tooth structures.

Table 1. A succinct summary of the selected studies delving into the application of AI in endodontics is presented below. The table encompasses crucial details such as the study title, author, publication year, employed algorithms, objectives, study factors, modality, and the number of patients or images involved. The results column succinctly outlines the key findings or outcomes of each study. The classification of studies is based on their research focus, with emphasis on automated root/tooth morphology detection systems, caries detection, pulpal diagnosis, working length determination, vertical root fracture detection, automated endodontic/periapical lesions detection, endodontic prediction, case difficulty, fluid behavior, and other applications of AI in endodontics. This structured categorization facilitates a nuanced exploration of AI's multifaceted contributions to various facets of endodontic practice

	Objective	Author Year [Ref.]	Algorithm	Study Factor	Modality	No. of Patients/ Images	Results
Automated canal/root/tooth morphology detection systems	Automated detection system for endodontic-treated teeth	Chen *et al.* 2022 [13]	CNN	Retained roots, endodontic treated teeth, implants	OPG	Not specified	Improved image segmentation and anomaly detection
	Detection of root canal obturation from noisy radiographs	Hasan et al. 2023 [14]	YOLOv5s, YOLOv5x, YOLOv7	Endodontic treatment outcomes	PRs	250 PRs	Successful classification of obturation and mishaps
	Assessment of root morphology on OPG	Hiraiwa *et al.* 2019 [15]	DLM	Root morphology of molars	OPGs	760 mandibular first molars	High accuracy in root morphology diagnosis
	Tooth and pulp segmentation in CBCTs	Duan *et al.* 2021 [16]	U-Net	Tooth and pulp segmentation	CBCT	Feature Pyramid Network	Accurate segmentation of tooth and pulp in CBCT images
	Tooth Segmentation	Lahoud *et al.* 2021 [17]	Feature Pyramid Network	Tooth morphology	CBCT	433 images	Fast and accurate tooth segmentation on CBCT imaging
	Tooth detection and segmentation	Leite *et al.* 2021 [18]	Deep CNN	Tooth detection	OPG	153 OPGs	Accurate and fast tooth detection and segmentation
	Pulp cavity and tooth segmentation	Lin *et al.* 2021 [19]	U-Net Network	Micro-CT data	CBCT	30 teeth	Enhanced tooth and pulp cavity segmentation
	C-shaped canal detection and classification	Sherwood *et al.* 2021 [20]	DL (U-Nets)	C-shaped canal classification	CBCT	100 training and 35 testing	Improved C-shaped canal detection and classification
	C-shaped Canals Prediction	Jeon *et al.* 2021 [21]	CNN	C-shaped canal prediction	OPGs	1020 patients	Accurate prediction of C-shaped canals on panoramic radiographs
	C-shaped Canal Classification	Yang *et al.* 2022 [22]	Deep CNN	C-shaped canal classification	PRs	1000 teeth	Effective C-shaped canal diagnosis in mandibular second molars
	Accurate/automatic root canal segmentation	Wang *et al.* 2023 [23]	DentalNet and PulpNet	Automatic tooth and root canal segmentation	CBCT	Two clinical datasets	Efficient, precise, and fully automatic tooth and root canal segmentation in difficult RCTs
Caries detection	Automatic diagnosis of dental diseases using CNN	Ghaznavi Bidgoli *et al.* 2021 [24]	Deep NN	Dental diseases diagnosis	OPG	Standard dataset	Automatic diagnosis of decayed, root-canaled, and restored teeth
	Dental Caries Detection	Oztekin *et al.* 2023 [25]	ML models	Different pre-trained models	OPGs	562 subjects	Accurate dental caries detection
Pulpal diagnosis	To identify pulpitis through PRs	Tumbelaka *et al.* 2014 [26]	ANN	Normal pulp, pulpitis, necrotic pulp	PRs	20 (10 molar and 10 canine teeth)	Direct reading radiography is better to be digitized for improved diagnosis validation
	To diagnose deep caries and pulpitis on PRs	Zheng *et al.* 2021 [27]	CNN (VGG19, Inception V3, ResNet18)	Deep caries and pulpitis	PRs	844 PRs (717 for training, 127 for testing)	Multi-modal CNN (ResNet18 integrated with clinical parameters) demonstrated significantly enhanced performance

WL determination	To locate the minor apical foramen using radiograph features	Saghiri *et al.* 2012 [28]	ANN	Perceptron ANN model	PRs	50 straight single-rooted teeth	ANN enhances accuracy in WL determination by radiography.
	To evaluate ANN's accuracy in a cadaver model	Saghiri *et al.* 2012 [29]	ANN	Location of the file in relation to AF	Human cadaver	50 single-rooted teeth	ANN outperformed endodontists in WL determination when compared to real measurements
	To measure working length (WL) using multifrequency impedance	Qiao *et al.* 2020 [30]	NN	Impedance ratios, type of tooth, and file	Circuit system & impedance ratios	Not specified	The multifrequency impedance method using NNs showed improved accuracy and robustness in WL measurement.
Vertical root fracture detection	Develop a PNN for VRF detection using DR	Kositbowornchai *et al.* 2013 [31]	Probabilistic NN	150 VRF and 50 sound teeth	DR	200 images	PNN proves to be an effective model for VRF detection in DR
	Design a PNN to diagnose VRFs	Johari *et al.* 2017 [32]	Probabilistic NN	Intact/endodontically treated teeth	PRs, CBCTs	240 radiographs of teeth	PNN-based models effectively diagnose VRFs in both PRs and CBCT images
	Demonstrate DSR in the detection of VRFs	Mikrogeorgis *et al.* 2018 [33]	DSR	Endodontically treated teeth	DSR images	Four clinical cases	DSR proves to be a useful diagnostic tool for VRF detection
	Evaluate the use of CNN for detecting VRF on OPG	Fukuda *et al.* 2020 [34]	CNN	CNN-based DLM	OPG	300 OPGs	The CNN model detected VRFs on OPGs and serves as a CAD tool
	Develop an algorithm for detecting microfractures	Vicory *et al.* 2021 [35]	AIA and ML	Wavelet Features and ML	CBCTs	22 teeth (=14 microfractures)	The algorithm enables the quantification of microfractures in teeth
	Efficiency of DLM in diagnosing VRFs on CBCT images	Hu *et al.* 2022 [36]	DLM	Three DLNs	CBCTs	276 teeth	ResNet50 showed promise in diagnosing in vivo VRFs
Automated endodontic/periapical lesions detection	Differential diagnosis of periapical lesions in CBCT scans	Okada *et al.* 2015 [37]	CAD	Differential Diagnosis	Histology and CBCT	28 CBCT scans	CAD showed promise for noninvasive differential diagnosis of apical lesions
	Automated detection of apical lesions in OPGs	Birdal *et al.* 2016 [38]	DWT	Apical lesion	OPGs	Not specified	The used methodology can efficiently assist in examining radiographs for apical lesions
	DL for radiographic detection of apical lesions on OPGs	Ekert *et al.* 2019 [39]	7-layer Deep CNN	Apical Lesion Detection	OPG	2001 tooth segments	The deep CNN detected apical lesions on OPGs.
	DLA for periapical disease detection	Endres *et al.* 2020 [40]	DLA	OMF surgeons' assessments and DLM	OPG	2902 OPGs	DLA has the potential to assist in detecting periapical lesions.
	Diagnostic performance of AI in detecting periapical pathosis	Orhan *et al.* 2020 [41]	Deep CNN	Localization, lesion detection, and lesion volume	CBCTs	153 lesions in 109 patients	AI-based DLS were useful for detecting apical pathosis on CBCT
	AI for the CAD of apical lesions	Setzer *et al.* 2020 [42]	DL	Periapical lesion detection	CBCTs	20 scans	DL algorithm displayed high lesion detection accuracy

	Disease detection on PRs	Chen *et al.* 2021 [43]	Deep CNNs	Disease categories, severity levels, train strategies	PRs	Not specified	Deep CNNs detected diseases, with varying performance based on severity and training strategies
	CNNs for detecting apical lesions	Li *et al.* 2021 [44]	CNN	Image database of individual tooth images	Automatic diagnosis	Standardized database	The CNN model efficiently diagnosed apical lesions
	Diagnostic performance of CNNs vs. human observers	Pauwels *et al.* 2021 [45]	Convolutional CNNs	Comparison of CNNs and human observers	PRs, CBCTs	Simulated periapical lesions	CNNs showed promise for periapical lesion detection, surpassing human observers
	Automatic detection of endodontic lesions in CBCTs	Calazans *et al.* 2022 [46]	CNN (Siamese Network)	Apical lesion classification	CBCT	1000 scans	The proposed system achieved an accuracy of about 70%, offering diagnostic support in endodontics
	Determine the efficacy of AI in detecting apical radiolucencies	Hamdan *et al.* 2022 [47]	Denti.AI DL Tool	Dentists' performance	PRs	68 PRs	Enhanced diagnostic accuracy for apical radiolucencies
	Automated detection of osteolytic apical lesions	Kirnbauer *et al.* 2022 [48]	Deep CNNs	Tooth localization and lesion detection	CBCTs	144 CBCT images	The method provided excellent results in detecting osteolytic apical lesions in CBCT.
	DL for caries and apical periodontitis detection	Li *et al.* 2022 [49]	DLM	Detection of dental caries and apical periodontitis	PRs	4129 images	DLM achieved scores of 0.829 for dental caries and 0.828 for apical periodontitis
	Categorization of apical lesions based on PAI	Moidu *et al.* 2022 [50]	CNN	Different PAI scores	PRs	3000 areas (1950 digital PRs)	The CNN model performed well in categorizing endodontic lesions
	PRs image classification using Deep NN	Vasdev *et al.* 2022 [51]	Pipelined Deep NN (AlexNet model)	Healthy vs. Non-Healthy Classification	PRs	16000 images	The AlexNet model outperformed other models in dental disease classification
	Accuracy of AI in detecting periapical periodontitis on PRs	Issa *et al.* 2023 [52]	Diagnocat AI System	Diagnostic Test Accuracy	PRs	20 PRs (60 teeth)	The AI algorithm showed high accuracy in detecting apical periodontitis
	Automatic differential diagnosis of apical lesions	Patel *et al.* 2023 [53]	Image Processing Tool	Differential Diagnosis	PRs	60 images (gold standard dataset)	The tool achieved high sensitivity, specificity, and accuracy in differential diagnosis of apical lesions
Endodontic prediction	Predict the practicality of performing or not performing a retreatment	Campo *et al.* 2016 [54]	Case-Based Reasoning (CBR)	Dental retreatment	Not specified	Not specified	The system minimizes false negatives
	Assess factors influencing endodontic failure & and predict failure using ML	Herbst *et al.* 2022 [55]	ML (LogR, RF, GBM, XGB)	Tooth-, treatment-, and patient-level covariates	Endodontic treatments	458 patients (591 teeth)	Tooth-level factors strongly associated with failure
	Predict prognosis of endodontic microsurgery	Qu *et al.* 2022 [56]	GBM, RF	Tooth type, lesion size, type of bone defect, root filling density, etc.	CBCT	234 teeth (178 patients)	ML model improve the efficiency of clinical decision-making

	Automated evaluation of RCT results from X-ray images	Li *et al.* 2022 [57]	AGMB-Transformer Network	Anatomy features and multi-branch Transformer network	X-ray images	245 endodontically treated teeth	AGMB-Transformer significantly improved evaluation of RCT outcomes
	Predict endodontic treatment outcome based on preoperative PRs	Lee *et al.* 2023 [58]	Deep CNN	Seven clinical features	PRs	598 single-root premolars	Efficient, precise, and fully automatic root canal segmentation to support clinical decisions
	Identify factors affecting optimal RFL during RCT and predict RFL	Herbst *et al.* 2023 [59]	ML (LogR, SVM, DT, GBM, XGB)	Operator, indistinct canal paths, root canals reduced in size, retreatments	Apical extent prediction	555 completed RCTs (343 patients)	Limited predictive ability
	Enhancing endodontic precision	Latke & Narawade 2023 [60]	Hybrid Ensemble Classifier	Root canal curvature and calcification	Dental Imaging	N/A	Refining endodontic treatments
Case difficulty	Predict case difficulty in endodontic microsurgery	Qu *et al.* 2023 [61]	LR, SVR, XGB	Lesion size, anatomical structures, root filling density, etc.	CBCT	261 patients (341 teeth)	XGBoost outperformed LR and SVR models
	Automated assessment of case difficulty and referral decisions	Mallishery *et al.* 2020 [62]	ANN	AAE Endodontic Case Difficulty Assessment Form	Standardized AAE form	500 cases	Automation of case difficulty assessment
Fluid behavior	Fluid Motion Estimation	Peeters *et al.* 2022 [63]	AI	EDDY® tip fluid flow behavior	High-speed Imaging	N/A	Detailed fluid flow behavior analysis
	EndoActivator Fluid Behavior	Peeters *et al.* 2022 [64]	AI	EndoActivator tip fluid flow	High-speed Imaging	N/A	Visualization of fluid behavior and bubbles
Other uses of AI in endodontics	Detect and segment unobturated MB2 canals in CBCTs	Albitar *et al.* 2022 [65]	CNN (U-Net)	Unobturated MB2 canals	CBCT	57 scans	Potential for identifying obturated and unobturated canals
	Detect separated instruments on radiographs	Buyuk *et al.* 2023 [66]	CNN (Gabor filtered) and LSTM	Separated endodontic instrument	OPG	915 teeth	Gabor filtered-CNN model achieved the best performance
	Differentiating stress from EPT-induced electrodermal activity	Kong *et al.* 2023 [67]	Multilayer Perceptron	Stress and EPT stimulation	EDA Signals	51 subjects	Successful discrimination between stress and EPT stimulation
	Predicting pulp exposure risk in radiographic images	Ramezanzade *et al.* 2023 [68]	Multi-path NN	Dental pulp exposure	Bitewing radiographs	292 images	DenseNet provided best predictive effect for pulp exposure
	Interactive system for access cavity assessment in preclinic	Choi *et al.* 2023 [69]	Software	Access cavity assessment	Three-dimensional models	44/79 students	Integration into preclinical curriculum for dental students
	Evaluate consistency and accuracy of ChatGPT in endodontics	Suárez *et al.* 2023 [70]	ChatGPT (AI Chatbot)	ChatGPT performance	Clinical questions	91 dichotomous (yes/no) questions	Currently, ChatGPT is not capable of replacing dentists in clinical decision-making

AGMB: Anatomy-Guided Multi-Branch; AIA: Advanced Image Analysis; ANN: Artificial Neural Networks; CAD: Computer-Aided Detection; CBCT: Cone-beam Computed Tomography; CNN: Convolutional Neural Networks; DLA: Deep Learning Algorithm; DLM: Deep Learning Models; DLN: Deep Learning Networks; DLS: Deep Learning Segmentation; DR: Digital Radiography; DSR: Digital Subtraction Radiography; DT: Decision Tree; DWT: Discrete Wavelet Transformation; GBM: Gradient Boosting Machine; LogR: Logistic Regression; LR: Linear Regression; ML: Machine Learning; NN: Neural Networks; OPG: Panoramic Radiograph; PRs: Periapical Radiographs; RF: Random Forests; RFL: Root filling length; SVM: Support Vector Machine; SVR: Support Vector Regression; VRF: Vertical Root Fracture; XGB: Extremely Gradient Boosting

One study by Chen *et al.* [13] used a convolutional neural network (CNN) to create an automated detection system for endodontic-treated teeth using orthopantomograms (OPGs). This algorithm significantly improved image segmentation and anomaly detection, demonstrating its potential to enhance endodontic treatment planning. Another study by Hasan *et al.* [14] used YOLOv5s and YOLOv5x to detect root canal obturation from noisy periapical radiographs (PRs), successfully classifying obturation and mishaps, demonstrating the efficacy of these algorithms in assessing endodontic treatment outcomes. Hiraiwa *et al.* [15] utilized a Deep Learning Model (DLM) to assess root morphology, particularly focusing on mandibular first molars using OPGs. Their study achieved high accuracy in root morphology diagnosis, showcasing the potential of AI in enhancing diagnostic precision. Duan *et al.* [16] explored tooth and pulp segmentation in CBCT scans using the U-Net algorithm and Feature Pyramid Network, demonstrating accurate segmentation and showcasing the potential for AI to contribute to detailed diagnostic processes.

Lahoud *et al.* [17] utilized the Feature Pyramid Network for tooth segmentation, focusing on tooth morphology in CBCT imaging. This indicates the versatility of AI in addressing specific diagnostic needs. Leite *et al.* [18] implemented a Deep CNN for tooth detection using OPGs, demonstrating accurate and rapid detection and segmentation of teeth, emphasizing the efficiency AI can bring to diagnostic processes in endodontics.

Lin *et al.* [19] applied a U-Net Network to enhance pulp cavity and tooth segmentation using micro-CT data in CBCT scans, showcasing improved segmentation and contributing to the precision of endodontic diagnostics. Sherwood *et al.* [20] utilized Deep Learning (DL; U-Nets) for the detection and classification of C-shaped canals in CBCT scans, significantly improving C-shaped canal detection and classification. Jeon *et al.* [21] focused on CNN for the prediction of C-shaped canals on OPGs, accurately predicting C-shaped canals and showcasing the potential of AI in addressing complex diagnostic challenges.

Finally, Yang *et al.* [22] explored the application of Deep CNNs for the classification of C-shaped canals in PRs, demonstrating effective C-shaped canal diagnosis in mandibular second molars. Wang *et al.* [23] employed DentalNet and PulpNet for automatic tooth and root canal segmentation in CBCT scans, showcasing efficient, precise, and fully automatic segmentation that is particularly beneficial in challenging root canal treatments.

Caries detection

Caries detection is an important area where AI has made significant strides. Machine learning algorithms have enabled accurate identification of carious lesions in dental images. For instance, Ghaznavi Bidgoli *et al.* [24], utilized a CNN in a deep NN framework to diagnose dental diseases automatically, using an OPG and a standard dataset. Their approach included identifying decayed, root-canaled, and restored teeth, which showcases the potential of AI in comprehensive dental disease diagnosis. Similarly, Oztekin *et al.* [25] focused on dental caries detection using various ML models and pre-trained models. They conducted their study on OPGs, with a dataset comprising 562 subjects, and demonstrated the accuracy of AI in detecting dental caries. These studies highlight the versatility of AI applications in dentistry, particularly in the area of caries detection, where ML models are effective in providing precise and automated diagnoses.

Pulpal diagnosis

The field of pulpal diagnosis has benefited greatly from the integration of AI, as demonstrated by various studies. For example, Tumbelaka *et al.* [26] used an ANN to differentiate between normal pulp, pulpitis, and necrotic pulp based on PRs. Their study, which involved 20 teeth (10 molars and 10 canine teeth), showed that digitizing direct reading radiography could enhance the validation of pulpal diagnoses. In a more recent investigation, Zheng *et al.* [27] explored the diagnosis of deep caries and pulpitis on PRs, using convolutional neural networks (CNNs) such as VGG19, Inception V3, and ResNet18. Their study, which involved a comprehensive dataset of 844 PRs (717 for training and 127 for testing), revealed that a multi-modal CNN, particularly ResNet18 integrated with clinical parameters, significantly improved the accuracy of diagnosing deep caries and pulpitis.

Although AI has shown promise in distinguishing between different pulpal conditions using radiographs, it is important to recognize the limitations associated with relying solely on radiographic assessment. It is crucial to emphasize the complementary role of clinical and radiographic examinations alongside other diagnostic tools, such as pulp and periapical tests. This integrated diagnostic approach ensures a thorough evaluation, thereby enhancing the accuracy and reliability of pulpal diagnoses in clinical practice.

Working length determination

Determination the WL accurately is crucial for successful endodontic treatments, and AI has played a significant role in improving this process. Saghiri *et al.* [28] conducted a study on locating the minor apical foramen using radiograph features, which involved employing an ANN with a Perceptron model on PRs of 50 straight single-rooted teeth. The study concluded that the ANN model was effective in enhancing the accuracy of WL determination through radiography. In another study, Saghiri *et al.* [29] evaluated the accuracy of ANN in a cadaver model by determining the location of the file in relation to the apical foramen. The study demonstrated that the ANN outperformed endodontists in determining the WL when compared to real measurements, using human cadavers with 50 single-rooted teeth. This suggests that AI, particularly ANN, has the potential to provide more precise WL measurements, even surpassing human expertise in certain scenarios. Qiao *et al.* [30] explored a different approach by utilizing a NN to measure WL using multifrequency impedance. They incorporated factors such as impedance ratios, type of tooth, and file characteristics into the circuit system. Although the number of specified cases is not provided, the multifrequency impedance method using NNs demonstrated improved accuracy and robustness in WL measurement. These studies collectively emphasize the potential of AI in revolutionizing the determination of WL in endodontic procedures, offering more accurate and reliable outcomes.

Vertical root fracture detection

The detection of VRF is a difficult aspect of endodontic diagnosis, but AI has made significant advancements in this field. Several studies have contributed to the development and validation of AI models that accurately detect VRF, providing clinicians with valuable tools to identify potential treatment complications.

Kositbowornchai *et al.* [31] used a Probabilistic Neural Network (PNN) to develop an effective model for VRF detection using dental radiographs. Their study included 150 cases of VRF and 50 sound teeth, utilizing 200 images for training and validation. The PNN-based model demonstrated effectiveness in VRF detection in dental radiographs, showcasing the potential of AI in addressing this challenging aspect of endodontic diagnosis. Johari *et al.* [32] designed a PNN to diagnose VRFs in both intact and endodontically treated teeth. Their study utilized PRs and CBCT, involving 240 radiographs for evaluation. The PNN-based models were found to be effective in diagnosing VRFs in both PRs and CBCT images, highlighting the versatility of AI in fracture detection across different imaging modalities. Mikrogeorgis *et al.* [33] demonstrated the utility of Digital Subtraction Radiography (DSR) in the detection of VRFs in endodontically treated teeth. The study, based on four clinical cases and DSR images, showed that DSR could be a useful diagnostic tool for VRF detection, adding to the array of AI applications in this domain.

Fukuda *et al.* [34] explored the use of CNN for detecting VRFs on OPGs. Analyzing 300 OPGs, the CNN-based DLM effectively detected VRFs, serving as a computer-aided diagnosis (CAD) tool for clinicians. Vicory *et al.* [35] introduced an algorithm for detecting microfractures, employing AI and MLs (AIA and ML) with wavelet features. Utilizing CBCTs with 22 teeth (14 with microfractures), their algorithm demonstrated the capability to quantify microfractures in teeth, showcasing the potential for AI in addressing subtler aspects of fracture detection. Hu *et al.* [36] evaluated the efficiency of DLM in diagnosing VRFs on CBCT images. Utilizing three different Deep Learning Networks (DLNs) and 276 teeth, ResNet50 showed promise in diagnosing in vivo VRFs, emphasizing the potential for AI in real-world clinical scenarios. These studies collectively highlight the positive impact of AI in enhancing the detection of VRF, providing clinicians with valuable tools for improved diagnostic accuracy and treatment planning.

Automated endodontic/periapical lesion detection

The use of AI in the automated detection of endodontic and periapical lesions has revolutionized dental diagnostics. Multiple studies have demonstrated the feasibility of using ML algorithms to identify and classify lesions, leading to faster diagnosis and targeted treatment planning.

Okada *et al.* [37] employed CAD to distinguish between periapical lesions in CBCT scans. The study, which included 28 CBCT scans, demonstrated the potential of CAD in non-invasive differential diagnosis of apical lesions, highlighting the usefulness of AI in identifying different pathologies. Birdal *et al.* [38] utilized Discrete Wavelet Transform (DWT) to detect apical lesions in OPGs. Although the number of subjects was not specified, the methodology efficiently assisted in examining radiographs for apical lesions, showcasing the versatility of AI applications in different imaging modalities. Ekert *et al.* [39] implemented a 7-layer deep CNN for the radiographic detection of apical lesions on OPGs. With 2001 tooth segments involved in the study, the deep CNN demonstrated effectiveness in detecting apical lesions, highlighting the potential of DL in enhancing lesion detection.

In 2020, Endres *et al.* [40] introduced a Deep Learning Algorithm (DLA) for periapical disease detection. Utilizing 2902 OPGs and incorporating assessments by oral and maxillofacial surgeons, the DLA showed promise in assisting in the detection of periapical lesions, demonstrating the collaborative potential between AI and clinical expertise. Orhan *et al.* [41] investigated the diagnostic performance of AI in detecting periapical pathosis using Deep CNNs. Analyzing 153 lesions in 109 patients through CBCTs, AI-based Deep Learning Systems (DLS) were found to be useful for detecting apical pathosis, underscoring the potential for AI in contributing to accurate diagnoses. Setzer *et al.* [42] focused on the use of DLA for periapical lesion detection in CBCTs. With 20 scans included in the study, the DL algorithm displayed high accuracy in lesion detection, emphasizing its potential as a valuable tool in endodontic diagnostics.

In 2021, Chen *et al.* [43] used Deep CNNs to detect disease on PRs achieving varying performance based on severity and training strategies. Li *et al.* [44] implemented CNNs for detecting apical lesions using a standardized image database, demonstrating the potential for AI in lesion detection in diverse clinical scenarios. Pauwels *et al.* [45] compared the diagnostic performance of Convolutional CNNs with human observers in the detection of simulated periapical lesions. The CNNs surpassed human observers in certain aspects, showcasing their potential for periapical lesion detection.

In 2022, Calazans *et al.* [46] proposed a CNN-based Siamese Network for apical lesion classification in CBCTs. The proposed system achieved an accuracy of about 70%, offering diagnostic support in endodontics. Hamdan *et al.* [47] evaluated the Dentist.AI DL Tool for the automated detection of apical radiolucencies, showcasing its potential as an adjunctive diagnostic tool. Kirnbauer *et al.* [48] utilized Deep CNNs for the automated detection of osteolytic apical lesions in CBCTs, emphasizing the precision and efficiency of AI in lesion detection. Li *et al.* [49] explored the use of DLM for the detection of dental caries and apical periodontitis in PRs, achieving high scores for both pathologies. Moidu *et al.* [50] employed CNNs for the categorization of apical lesions based on Periapical Index (PAI) scores, indicating its potential for precise lesion classification. Vasdev *et al.* [51] utilized a Pipelined Deep NN model (AlexNet) for PR image classification, outperforming other models in dental disease classification.

In the current year, Issa *et al.* [52] assessed the diagnostic test accuracy of the Diagnocat AI System in detecting apical periodontitis on PRs, showing high accuracy in detecting apical periodontitis. Patel *et al.* [53] developed an Image Processing Tool for the automatic differential diagnosis of apical lesions in PRs, achieving high sensitivity, specificity, and accuracy in the differential diagnosis of apical lesions.

Overall, these studies demonstrate the versatility and transformative potential of AI in automating the detection and classification of endodontic and periapical lesions, providing valuable tools for clinicians in their diagnostic and treatment-planning endeavors.

Endodontic prediction

Predictive modeling in endodontics has gained momentum through AI applications. In one study, Campo *et al.* [54] introduced a predictive model that utilized Case-Based Reasoning (CBR) to assess the practicality of performing or not performing retreatment for dental cases. The system was designed to minimize false negatives, offering valuable insights into the decision-making process. Herbst *et al.* [55] delved into assessing factors influencing endodontic failure and predicting failure using ML techniques such as Logistic Regression (LogR), Random Forest (RF), Gradient Boosting Machine (GBM), and XGBoost. With a study involving 458 patients and 591 teeth, the research highlighted tooth-level factors strongly associated with failure, contributing to a more nuanced understanding of treatment outcomes.

Qu *et al.* [56] ventured into predicting the prognosis of endodontic microsurgery using a Gradient Boosting Machine (GBM) and Random Forest (RF). The study considered factors such as tooth type, lesion size, type of bone defect, and root filling density with a dataset of 234 teeth from 178 patients, demonstrating enhanced efficiency in clinical decision-making. Li *et al.* [57] explored the automated evaluation of root canal treatment (RCT) outcomes from X-ray images, introducing an AGMB-Transformer Network. By incorporating anatomy features and a multi-branch Transformer network, the study focused on 245 endodontically treated teeth, showcasing that the AGMB-Transformer significantly improved the evaluation of RCT outcomes.

Lee *et al.* [58] employed a Deep CNN to predict endodontic treatment outcomes based on preoperative PRs. The study demonstrated the efficiency, precision, and full automation of root canal segmentation to support clinical decisions for 598 single-root premolars. In another study by Herbst *et al.* [59], ML techniques including LogR, Support Vector Machine (SVM), Decision Trees (DT), Gradient Boosting Machine (GBM), and XGBoost were employed to identify factors affecting optimal root filling length (RFL) during RCT and predict RFL. The study, based on 555 completed RCTs involving 343 patients, revealed limited predictive ability in this context. Latke and Narawade [60] focused on enhancing endodontic precision through a Hybrid Ensemble Classifier, considering root canal curvature and calcification in dental imaging. Although specific case numbers were not provided, the research aimed at refining endodontic treatments through improved classification methods.

Case difficulty

The difficulty of endodontic cases can be predicted using AI applications, which can provide valuable insights for practitioners. A study by Qu *et al.* [61] used LR, SVR, and XGB models to assess case difficulty in endodontic microsurgery. By considering factors such as lesion size, anatomical structures, and root filling density from CBCT scans of 261 patients (341 teeth), the study found that XGBoost outperformed LR and SVR models. This makes it an advanced tool for anticipating surgical challenges. Another approach developed by Mallishery *et al.* [62] involved an automated system that uses ANN to assess case difficulty and support referral decisions. The system analyzed 500 cases, using the AAE Endodontic Case Difficulty Assessment Form as a standardized input. This demonstrated the potential for automation in evaluating the complexity of endodontic cases. This innovative use of AI contributes to more efficient and standardized case difficulty assessments in clinical practice.

Fluid behavior

In recent years, AI has been used in innovative studies that explore the potential of AI in endodontics beyond traditional diagnostic tasks. Peeters *et al.* [63] conducted a study on fluid behavior during endodontic procedures using AI for Fluid Motion Estimation. The study utilized high-speed imaging to analyze the EDDY® tip fluid flow behavior, providing valuable insights into the complex dynamics of fluid motion. Another study by Peeters *et al.* [64] focused on the fluid behavior associated with the EndoActivator, using AI to analyze EndoActivator tip fluid flow. Through high-speed imaging, the study aimed to visualize fluid behavior and bubbles, contributing to a comprehensive understanding of the dynamics involved in this specific endodontic procedure. These studies highlight the versatility of AI applications in endodontics, showcasing its potential in addressing practical challenges and enhancing procedural insights, in addition to its diagnostic capabilities.

Other uses of AI in endodontics

AI has a wide range of applications in endodontics beyond traditional diagnostic tasks. It can address various challenges in clinical practice, improve procedural outcomes, and provide valuable insights for comprehensive endodontic assessments. For instance, a study by Albitar *et al.* [65] utilized a CNN with U-Net architecture to identify both obturated and unobturated canals, while Buyuk *et al.* [66] introduced a CNN model with Gabor filtering and Long Short-Term Memory (LSTM) networks to detect separated endodontic instruments in OPGs. Kong *et al.* [67] used a Multilayer Perceptron to differentiate stress from Electric Pulp Tester (EPT)-induced electro dermal activity signals, and Ramezanzade *et al.* [68] introduced a Multi-path NN to predict pulp exposure risk in Bitewing radiographs. Choi *et al.* [69] developed an interactive software system for access cavity assessment using three-dimensional models, while Suárez *et al.* [70] evaluated the consistency and accuracy of ChatGPT, an AI chatbot, in endodontics. Additionally, it was seen that ChatGPT has weaknesses and limitations in understanding the situation and making decisions in treatment planning [71].

These studies highlight the transformative potential of AI in endodontics and how it can redefine the standards of dental practice. The following subsections provide a detailed exploration of each thematic area, highlighting key methodologies, outcomes, and the implications of these studies for the broader landscape of endodontics.

Limitations

It is important to note that this review is limited to articles published before October 15, 2023, which means that it excludes more recent publications.

Ethical considerations and future directions

The integration of AI into endodontic practice shows great promise, but it is crucial to address ethical considerations, limitations, and emerging challenges to ensure responsible and effective implementation [72]. Ethical concerns regarding patient privacy, data security, and algorithmic bias require careful scrutiny and robust regulatory frameworks to safeguard patient welfare and uphold professional standards. The use of historical datasets for AI training raises concerns about representativeness and generalizability, highlighting the need for diverse and inclusive datasets to mitigate bias and improve model reliability. Additionally, the lack of interpretability of AI algorithms remains a challenge, limiting their acceptance and adoption by clinicians. Future research should prioritize transparency and explainability, facilitating trust and comprehension among endodontic practitioners. Furthermore, exploring novel applications such as predictive modeling for treatment outcomes, real-time procedural guidance, and patient-centered decision support systems offers exciting prospects for advancing clinical practice. Continuous interdisciplinary dialogue, ethical reflexivity, and technological innovation are essential to harnessing the transformative potential of AI while ensuring its ethical and equitable integration into endodontic healthcare.

Conclusions

The integration of AI in endodontics has had a transformative impact on the field. This has been exemplified by the use of CNN, ANN, and various ML models, which have enabled greater diagnostic precision, better treatment planning, and improved clinical decision-making. There are many diverse applications of AI in this field, from automated canal morphology detection to caries diagnosis, pulpal condition assessment, WL determination, and VRF detection. These applications underscore the multifaceted impact of AI on endodontic practice. The findings presented in this review are robust and supported by studies employing PNN, DLM, and innovative algorithms like CBR and AGMB networks. They emphasize AI's potential to enhance efficiency, accuracy, and personalized treatment strategies. As AI continues to demonstrate its prowess in predicting treatment outcomes, assessing case difficulty, analyzing fluid behavior, and venturing into novel applications, it emerges as an invaluable ally in elevating standards in patient care and reshaping the landscape of endodontic healthcare.

While acknowledging these strides, careful considerations of reliability, practicality, and cost-effectiveness are paramount for the seamless integration of AI into routine endodontic procedures. This will ensure sustained advancements in clinical outcomes. It is imperative to recognize the ongoing evolution of AI and to address any associated limitations or challenges to foster its responsible and effective use in the endodontics.

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During the preparation of this paper, the author utilized the assistance of chat.openai to improve language/readability. The AI model provided suggestions/guidance, which were then reviewed/edited by the author. The author takes full responsibility for the final content of the publication and its accuracy.

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