REVIEW ARTICLE

Artificial Intelligence in Endodontics: Current Applications and Future Directions

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SIGNIFICANCE

AI can be used in clinical scenarios like appointments, scheduling, diagnosis, treatment, and disease prediction in endodontics. AI models are designed to provide guidance and support to a dentist in his or her clinical practice.

ABSTRACT

Introduction: Artificial intelligence (AI) has the potential to replicate human intelligence to perform prediction and complex decision making in health care and has significantly increased its presence and relevance in various tasks and applications in dentistry, especially endodontics. The aim of this review was to discuss the current endodontic applications of AI and potential future directions. **Methods:** Articles that have addressed the applications of AI in endodontics were evaluated for information pertinent to include in this narrative review. **Results:** AI models (eg, convolutional neural networks and/or artificial neural networks) have demonstrated various applications in endodontics such as studying root canal system anatomy, detecting periapical lesions and root fractures, determining working length measurements, predicting the viability of dental pulp stem cells, and predicting the success of retreatment procedures. The future of this technology was discussed in light of helping with scheduling, treating patients, drug-drug interactions, diagnosis with prognostic values, and robotic-assisted endodontic surgery. **Conclusions:** AI demonstrated accuracy and precision in terms of detection, determination, and disease prediction in endodontics. AI can contribute to the improvement of diagnosis and treatment that can lead to an increase in the success of endodontic treatment outcomes. However, it is still necessary to further verify the reliability, applicability, and cost-effectiveness of AI models before transferring these models into day-to-day clinical practice. *(J Endod 2021;47:1352–1357.)*

KEY WORDS

Artificial intelligence; artificial neural networks; convolutional neural networks; endodontics

Artificial intelligence (AI) is a branch of applied computer science that was first described by John McCarthy in 1956[1]. AI has been described as the "fourth industrial revolution," which uses computer technology to simulate intelligent behavior, critical thinking, and decision making similar to humans[2,3]. AI has been shown to improve efficiency, accuracy, and precision similar to medical professionals in a more timely manner at a lower cost[3].

In health care, 2 types of AI are available: virtual and physical (robotics)[4]. The virtual type deals with mathematical algorithms used for diagnosis and prognosis[5], imaging and osteoporosis[6], scheduling appointments[7], drug dosage algorithms[8], drug interactions[9], and electronic health records[4]. The physical aspect includes robotic assistance in surgery[10], telepresence[11], rehabilitation[12], and socially assistive robots in the care of the elderly[13].

AI can exist of expert systems whereby a system is built to follow rules, sometimes fuzzy rules, created by a domain expert[2]. In machine learning, software algorithms are used that can learn relationships from examples without explicit instructions[14,15]. Although there are unsupervised learning systems that can identify clusters (eg, a system to identify different patient phenotypes from data in endodontics), most applications in dentistry use supervised learning in which training data include many samples, each with a variety of characteristics or features (eg, images of a patient, sex, age, number of caries, and more) and a ground truth determination (eg, endodontic visit or no endodontic visit)[2].

The AI algorithm learns the relationship between the features and ground truth using standard approaches (eg, random forest or support vector machine) or artificial neural networks (ANNs), which mimic a system of biological neurons with many neural connections that are adapted in "learning."

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With the advent of advanced graphics cards and algorithmic innovations, deep learning networks are now used. In deep learning, one uses ANNs with many layers of neurons, generating millions of neural connection weights to be adapted and enabling the system to learn very nonlinear relationships between features and ground truth determinations[16]. In imaging, because of the size of the data and because the actual feature of interest might be small (eg, the apex), convolutional neural networks (CNNs) are used whereby a network examines a subregion of the image that is moved about the image to make determinations[17]. In essence, CNNs process multiple images and use filtration to analyze those images[18].

Ethical challenges and potential risks are emerging legal considerations that add to the complexity of the system[19]. Applications of AI in dentistry have not been routine in dental practices[20]. However, the advent of these technologies has influenced imaging and pathology[21], dental image diagnostics[18,22], caries detection[23], electronic records[24], and robotic assistance[25].

AI systems have the potential to revolutionize the field of medicine and dentistry by identifying solutions in managing multiple clinical problems that have also made clinicians' tasks easier. AI research in endodontics has grown in parallel to other specialties in dentistry. The knowledge of the endodontist has to be updated in regard to the application of AI. Hence, the aim of this review was to discuss the literature related to the applications of AI in terms of diagnosis, clinical decision making, and predicting successful treatment in endodontics and, additionally, to identify existing gaps in the application of AI.

CURRENT APPLICATIONS OF AI IN ENDODONTICS

Detection

AI has been used in endodontics mostly by virtual employment such as the detection of periapical lesions, crown, and root fractures; working length determination; and morphology detection. These procedures describe the virtual aspect of AI (Table 1).

Detection of Periapical Lesions

The diagnosis and treatment planning of teeth with periapical lesions and/or symptoms can be challenging to clinicians. Apical periodontitis is a common disease that comprises approximately 75% of radiolucent jaw lesions[26]. Early detection might increase successful treatment outcomes[27], avoid spreading of the disease to surrounding tissues, and minimize further complications[28]. The most common 2-dimensional diagnostic aids used to identify apical periodontitis in day-to-day clinical practice are intraoral periapical radiographs and panoramic radiographs. Periapical lesions are usually noted as radiolucencies in the radiographs. However, information obtained from periapical radiographs is not accurate because the actual 3-dimensional anatomy is converted into a 2-dimensional image[29]. Hence, cone-beam computed tomographic (CBCT) imaging, a 3-dimensional imaging technology, was developed and has been used to accurately detect periapical lesions as well as their size and location. A meta-analysis reported that the accuracy values for detecting periapical lesions were 0.96, 0.73, and 0.72 for CBCT imaging, conventional periapical radiography, and digital periapical radiography, respectively[30]. However, the use of CBCT imaging resulted in less accuracy in diagnosing apical periodontitis in root-filled teeth[31].

Endres et al[32] reported that a deep learning algorithm model can match the diagnostic performance of 24 oral and maxillofacial surgeons in detecting periapical radiolucencies on panoramic radiographs. One study compared the ability of CNN models with 3 oral and maxillofacial radiologists in detecting simulated periapical lesions on intraoral radiographs. They concluded that the mean values of sensitivity, specificity, and area under the receiver operating characteristic curve per fold were greater in the CNN group compared with oral and maxillofacial radiologists' interpretations[33]. Ekert et al[34] reported that the potential of deep CNNs was accurate in the discriminatory ability to detect apical lesions on panoramic radiographs compared with dentists with more than 10 years of clinical experience. However, both the studies were conducted with a limited sample size and used panoramic radiography, a tool used very infrequently by endodontists for diagnosis[33,34]. Generally, the detection of a periapical lesion by a radiograph is subject to large variations between examiners, and discriminatory ability is based highly on an examiner's experience[34]. The variations between the examiners and bias can be reduced by using AI systems[27,34].

Deep learning segmentation proved to have excellent accuracy in detecting a periapical lesion on CBCT images[27]. The reliability of correctly detecting a periapical lesion from CBCT images by a CNN system was around 92.8%. Some authors have also reported that volume measurements conducted by a deep CNN system and humans were similar[35], whereas the volume deviation of lesions has not been considered, which might affect the reliability of the study[2].

The application of AI systems in detecting a periapical lesion from radiographs and CBCT scans might improve reliability and aid clinicians to reach detection accuracies similar to, or superior to, experienced specialists[27,32,34,35]. Additionally, it may reduce the diagnostic efforts of the dentist by saving assessment time and allowing semiautomated documentation. However, the sensitivity of AI systems should be improved, and additional studies should be conducted before its clinical application[34].

Poswar Fde et al[36] reported on different gene expressions for a periapical cyst versus a periapical granuloma. The authors analyzed the gene expression to differentiate between a cyst and a granuloma using a multilayer perceptron neural network for gene classification. The limitation of the study was that some data in the algorithm might not be present. The algorithm did not differentiate between physiological and inflammatory cytokines. However, the authors proposed that this methodology might be useful for distinguishing other biological processes (eg, biomarkers for cancers).

Zheng et al[37] compared an anatomically constrained Dense U-Net with existing biomedical image analysis algorithms regarding lesion detection accuracy and dice coefficient indices of a multilabel segmentation. Despite a small sample size, the authors reported that the novel deep learning algorithm allowed CBCT segmentation and the detection of pathosis with an increase in sensitivity and specificity.

Detection of Root Fractures

Vertical root fractures (VRFs) represent 2%–5% of crown/root fractures and are considered a serious complication that could result in either root resection or tooth extraction[38,39]. Radiographs and CBCT imaging help in detecting a VRF that can be difficult to diagnose. The lack of a definitive diagnosis may result in an unnecessary surgical procedure or tooth extraction. The clinical presentation and low sensitivity of conventional radiographs in the detection of VRFs frequently pose a diagnostic dilemma for a clinician. In their meta-analysis, Talwar et al[39] reported that CBCT imaging was better in detecting VRFs in unfilled teeth compared with radiographs, whereas radiographs were marginally better than CBCT imaging in root-filled teeth. Because of the inability of conventional methods to accurately detect VRFs, there has been a call for the development of alternative methods to improve

TABLE 1 - Current Applications of Artificial Intelligence (AI) in Endodontics

Aim	AI methods	Results
Detection of periapical lesions	ML, CNN, DL	The periapical lesion from radiographs and CBCT scans detected by AI might improve reliability and allow any clinician to reach diagnostic accuracies similar, or superior to, experienced specialists.
Detection of periapical cyst or granuloma	ML, ANN	The gene expression was analyzed to differentiate between a cyst and a granuloma using AI.
Detection of root fractures	ML, CNN, PNN	AI might be helpful in the detection of root fractures. Research in this area is promising and ongoing.
Working length determination	ML, ANN	AI might be helpful as an adjunct in aiding clinicians with working length determination.
Determination of morphology	DL, ML, CNNs	The algorithm developed by AI and information analysis was reported to measure the root canal curvature and its 3-dimensional modification after the instrumentation.
Prediction of retreatment	ML, CBR	The combination of methods was able to predict statistical probabilities for extraction.
Prediction of stem cell viability	ML, ANN (NFIS)	NFIS predicted cell viability after various regenerative protocols and challenges with microbial infection.

ANN, artificial neurons network; CBR, case-based reasoning; CNN, convolutional neurons network; DL, deep learning; ML, machine learning; NFIS, neuro-fuzzy inference system; PNN, probabilistic neural network.

the diagnosis of VRFs. Fukuda et al[40] reported that CNNs may be a promising tool to detect (recall = 0.75 [sensitivity], precision = 0.93 [positive predictive value], and F measure = 0.83 [index used to evaluate machine learning performance]) VRFs on panoramic radiographs. Another study sought to develop a probabilistic neural network to diagnose VRFs in intact and root-filled teeth on periapical radiographs and CBCT images[41]. They concluded that the detection of a root fracture on CBCT images is better in terms of accuracy, sensitivity, and specificity compared with images from 2-dimensional radiographs. However, this conclusion was made from an analysis of single-rooted premolar teeth. Future research should be conducted to study the ability of a probabilistic neural network to detect vertical root fractures in multirooted teeth.

Using synthetic data, Shah et al[42] created cracks in second molars and analyzed them with wavelets. These mathematical functions allow weak signal recovery from noisy environments in a machine learning approach. Despite a small sample size, cracks were reliably detected with high-resolution CBCT images using steerable wavelets. The authors proposed that the validity of this technique needed to be confirmed by *ex vivo* and clinical methodologies. In an *ex vivo* experiment, Vicory et al[43] simulated microfractures in 22 teeth with 14 teeth kept as the negative control group. Using wavelets and machine learning, the authors reported that a micro–computed tomographic image was more accurate than CBCT images in detecting fractured teeth. The authors reported that the positive predictive value of machine learning was superior to the observers' interpretation, but there was room for improvement. The authors stated that future research should have a larger sample size.

Working Length Determination

Correct working length determination is an important step in achieving success in root canal treatment outcomes. Various methods used for working length determination have included radiographic, digital tactile sense, the patient's response to a file or paper point inserted into a root canal system, electronic apex locators, and CBCT imaging[44–47]. In general, radiography and electronic apex locators are the most common methods used routinely by clinicians in dental practice. In digital radiography, the quality of the images plays a key role in the accurate interpretation of root canal system morphology[48]. However, various other factors influence radiographic interpretations, which could result in an incorrect diagnosis[49]. Hence, a need arises to develop computer-based methods to determine consistently accurate working lengths. Saghiri et al[47] reported that ANNs can be used as a second opinion to locate the apical foramen on radiographs, which can ultimately improve the accuracy of working length determination. In another study, Saghiri et al[50] investigated the accuracy of working length determination by an ANN in a human cadaver model to mimic the clinical situation. They found no difference in root length measurements when comparing an ANN with actual measurement after extraction. They also reported that the ANN (96%) performed superiorly in minor anatomic constriction determination compared with an endodontist (76%) using periapical radiographs. Hence, an ANN can be considered as an accurate method for working length determination.

Root and Root Canal System Morphology

Knowledge of root and root canal system variations is an important factor that influences the success of nonsurgical root canal treatment. Generally, periapical radiographs and CBCT imaging have been used for this purpose. CBCT imaging has demonstrated higher accuracy to assess the root and root canal configurations compared with radiographs. However, because of radiation issues, it cannot be recommended in routine clinical practice. Hiraiwa et al[17] reported that the deep learning system on panoramic radiographs demonstrated high accuracy in the differential diagnosis of a single or multiple root(s) in the distal roots of mandibular first molars. Learning models were created by extracting image patches from panoramic radiographs and inputting them into deep learning systems. The algorithm developed by AI and information analysis demonstrated the ability to measure the root canal curvature and its 3-dimensional modification after the instrumentation[51]. However, more studies are required to confirm the results of this study.

Lahoud et al[52] reported an automated 3-dimensional tooth segmentation using the CNN approach. The authors evaluated 433 CBCT radiographic segmentations of teeth in a timely, accurate, and efficient clinical reference and reported that AI performed as good as a human operator but much faster.

In another study but with panoramic radiography, the authors combined 2 deep CNNs and expert refinement[53]. Using 153 panoramic radiographs, the authors reported that the AI tool yielded a high sensitivity and specificity in a very fast performance for the detection and segmentation of teeth.

Predictions

Retreatment Predictions

Campo et al[54] reported on a case-based reasoning paradigm to predict the outcome of nonsurgical root canal retreatment with risks and benefits. The system in essence reported whether one should perform retreatment or not. The system included data from areas such as performance, recall, and statistical probabilities. The strength of the system is that it might be able to accurately predict the outcome of retreatment. The limitation was that the system would be only as good as the information in the data.

Case-based reasoning is the process of creating solutions to problems based on a previous encounter with similar past problems. By retrieving similar cases, important information and knowledge can be integrated. The issue with variability and the abundance of different approaches could create heterogeneity with this system[55]. It is important that future articles take this heterogeneity of a human approach under consideration and perhaps increase the sample size to achieve better sensitivity, specificity, and accuracy.

Predicting the Viability of Stem Cells

Bindal et al[56] evaluated the dental stem cells isolated from the dental pulp in various regenerative therapies using the neuro-fuzzy inference system. In a simulated clinical scenario, this system predicted the outcome by testing the viability of the stem cells after treatment with bacterial lipopolysaccharides. The neuro-fuzzy inference system was a tool to predict cell viability after various regenerative protocols that are challenged with microbial infection[56]. The authors measured the viability of dental pulp stem cells after lipopolysaccharide treatment to induce an inflammatory reaction. The authors then analyzed the accuracy level of the outcome using adaptive neuro-fuzzy interferences to predict cell viability of these stem cells after microbial invasion.

Gaps in AI and Endodontic Treatment

To date, there is no

1. Programming technology in appointment scheduling, patient management, and recall; as decisions on scheduling, appointment, delegation, and recall are constantly updated to meet the demands of the health care system, AI can schedule patient treatments based on the continuous needs and acquired medical information.
2. Procedure to inform the clinician about drug interactions and/or treatment adjustments based on the available electronic health record; as the population grows and more people live longer, they are taking more medications. If health care records can be made available, there is a potential for AI to predict patient-specific drug-drug complications.
3. Procedure to provide an accurate endodontic diagnosis based on medical, dental, and clinical findings; based on the acquired information and data collection, AI would be able to improve diagnosis and staging and to predict outcomes. This would include outcome prediction or prognostic risk determination.
4. Accurate physical and robotic microsurgical treatment available to the endodontist; in implant technology, robotic-assisted dental surgery can help the surgeon with proper navigation of the implant placement[57].

It would be expected that the same system would assist endodontists in navigation in endodontic surgery. The authors reported that the mean deviations of the implant robotic placement were as accurate as both static and dynamic navigations, but to date no comparative cohort studies have been done comparing robotic technology with traditional endodontic surgery or treatment. Future studies should compare the different techniques in accuracy and safety with a robotically guided placement.

CONCLUSION

In endodontics, AI might aid in clinical applications, particularly in the detection of periapical pathosis, root fractures, determination of working length, and prediction of disease. There is a need for high-quality evidence to evaluate the performance of AI regarding its reliability, applicability, legal and ethical considerations, and cost-effectiveness before widespread adoption into routine clinical practice.

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