Artificial Intelligence and Prognosis of Treatment in Endodontics

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KEYWORDS

• Prognosis • Treatment outcome • Artificial intelligence • AI • Machine learning • Deep learning • Endodontics • Root canal therapy

KEY POINTS

- Artificial intelligence (AI) is a promising tool for more effective treatment planning and predicting outcomes in the field of endodontics.
- This article focuses on the role of AI in evaluating factors that can directly/indirectly affect treatment outcomes/prognosis.
- Data on the application of AI to predict endodontic treatment prognosis are still limited and heterogeneous, which limits its translation to routine clinical practice.

INTRODUCTION

The term "Prognosis" means prediction of the outcome or course of a disease or a condition.[1] Treatment prognosis is crucial for informed clinical decision-making and improving patient outcomes in health care. Artificial intelligence (AI) is emerging as a tool in the health care sector, providing clinicians with data-driven insights for more effective treatment planning. In dentistry, the application of AI in terms of prognosis has reported promise in predicting tooth loss, dental implant survival, caries outcome, and orthodontic treatment outcomes, among others.[2]

One of the most critical aspects of prognosis in endodontics is to establish the definition of the intended outcome. Traditionally, the term "prognosis" or "success" in

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Abbreviations	
2D	2 dimensional
3D	3 dimensional
AAE	American Association of Endodontists
AGMB	Anatomy-Guided Multi-Branch
AI	artificial intelligence
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
AUC	area under the curve
BP-ANN	backpropagation ANN
CBCT	cone beam computed tomography
CNNs	convolutional neural networks
DPSCs	dental pulp stem cells
EMS	endodontic microsurgery
GBMs	gradient boosting machines
KNN	K-Nearest Neighbors
LPS	lipopolysaccharide
ML	machine learning
Ni-Ti	nickel titanium
NSRCTs	nonsurgical root canal treatments
PA	periapical
RCT	root canal treatment
REP	regenerative endodontic procedures
RF	Random Forest
ROC	receiver operating characteristics
SVR	support vector regression
XGBoost	extreme gradient boosting

endodontics has been based on clinical-centered outcomes such as the absence of radiographic findings and clinical signs and symptoms.[3] However, there has been a shift toward understanding and reporting patient-centered outcomes such as function, esthetics, pain, and retention of teeth. It is essential to understand that several preoperative, intraoperative, and postoperative factors can affect the prognosis or outcome of endodontic treatment.[4] In addition to the use of AI models to predict the success of nonsurgical and surgical endodontic treatments, studies have evaluated the application of AI on factors that could indirectly affect or predict endodontic outcomes. These include AI's application in assessing case difficulty and referral decisions, advancing endodontic instrumentation, deep caries management, regenerative endodontic procedures (REP), and postoperative care (**Table 1**).[5–10] By analyzing clinical variables and predicting outcomes, the application of AI can help refine endodontic treatment modalities.

ARTIFICIAL INTELLIGENCE IN ASSESSING CASE DIFFICULTY AND DECISION-MAKING

AI holds immense potential in evaluating case complexity by analyzing clinical, radiographic, and patient-related data. Machine learning (ML) techniques, such as decision tree classifiers and convolutional neural networks (CNN), are trained on large datasets to identify patterns and predict difficulty levels.[11] For example, AI systems trained using the American Association of Endodontists (AAE) Case Difficulty Assessment form have achieved notable sensitivity rates of 94.96%.[5] Lee and colleagues[2] demonstrated that decision tree classifiers could process radiographic data with an accuracy of 84.13%, considering factors such as canal morphology, lesion size, and apical anatomy. These advancements provide a consistent, objective framework for determining case difficulty and supporting referral decisions.[2,5]

Table 1
Main applications of included studies

Reference	AI Method	Application
AI in Assessment of Case Difficulty		
Herbst et al,[4] 2022	RF, GBM, and extremely gradient boosting (XGBoost)	Identification of significant associations between covariates and failures of NSRCT for predicting outcomes of RCT
Mallishery et al,[5] 2020	Machine learning-based analysis	Utilized AAE Case Difficulty Form and MI algorithms for predicting case difficulty and referral decisions
Bennasar et al,[12] 2023	Logistic regression, RF, Naive-Bayes, and KNN	ML models as a second opinion to support the clinical decision on whether to perform NSRCT
Signor et al,[13] 2021	J48 algorithm and Weka software	Predictability of NSRCT using clinical and radiographic features of apical periodontitis and the technical quality of endodontic treatment
AI in Deep Caries Management		
Ramezanzade et al,[6] 2023	ResNet-50	Predicting pulp exposure as an outcome measure after caries excavation
Zheng et al,[20] 2021	Convolutional Neural Networks (CNNs) of ResNet18 + C	Estimating deep caries and pulpitis
Wang et al,[21] 2023	DenseNet CNN and ResNet model	Predicting pulp exposures
AI in Regenerative Endodontic Procedures		
Bindal et al,[7] 2017	ANFIS-neural network learning algorithm	Predict the effect of LPS administration with different times and concentrations on the growth and viability of DPSCs.
Shetty et al,[26] 2021	OsiriX MD and 3D Slicer	3D software programs for pulp volume detection following REP.
AI and Non-surgical Endodontic Procedures		
Kazimierczak et al,[14] 2024	CNNs	AI-driven Diagnocat platform for CBCT evaluation to evaluate obturation quality, root canal filling density, and voids

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Table 1
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Reference	AI Method	Application
Guo et al,[8] 2021	ANN	Prediction and optimization of the force and torque applied during cleaning and shaping
Li et al,[34] 2022	AGMB Transformer Network	Evaluation of obturation quality on radiographic images
AI and Endodontic Microsurgery		
Qu et al,[15] 2023	Vector regression (SVR), and XGBoost	Determination of the difficulty level in surgical cases
Qu et al,[9] 2022	GBM and RF	Provides with surgical outcome when the required factors are entered and helps in decision-making
AI in Postoperative Pain and Flare-ups		
Nosrat et al,[10] 2023	RF algorithm	ML model to predict flare up
Gao et al,[44] 2021	MLstudy utilizing Backpropagation (BP) ANN	Predicting postoperative pain after RCT using patient demographics, inflammatory factors, and operative details

ML models like Random Forest (RF), a model based on multiple baseline variables or characteristics, and K-Nearest Neighbors (KNN) have been evaluated to assess the complexity and success of nonsurgical root canal treatments (NSRCTs).[12] A retrospective analysis of 119 NSRCT cases demonstrated that ML models outperformed expert clinical judgment in treatment prognosis, achieving up to 77% accuracy compared to 60%, therefore showing enhanced diagnostic sensitivity and decision-making when compared to clinician-based assessments.[12] By synthesizing these variables, AI provides a structured, data-driven approach that aligns seamlessly with clinical needs.

Herbst and colleagues[4] investigated the application of ML in predicting failure to heal after NSRCT. Analyzing 591 teeth, the study identified tooth-level factors such as alveolar bone loss and periapical (PA) index scores as the most critical predictors of failure (**Fig. 1**). ML models like RF and gradient boosting machines (GBMs) exhibited moderate predictive performance, achieving an area under the curve (AUC) of approximately 0.6 and accuracy levels between 75% and 80.5%. The research underscored the potential of ML for identifying high-risk cases and improving clinical prognosis.

AI has also been applied to retreatments. Signor and colleagues[13] used regression analysis and decision trees (J48 algorithm) to predict technical quality and PA healing in retreatments. Factors like root curvature, altered root canal morphology, and pre-existing PA lesions significantly influenced outcomes. The predictive models used

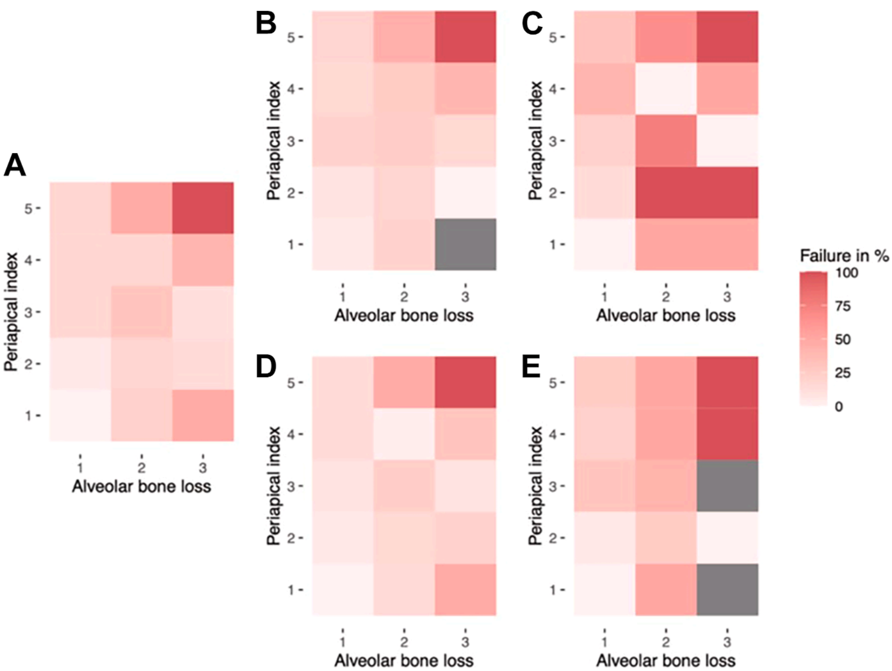

Fig. 1. Heat map of risk for failure of RT. Combined presence of a high periapical index (scored 1–5) and alveolar bone loss (scored 1: mild to none, 2: moderate, 3: severe alveolar bone loss) increased the risk of failure. (*A*) All risks factors pooled. (*B*) Nonsmokers. (*C*) Smokers. (*D*) Primary treatments. (*E*) Retreatments gray: no cases. (Herbst CS, Schwendicke F, Krois J, et al. Association between patient-, tooth- and treatment-level factors and root canal treatment failure: A retrospective longitudinal and machine learning study. J Dent 2022;117:103937.)

demonstrated an accuracy of 66.66% for assessing the technical quality of the root canal retreatment and 79.66% for predicting PA healing outcomes. These findings highlight the potential of decision tree analysis in evaluating the impact of clinical variables, such as root canal morphology and PA lesion size, on treatment success. The study highlighted that lesion size and root resorption strongly correlated with healing, emphasizing the importance of integrating clinical and radiographic data to enhance retreatment success.

Commercial AI-powered tools, like Diagnocat Ltd (San Francisco, CA, USA), demonstrate AI's clinical utility. Diagnocat analyses CBCT images to evaluate obturation quality, root canal filling density, and voids, providing actionable insights for treatment planning.[14] Kazimierczak and colleagues[14] demonstrated that Diagnocat achieved 84.1% accuracy in evaluating obturation quality, 88.6% accuracy in detecting voids in fillings, and 95.5% accuracy in detecting parameters such as overfilling and short fillings, significantly enhancing clinical decision-making.

Qu and colleagues[15] developed and validated ML models of support vector regression (SVR) and extreme gradient boosting (XGBoost) algorithms for case difficulty prediction in endodontic microsurgery (EMS). The study used dataset from 261 patients with 341 teeth, which had undergone apicoectomy. The XGBoost model was accurate in determining the difficulty level and had good generalization performance (mean absolute error = 0.1010, mean squared error = 0.0391, and median absolute error = 0.235). The top 3 factors that predicted the difficulty were lesion size, the distance between apex of the tooth and adjacent important anatomic structures and, root filling density (**Fig. 2**). This study did not take into consideration the thickness of the cortical bone over the roots to be treated, the buccal approach to palatal roots, or the proximity to the lingual cortical plate, grafting, periodontal status, restricted mouth opening, iatrogenic errors, and systemic factors that could alter clinical outcomes. ML models can be efficient in complex quantitative analysis and are independent of human skills and knowledge. Thus, they can provide accurate and objective suggestions to the clinicians to achieve predictable outcomes.

Schwendicke and colleagues[16] noted that AI significantly enhances decision-making by integrating diverse and complex datasets, such as imagery, medical histories, and sociodemographic data. With an accuracy of 84%, Hung and colleagues[17]

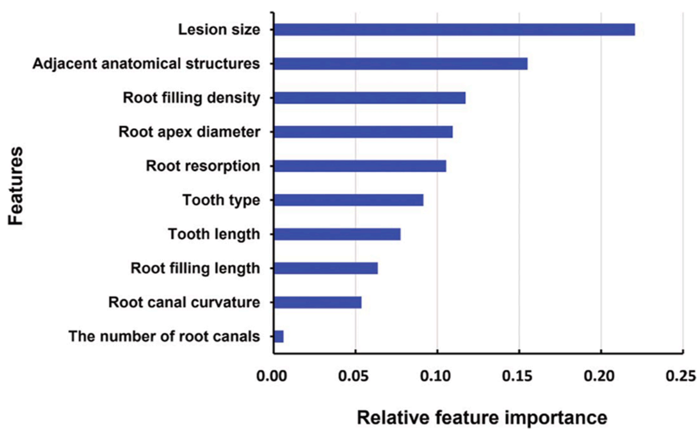

Fig. 2. Relative feature importance based on the XGBoost model. (Qu Y, Wen Y, Chen M, et al. Predicting case difficulty in endodontic microsurgery using machine learning algorithms. J Dent 2023;133:104522.)

demonstrated that ML, particularly RF and classification and regression trees, could effectively prioritize high-risk patients, enabling earlier interventions and better outcomes. However, current AI applications often provide limited information, which only partially supports the complexity of clinical decision-making. This highlights the need for outputs to be more actionable and transparent.[16]

ARTIFICIAL INTELLIGENCE AND DEEP CARIES MANAGEMENT

Deep caries management strategies have witnessed trends toward minimally invasive therapies, shifting from nonselective caries (complete) removal to selective caries (partial) removal, resulting in a lesser chance of pulp exposure.[18] Carious pulp exposures in nonselective caries removal have also been implicated with lower success rates for direct pulp capping and pulpotomy when compared to selective caries removal.[18] PA radiographs or bitewings have traditionally been used to assess caries depth.[19] However, the interpretation can be variable because of the 2 dimensional (2D) nature of radiographs, subjectivity among operators, and operator expertise.[6]

Pulp exposure has often been cited as a negative outcome during deep caries management, necessitating vital pulp therapy or endodontic treatment.[6] Zheng and colleagues[20] tested 3 different CNN models based on deep learning to estimate the depth of deep caries and predict pulpitis using PA radiographs. After training the CNNs, 127 periapical radiographs (PAs) were used to test the CNNs. The multimodal CNN of ResNet18 + C (ResNet18 integrated with clinical parameters) demonstrated significantly better performance in estimating deep caries and pulpitis.[20] This study has been corroborated by the findings of a study by Wang and colleagues,[21] wherein the DenseNet CNN and ResNet model had an AUC of 0.89 and 0.97, respectively, which was similar to the accuracy of experienced dentists in predicting pulp exposures. However, this study did not consider any clinical parameters for pulp exposure prediction.[21] A recent study by Ramezanzade and colleagues[6] employed a multipath neural network based on ResNet-50 architecture for predicting pulp exposure as an outcome measure after caries excavation. In addition, the study investigated the effect of providing AI-based radiographic information versus standard radiographic information to 25 dental students in assessing how this would affect their predictions of pulp exposure. Multipath neural networks outperformed the students, achieving a significantly higher F1 score when predicting pulp exposure. Interestingly, there was no statistical difference between dental students with and without access to AI predictions. This might be attributed to the expertise level in interpreting caries depth as the students were in the fourth and fifth years of dental school.[6]

The use of AI technology, especially CNNs based on deep learning, has significantly advanced image analysis. Cumulatively, these studies demonstrate the acceptable accuracy of these models in predicting pulp exposures.[6,20,21] This might help dentists determine prognoses of deep caries management and customize treatment plans accordingly. It is important to note that several factors, such as operator expertise, type of CNN and associated learning curve, tooth type, depth, and location of caries, can affect the accuracy. To extrapolate the results of these studies to routine clinical settings, more studies are needed to validate the effect of these factors in AI interpretation and integration.

ARTIFICIAL INTELLIGENCE AND REGENERATIVE ENDODONTIC PROCEDURES

REPs have emerged as a promising treatment modality for managing immature teeth with infected root canal spaces.[22] The primary outcome of successful REP is to achieve radiographic bony healing and resolve clinical signs and symptoms. In addition, continued root maturation regarding root length and width is another more pertinent outcome while managing immature teeth.[22] This latter outcome has been attributed to the deposition of dentin-like or osteoid tissue subsequent to differentiation of dental mesenchymal stem cells into different cell phenotypes.[22]

Survival and differentiation of dental mesenchymal stem cells is a crucial prognostic factor in the outcome of regenerative therapies.[23] Several studies have reported the effect of microbes and their toxins, such as lipopolysaccharide (LPS), on dental stem cells' differentiation, proliferation, and migration.[24] However, evaluating the synergistic impact of varying concentrations of LPS and treatment times on stem cells has been challenging. To overcome this, a recent study by Bindal and colleagues[7] has investigated using an adaptive neuro-fuzzy inference system (ANFIS), an AI computational model that combines the fuzzy inference system with a neural network-learning algorithm, to predict dental pulp stem cells (DPSCs) viability. In this in vitro study, DPSCs were systematically isolated and subject to varying concentrations of LPS for different time intervals of up to 72 hours. The AI model displayed sufficient accuracy (root mean square error [RMSE] = 0.0288, R^2 = 0.81) in predicting the simultaneous effect of LPS concentration and treatment time on the viability of DPSCs.[7]

Continued root formation due to mineralized tissue deposition is an important outcome of REPs in immature teeth.[25] This outcome has traditionally been evaluated using 2D imaging, such as PA radiographs.[26] Utilizing a segmentation model, Shetty and colleagues[26] have demonstrated the accuracy of 2 AI-based imaging programs, that is, OsiriX MD and 3D Slicer, to estimate the difference in pulp space volume following a REP.[26] In vitro assessments were performed initially to assess the 2 programs' sensitivity and reliability, followed by clinical validation on 35 permanent immature teeth with necrotic pulps and PA pathoses. The results demonstrated a statistically significant decrease (P<.05) in pulp volume after REP; however, there was no significant difference between the 2 imaging programs in estimating pulp space volumes.[26] Compared to the Food and Drug Administration-approved program OsiriX MD, the 3 dimensional (3D) slicer is a free, open-source imaging program that turned out to be faster to use with less user interaction, showing more promise for clinical application.[26]

The limited amount of AI data on evaluating REP prognosis outcomes is focused on assessing stem cell viability and estimating pulp space volume.[7,26] Owing to the in vitro nature of study by Bindal and colleagues[7] on assessing stem cell viability, several in vivo variables that could affect stem cell survival were not considered during the study. This limits the extrapolation of the results to clinical settings. In addition, as the study focused only on DPSCs, the results cannot be generalized to other stem cell populations, especially Stem Cells from Apical Papilla, which plays a significant role in REP.[22] Despite these limitations, the neuro-fuzzy AI model is a promising tool for conducting future studies to evaluate the effect of other treatment-related and in vivo factors on the viability of various stem cells. The AI imaging programs used by Shetty and colleagues[26] were limited by the ability to accurately quantify the hard tissue deposition on the canal walls, which questions whether the reduction in volume was because of increased thickness in root width or a result of intracanal calcification, which can be a potential complication for future endodontic intervention. This was attributed to limitations of cone beam computed tomography (CBCT) imaging, such as low contrast and background noise.[26] Despite these limitations, this study can be a foundation for future research to analyze the use of segmentation models with AI-based imaging programs to assess volumetric changes in endodontic outcomes.

ARTIFICIAL INTELLIGENCE AND NONSURGICAL ROOT CANAL TREATMENT AND RETREATMENT

The aim of endodontic instrumentation is cleaning, shaping, and preparing the root canal system for disinfection and obturation. Rotary nickel titanium (Ni-Ti) files have revolutionized root canal shaping by reducing the risk of file fracture and improving canal cleaning efficiency.[27] Advances in technology, such as electronic apex locators and CBCT have reduced procedural errors and help achieve more predictable treatment results.[28] Despite these advances, challenges such as instrument separation, canal transportation, and obstruction still pose a clinical challenge.[29,30]

A recent study by Guo and colleagues[8] used the ML model of artificial neural network (ANN) for the prediction and optimization of the force and torque applied during cleaning and shaping. In this in vitro study, the proposed model had an accurate precision in the force and torque prediction (error <14%). Based on the data, this ML model can help dentists to accurately select the size of Ni-Ti file and set the speed of the rotary instrument below the suggested range to avoid file separation and perforation.

After thorough instrumentation of the canals, obturation aims to achieve a complete, 3D seal from the apex to the coronal end of the canal to effectively prevent microbial leakage.[31] Adequate obturation ensures the long-term success by preventing post-treatment apical periodontitis.[32] Precise evaluation of the obturation is very significant since underfilling and overfilling can lead to endodontic treatment failures.[33]

Li and colleagues[34] proposed an automatic and accurate evaluation method for the root canal therapy results using ML tools. This clinical study utilized medical image classification and segmentation to automate the evaluation of obturation quality on radiographic images by employing advanced computer vision and AI techniques. The AI model of Anatomy-Guided Multi-Branch (AGMB) Transformer Network can improve the diagnosis accuracy from 57.96% to 90.20%.

Integrating AI into endodontic instrumentation holds the potential to significantly enhance the precision, efficiency, and predictability of root canal therapy. AI's ability to monitor instrument usage and canal shaping can help improve clinical outcomes by minimizing complications like instrument separation and canal transportation. While challenges such as data integration, clinician acceptance, regulatory considerations, and limited clinical studies remain, the continued development of AI in endodontics promises to revolutionize the field.

ARTIFICIAL INTELLIGENCE AND ENDODONTIC MICROSURGERY

EMS aims at addressing complex cases of endodontic treatment failure or infection. Successful surgical outcome hinges on precise clinical and radiographic diagnosis, careful treatment planning, and execution.[35] AI is leveraging on data analysis and ML algorithms to enhance surgical outcome forecasting. Recent studies have used AI-driven systems that analyze extensive datasets of patient records and radiographic imaging, identifying patterns and correlating clinical variables that human practitioners might overlook.[36–38]

A recent study by Qu and colleagues[9] aimed at establishing ML models to predict the prognosis of EMS. They trained and evaluated the GBM and RF models of ML. For the GBM model, the predictive accuracy was 0.80, with a sensitivity of 0.92, specificity of 0.71. For the RF model, the accuracy was 0.80, with a sensitivity of 0.85, specificity of 0.76 (**Fig. 3**). The GBM and RF models can immediately output a most likely surgical outcome when the required factors are entered, thus providing an objective reference for clinicians in decision-making. The study analyzed their algorithm on a dataset of

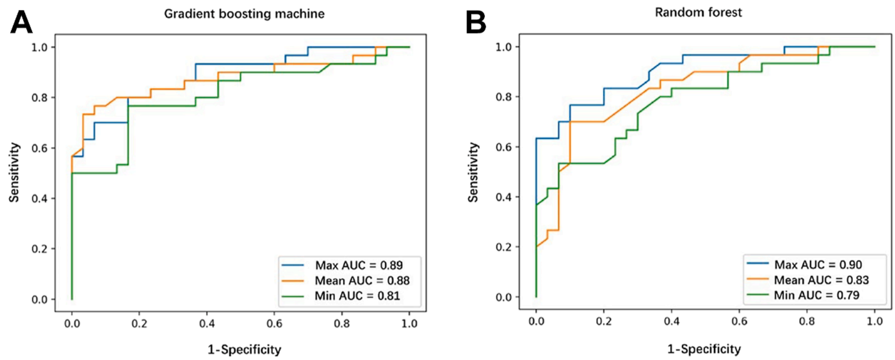

Fig. 3. Receiver operating characteristics (ROC) curves and the resulting area under the curves (AUCs). (*A*) ROC curves of the gradient boosting machine model, mean AUC = 0.88 (95% CI 0.81–0.89); (*B*) ROC curves of the Random Forest model, mean AUC = 0.83 (95% CI 0.79–0.90). (Qu Y, Lin Z, Yang Z, et al. Machine learning models for prognosis prediction in endodontic microsurgery. J Dent 2022;118:103947.)

234 teeth from 178 patients and found that out of the 8 variables used to predict prognosis, both models contained sex, age, size of the lesion, and type of bone defect in the top-ranking features (**Fig. 4**). The study was limited by the small datasets of unhealed cases.

The success rate of EMS is greater than 90%.[39–41] Integrating AI in predicting success rate of EMS can revolutionize outcomes by helping endodontists in providing personalized treatment recommendations, risk assessment, assist in robotic surgery, and provide real-time and posttreatment monitoring in EMS.[42] AI models need diverse and accurate data to make reliable predictions as it depends largely on the quality and quantity of the data it is trained on. To predict success of EMS, the data availability of high-resolution CBCT imaging and patient history is limited. AI lacks the refined clinical judgment as that of trained clinician. It faces significant limitations related to adaptability and integration with the existing diagnostic, imaging, and surgical systems used in endodontics. Consolidating the static and historical data that the AI is trained on along with complex biological systems that affect tissue and immune response, healing rates, and complications during EMS is yet another challenge that researchers and clinicians are facing. As AI continues to evolve and as more high-quality data becomes available, it is a promising tool to improve surgical care and will likely complement and augment the expertise of human clinicians.

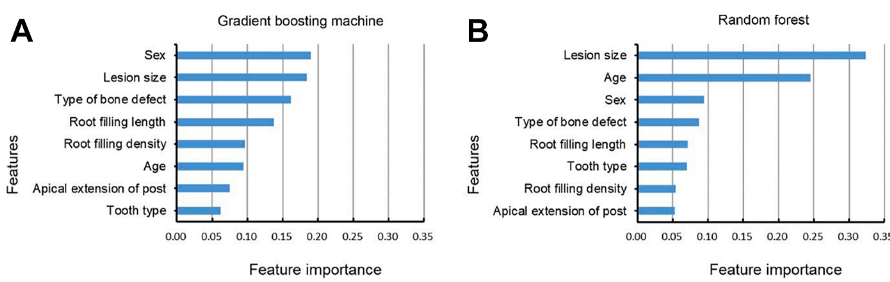

Fig. 4. Feature importance of top 8 features contributing to (*A*) the gradient boosting machine model and (*B*) random forest model. The values were normalized to the range from 0 to 1. (Qu Y, Lin Z, Yang Z, et al. Machine learning models for prognosis prediction in endodontic microsurgery. J Dent 2022;118:103947.)

ARTIFICIAL INTELLIGENCE AND POSTOPERATIVE PAIN AND FLARE UPS

Pain is one of the most significant health care crises in the United States.[43] Despite our best efforts, 15% to 25% of patients suffer from postoperative pain after root canal treatment (RCT), which can affect the quality of life and other patient-centered outcomes.[44] In some instances, flare-ups can occur, which are unexpected occurrences or exaggeration of pain and/or swelling after endodontic intervention.[10]

Gao and colleagues[45] evaluated using backpropagation ANN (BP-ANN) with 13 variables as inputs to predict postoperative pain 1 week after RCT. The accuracy of this BP neural network model was 95.60% for the prediction of postoperative pain following RCT. Most of the variables used as inputs for this model are well-established factors associated with postoperative pain.[45] However, this study did not account for psychological factors associated with pain and only evaluated short-term postoperative pain for 1 week.[45] A study by Nosrat and colleagues[10] evaluated an RF algorithm, an ML model based on multiple baseline variables or characteristics, to predict the occurrence of flare-ups following nonsurgical retreatment in 2846 patients. Their results indicated a weak performance of the model to predict the occurrence of flare-ups (precision = 0.13). This was attributed to the rarity of flare-ups in their study (4%), and the validity of baseline characteristics was questioned to predict flare-ups in clinical settings.[10]

Pain is an important patient-reported outcome measure that has garnered significant interest in clinical research and practice. Postoperative discomfort and pain can be disruptive and can affect dentist–patient relationships. The use of BP-ANN by Gao and colleagues[45] showed high accuracy in predicting postendodontic pain. This high accuracy was attributed to applying the BP-ANN AI model, which can run complex analyses of numerous strongly coupled variables and effectively deal with nonlinear problems. The BP-ANN model also benefits from its self-learning capability and strong simulation ability.[45] In contrast, the RF algorithm based on the ML model in the study by Nosrat and colleagues[10] displayed a limited ability to predict “flare-ups.” This result was also attributed to the rare nature of the event. As there is data scarcity to train the model, it suffers from a problem known as “class imbalance,” where the skewed dataset can lead to biased results in poor prediction of a rare event.[46]

SUMMARY

AI is becoming an integral part of endodontic practice with the potential to transform how clinicians predict treatment prognosis and make critical decisions. It can provide actionable insights by analyzing complex data, assessing case difficulty, optimizing procedures, and improving patient outcomes. Specifically, in the field of endodontics, AI’s impact is evident by its use in deep caries management, regenerative procedures, postoperative pain prediction and microsurgery case selection and outcomes. Although AI has demonstrated significant potential in predicting treatment outcomes, there can be further refinements. Continued research is critical to improve its accuracy and dependability. Advances in data integration and algorithm development will play an integral role in pushing AI closer to its full potential in the field of endodontics.

CLINICS CARE POINTS

- Clinicians should be aware that multiple prognostic factors can directly or indirectly affect the outcome/prognosis of endodontic treatment.

- The application of AI to analyze clinical, radiographic, and patient-related data can help accurately assess case complexity and help in decision-making and referral decisions, impacting the outcome of the intended treatment.
- The influence of AI in predicting the prognosis of nonsurgical and surgical endodontic treatments can significantly impact patient care.
- AI models will help clinicians in patient counseling and customize treatment plans based on case complexity, patient needs, and predictive data analytics.
- AI models must be trained and validated on large and diverse datasets to serve as reliable tools suitable for clinical practice.
- Ethical and regulatory concerns must be addressed before the routine application of AI in endodontic practice.

DISCLOSURE

None.

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