

Review

Artificial Intelligence in Endodontic Diagnostics: Current Applications, Clinical Performance, Limitations, and Future Perspectives—A Narrative Review

Mateusz Radwanski ^{1,*}, Ewa Zmysłowska-Polakowska ¹, Tan Fırat Eyüboğlu ^{2,3}, Mutlu Özcan ³
and Monika Lukomska-Szymanska ⁴

¹ Department of Endodontics, Medical University of Lodz, 251 Pomorska Str., 92-213 Lodz, Poland; ewa.zmyslowska-polakowska@umed.lodz.pl

² Department of Endodontics, Faculty of Dentistry, Istanbul Medipol University, Cibali Mahallesi, Atatürk Bulvarı, No: 27, 34083 Istanbul, Turkey; tfeyuboglu@yahoo.com

³ Clinic of Masticatory Disorders and Dental Biomaterials, Center for Dental Medicine, University of Zurich, Plattenstrasse 11, CH-8032 Zurich, Switzerland; mutlu.ozcan@zzm.uzh.ch

⁴ Department of General Dentistry, Medical University of Lodz, 251 Pomorska Str., 92-213 Lodz, Poland; monika.lukomska-szymanska@umed.lodz.pl

* Correspondence: mateusz.radwanski@umed.lodz.pl; Tel.: +48-426757418

Abstract

Artificial intelligence (AI) has emerged as a promising tool in endodontic diagnostics, particularly in radiographic interpretation and treatment outcome prediction. This narrative review provides a comprehensive overview of current applications of machine learning (ML) and deep learning (DL) algorithms in endodontics, focusing on periapical lesion detection, assessment of root canal morphology, prognosis prediction, and navigation-guided procedures. A literature search was conducted in PubMed, Scopus, and Web of Science for studies published between 2021 and 2026. Following qualitative screening, 45 studies were included in the evidence synthesis. Given the narrative design of the review, no formal meta-analysis was performed. The reviewed evidence indicates that convolutional neural networks (CNNs), U-Net architectures, YOLO-based systems, and other AI models have demonstrated promising diagnostic performance across multiple imaging modalities, with the highest performance generally reported for CBCT-based applications. However, the current body of evidence remains limited by retrospective study designs, small datasets, methodological heterogeneity, and insufficient external validation. Overall, AI should be considered a valuable adjunctive decision-support tool in endodontic diagnostics rather than a replacement for clinical expertise. Further prospective multicenter studies, external validation, and standardized methodological frameworks are required to support its reliable integration into routine clinical practice.

Keywords: artificial intelligence; navigation-guided endodontics; periapical lesions; prognosis; root canal morphology



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1. Introduction

Endodontic diagnosis is a complex process focused on assessing the condition of the dental pulp and periapical tissues in order to establish an appropriate treatment plan. It is based on the correlation of patient symptoms, clinical examination, and radiographic assessment, including medical and dental history, pain analysis, pulp sensibility tests, percussion and palpation tests, periodontal evaluation, and imaging [1,2].

One of the main challenges is the subjective nature of symptoms and the often limited correlation between clinical findings and the actual pulpal condition. In addition, some pathologies may remain asymptomatic, making differential diagnosis difficult [1,3]. Radiographic examination plays a key role in endodontics. Conventional periapical radiographs are widely used but have limitations inherent to two-dimensional imaging, including anatomical superimposition and reduced sensitivity for early lesions. Therefore, cone-beam computed tomography (CBCT) has become increasingly important, especially in complex cases, due to its ability to provide three-dimensional visualization of dental structures [4,5].

Despite technological advances, accurate endodontic diagnosis still largely depends on the clinician's experience and interpretive skills, highlighting the growing need for more objective and advanced diagnostic approaches, including the use of artificial intelligence [6,7].

Artificial intelligence (AI) has become one of the fastest-growing technologies in modern medicine and dentistry, offering new possibilities for improving diagnostic accuracy, treatment planning, and clinical decision-making [8,9]. Recent advances in machine learning (ML) and deep learning (DL), particularly convolutional neural networks (CNNs), have significantly contributed to the development of AI applications in dentistry and endodontics [7].

In dental imaging, AI systems are trained on large collections of annotated datasets, including radiographs, CBCT scans, and intraoral images, enabling the identification of patterns associated with both normal anatomy and pathological conditions. Deep learning models, particularly convolutional neural networks (CNNs), can automatically extract relevant features such as shape, density variations, and spatial relationships, enabling automated detection, classification, and segmentation in dental image analysis [10–12]. The general workflow of AI-based diagnostic systems, including data acquisition, annotation, model training, and clinical prediction processes, is illustrated in Figure 1.

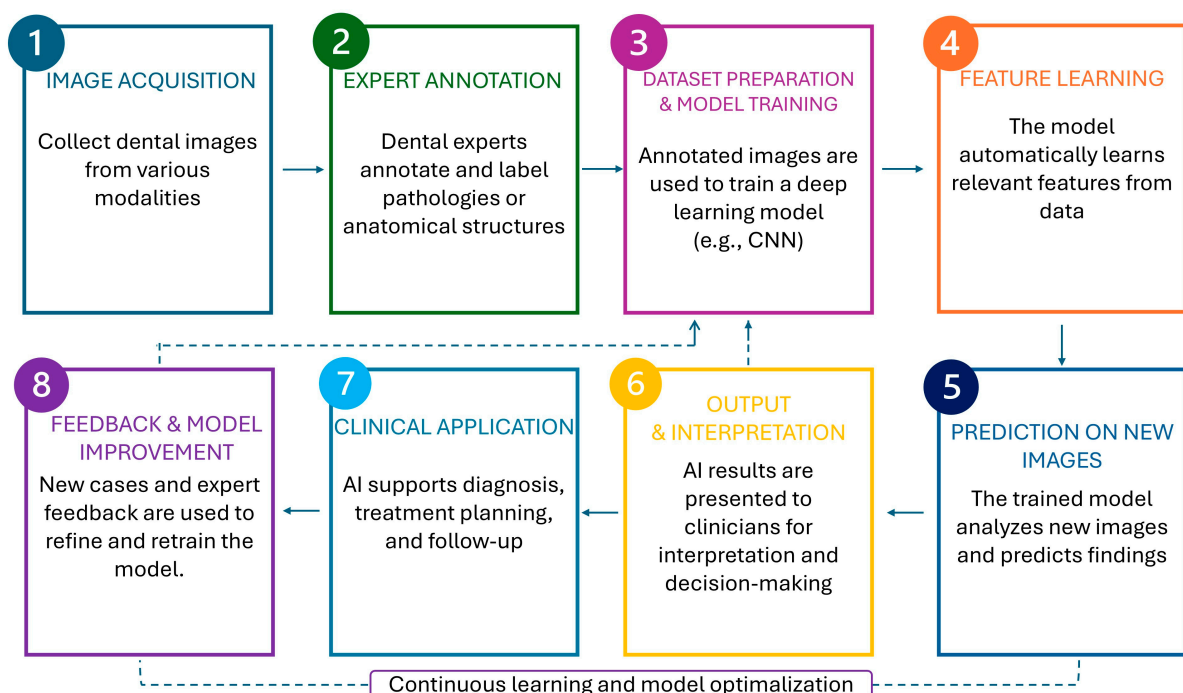


Figure 1. Workflow of artificial intelligence (AI) in dental image analysis, from image acquisition and model training to automated diagnosis and clinical decision support.

Although these technological developments have demonstrated promising diagnostic performance in various imaging-based applications, including CBCT-based lesion detection, the current body of literature remains highly heterogeneous, encompassing variations in imaging modalities, dataset characteristics, annotation protocols, and evaluation metrics.

Furthermore, many studies rely on retrospective datasets and controlled experimental conditions with limited external validation, which may affect the generalizability and clinical applicability of reported results [13–15].

Due to their ability to rapidly and consistently process large numbers of radiographic images, AI algorithms have the potential to enhance diagnostic precision, reduce human error, and support clinicians in everyday endodontic practice [9,12]. However, the performance of AI systems is strongly influenced by factors such as dataset quality, imaging modality, anatomical complexity, and validation methodology; therefore, reported high accuracy values should be interpreted with caution, particularly in the absence of prospective and real-world clinical validation [14,15]. Furthermore, although the number of published studies is rapidly increasing, a large proportion of research focuses on a limited set of diagnostic tasks and similar methodological frameworks, which may restrict the translation of AI developments into broader clinical applications [16]. Consequently, AI is becoming an increasingly important tool in modern endodontic diagnostics.

Nevertheless, the integration of AI into routine clinical workflows remains challenging, and its actual impact on clinical decision-making and patient outcomes is still not fully established. Therefore, a critical synthesis of the available literature is required to better understand the real clinical value of AI systems and to identify existing gaps and limitations.

Therefore, the aim of this narrative review is to provide a structured and comprehensive synthesis of current applications of artificial intelligence in endodontic diagnosis, with particular emphasis on diagnostic performance, clinical applicability, methodological limitations, and future perspectives. In contrast to previous reviews focusing on specific aspects of artificial intelligence in endodontics, the present review integrates evidence across the major domains of endodontic diagnosis, thereby providing a clinically oriented perspective on the current status, limitations, and future role of AI in endodontic practice.

2. Materials and Methods

2.1. Review Design

This narrative review provides a structured, comprehensive synthesis of current knowledge on the applications of AI in endodontic diagnosis. Due to the rapidly evolving and interdisciplinary nature of the topic, encompassing artificial intelligence, machine learning, deep learning algorithms, dental imaging, and endodontic diagnostics, a narrative review approach was considered appropriate to enable a flexible, clinically oriented interpretation of heterogeneous evidence.

The review is designed to summarize major application areas, evaluate reported diagnostic performance, and highlight key methodological limitations and considerations relevant to clinical practice.

2.2. Search Strategy

A literature search was conducted using the electronic databases PubMed, Scopus, and Web of Science to identify studies investigating the applications of AI in endodontic diagnostics. The search strategy incorporated combinations of keywords and indexed terms related to AI, dental imaging, and endodontics, including: “artificial intelligence,” “machine learning,” “deep learning,” “convolutional neural networks,” “CNN,” “endodontics,” “endodontic diagnosis,” “periapical lesions,” “root canal morphology,” “CBCT,” “cone-beam computed tomography,” “dental imaging,” “navigation-guided endodontics,” and “augmented reality,” combined using Boolean operators (AND, OR).

Articles published in English between 2021 and 2026 were considered for inclusion. The retrieved records were independently screened by two reviewers, and duplicate records identified across the databases were manually removed. Additionally, the reference lists

of selected articles and relevant review papers were manually screened to identify further eligible studies. A total of 58 records were identified through searches of PubMed, Scopus, and Web of Science. After screening according to the predefined inclusion and exclusion criteria, 13 records were excluded, leaving 45 studies for inclusion in the review. These studies addressed periapical lesion detection ($n = 20$), root canal morphology and anatomical variation detection ($n = 15$), prognosis prediction and treatment outcome assessment ($n = 4$), and AI applications in navigation-guided endodontics ($n = 6$).

2.3. Inclusion and Exclusion Criteria

The included studies comprised original research articles, clinical studies, and observational studies published in peer-reviewed journals that investigated the application of AI in endodontic diagnostics. Previously published systematic and narrative reviews were considered only for contextual background and were not used as primary evidence in the synthesis of results.

Studies focusing on AI-assisted detection of periapical lesions, assessment of root canal morphology, radiographic interpretation, working-length determination, and prediction of endodontic treatment outcomes were included.

Publications were excluded if they were not directly related to endodontics, published in languages other than English, lacked sufficient methodological description, represented conference abstracts, editorials, or opinion papers, or if the full text was unavailable.

2.4. Diagnostic Performance Metrics

The diagnostic performance of AI models was evaluated using commonly reported metrics, including sensitivity (recall), specificity, accuracy, area under the receiver operating characteristic curve (AUC), F1-score, and Dice coefficient. Sensitivity reflected the ability of AI systems to correctly identify positive cases, whereas specificity indicated the ability to correctly identify negative cases. Accuracy represented the overall proportion of correctly classified findings. AUC was used to evaluate the overall discriminative performance of AI models across different decision thresholds, with values closer to 1.0 indicating superior diagnostic capability. F1-score and Dice coefficient were mainly used in classification and segmentation studies to evaluate detection and segmentation agreement performance.

Given the narrative nature of this study, no formal meta-analysis, quantitative synthesis, or quality assessment, including risk-of-bias evaluation of the included studies, was conducted. Instead, the selected literature was qualitatively and thematically analyzed and organized into five key domains: (i) detection of periapical lesions, (ii) assessment of root canal morphology and anatomical variations, (iii) prognosis prediction and treatment outcome assessment, (iv) applications of artificial intelligence in navigation-guided endodontics, and (v) limitations and future perspectives.

3. Applications of AI in Endodontic Diagnosis

3.1. Detection of Periapical Lesions

Periapical lesions are radiographic manifestations of apical periodontitis that significantly influence the prognosis and outcome of root canal treatment. AI has demonstrated promising diagnostic performance in detecting periapical lesions across multiple imaging modalities, including panoramic radiographs, periapical radiographs, and CBCT scans.

The highest overall diagnostic performance was generally reported in studies using CBCT imaging. CBCT-based AI systems, including PAL-Net, SpatialConfiguration-Net, modified U-Net architectures, and CBCT-SAM models, frequently achieved excellent accuracy and specificity values, often reported to exceed 0.97–0.99 under specific conditions [13–15]. Particularly high specificity values approaching 1.0 were observed in several CBCT segmen-

tation studies, indicating very few false-positive detections. However, sensitivity values in some CBCT-based segmentation systems remained relatively moderate, especially in models primarily optimized for lesion segmentation rather than initial lesion detection. For example, Chau et al. [15] reported specificity values above 0.99 for CBCT-SAM and PAL-Net models, whereas sensitivity values ranged from approximately 0.62 to 0.72. These findings suggest that CBCT-based AI systems may be highly effective in confirming the presence of lesions.

Studies using periapical radiographs generally showed the most balanced and stable diagnostic performance across imaging modalities. Most AI systems achieved sensitivities of approximately 0.90 to 0.98, while maintaining high accuracy, often above 0.90 [16–19]. Particularly strong performance was reported for conventional CNN-based architectures such as AlexNet, GoogleNet, ResNet, and ConvNeXt, as well as YOLOv3-based systems and commercial platforms including Diagnocat. High diagnostic performance was consistently reported across studies, with sensitivity and accuracy reaching up to 0.985 and 0.962, respectively. CNN-based systems also demonstrated high specificity and overall diagnostic accuracy [18,19]. The consistently strong performance observed with periapical radiographs may be related to the high spatial resolution and improved visualization of the apical region afforded by intraoral imaging, thereby facilitating the identification of small inflammatory lesions by AI algorithms. These findings suggest that conventional periapical radiographs may serve as effective data sources for AI-assisted detection, particularly in controlled or well-defined imaging conditions.

The greatest variability in diagnostic performance was observed in studies based on panoramic radiographs (OPG). Sensitivity values ranged widely, from 0.33 in the study by Kazimierczak et al. [20] to 0.98 in the YOLOv3 Darknet model evaluated by İçöz et al. [21]. However, considerable variability in diagnostic performance was observed across studies, as discussed in previous reviews, with some AI models achieving very high specificity, approaching 1.00, but comparatively lower sensitivity, suggesting limitations in detecting certain periapical lesions [22,23]. In contrast, studies using Faster R-CNN, YOLOv3, DentisToday CNN, U-Net, RetinaNet, Cascade R-CNN, and hybrid CNN architectures demonstrated generally promising diagnostic capability, with several investigations reporting accuracy values approaching or exceeding 0.90 [24–27]. Some studies additionally observed that AI systems achieved higher specificity than sensitivity, suggesting greater ability to exclude healthy cases than to detect small or early lesions [20,22,23,28]. The substantial heterogeneity observed among panoramic imaging studies likely reflects the intrinsic limitations of panoramic radiography, including anatomical superimposition, geometric distortion, variable image quality, and lower spatial resolution compared with CBCT and periapical radiographs. Nevertheless, several AI systems achieved very high sensitivity values, indicating that appropriately trained deep learning models may still provide clinically useful support.

Overall, AI performance in detecting periapical lesions was influenced by tooth group and anatomical location. The evaluated studies reported higher diagnostic accuracy for mandibular teeth and lower performance in the posterior maxillary regions due to anatomical superimposition and interference from the maxillary sinus [29,30]. Similarly, İçöz et al. [21] observed more accurate lesion detection in mandibular compared with maxillary teeth on panoramic radiographs. In contrast, Ngoc et al. [17] found no significant differences between anterior and posterior teeth on periapical radiographs. Overall, posterior maxillary anatomy remains one of the major challenges for AI-assisted radiographic interpretation.

Collectively, analysis of different AI model families also revealed important functional differences among architectures. YOLO- and Faster R-CNN-based systems generally demonstrated strong lesion detection and localization capabilities, achieving high sensitivity and effectively identifying pathological regions on radiographic images [26,31]. In contrast, U-Net-based architectures and their modifications were predominantly used for

segmentation tasks, particularly in CBCT studies involving lesion outlining and volumetric analysis [15,29]. Commercial AI systems such as Diagnocat frequently demonstrated very high specificity but more variable sensitivity across different datasets and imaging modalities [28,30,32]. This pattern may reflect differences in model optimization strategies, with some systems prioritizing the reduction in false-positive findings at the potential expense of sensitivity for smaller or less distinct lesions.

3.2. AI Applications in Root Canal Morphology Assessment and Anatomical Variation Detection

Accurate assessment of root canal anatomy is essential for successful endodontic treatment, as missed canals or anatomical variations may lead to inadequate debridement, persistent infection, and treatment failure. Anatomical structures such as mesiobuccal (MB2) canals, C-shaped canals, accessory canals, and canal bifurcations are often difficult to identify using conventional dental radiographs, particularly in molars [33–35].

The studies summarized in Table 1 and Figure 2 demonstrate that artificial intelligence (AI) models have reported high diagnostic performance in detecting, classifying, and segmenting root canal morphology and anatomical variations. AI has shown promising results, particularly in MB2 canals, C-shaped canals, pulp stones, and taurodontism. Most studies applied convolutional neural networks (CNNs), U-Net architectures, YOLO-based models, or machine learning algorithms to panoramic radiographs and CBCT scans [36–38].

Table 1. Summary of studies evaluating artificial intelligence models for detection, classification, and segmentation of root canal morphology and anatomical variations.

Study	Imaging Modality	AI Model	Compared Against	Key Outcome
MB2 detection				
Caraiane et al., 2025 [39]	PA radiographs	CNN + heatmaps	Two experienced endodontists	AI achieved higher sensitivity and accuracy in MB2 detection
Ourang et al., 2025 [40]	PA radiographs	ResNet, DenseNet, MobileNet, DINO, BYOL, SimCLR	Endodontist, resident, OMFR	AI models performed similarly to clinician experts
Albitar et al., 2022 [35]	CBCT	3D U-Net CNN	Clinical/radiographic ground truth	High accuracy in detection and segmentation of unobturated MB2 canals
Duman et al., 2024 [33]	CBCT	YOLOv5x	Expert radiologist annotations	Successful automatic segmentation of MB2 canals
Mansour et al., 2025 [36]	CBCT	CNN + U-Net	Experienced oral radiologists	Excellent recall and segmentation performance for MB2 canals
Güllü et al., 2026 [38]	CBCT	nnU-Net v2	Manual segmentation labels	Demonstrated feasibility of 3D MB2 canal segmentation
Shetty et al., 2025 [37]	CBCT	Logistic Regression (LR), Support Vector Machine (SVM), Neural Network (NN), Random Forest (RF), K-Nearest Neighbours (KNN), and Naïve Bayes (NB)	Human-labelled datasets	ML models achieved high recall and AUC values
C-shaped canals				
Zhang et al., 2022 [41]	Panoramic radiographs + CBCT reference	FARFB lightweight CNN	Dentists and conventional CNNs	Excellent diagnostic performance for C-shaped canal detection
Jin et al., 2024 [34]	Panoramic radiographs + CBCT-generated panoramic images	ResNet, DenseNet, Inception-V3	Dental professionals	CNNs outperformed clinicians in C-shaped canal classification

Table 1. Cont.

Study	Imaging Modality	AI Model	Compared Against	Key Outcome
Uysal et al., 2026 [42]	Panoramic radiographs + CBCT gold standard	Multiple DCNNs + majority voting	Individual DCNN models	Combined models improved detection accuracy
Çakmak & Er, [43]	Panoramic radiographs + CBCT reference	YOLOv8 + ensemble CNNs	Single CNN architectures	Two-stage pipeline enabled automated C-shaped canal detection
Pulp stones				
Madiraju et al., 2026 [44]	CBCT	K-Means clustering + PCA	Conventional statistical analysis	AI clustering identified prevalence phenotypes and risk groups
Firinciogluglari et al., 2025 [45]	Panoramic radiographs	U2-Net deep learning	Human expert annotations	Accurate segmentation of pulp stones and pulp tissue
Altındağ et al., 2024 [46]	Panoramic radiographs	YOLOv5	OMFR annotations	AI demonstrated successful pulp stone detection
Taurodontism				
Duman et al., 2023 [47]	Panoramic radiographs	U-Net CNN	Expert-labelled radiographs	CNN achieved near expert-level taurodontism detection

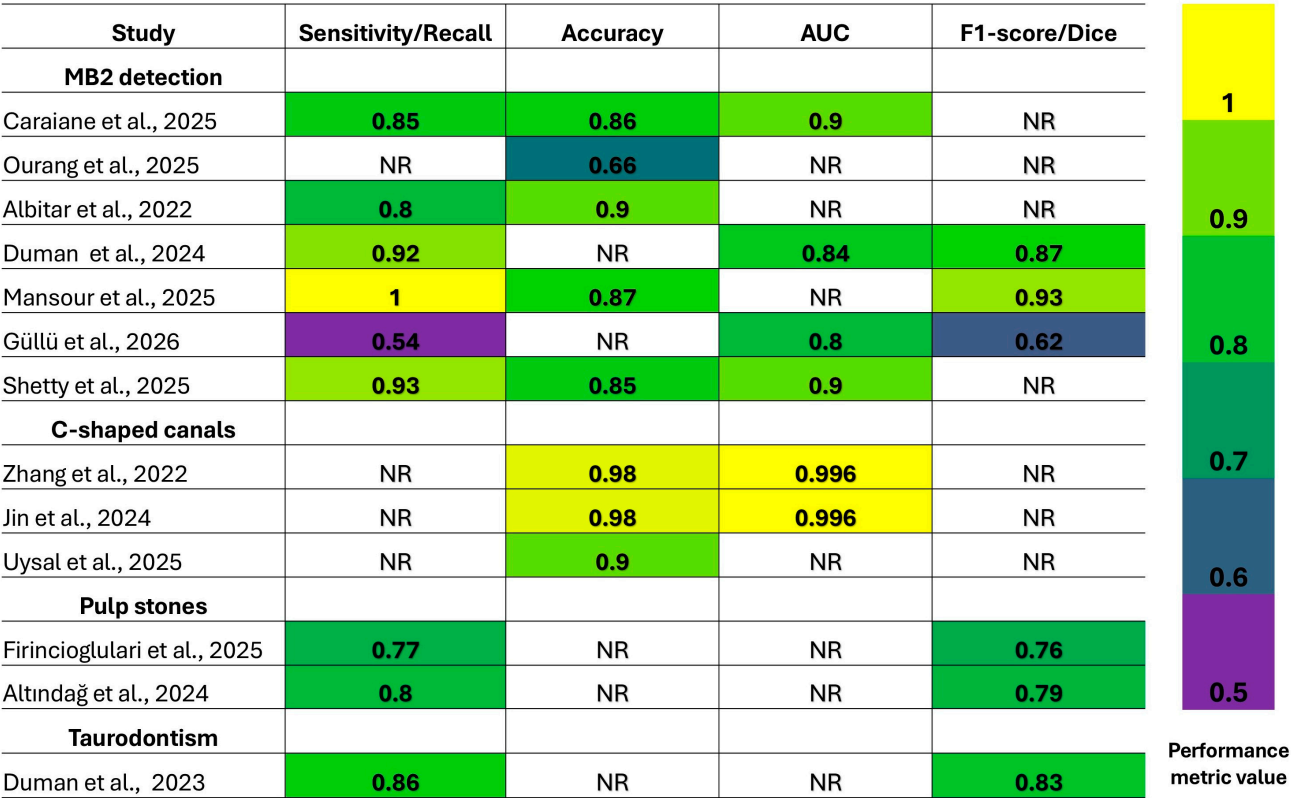


Figure 2. Heatmap summarizing the diagnostic performance of artificial intelligence models for detection, classification, and segmentation of root canal morphology and anatomical variations in endodontic imaging studies. Reported values correspond to the best-performing model from each study. NR = not reported in the included study or unavailable in the reviewed article excerpt [33–42,45–47].

In MB2 detection, CBCT-based AI systems generally achieved higher diagnostic performance than periapical radiographs, with sensitivity values reaching up to 1.00 and AUC values approaching 0.90 [36,39]. Models such as YOLOv5x, U-Net, and nnU-Net

demonstrated strong ability in canal localization and segmentation, while machine learning models, including Support Vector Machine and Neural Network classifiers, also showed high recall and AUC values [33,37].

Similarly, in detecting C-shaped canals, deep learning systems achieved very high diagnostic accuracy under specific study conditions, with some studies reporting AUC values up to 0.996 and accuracies above 98%, especially when CBCT reference standards were used [34,41]. CNN-based systems consistently outperformed less experienced clinicians and demonstrated strong potential as clinical decision-support tools in endodontic diagnosis [42,43].

AI applications for pulp stone detection and taurodontism also produced encouraging results. YOLOv5, U2-Net, and U-Net-based CNN models achieved sensitivities ranging from approximately 0.77 to 0.87 with high F1-scores, demonstrating diagnostic performance close to expert-level interpretation in selected datasets [45–47].

3.3. Artificial Intelligence in Treatment Outcome and Prognosis of Endodontic Therapy

Treatment outcome and prognosis in endodontics are essential components of clinical decision-making because they help estimate the likelihood of healing and long-term tooth survival. Traditionally, prognosis has been based on clinical signs, symptoms, and radiographic healing; however, artificial intelligence (AI) has recently emerged as a potential tool for improving predictive accuracy.

AI applications for treatment outcome prediction in endodontics are primarily based on machine learning (ML) and deep learning (DL) algorithms trained on radiographic and clinical datasets. These models analyze preoperative periapical radiographs and CBCT scans, together with long-term treatment outcomes classified as healed, healing, or diseased [48]. Training datasets are generated through expert annotation of anatomical and pathological structures, including periapical lesions, root morphology, fractures, and obturation defects, establishing the reference standard (“ground truth”) for algorithm development [49]. Model calibration involves preprocessing steps such as normalization, feature selection, segmentation, and the division of data into training and validation subsets, typically using 80/20 data splitting and stratified 5-fold cross-validation to reduce overfitting and improve reliability [50]. Deep learning architectures, including convolutional neural networks (CNNs), ResNet-18, and Mask R-CNN, automatically extract diagnostically relevant image features such as lesion borders, density variations, and anatomical relationships directly from radiographic data [48,49].

In clinical practice, AI systems typically provide clinicians with visual and quantitative decision-support outputs by automatically highlighting suspected periapical lesions, root fractures, missed canals, or obturation defects directly on radiographic or CBCT images using color overlays, segmentation masks, heatmaps, or bounding boxes. Some systems (e.g., Diagnocat, Pearl Second Opinion, and Overjet) may additionally generate probability scores, lesion measurements, volumetric analysis, or treatment outcome predictions classified as healed, healing, or diseased.

Current studies report promising predictive performance of AI systems in endodontics. The Gradient Boosting Machine (GBM) model achieved 80% accuracy with an AUC of 0.88, while the Random Forest (RF) model achieved an AUC of 0.83 in predicting outcomes of endodontic microsurgery [50]. The Mask R-CNN deep learning model achieved mean average precision (mAP) values of 0.88 for healed cases and 0.91 for disease classification, additionally improving clinicians’ diagnostic performance [48]. Furthermore, as summarized by Zebouni et al. [51], multiple AI models, including CNNs, RF, GBM, XGBoost, and ResNet-based architectures, demonstrated encouraging results in prognosis prediction, case difficulty assessment, and treatment outcome evaluation in endodontics (Table 2).

Table 2. Summary of artificial intelligence models used for prognosis prediction and treatment outcome assessment in endodontics.

Study	Imaging Modality	AI Model	Compared Against	Sensitivity/Recall	Specificity	Accuracy/AUC
Qu et al., 2022 [50]	CBCT + clinical variables	Gradient Boosting Machine (GBM), Random Forest (RF)	Comparison between ML models	GBM: 0.92; RF: 0.85	GBM: 0.71; RF: 0.76	Accuracy: 0.80; AUC: 0.88 (GBM), 0.83 (RF)
Zebouni et al., 2025 [51]	Periapical radiographs + clinical/radiographic variables	RF, GBM, KNN, Logistic Regression, CNN-based systems	Clinician-based prognosis and conventional assessment	Up to 94.96% in case difficulty assessment	NR	Accuracy up to 84.13%; AUC around 0.60–0.84 depending on model
Bennasar et al., 2025 [49]	Two-dimensional periapical radiographs	Deep Learning + Logistic Regression (DL-LR), RF, ResNet-18 CNN	Clinician prognosis (DP)	DL-LR significantly higher than clinicians	NR	Improved accuracy versus clinicians; statistically superior sensitivity and NPV
Dennis et al., 2024 [48]	Periapical radiographs	Mask R-CNN segmentation model	General practitioners and endodontists	Improved from 0.75 to 0.84 (GPs) and 0.88 to 0.92 (endodontists) with AI assistance	NR	mean Average Precision: 0.88; AUC up to 0.91

Abbreviations: NR, not reported.

Despite these promising findings, the available evidence remains limited to a relatively small number of heterogeneous studies with different study designs, datasets, and AI models. Therefore, further prospective multicenter studies and external validation are required before AI-based prognosis can be routinely implemented in clinical practice.

3.4. Artificial Intelligence in Navigation-Guided Endodontics

Navigation-guided endodontics is an emerging digital technique that has been reported to improve the accuracy and safety of endodontic procedures while preserving healthy tooth structure [52]. It should be noted that not all components of navigation-guided endodontics are AI-driven. Artificial intelligence is primarily involved in automated image segmentation and AI-assisted surgical pathway planning, whereas technologies such as CAD/CAM workflows, 3D-printed static guides, and augmented reality represent conventional digital navigation technologies that facilitate the clinical implementation of the treatment plan.

The workflow begins with the acquisition of diagnostic imaging data, primarily CBCT combined with intraoral scanning. These datasets may form the basis for AI-assisted segmentation, digital treatment planning, and navigation-guided procedures.

Following image acquisition, artificial intelligence (AI) algorithms are used to automate segmentation of the pulp space and root canal system in CBCT images. A CNN-based AI segmentation tool using the Virtual Patient Creator platform achieved high segmentation accuracy, with a Dice similarity coefficient (DSC) of 89–93% compared with expert-generated reference models, while being 54 times faster than manual methods [53].

Similarly, a systematic review including 13 studies reported that most AI systems utilized U-Net or modified U-Net convolutional neural network (CNN) architectures for CBCT pulp space segmentation, achieving Dice similarity coefficient (DSC) values ranging from 0.60 to 0.98 and segmentation times of only 13–33 s [54–56]. These findings highlight the potential efficiency advantages of AI-assisted segmentation in digital workflows. Generally, AI models showed better performance for pulp chamber segmentation and single-rooted teeth, whereas MB2 canal segmentation also demonstrated promising results (F1-score of 0.87) [33].

The segmented anatomical models are then integrated into digital planning software, such as the DCARE Navigation System, to design precise endodontic access pathways. Chen et al. demonstrated that AI-assisted planning significantly reduced surgical pathway planning time (55 s vs. 379 s) while maintaining high procedural accuracy [57].

The digitally planned access pathway can then be transferred to various navigation systems, including static, dynamic, and augmented reality (AR)-guided navigation.

Static navigation uses CAD/CAM-designed 3D-printed guides to direct the bur along a predefined pathway. Although this approach is an important component of digital endodontics, it does not itself constitute an AI-driven technology; rather, it serves to accurately transfer the treatment plan generated during the planning stage to the clinical procedure. Guides fabricated using SLA, DLP, and PolyJet 3D-printing technologies achieved an accuracy of approximately 0.2 mm relative to the planned trajectory, thereby improving treatment predictability while minimizing dentin loss and the risk of perforation [52].

Dynamic navigation systems incorporate real-time optical tracking technologies that continuously monitor instrument position and angulation during treatment, thereby improving procedural flexibility and operator control. AI-integrated navigation systems have also been associated with reduced planning time while maintaining a level of surgical accuracy comparable to manually designed pathways [57].

Augmented reality (AR)-guided navigation is an advanced form of dynamic navigation that overlays virtual anatomical structures directly onto the clinician’s field of view using devices such as the HoloLens 2. AR-guided systems integrated with digital planning software demonstrated significantly greater coronal ($p = 0.0029$) and apical ($p = 0.0063$) accuracy compared with conventional freehand techniques, while maintaining comparable angular deviation [58]. In addition, custom AR navigation systems based on visual-inertial odometry and LiDAR technology using an iPad Pro platform reported mean coronal and apical deviations of 0.51 mm and 0.77 mm, respectively, with an angular deviation of 8.5° and surface overlap ranging from 57% to 82% [59].

Collectively, the presented findings suggest that AI-assisted technologies, together with conventional digital navigation systems, have the potential to enhance the precision, efficiency, and predictability of minimally invasive endodontic procedures (Table 3).

Table 3. Summary of artificial intelligence applications in navigation-guided endodontics.

Study	Imaging Modality	AI Model/Software Platform	Compared Against	Key Outcome
Static navigation & digital workflow				
Choudhury et al., 2025 [52]	CBCT + intraoral scanning	CAD/CAM-guided workflow + 3D printing	Conventional access cavity preparation	Guided endodontics improved access precision, minimized dentin removal, and enhanced treatment predictability in calcified canals

Table 3. Cont.

Study	Imaging Modality	AI Model/Software Platform	Compared Against	Key Outcome
Santos-Junior et al., 2025 [53]	CBCT	CNN-based automated root canal segmentation (Virtual Patient Creator)	Manual segmentation	AI segmentation achieved high accuracy (DSC: 89–93%; accuracy up to 99%) and was approximately 54 times faster than manual segmentation
Dynamic navigation systems				
Chen et al., 2026 [57]	CBCT	AI-generated surgical pathway planning (DCARE Navigation System)	Manually designed pathways	AI-assisted pathway planning significantly reduced design time (55 s vs. 379 s) while maintaining clinically acceptable accuracy
Augmented reality (AR)-guided navigation				
Farronato et al., 2023 [59]	CBCT + AR workflow	Markerless AR navigation system with visual-inertial odometry (VIO)	Virtual treatment plan	AR-guided access cavities demonstrated mean coronal deviation of 0.51–0.63 mm and showed promising accuracy for minimally invasive access preparation
Faus-Matoses et al., 2022 [58]	CBCT + intraoral scan	HoloLens2 + AR navigation software + NemoScan	Conventional freehand access cavities	AR-guided access cavities achieved significantly lower coronal and apical deviations and eliminated perforations compared with freehand techniques
AI-driven segmentation & workflow optimization				
Alfadley et al., 2024 [54]	CBCT	AI-driven automated pulp space segmentation models	Manual/semi-automated segmentation	AI models demonstrated high segmentation accuracy and improved computational efficiency for pulp space and root canal analysis

Although AI-assisted and navigation-guided technologies have demonstrated encouraging results, the available evidence is still limited and largely based on in vitro studies and retrospective investigations. Consequently, further well-designed prospective clinical studies are required to confirm their effectiveness and clinical applicability.

4. Limitations and Future Perspectives

Despite rapidly growing interest in artificial intelligence applications in endodontics and generally promising diagnostic results, several important limitations and challenges remain to be addressed before routine clinical implementation can be achieved.

Although CBCT demonstrated the highest diagnostic performance across many of the included studies, its routine use is limited by higher radiation exposure, increased cost, and

lower availability compared with conventional intraoral radiography. Furthermore, current clinical recommendations reserve CBCT for cases in which the additional three-dimensional information is expected to influence diagnosis or treatment planning rather than for routine use in all patients.

In periapical lesion detection, AI accuracy may be affected by lesion size, image quality, anatomical complexity, and dataset characteristics [20,26,30]. Most studies reported higher sensitivity for medium and large lesions, whereas early or small periapical changes remained more difficult to detect [14,15]. Reduced diagnostic performance has also been observed in root-filled teeth because of beam-hardening artifacts, radiopacity, and altered anatomy, particularly in maxillary molars adjacent to the maxillary sinus [29,30].

Current AI systems used for root canal morphology assessment may perform worse in cases involving severe calcifications, narrow canals, image artifacts, low image resolution, or highly variable anatomy [35,38]. In addition, many studies relied on two-dimensional radiographs, where anatomical superimposition and distortion may further reduce diagnostic accuracy [34,42]. In complex clinical scenarios, experienced clinicians using high-quality CBCT imaging may still outperform AI systems, particularly when interpretation requires integration of anatomical knowledge and clinical judgment [40].

Regarding treatment outcome prediction and prognosis assessment, many studies excluded clinically challenging cases, including teeth with severe anatomical distortion, vertical root fractures, poor image quality, or CBCT indications, potentially leading to an overestimation of AI performance under idealized conditions [48,49].

AI-assisted navigation systems also present practical limitations, including the need for additional operator training, complex digital workflows, interoperability with existing digital dental systems, CBCT imaging, and expensive navigation equipment, which may reduce their accessibility and limit routine clinical implementation [52,57]. Potential inaccuracies arising from image artifacts, registration errors, and real-time tracking systems may also affect procedural precision, particularly in anatomically complex or multirooted teeth [53].

Additionally, most available studies were retrospective and based on relatively small or single-center datasets, which may increase the risk of overfitting and limit external validation, generalizability, and clinical applicability in routine practice [29,32,48–50]. Methodological heterogeneity in imaging modalities, imaging protocols, annotation methods, reference standards, AI architectures, and evaluation metrics further complicates direct comparison between studies and may influence reported outcomes [15,48,50]. Many investigations relied on manually annotated datasets and expert-defined “ground truth”, introducing potential observer-related variability and bias [48,49]. Furthermore, the rapid pace of AI development means that some studies evaluated earlier generations of algorithms and software platforms, which may not fully reflect the performance of currently available systems.

Several studies were conducted under controlled experimental or in vitro conditions rather than real clinical environments, emphasizing the need for larger prospective multi-center studies and standardized validation protocols before widespread clinical implementation of AI systems can be achieved [14,48].

Current AI systems should be regarded primarily as adjunctive decision-support tools that enhance radiographic interpretation, improve diagnostic confidence, reduce the risk of missed canals, and support treatment planning rather than replace clinician expertise. Despite substantial technological progress, ongoing clinician supervision and verification remain valuable components of the process. At the same time, the growing integration of AI into dental diagnostics raises important questions regarding education, ethics, and clinical responsibility. AI should be considered a supportive tool rather than a replacement

for clinical expertise, as interpretation of AI-generated findings still requires knowledge of radiology, endodontic pathology, and clinical decision-making [6]. Accordingly, recent European guidelines, including the European Commission's Ethics Guidelines for Trustworthy AI (2019) and the European Union AI Act (2024), emphasize transparency, safety, human oversight, and clinician responsibility in medical AI applications [60,61]. Although AI may improve diagnostic accuracy and support image interpretation, the dentist remains closely involved in the final diagnosis and treatment decision. Successful implementation of AI in endodontics will require incorporating AI-related competencies into undergraduate dental curricula and postgraduate specialty training programs. Moreover, clinicians should be aware of the learning curve associated with AI-assisted software, navigation systems, and digital workflows to ensure the safe and effective use of these tools in clinical practice.

Future perspectives of AI in endodontics remain promising. Further development of deep learning algorithms and integration with advanced imaging modalities, particularly CBCT, may improve diagnostic precision and facilitate real-time clinical decision support. AI-assisted systems are likely to become increasingly incorporated into chairside diagnostic workflows and digital treatment planning. However, prospective multicenter studies, robust external validation, and standardized methodological protocols remain essential to ensure the safety, reliability, and clinical applicability of AI technologies in endodontic practice.

5. Conclusions

1. AI demonstrates considerable potential in endodontics, particularly in enhancing radiographic interpretation, diagnostic consistency, and supporting clinical decision-making, including treatment planning and prognosis assessment.
2. The highest diagnostic performance was generally reported for CBCT-based applications, particularly in the detection of periapical lesions and assessment of root canal anatomy, whereas greater variability was observed in panoramic radiographs.
3. AI-assisted systems may be especially valuable in identifying complex anatomical variations (MB2 canals, C-shaped canals, taurodontism, and pulp stones), thereby reducing the risk of missed anatomical structures and pathological findings that may compromise treatment outcomes.
4. Despite promising results, AI performance remains dependent on image quality, anatomical complexity, and methodological variability. Current evidence is largely derived from retrospective and experimental studies; therefore, AI applications should be regarded primarily as adjunctive decision-support tools rather than replacements for clinician expertise and clinical judgment. Although AI for periapical lesion detection and root canal morphology assessment appears closest to routine clinical implementation, prognosis prediction and navigation-guided endodontics require further prospective multicenter clinical validation and standardized reporting frameworks.

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References

1. Duncan, H.F.; Galler, K.M.; Tomson, P.L.; Simon, S.; El-Karim, I.; Kundzina, R.; Krastl, G.; Dammaschke, T.; Fransson, H.; Markvart, M.; et al. European Society of Endodontology Position Statement: Management of Deep Caries and the Exposed Pulp. *Int. Endod. J.* **2019**, *52*, 923–934. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Abbott, P.V. Classification, Diagnosis and Clinical Manifestations of Apical Periodontitis. *Endod. Top.* **2004**, *8*, 36–54. [\[CrossRef\]](#)
3. Siqueira, J.F.J.; Rôças, I.N. Present Status and Future Directions: Microbiology of Endodontic Infections. *Int. Endod. J.* **2022**, *55*, 512–530. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Patel, S.; Brown, J.; Pimentel, T.; Kelly, R.D.; Abella, F.; Durack, C. Cone Beam Computed Tomography in Endodontics—A Review of the Literature. *Int. Endod. J.* **2019**, *52*, 1138–1152. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Patel, S.; Durack, C.; Abella, F.; Shemesh, H.; Roig, M.; Lemberg, K. Cone Beam Computed Tomography in Endodontics—A Review. *Int. Endod. J.* **2015**, *48*, 3–15. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Asgary, S. Artificial Intelligence in Endodontics: A Scoping Review. *Iran. Endod. J.* **2024**, *19*, 85–98. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Chen, Y.; Su, Z.J.; Zhang, R.; Huang, S. AI Meets Endodontics a Deep Learning Approach to Precision Diagnosis. *Sci. Rep.* **2025**, *15*, 42727. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Schwendicke, F.; Samek, W.; Krois, J. Artificial Intelligence in Dentistry: Chances and Challenges. *J. Dent. Res.* **2020**, *99*, 769–774. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Setzer, F.; Li, J.; Khan, A. The Use of Artificial Intelligence in Endodontics. *J. Dent. Res.* **2024**, *103*, 853–862. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Hung, M.; Voss, M.W.; Rosales, M.N.; Li, W.; Su, W.; Xu, J.; Bounsanga, J.; Ruiz-Negrón, B.; Lauren, E.; Licari, F.W. Application of Machine Learning for Diagnostic Prediction of Root Caries. *Gerodontology* **2019**, *36*, 395–404. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; van der Laak, J.A.W.M.; van Ginneken, B.; Sánchez, C.I. A Survey on Deep Learning in Medical Image Analysis. *Med. Image Anal.* **2017**, *42*, 60–88. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Ourang, S.; Sohrabniya, F.; Mohammad-Rahimi, H.; Dianat, O.; Aminoshariae, A.; Nagendrababu, V.; Dummer, P.; Duncan, H.; Nosrat, A. Artificial Intelligence in Endodontics: Fundamental Principles, Workflow, and Tasks. *Int. Endod. J.* **2024**, *57*, 1546–1565. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Kirnbauer, B.; Hadzic, A.; Jakse, N.; Bischof, H.; Stern, D. Automatic Detection of Periapical Osteolytic Lesions on Cone-Beam Computed Tomography Using Deep Convolutional Neuronal Networks. *J. Endod.* **2022**, *48*, 1434–1440. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Fu, W.T.; Zhu, Q.K.; Li, N.; Wang, Y.Q.; Deng, S.L.; Chen, H.P.; Shen, J.; Meng, L.Y.; Bian, Z. Clinically Oriented CBCT Periapical Lesion Evaluation via 3D CNN Algorithm. *J. Dent. Res.* **2024**, *103*, 5–12. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Chau, K.-K.; Zhu, M.; AlHadidi, A.; Wang, C.; Hung, K.; Wohlgemuth, P.; Lam, W.Y.H.; Liu, W.; Yuan, Y.; Chen, H. A Novel AI Model for Detecting Periapical Lesion on CBCT: CBCT-SAM. *J. Dent.* **2025**, *153*, 105526. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Li, C.-W.; Lin, S.-Y.; Chou, H.-S.; Chen, T.-Y.; Chen, Y.-A.; Liu, S.-Y.; Liu, Y.-L.; Chen, C.-A.; Huang, Y.-C.; Chen, S.-L.; et al. Detection of Dental Apical Lesions Using CNNs on Periapical Radiograph. *Sensors* **2021**, *21*, 7049. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Ngoc, V.; Hoang Viet, D.; Anh, L.; Minh, D.; Nghia, L.; Loan, H.; Tuan, T.; Ngan, T.; Nguyen, T. Periapical Lesion Diagnosis Support System Based on X-Ray Images Using Machine Learning Technique. *World J. Dent.* **2021**, *12*, 189–193. [\[CrossRef\]](#)
18. Chuo, Y.; Lin, W.-M.; Chen, T.-Y.; Chan, M.-L.; Chang, Y.-S.; Lin, Y.-R.; Lin, Y.-J.; Shao, Y.-H.; Chen, C.-A.; Chen, S.-L.; et al. A High-Accuracy Detection System: Based on Transfer Learning for Apical Lesions on Periapical Radiograph. *Bioengineering* **2022**, *9*, 777. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Issa, J.; Jaber, M.; Rifai, I.; Mozdzia, P.; Kempisty, B.; Dyszkiewicz-Konwińska, M. Diagnostic Test Accuracy of Artificial Intelligence in Detecting Periapical Periodontitis on Two-Dimensional Radiographs: A Retrospective Study and Literature Review. *Medicina* **2023**, *59*, 768. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Kazimierczak, W.; Wajer, R.; Wajer, A.; Kiian, V.; Kloska, A.; Kazimierczak, N.; Janiszewska-Olszowska, J.; Serafin, Z. Periapical Lesions in Panoramic Radiography and CBCT Imaging-Assessment of AI's Diagnostic Accuracy. *J. Clin. Med.* **2024**, *13*, 2709. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Icoz, D.; Terzioğlu, H.; Ozel, M.A.; Karakurt, R. Evaluation of an Artificial Intelligence System for the Diagnosis of Apical Periodontitis on Digital Panoramic Images. *Niger. J. Clin. Pract.* **2023**, *26*, 1085–1090. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Krois, J.; Garcia Cantu, A.; Chaurasia, A.; Patil, R.; Chaudhari, P.K.; Gaudin, R.; Gehrung, S.; Schwendicke, F. Generalizability of Deep Learning Models for Dental Image Analysis. *Sci. Rep.* **2021**, *11*, 6102. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Pul, U.; Schwendicke, F. Artificial Intelligence for Detecting Periapical Radiolucencies: A Systematic Review and Meta-Analysis. *J. Dent.* **2024**, *147*, 105104. [\[CrossRef\]](#) [\[PubMed\]](#)

24. Kim, C.; Jeong, H.; Park, W.; Kim, D. Tooth-Related Disease Detection System Based on Panoramic Images and Optimization Through Automation: Development Study. *JMIR Med. Inform.* **2022**, *10*, e38640. [[CrossRef](#)] [[PubMed](#)]
25. Ba-Hattab, R.; Barhom, N.; Osman, S.A.A.; Naceur, I.; Odeh, A.; Asad, A.; Al-Najdi, S.A.R.N.; Ameri, E.; Daer, A.; Da Silva, R.L.B.; et al. Detection of Periapical Lesions on Panoramic Radiographs Using Deep Learning. *Appl. Sci.* **2023**, *13*, 1516. [[CrossRef](#)]
26. Çelik, B.; Savaştaer, E.F.; Kaya, H.I.; Çelik, M.E. The Role of Deep Learning for Periapical Lesion Detection on Panoramic Radiographs. *Dentomaxillofacial Radiol.* **2023**, *52*, 20230118. [[CrossRef](#)] [[PubMed](#)]
27. Güneç, H.G.; Ürkmez, E.Ş.; Danacı, A.; Dilmaç, E.; Onay, H.H.; Cesur Aydın, K. Comparison of Artificial Intelligence vs. Junior Dentists' Diagnostic Performance Based on Caries and Periapical Infection Detection on Panoramic Images. *Quant. Imaging Med. Surg.* **2023**, *13*, 7494–7503. [[CrossRef](#)] [[PubMed](#)]
28. Zadrożny, Ł.; Regulski, P.; Brus-Sawczuk, K.; Czajkowska, M.; Parkanyi, L.; Ganz, S.; Mijiritsky, E. Artificial Intelligence Application in Assessment of Panoramic Radiographs. *Diagnostics* **2022**, *12*, 224. [[CrossRef](#)] [[PubMed](#)]
29. Hadzic, A.; Urschler, M.; Press, J.-N.A.; Riedl, R.; Rugani, P.; Štern, D.; Kirnbauer, B. Evaluating a Periapical Lesion Detection CNN on a Clinically Representative CBCT Dataset-A Validation Study. *J. Clin. Med.* **2023**, *13*, 197. [[CrossRef](#)] [[PubMed](#)]
30. Allihaibi, M.; Koller, G.; Mannocci, F. The Detection of Apical Radiolucencies in Periapical Radiographs: A Comparison between an Artificial Intelligence Platform and Expert Endodontists with CBCT Serving as the Diagnostic Benchmark. *Int. Endod. J.* **2025**, *58*, 1146–1157. [[CrossRef](#)] [[PubMed](#)]
31. Wu, P.-Y.; Mao, Y.-C.; Lin, Y.-J.; Li, X.-H.; Ku, L.-T.; Li, K.-C.; Chen, C.-A.; Chen, T.-Y.; Chen, S.-L.; Tu, W.-C.; et al. Precision Medicine for Apical Lesions and Peri-Endo Combined Lesions Based on Transfer Learning Using Periapical Radiographs. *Bioengineering* **2024**, *11*, 877. [[CrossRef](#)] [[PubMed](#)]
32. Nagareddy, B.; Vadlamani, R.; Venkannagari, N.R.; Jain, S.; Basheer, S.N.; Murugesan, S. Comparison of the Artificial Intelligence Versus Traditional Radiographic Interpretation in Detecting Periapical Periodontitis: A Diagnostic Accuracy Study. *J. Pharm. Bioallied Sci.* **2024**, *16*, S3676–S3678. [[CrossRef](#)] [[PubMed](#)]
33. Duman, Ş.B.; Çelik Özen, D.; Bayrakdar, I.Ş.; Baydar, O.; Alhaija, E.S.A.; Helvacioğlu Yiğit, D.; Çelik, Ö.; Jagtap, R.; Pileggi, R.; Orhan, K. Second Mesiobuccal Canal Segmentation with YOLOv5 Architecture Using Cone Beam Computed Tomography Images. *Odontology* **2024**, *112*, 552–561. [[CrossRef](#)] [[PubMed](#)]
34. Jin, L.; Tang, Y.; Zhou, W.; Bai, B.; Yu, Z.; Zhang, P.; Gu, Y. Detection of Three-Rooted Mandibular First Molars on Panoramic Radiographs Using Deep Learning. *Sci. Rep.* **2024**, *14*, 30392. [[CrossRef](#)] [[PubMed](#)]
35. Albitar, L.; Zhao, T.; Huang, C.; Mahdian, M. Artificial Intelligence (AI) for Detection and Localization of Unobturator Second Mesial Buccal (MB2) Canals in Cone-Beam Computed Tomography (CBCT). *Diagnostics* **2022**, *12*, 3214. [[CrossRef](#)] [[PubMed](#)]
36. Mansour, S.; Anter, E.; Mohamed, A.K.; Dahaba, M.M.; Mousa, A. Two Step Approach for Detecting and Segmenting the Second Mesiobuccal Canal of Maxillary First Molars on Cone Beam Computed Tomography (CBCT) Images via Artificial Intelligence. *BMC Oral Health* **2025**, *25*, 1404. [[CrossRef](#)] [[PubMed](#)]
37. Shetty, S.; Yuvali, M.; Ozsahin, I.; Al-Bayatti, S.; Narasimhan, S.; Alsaegh, M.; Al-Daghestani, H.; Shetty, R.; Castelino, R.; David, L.R.; et al. Machine Learning Models in the Detection of MB2 Canal Orifice in CBCT Images. *Int. Dent. J.* **2025**, *75*, 1640–1648. [[CrossRef](#)] [[PubMed](#)]
38. Güllü, D.M.; Orhan, K.; Kartal, N. Three-Dimensional Automatic Segmentation of Root Canals with Focus on the Second Mesiobuccal Canal Using NnU-Netv2 on CBCT Images: Deep Learning Approach. *BMC Oral Health* **2026**, *26*, 973. [[CrossRef](#)] [[PubMed](#)]
39. Caraiane, A.; Puşcaşu, C.G.; Raftu, G.; Bartok-Nicolae, C.; Sin, C.E.; Buştiuc, S.G.; Şachir, E.E. AI-assisted detection of the second mesiovestibular canal in maxillary first molars on periapical radiographs. *Rom. J. Med. Dent. Educ.* **2025**, *14*, 103–109.
40. Ourang, S.A.H.; Sohrabniya, F.; Sadr, S.; Lee, J.; Ramzy, N.; Law, A.S.; Lam, E.W.N.; Khan, A.A.; Nosrat, A. Artificial Intelligence in the Detection of Clinically Negotiable Second Mesio-Buccal Canals in Periapical Images of Maxillary Molars. *Int. Endod. J.* **2025**, 1–13. [[CrossRef](#)] [[PubMed](#)]
41. Zhang, L.; Xu, F.; Li, Y.; Zhang, H.; Xi, Z.; Xiang, J.; Wang, B. A Lightweight Convolutional Neural Network Model with Receptive Field Block for C-Shaped Root Canal Detection in Mandibular Second Molars. *Sci. Rep.* **2022**, *12*, 17373. [[CrossRef](#)] [[PubMed](#)]
42. Uysal, O.; Polat, M.; Akgül, H.M. Evaluation of the Accuracy of Detecting C-Shaped Canals in Mandibular Second Molars Identified by Cone-Beam Computed Tomography on Panoramic Radiographs Using Artificial Intelligence Algorithms Developed with Deep Learning Methods. *Oral Radiol.* **2026**, *42*, 558–573. [[CrossRef](#)] [[PubMed](#)]
43. Çakmak, Y.E.; Er, K. Automated Detection of C-Shaped Canals in Mandibular Second Molars from Panoramic Radiographs: Comparing Single and Ensemble Convolutional Neural Networks within a 2-Stage Pipeline. *Clin. Oral Investig.* **2026**, *30*, 190. [[CrossRef](#)] [[PubMed](#)]
44. Madiraju, G.S.; Bello, S.M.; Abraham, S.; Mahabob, N. Artificial Intelligence-Assisted Analysis of Prevalence Patterns and Phenotypic Distribution of Dental Pulp Stones Using Cone-Beam Computed Tomography Imaging. *Niger. J. Clin. Pract.* **2026**, *29*, 280–287. [[CrossRef](#)] [[PubMed](#)]

45. Firincioglugulari, M.; Boztuna, M.; Mirzaei, O.; Karanfiller, T.; Akkaya, N.; Orhan, K. Segmentation of Pulp and Pulp Stones with Automatic Deep Learning in Panoramic Radiographs: An Artificial Intelligence Study. *Dent. J.* **2025**, *13*, 274. [[CrossRef](#)] [[PubMed](#)]
46. Altındağ, A.; Bahrilli, S.; Çelik, Ö.; Bayrakdar, İ.Ş.; Orhan, K. The Detection of Pulp Stones with Automatic Deep Learning in Panoramic Radiographies: An AI Pilot Study †. *Diagnostics* **2024**, *14*, 890. [[CrossRef](#)] [[PubMed](#)]
47. Duman, S.; Yılmaz, E.F.; Eşer, G.; Çelik, Ö.; Bayrakdar, İ.S.; Bilgir, E.; Costa, A.L.F.; Jagtap, R.; Orhan, K. Detecting the Presence of Taurodont Teeth on Panoramic Radiographs Using a Deep Learning-Based Convolutional Neural Network Algorithm. *Oral Radiol.* **2023**, *39*, 207–214. [[CrossRef](#)] [[PubMed](#)]
48. Dennis, D.; Suebnukarn, S.; Vicharueang, S.; Limprasert, W. Development and Evaluation of a Deep Learning Segmentation Model for Assessing Non-Surgical Endodontic Treatment Outcomes on Periapical Radiographs: A Retrospective Study. *PLoS ONE* **2024**, *19*, e0310925. [[CrossRef](#)] [[PubMed](#)]
49. Bennasar, C.; Nadal-Martínez, A.; Arroyo, S.; Gonzalez-Cid, Y.; López-González, Á.A.; Tárraga, P.J. Integrating Machine Learning and Deep Learning for Predicting Non-Surgical Root Canal Treatment Outcomes Using Two-Dimensional Periapical Radiographs. *Diagnostics* **2025**, *15*, 1009. [[CrossRef](#)] [[PubMed](#)]
50. Qu, Y.; Lin, Z.; Yang, Z.; Lin, H.; Huang, X.; Gu, L. Machine Learning Models for Prognosis Prediction in Endodontic Microsurgery. *J. Dent.* **2022**, *118*, 103947. [[CrossRef](#)] [[PubMed](#)]
51. Zebouni, C.; Shirodkar, G.; Ather, A.; Sarkis, R.A. Artificial Intelligence and Prognosis of Treatment in Endodontics. *Dent. Clin. N. Am.* **2025**, *69*, 527–540. [[CrossRef](#)] [[PubMed](#)]
52. Choudhury, S.A.; Pal, S.; Sen, S.; Srivastava, S.K.; Sikdar, C. 3D Printing and Guided Endodontics: The Future of Precision Access Cavity Design. *Cureus* **2025**, *17*, 3–6. [[CrossRef](#)] [[PubMed](#)]
53. Santos-Junior, A.O.; Fontenele, R.C.; Neves, F.S.; Tanomaru-Filho, M.; Jacobs, R. A Novel Artificial Intelligence-Powered Tool for Automated Root Canal Segmentation in Single-Rooted Teeth on Cone-Beam Computed Tomography. *Int. Endod. J.* **2025**, *58*, 658–671. [[CrossRef](#)] [[PubMed](#)]
54. Alfadley, A.; Shujaat, S.; Jamleh, A.; Riaz, M.; Aboalela, A.A.; Ma, H.; Orhan, K. Progress of Artificial Intelligence-Driven Solutions for Automated Segmentation of Dental Pulp Space on Cone-Beam Computed Tomography Images. A Systematic Review. *J. Endod.* **2024**, *50*, 1221–1232. [[CrossRef](#)] [[PubMed](#)]
55. Song, Y.; Yang, H.; Ge, Z.; Du, H.; Li, G. Age Estimation Based on 3D Pulp Segmentation of First Molars from CBCT Images Using U-Net. *Dentomaxillofacial Radiol.* **2023**, *52*, 20230177. [[CrossRef](#)] [[PubMed](#)]
56. Yang, H.; Wang, X.; Li, G.; Yang, H. Tooth and Pulp Chamber Automatic Segmentation with Artificial Intelligence Network and Morphometry Method in Cone-Beam CT Segmentación Automática de Cámaras Dentales y Pulpares Con Red de Inteligencia Artificial y Método de Morfometría En TC de Haz Cónico. *Int. J. Morphol.* **2022**, *40*, 407–413. [[CrossRef](#)]
57. Chen, C.; Zhang, X.; Qin, L.; Meng, L. Comparative Analysis of AI-Generated and Manually Designed Approaches in Accuracy and Design Time for Surgical Path Planning of Dynamic Navigation-Aided Endodontic Microsurgery: A Retrospective Study. *Int. Endod. J.* **2026**, *59*, 288–298. [[CrossRef](#)] [[PubMed](#)]
58. Faus-Matoses, V.; Faus-Llácer, V.; Moradian, T.; Riad Deglow, E.; Ruiz-Sánchez, C.; Hamoud-Kharrat, N.; Zubizarreta-Macho, Á.; Faus-Matoses, I. Accuracy of Endodontic Access Cavities Performed Using an Augmented Reality Appliance: An In Vitro Study. *Int. J. Environ. Res. Public Health* **2022**, *19*, 11167. [[CrossRef](#)] [[PubMed](#)]
59. Farronato, M.; Torres, A.; Pedano, M.S.; Jacobs, R. Novel Method for Augmented Reality Guided Endodontics: An in Vitro Study. *J. Dent.* **2023**, *132*, 104476. [[CrossRef](#)] [[PubMed](#)]
60. European Commission. *Directorate-General for Communications Networks, Content and Technology and High-Level Expert Group on Artificial Intelligence, Ethics Guidelines for Trustworthy AI*; Publications Office: Luxembourg, 2019.
61. van Kolschooten, H.; van Oirschot, J. The EU Artificial Intelligence Act (2024): Implications for Healthcare. *Health Policy* **2024**, *149*, 105152. [[CrossRef](#)] [[PubMed](#)]

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