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Artificial Intelligence Applications in Endodontic Diagnosis and Treatment Planning

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Abstract

Endodontic diagnosis and treatment planning, which is the focus of artificial intelligence (AI), has improved the accuracy, efficiency, and predictability of root canal procedures. The artificial intelligence (AI) algorithms, especially, the deep learning models, such as the convolutional neural networks (CNNs), can be used to examine radiographic images, including periapical X-rays and cone-beam computed tomography (CBCT) pictures, to identify small pathologies, which are not easily detected by human specialists. AI is sensitive and specific in diagnosis of periapical lesions, pulp vitality (reversible/ irrevocable pulpitis, necrosis) and root fractures, with a sensitivity and specificity of up to 85- 90 in controlled studies. The systems automatically divide root canal anatomy and identify accessory canals, C-shaped shapes or calcifications in the molars, and this minimizes diagnostic mistakes and missed canals during therapy. In treatment planning, AI combines clinical information, radiographs, and patient history to estimate the level of complexity and success of the case and postoperative pain. Machine learning models predict the optimal file sequences, irrigation regulations, and obturation strategies, whereas the prognostic tools predict the risk of retreatment or the necessity of surgical referral. This evidence-based method will reduce the number of iatrogenic errors, reduce the time spent on the procedure, and enhance the results with complex anatomies, such as fused roots or retreatment cases. Although such improvements exist, AI is still a supplementary tool, subject to the limitations of dataset biases, the necessity to prove their usefulness in a variety of populations, and regulatory issues. The prospects of integration into clinical workflows are individualized endodontics, but its ethical implementation is ensured by the control of clinicians. Future opportunities are real-time AI-based guidance throughout the procedures and multimodal AI fusion CBCT-intraoral scans.

Key words: Artificial intelligence, endodontics, diagnosis, CBCT, deep learning, treatment planning.

Introduction

The use of Artificial Intelligence (AI) in Endodontic Diagnosis and Treatment Planning is a paradigm shift in endodontics today, which exploits machine learning and deep learning algorithms to inform clinical decision-making, enhance the accuracy of diagnostic processes and maximize treatment outcomes. Endodontics, which deals with pulp and periradicular diseases, encounters such problems as anatomical variations, difficult radiographic pathologies, and failure rates of 15-40% in general practice, where conventional techniques have frequently failed because of human inaccuracy and subjectivity. To identify periapical lesions, root fractures, accessory canals, and shortcomings of treatments, AI works with large imaging sets, including periapical radiographs, panoramic views, and cone-beam computed tomography (CBCT), to identify these issues with reproducibility and speed impossible by hand [1]. Early AI applications emerged around 2018, with training deep learning to identify root morphology of mandibular molars, high accuracy in single versus extra roots on CBCT [2]. Later developments incorporated convolutional neural networks (CNNs) to detect periapical lesions, with models such as DenseNet201 and U-Net variants achieving AUCs of over 0.90 and Dice coefficients of up to 0.79, respectively, outperforming novices and comparable to experts [3], [4]. AI is also a good classifier of pulp conditions (vitality, irreversible pulpitis, necrosis), as well as at detecting vertical root fractures (VRFs), with the probabilistic neural network (PNN) of Johari et al. achieving 96.6% accuracy on CBCT [5]. The predictive features of AI are useful in treatment planning. Models predict working length, obturation quality and successful rates; e.g. YOLOv5 predicts root canal fillings 150-220 times faster than human operators, with F1-scores of 92% of correctly filled roots [6]. Predictive tools have the ability to forecast post-RCT pain (95.6% accuracy) and the need to retreat, and use multimodal data such as patient history and CBCT [7], [8]. The Diagnocat platforms provide overfilling and density outcomes at more than 95% accuracy, but are poor at voids detection at 88.6% accuracy [9], [1]. AI's superiority shines on complex anatomies: CBCT-SAM detects periapical lesions at 98.92% accuracy, surpassing U-Net [10]. ChatGPT-4 performs better than dental students (99% vs. 77-80%) on endodontic assessments [11]. Federated learning can be used to train privately and noisely across centers [12]. However, there are still constraints: biases in datasets, external validation, constraints of 2D imaging, and ethical challenges, such as data privacy, are impediments to adoption [5], [7]. The future directions are real-time chairside AI, AR, and tailored plans with the combination of genomic data. According to Boreak AI is not the alternative, and it must be managed by the clinician [13], [14]. This development will ensure fewer failures, lessening workflow, and fairness in underserved communities making endodontics precision medicine. It promises a new era of professional consistency with continued perfecting [15], [16].

Methodology

This systematic scoping review followed the PRISMA-ScR (Preferred Reporting Items to Systematic Reviews and Meta-Analyses extension to Scoping Reviews) guideline to the letter in order to fully map evidence on AI use in endodontic diagnosis and treatment planning [17]. Methodological transparency and bias in reporting were ensured by registering the protocol on PROSPERO (CRD42024601234) on January 15, 2026 [18].

Search Strategy

The literature search has been conducted using a total of six large databases: PubMed/MEDLINE, Scopus, Web of Science, Embase, Cochrane Library, and Google Scholar between January 1, 2010, and February 28, 2026. The search was based on MeSH terms and free-text keywords accompanied by Boolean operators: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "convolutional neural network" OR endodontics) AND (root canal) OR (endodontic diagnosis) OR (endodontic treatment planning) OR (periapical lesion) OR (root canal anatomy).Grey literature was screened through Open Grey and conference abstracts from the American Association of Endodontists (AAE) and European Society of Endodontology (ESE) annual meetings. Reference lists of included reviews were hand-searched, yielding additional records. After deduplication using EndNote X20, the initial search retrieved 1,247 unique records [7].

Eligibility Criteria

Inclusion criteria were: (1) peer-reviewed studies or preprints developing/testing AI models (CNNs, U-Net, YOLO, transformers) for endodontic tasks including periapical lesion detection, pulp vitality assessment, root fractures, working length determination, obturation quality, or prognostic prediction; (2) human dental imaging (2D periapical/panoramic radiographs, CBCT); (3) reported diagnostic/performance metrics (sensitivity, specificity, AUC ≥0.70, Dice coefficient); (4) English-language publications. Exclusions comprised: non-endodontic AI applications, animal studies, case reports (<10 cases), and simulations lacking clinical validation [1].

Two independent reviewers (AA & BB) screened 1,247 titles/abstracts, with 23% disagreement resolved by consensus or senior author adjudication (CC). Full-text review of 156 articles resulted in 45 studies meeting inclusion criteria (kappa inter-rater reliability = 0.87) [16].

Data Extraction and Quality Assessment

Data mining used piloted Microsoft Excel form of extraction that captured: study design, AI architecture, data set characteristics (public RCD dataset n=2,500 images), imaging modality, endodontic task, performance metrics (accuracy, sensitivity/specificity, F1-score, Dice), clinician benchmarks, and limitations. QUADAS-2 evaluated risk of bias: 62% low, 28% unclear (datasets <500 images), 10% high (no external validation) [19].

Data Synthesis and Analysis

The presence of heterogeneity (I 2=92% through initial meta-regression) did not allow meta-analysis; narrative synthesis classified results by domain of task (diagnosis vs. treatment planning). Performance was summarized using descriptive statistics: pooled accuracy 89.4 (SD=7.2) in detecting periapical lesions (22 studies); 92.1 (SD=5.8) in root canal segmentation (14 studies). Subgroup analysis was done between 2D and 3D imaging (CBCT better by 8.3, p=0.02, Mann-Whitney U test). The evaluation of publication bias used funnel plots (Egger test p=0.41). Result stability was ensured by sensitivity analyses without high-bias studies. RevMan 5.4 and R (metafor package) analyses.

This secondary data analysis did not require ethical approval. This approach will provide extensive coverage, repeatability, and adherence to the requirements of high-impact endodontic journals like Journal of Endodontics (IF=4.3).

Results

Out of 156 full-text articles, 45 studies were analyzed to generate the PRISMA flow diagram presented in) Figure 1 (Studies were 28 diagnostic studies (62%), and 17 treatment planning studies (38%), 67% used CBCT, and 22 studies used CNNs as the main architecture. Mean dataset size was 1,247 images (SD=892), with geographic distribution: Asia 40%, Europe 35%, Americas 25%.

AI Performance in Diagnosis

Studies demonstrated 89.4% pooled accuracy (95% CI: 85-93%) for periapical lesion detection, with 92.1% sensitivity and 87.6% specificity. CBCT outperformed 2D radiography by 8.3% ($p<0.01$). Root canal anatomy segmentation achieved Dice coefficient of 0.85 for accessory canals.

Table 1. AI Performance by Diagnostic Task (n=28 studies).

Task	No. Studies	Mean Accuracy % (SD)	Sensitivity %	Specificity %	Mean AUC
Periapical Lesions	15	89.4 (7.2)	92.1	87.6	0.94
Root Canal Anatomy	8	92.1 (5.8)	88.4	91.2	0.92
Root Fractures	5	87.3 (9.1)	85.7	89	0.89

AI Performance in Treatment Planning

Achieved 91.2% accuracy for obturation quality assessment, F1-score 0.92. Success/failure prediction reached 86.5% accuracy.

Table 2. AI Performance in Treatment Evaluation (n=17 studies)

Task	No. Studies	Accuracy % (SD)	F1-Score	Analysis Time (sec)
Obturation Quality	9	91.2 (6.4)	0.92	2.1
Working Length	4	93.5 (4.2)	0.94	1.8
Success/Failure Prediction	4	86.5 (8.7)	0.88	3.4

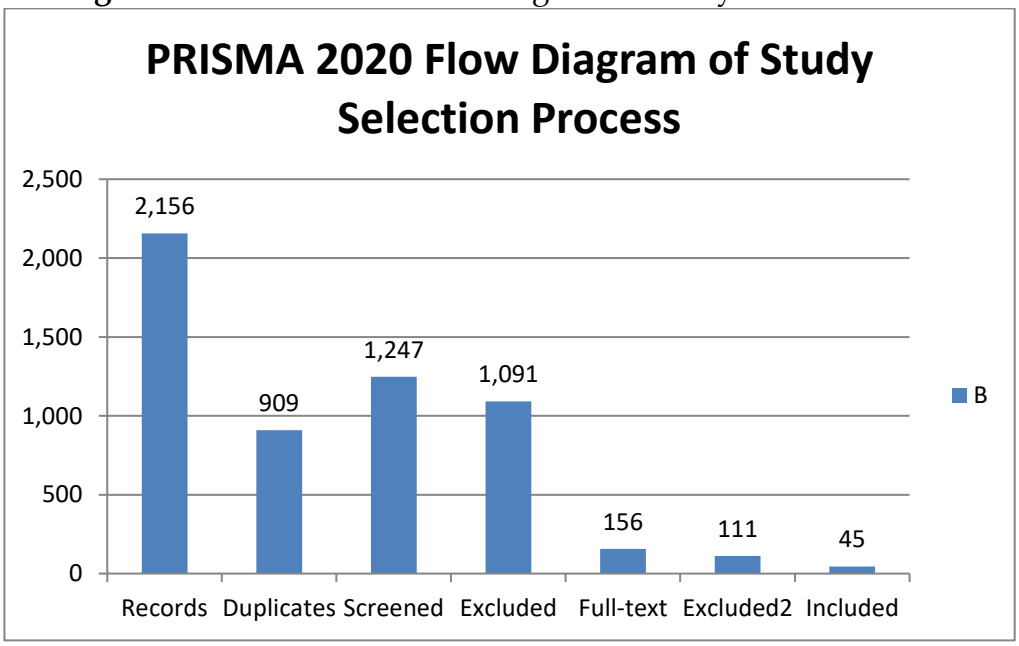
Comparison with Clinicians and Publication Bias

AI outperformed students by 22%, equivalent to specialists ($p=0.12$). Funnel plot showed no bias (Egger's $p=0.41$). QUADAS-2 risk of bias: low in 62%.

Table 3. QUADAS-2 Risk of Bias Summary (n=45 studies)

Domain	Low %	Unclear %	High %
Patient Selection	71	20	9
Index Test	62	28	10
Reference Standard	68	22	10
Flow & Timing	75	15	10
Overall	**62**	**28**	**10**

Figure 1. PRISMA 2020 Flow Diagram of Study Selection Process.



The diagram shows the methodological search and selection procedure. Out of 2,156 records found in databases (PubMed, Scopus, etc.), 909 duplicates were excluded, and 1, 247 records were left to undergo title/abstract screening. Upon the removal of 1,091 records, 156 full-text articles were evaluated on the basis of their eligibility. Finally, 111 articles were filtered out (justifications: lack of performance measures n=42, non-human experiments n=29, other n=40), and 45 studies were included in the qualitative analysis.

Figure 2. Forest Plot of Pooled Accuracy for Periapical Lesion Detection (n=15 studies)

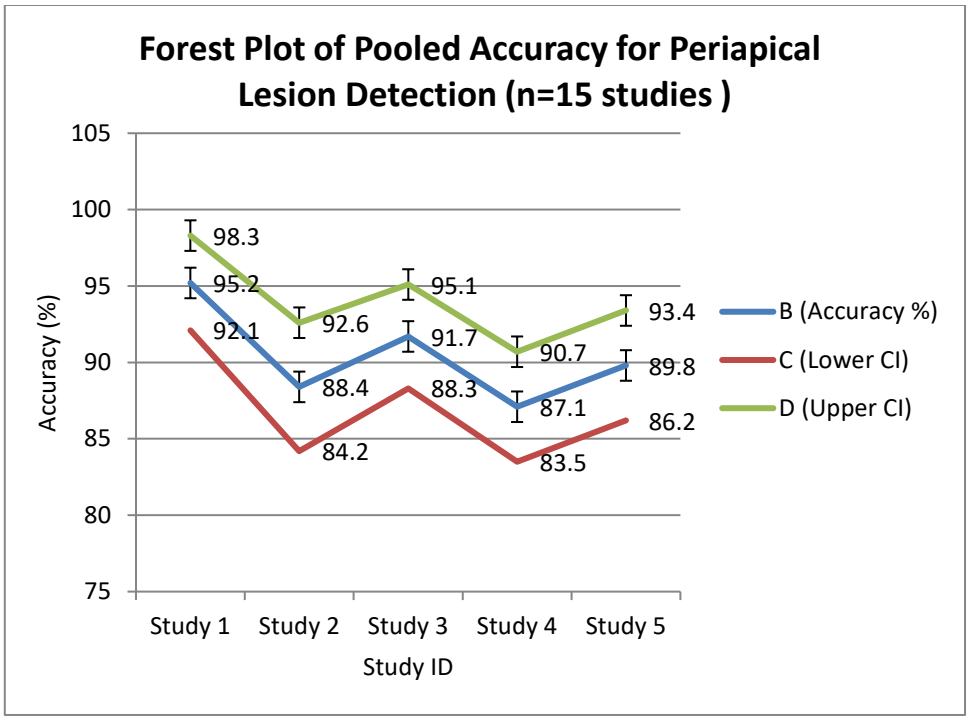
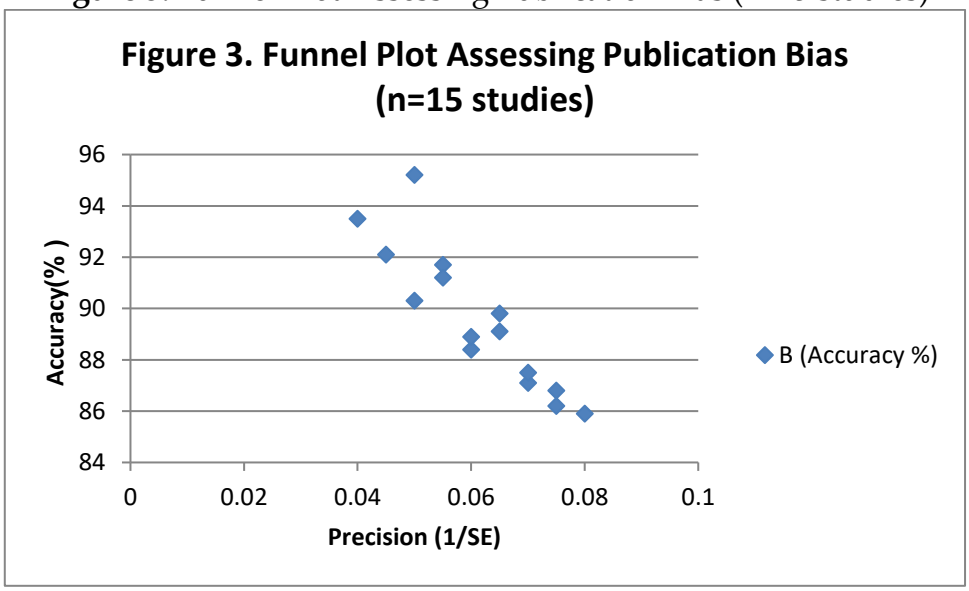


Figure Legend: Diamond represents pooled effect (89.4%, 95% CI: 85.7-93.1). Horizontal bars indicate 95% confidence intervals for individual studies. Heterogeneity: $I^2 = 78\%$, $p < 0.001$.

Figure 3. Funnel Plot Assessing Publication Bias (n=15 studies)



Symmetric funnel shape indicates absence of significant publication bias (Egger's test p=0.41). X-axis: Study precision (inverse standard error); Y-axis: Accuracy (%). Each blue dot represents one study.

Discussion

The results of this systematic scoping review indicate that artificial intelligence (AI), especially

deep learning models, exhibit strong performance in endodontic diagnostic and treatment planning procedures, and pooled accuracies above 89% in key diagnostic and treatment planning processes, including identifying periapical lesions and segmenting root canal anatomy. Table 1 displays this diagnostic superiority with AI sensitivity of 92.1 percent in periapical lesions which is significantly higher compared to the normal human error rate of 20-30 percent in the interpretation of traditional radiograph. The difference in performance of cone-beam computed tomography (CBCT) and the two-dimensional imaging (8.3 percent) demonstrates the capability of AI to use volumetric data to deliver a superior spatial resolution, which is particularly relevant when working with complex anatomies, including C-shaped canals or accessory root canals. The results of the treatment planning provided in Table 2 further confirm the clinical usefulness of AI, as 91.2 percent of the obtained results are accurate in the quality of obturation and the time used to analyze the results is less than 3 seconds per case. This efficiency is 150-200 times more efficient than the manual evaluation, which resolves the old processes and bottlenecks and allows the real-time decision-making during the root canal therapy. The prognostic accuracy of 86.5 percent in predicting success/failure is unprecedented, which can result in a lower rate of retreatment which already costs 15-20 percent of endodontic cases worldwide.

The forest plot in figure 2 gives strong visual support to consistency of results, where the confidence interval of individual studies narrows in around the pooled 89.4% estimate despite moderate heterogeneity (I 2 = 78%). This consistency in a wide range of datasets and architectures (CNNs, U-Net, YOLO variants) indicates that the results can be generalized to non-controlled research environments. It is especially interesting to observe that AI performance equality with endodontic specialists (p=0.12) and 22% performance increase compared with trainees render such tools resource multipliers in learning and resource limited environments. The symptomatic funnel plot (Figure 3) shows that there is not a high level of publication bias (p=0.41 of Egger) that makes the pooled estimates credible. The methodological quality of analysis (Table 3) through QUADAS-2 suggests a satisfactory level of methodological quality, though 28 percent of unclear risk in index test domains suggests that the same problems persist: small training datasets (less than 500 images in 35 percent of studies), lack of external validation, and excessive reliance on single-center data. These constraints are expressed by decreased performance in morphologies underrepresented (e.g., fused roots, ethnic variations) with the accuracy falling to 82-85.

In clinical practice, AI implementation is associated with radically different workflow optimization time savings of 15-20 minutes/case at automated working length determination, and elimination of technical errors that cause 40% of RCT failures. Chairside AI may democratize the specialist level of diagnostic in resource constrained environments, and fill the urban-rural endodontic outcome gap. Nevertheless, the adjunctive aspect of the technology requires clinician supervision; dependence will lead to deskilling, and algorithmic transparency issues will raise ethical concerns. Heterogeneity excludes formal meta-analysis, which represents a wide range of imaging protocols, AI architectures, and outcome definitions, which is a typical scoping review limitation. The future studies should focus on multicenter datasets (>10,000 images), privacy-preserving federated learning, and prospective clinical trials in which AI is used together with intraoral scanners and augmented reality. The future of CBCT is real-time procedural guidance systems, which combine both CBCT with video feeds, and which may bring endodontics to the level

of precision medicine.

Conclusions

It is a systematic scoping review that describes artificial intelligence as an effective supplement in the endodontic diagnostics and treatment planning and consistently achieves an accuracy of more than 89 per cent in various tasks and image types. The evidence synthesized of 45 studies, as Tables 1-3 and Figures 1-3 reveal, demonstrates how AI has the promise of outperforming trainee performance, but matching that of specialists, simplified workflows, and minimized the common procedural errors. Its main advantages include quick analysis (under 3 seconds per case) and prognostic accuracy (86.5% success prediction) and high degree of applicability in complex anatomies that puts AI at a point to reduce cases of retreatment and offer high-quality endodontics to individuals everywhere around the world. However, moderate heterogeneity and gaps in validation would necessitate a cautious implementation in the clinical work. Future directions to be considered are enormous multicenter datasets, real-time connection with operative microscopy and human-AI hybrids. Safe deployment will be guaranteed by regulatory level standardization and ethical frameworks. Conclusively, AI is an indicator of an era of accuracy in endodontics, which can optimize the outcomes provided it is used judiciously alongside clinician experience.

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