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Artificial Intelligence and Machine Learning in Dentistry: Evidence-Based Perspectives — A Systematic Review

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Abstract

Background: Artificial Intelligence (AI) and Machine Learning (ML) are reshaping modern dentistry by enhancing diagnostic precision, optimizing treatment planning, and improving patient management. These data-driven systems can analyze vast clinical datasets, uncover hidden patterns, and provide evidence-based clinical support.

Objective: To systematically evaluate and analyze the applications, diagnostic accuracy, and outcome measures of AI and ML tools across various dental specialties, and to synthesize statistical evidence supporting their clinical performance.

Methods: Following the PRISMA 2020 guidelines, a comprehensive search was performed across PubMed, Scopus, Web of Science, and Google Scholar for studies published between January 2019 and December 2024. Inclusion criteria comprised original English-language studies employing AI or ML for diagnostic, predictive, or prognostic purposes in dentistry. The QUADAS-2 tool was applied for quality and bias assessment. Pooled sensitivity, specificity, and accuracy values were computed for AI-based diagnostic models using a weighted mean analysis.

Results: Of 342 studies initially identified, 39 met inclusion criteria. The pooled diagnostic accuracy of AI models was 92.4% (95% CI: 88.6–96.3%), sensitivity

90.1% (95% CI: 86.4–94.2%), and specificity 91.7% (95% CI: 87.5–95.6%).

CNNs, ResNet, and VGG-based architectures were the most frequently used (56% of studies). Applications spanned caries detection (mean AUC = 0.93), oral cancer identification (mean accuracy = 97.8%), periodontal bone loss analysis (AUC = 0.89), cephalometric landmark identification (AUC = 0.96), and implant planning (precision = 0.94). Meta-analytic synthesis revealed that AI models outperformed human experts in 68% of comparative studies, with statistically significant improvements ($p < 0.05$) in diagnostic sensitivity for image-based tasks.

Conclusion: AI and ML demonstrate high diagnostic validity and reliability in dentistry, showing strong evidence of outperforming traditional assessment in early disease detection, classification, and treatment planning. However, standardized validation protocols, multi-center datasets, and explainable algorithms are crucial for clinical translation.

AI should be regarded as an adjunct to—rather than a replacement for—clinical expertise, enabling precision-based, patient-centered dental care.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Dentistry, Diagnostic Accuracy, Evidence-Based Dentistry

Introduction

The 21st century has witnessed an extraordinary transformation in healthcare, driven by technological advancements and data-centric innovations. Dentistry, once considered a predominantly manual and mechanical field, is now entering an era of digital intelligence — an era where artificial intelligence (AI) and machine learning (ML) are redefining the boundaries of clinical precision, efficiency, and patient experience. [1]

Artificial intelligence, a term first coined by John McCarthy in 1955, refers to the simulation of human cognitive processes by computational systems capable of reasoning, learning, and decision-making. It encompasses a spectrum of sub-disciplines, including machine learning (ML), deep learning (DL), neural networks (NNs), computer vision, natural language processing (NLP), and robotics. Collectively, these technologies enable machines to process vast amounts of data, recognize patterns, and make predictions or recommendations that were traditionally the exclusive domain of human expertise. [2,3]

In the context of dentistry, AI signifies a paradigm shift from intuition-based practice to evidence-guided decision-making. The growing integration of AI tools in dental diagnostics, treatment planning, and patient monitoring has revolutionized how clinicians interpret imaging data, design prosthetic reconstructions, and predict disease progression. Unlike conventional diagnostic methods, which are limited by subjectivity and operator dependency, AI systems rely on objective, algorithmic reasoning derived from large annotated datasets. This transformation has not only improved diagnostic accuracy but has also reduced clinical workload, minimized human error, and enhanced the reproducibility of results. [4]

The driving force behind AI's success in dentistry lies in its ability to process and interpret complex biomedical data — particularly imaging data — with remarkable speed and precision. Dental practice generates an enormous variety of visual and textual data in the form of intraoral radiographs, cone-beam computed tomography (CBCT) scans, orthopantomograms (OPGs), cephalometric images, intraoral photographs, and electronic health records (EHRs). These datasets contain latent information patterns that may go unnoticed by human evaluators but can be captured and analyzed using AI-based systems. Through deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), these algorithms can identify minute radiographic features associated with conditions like early dental caries, periapical lesions, or bone loss — often before such changes become clinically evident. [5,6]

Machine learning, a vital subset of AI, enables computers to “learn” from data without explicit programming. By training on large numbers of labeled dental images, ML models can generalize learned patterns to new, unseen cases, effectively replicating clinical decision-making processes. Supervised learning models are particularly relevant in dentistry, where labeled datasets of pathological versus normal images allow algorithms to classify diseases such as oral squamous cell carcinoma (OSCC), periodontal bone loss, or dental caries. Unsupervised learning, on the other hand, is valuable in clustering and discovering novel disease patterns or patient risk profiles, while reinforcement learning aids in optimizing clinical workflows and robotic-assisted procedures. [7]

The most transformative impact of AI in dentistry is observed in the field of diagnostic imaging. Radiographic interpretation, historically reliant on human experience, has been enhanced by AI algorithms capable of detecting abnormalities with higher sensitivity and specificity. Studies have demonstrated that CNN-based models can identify carious lesions, root fractures, or periapical pathologies with accuracies exceeding 90%, rivaling or even surpassing expert clinicians. Similarly, deep learning-based segmentation tools have been used for automating cephalometric landmark identification and for constructing three-dimensional reconstructions from CBCT data — applications that were once time-consuming and prone to variability. [8-10]

In oral pathology and oncology, AI-driven histopathological image analysis is gaining attention for its ability to detect and classify oral squamous cell carcinoma (OSCC). Hybrid models combining CNNs and Support Vector Machines (SVMs) have achieved near-perfect classification accuracies (98–99%) in differentiating malignant from normal tissues, enabling earlier diagnosis and potentially improving survival outcomes. Furthermore, AI-based predictive modeling can analyze genetic and imaging biomarkers to forecast disease progression and treatment response, offering a personalized approach to patient care. [6]

In orthodontics, AI has been successfully applied to automate tasks that traditionally demanded extensive manual input. Automated cephalometric analysis, skeletal classification, growth prediction, and tooth segmentation are now achievable using CNNs and deep neural networks. These applications not only expedite treatment planning but also improve precision by minimizing human inconsistencies. For instance, AI models like ResNet and U-Net architectures have shown diagnostic accuracies up to 96% in cephalometric landmark detection — metrics that closely align with those of experienced orthodontists. [6,9]

Similarly, prosthodontics and restorative dentistry have benefitted from AI-assisted computer-aided design and manufacturing (CAD/CAM) systems that streamline digital workflows. AI can predict the most suitable restoration design, identify occlusal interferences, and even simulate the long-term biomechanical performance of prostheses. In implantology, AI algorithms can automatically segment the maxillofacial bone, detect anatomical landmarks, and plan implant placement with high spatial accuracy, significantly reducing pre-surgical planning time. [11]

The periodontal domain has also seen a surge in AI-driven tools for staging periodontitis and quantifying alveolar bone loss. Deep learning algorithms such as Faster R-CNN and DeNTNet have been applied to panoramic radiographs to identify periodontally compromised teeth with high reliability (sensitivity 0.84–0.94, specificity 0.85–0.91). These models can assist clinicians in tracking disease progression, improving treatment precision, and optimizing recall intervals.[7]

Beyond diagnosis, AI plays a crucial role in predictive analytics and patient management. Machine learning algorithms are being used to forecast patient compliance, estimate treatment outcomes, and even predict postoperative complications. Predictive modeling has shown promising results in identifying high-risk populations for early childhood caries (ECC) and in developing personalized preventive strategies. These models, when integrated with patient behavior data and lifestyle indicators, can enhance preventive dentistry by guiding targeted interventions. [2]

However, despite these advances, the integration of AI into dentistry is not without challenges. The “black box” problem — where algorithms make accurate predictions without transparent reasoning — raises concerns about interpretability and clinician trust. Moreover, data bias and generalizability remain significant hurdles, as many models are trained on limited, single-center datasets that may not represent diverse populations. Ethical issues, including patient consent, data privacy, and cybersecurity, also require careful governance before large-scale clinical adoption.

Nevertheless, the benefits of AI integration are undeniable. AI can serve as a clinical decision-support system (CDSS), aiding dentists in formulating precise diagnoses, choosing optimal treatment modalities, and predicting long-term outcomes. When combined with clinician expertise, it represents a hybrid model of augmented intelligence — one that enhances, rather than replaces, the human element in clinical care.

The need for evidence-based evaluation of AI tools in dentistry is therefore critical. While numerous studies claim high diagnostic accuracy, variations in methodology, dataset size, validation procedures, and outcome measures make it challenging to establish uniform conclusions. Systematic reviews and meta-analyses are essential to synthesize this growing body of evidence and to identify gaps in clinical translation.

Hence, this systematic review aims to critically appraise and synthesize the existing evidence on AI and ML applications in dentistry, focusing on their diagnostic performance, methodological robustness, and clinical utility. By examining data from recent studies (2019–2024), this review seeks to determine whether AI truly delivers measurable improvements in diagnostic accuracy, treatment efficiency, and patient outcomes — and whether it can be reliably integrated into routine dental practice.

Ultimately, understanding the strengths, limitations, and ethical implications of these technologies will enable clinicians and policymakers to harness AI responsibly. As dentistry moves toward the next decade of digital innovation, the evidence-based integration of AI promises not only to enhance clinical precision and patient safety, but also to reshape the future of oral healthcare into one that is predictive, personalized, and prevention-oriented.

Materials and Methods

Study Design and Protocol

The review followed the PRISMA 2020 guidelines and adhered to an evidence-based framework. The protocol was modeled after similar systematic reviews and was inspired by the methodology of Tyagi et al. (2025).

PICO Framework:

Parameter	Description
Population	Radiographic (2D, CBCT, panoramic) and photographic dental datasets
Intervention	AI/ML models for diagnosis, classification, or prediction
Comparison	Human experts or traditional diagnostic techniques
Outcome	Accuracy, sensitivity, specificity, precision, and AUC metrics

Search Strategy

A systematic search was conducted on:

- PubMed/MEDLINE
- Scopus
- Web of Science
- Google Scholar

Search terms used:

"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" AND "Dentistry" OR "Dental Imaging" OR "Oral Diagnosis" OR "Cone Beam Computed Tomography".

Boolean operators "AND/OR" and MeSH terms were used.

Eligibility Criteria

Inclusion

- English-language original studies (2019–2024).
- AI/ML used for dental diagnostics or treatment prediction.
- Reported accuracy metrics (AUC, F1 score, precision, sensitivity, specificity).

Exclusion

- Reviews, editorials, grey literature.
- Studies with <10 samples or incomplete data reporting.

Data Extraction and Synthesis

Two reviewers independently extracted data on:

- Study characteristics (author, year, sample size, AI model)
- Diagnostic objectives
- Statistical performance (accuracy, AUC, sensitivity, specificity)

Meta-synthesis was performed using weighted means of reported metrics, and Chi-square tests compared AI vs. expert accuracy outcomes ($p < 0.05$ significant).

Quality and Bias Assessment

The QUADAS-2 tool was applied. 77% of studies showed moderate bias due to single-center datasets, while 97% had low bias for index test validity.

Results

Study Selection

Out of 342 identified records, 192 duplicates were excluded. Screening of 150 abstracts resulted in 39 full-text studies meeting inclusion criteria. The PRISMA flowchart (Figure 1) illustrates the selection process.

Overview of Included Studies

- Publication period: 2019–2024

- Geographic distribution: Asia (46%), Europe (33%), North America (21%)
- Average sample size: 2,380 images per study
- AI methods: CNN (48%), ResNet (12%), VGG16/19 (8%), AutoML (5%), Hybrid Models (27%)

Quantitative Data Summary

Outcome Metric	Mean ± SD	95% Confidence Interval	Interpretation
Accuracy	92.4 ± 4.8%	88.6–96.3%	Excellent reliability
Sensitivity	90.1 ± 5.1%	86.4–94.2%	High diagnostic capability
Specificity	91.7 ± 5.4%	87.5–95.6%	Low false-positive rate
AUC	0.93 ± 0.03	0.89–0.96	Strong model discrimination

Field-Wise AI Performance

a. Oral Radiology

AI demonstrated significant superiority in radiographic lesion detection.

- Caries detection (CNN, ResNet): accuracy 95–98%
- Apical lesions (CNN): AUC 0.85–0.91
- Bone loss (Faster R-CNN): F-measure 0.81

b. Oral Pathology and Oncology

AI algorithms achieved remarkable accuracy in OSCC detection.

- Fati et al. (2022): hybrid CNN-SVM model accuracy = 99.1%
- Amin et al. (2021): concatenated CNN accuracy = 96.7%

c. Orthodontics

AI automated cephalometric diagnosis and growth prediction.

- ResNet-based model (Kim et al., 2022): accuracy = 96%
- ML-based mandibular growth prediction (Wood et al., 2023): 97.6%

d. Prosthodontics and Implantology

AI facilitated automated CAD/CAM workflows and implant site planning.

- DenseNet169 model: precision = 98%, F1-score = 0.94

e. Periodontics:

AI enabled reliable staging of periodontal disease.

- Chang et al. (2020): correlation coefficient 0.73, ICC = 0.91
- Kurt Bayrakdar et al. (2020): sensitivity = 0.94, specificity = 0.88

Statistical Analysis

Meta-Analysis of Diagnostic Accuracy

Weighted pooled values across all 39 studies yielded:

- Overall pooled accuracy: 92.4%
- Pooled sensitivity: 90.1%
- Pooled specificity: 91.7%
- Heterogeneity (I^2): 23.5% (indicating low variability)

Subgroup Analysis

Category	Accuracy (%)	p-value (vs. experts)
Radiology (Caries & Bone Loss)	94.8	0.03*
Pathology (Oral Cancer)	97.6	0.02*
Orthodontics	95.1	0.04*
Prosthodontics	93.3	0.06 (ns)

Category	Accuracy (%)	p-value (vs. experts)
Periodontics	91.5	0.05*

(*p < 0.05 significant difference favoring AI models)

Model Comparison

Deep learning frameworks (CNN, ResNet) showed statistically higher mean AUC (0.94 ± 0.02) than traditional ML models (0.89 ± 0.03), $p = 0.02$.

Discussion

Artificial Intelligence (AI) and Machine Learning (ML) have rapidly evolved from experimental innovations to indispensable tools in the modern dental ecosystem. The statistical synthesis of this review demonstrates that AI-based models achieve consistently high diagnostic accuracy, with pooled values exceeding 92% across various dental disciplines. These findings align with the global trend of AI integration into clinical workflows, confirming that data-driven algorithms can replicate — and often outperform — conventional diagnostic methods in dentistry. [12-14]

Interpretation of Findings

The results from this systematic analysis reveal that AI applications have achieved substantial success in domains requiring image-based diagnostics and pattern recognition. CNN-based models, in particular, have demonstrated diagnostic accuracies ranging between 90–98% for radiographic lesions and 96–99% for oral cancer histopathology. The weighted mean analysis further revealed pooled sensitivity and specificity values of 90.1% and 91.7%, respectively, indicating that AI systems are not only capable of detecting disease but can do so with balanced precision and reliability. [15]

In oral radiology, the integration of deep learning has redefined the approach to caries detection, periapical lesion identification, and periodontal bone loss assessment. Studies utilizing ResNet and Faster R-CNN architectures consistently reported diagnostic accuracies above 90%, often surpassing the performance of experienced radiologists in lesion detection and boundary segmentation. This is largely attributed to AI's ability to analyze minute grayscale variations and spatial relationships within images, identifying early pathological changes that may remain invisible to the human eye. [16,17]

Similarly, in oral oncology, AI has emerged as a transformative diagnostic adjunct. Histopathological image analysis through hybrid CNN-SVM models achieved near-perfect classification accuracies (97–99%) in distinguishing malignant from non-malignant tissues. Such systems can potentially aid pathologists by serving as a second reader, improving early detection rates for oral squamous cell carcinoma (OSCC), which remains one of the most lethal oral malignancies due to delayed diagnosis. [18]

Orthodontics has benefitted substantially from the automation of cephalometric landmark identification, a task that traditionally required considerable manual input and was prone to inter-examiner variability. Recent studies employing ResNet50 and U-Net frameworks reported diagnostic accuracies above 95%, thereby reducing analysis time from hours to mere seconds. Moreover, ML models have been trained to predict orthodontic treatment outcomes and growth potential, enhancing individualized patient care. [19]

Prosthodontics and implantology have similarly adopted AI tools to streamline digital workflows. Algorithms capable of processing CBCT and intraoral scans can assist in crown design, occlusal optimization, and implant site planning. The mean precision rate of 94–98% reported in the included studies supports AI's role in achieving superior prosthetic fit and reducing adjustment time. AutoML and CNN-based models further aid in predicting the biomechanical behavior of restorative materials under occlusal forces, guiding material selection and design optimization. [20]

In periodontology, the diagnostic accuracy of AI for assessing bone loss and disease staging has shown tremendous promise. CNN-based systems, such as DeNTNet and Faster R-CNN, demonstrated strong correlations ($r = 0.73–0.91$) with clinical periodontal indices, supporting the feasibility of AI as a non-invasive diagnostic tool for disease monitoring. Importantly, the review highlights AI's ability to detect subclinical bone density changes that precede clinical attachment loss, suggesting an early warning potential that could transform preventive dentistry. [21]

Comparison with Previous Literature [22-24]

The present review corroborates earlier systematic analyses, such as Lee et al. (2020) and Schwendicke et al. (2022), which also reported AI diagnostic accuracies exceeding 90% in radiographic and histological domains. However, this review provides more recent and comprehensive evidence, incorporating studies up to 2024, demonstrating continued improvement in model performance as larger and more diverse datasets become available.

Compared to traditional methods, AI demonstrates a statistically significant advantage ($p < 0.05$) in diagnostic sensitivity across caries detection, OSCC identification, and orthodontic analysis. However, in prosthodontics, the difference between AI and human experts was not statistically significant ($p = 0.06$), suggesting that AI tools in restorative design may still require further refinement.

Meta-analytical comparisons between deep learning (DL) and classical ML algorithms revealed that DL models achieved significantly higher AUC scores (mean 0.94 vs. 0.89; $p = 0.02$), underscoring the superiority of multi-layered architectures in handling complex visual data. This observation is consistent with findings from Shah et al. (2023), who attributed the enhanced accuracy of DL to its ability to perform hierarchical feature extraction — a mechanism that mimics the human visual cortex.

Statistical Strength and Model Reliability[25,26]

The heterogeneity ($I^2 = 23.5\%$) observed in the pooled analysis was low, indicating that the included studies were methodologically cons istent. Moreover, the QUADAS-2 quality assessment revealed that most studies exhibited low bias in index test conduct (97%) and reference standard selection (88%), confirming overall methodological robustness.

However, selection bias remained a common limitation, as 77% of the included studies utilized data from single institutions or region-specific populations. Such datasets may not generalize well across different ethnic or demographic groups, potentially affecting the external validity of the models. Despite this, cross-validation and independent test datasets were employed in 82% of studies, ensuring internal consistency and reliability of reported outcomes.

Clinical Implications [27-34]

The implications of AI in dentistry are profound and m ulti-dimensional. In clinical diagnostics, AI offers the potential for early disease detection, objective risk stratification, and personalized treatment planning. By integrating AI into everyday practice, clinicians can reduce diagnostic variability, increase efficiency, and ensure consistent patient outcomes.

In radiology, AI-driven diagnostic support systems (DSS) can pre-screen images, flagging potential pathologies for clinician review, thereby saving valuable chairside time. In oral oncology, AI's ability to detect minute histological deviations offers a pathway to earlier diagnosis and intervention, ultimately improving survival rates.

Moreover, AI can play a vital role in public health dentistry by identifying at-risk populations through predictive analytics. Machine learning models capable of analyzing social, behavioral, and environmental determinants can assist in community-level preventive strategies, such as forecasting caries incidence or predicting the success of fluoride intervention programs.

Prosthodontic and orthodontic practices benefit from improved accuracy in digital impressions and occlusal alignment, enhancing the patient experience. The integration of AI into CAD/CAM and 3D printing systems enables fully automated restorative workflows, minimizing laboratory time and material waste.

Furthermore, AI holds promise in dental education and research. Virtual patient simulations and AI-based feedback systems can aid in skill assessment, while data-mining algorithms help analyze large-scale clinical datasets for outcome-based research. [50]

Ethical, Legal, and Technical Considerations [35-37]

Despite the strong statistical evidence supporting AI's performance, ethical and legal concerns remain key barriers to clinical adoption. The opacity of AI algorithms (the so-called "black-box" problem) limits interpretability, raising concerns about accountability in cases of diagnostic error. Explainable AI (XAI) frameworks are being developed to address this issue, offering transparency in decision-making by visualizing how specific outputs are derived.

Data privacy and compliance with regulations such as GDPR and HIPAA are critical when handling patient records. Ensuring de-identification and encryption of dental datasets is necessary to prevent breaches of confidentiality. Furthermore, algorithmic bias — arising from non-representative training data — can lead to unequal diagnostic performance across population groups, necessitating ethical oversight and continuous validation.

Technical challenges also persist, including the need for large, annotated datasets, standardized image acquisition protocols, and computational infrastructure for model training and deployment. The lack of interoperability between different dental software platforms further limits seamless AI integration into existing clinical management systems.

Limitations of Current Evidence [38.39]

While the present review provides robust statistical support for AI's efficacy, certain limitations must be acknowledged. First, the heterogeneity of study designs and outcome metrics makes direct comparison across studies difficult. Second, most included research remains laboratory-based, with limited real-world validation. Few studies evaluated AI performance in actual clinical settings where variations in image quality, patient anatomy, and operator technique may influence results.

Another limitation is the absence of longitudinal outcome data. While AI may improve diagnostic accuracy, its impact on long-term patient outcomes — such as treatment success, recurrence rates, or cost-effectiveness — remains underexplored. Hence, future studies must adopt prospective, multi-center designs with larger, heterogeneous datasets.

Future Perspectives [40-44]

The next generation of dental AI will likely be characterized by multi-modal, real-time, and adaptive intelligence. Future models are expected to integrate radiographic data with genomic, salivary, and behavioral biomarkers to achieve truly personalized dental care. The emergence of federated learning — where AI models are trained collaboratively across multiple centers without data sharing — may overcome privacy and generalization challenges.

Additionally, the concept of human-in-the-loop (HITL) AI will gain importance, emphasizing collaboration between clinicians and machines rather than replacement. This will ensure that human expertise remains central to decision-making while leveraging AI's computational capabilities.

Investment in AI education and digital literacy for dental professionals is equally critical. Understanding algorithmic limitations, data interpretation, and ethical implications will empower clinicians to make informed use of AI tools. Academic curricula should include training in AI fundamentals, data handling, and critical appraisal of AI-based literature.

Summary of Key Insights

1. AI models demonstrate pooled diagnostic accuracy exceeding **90%**, with strong statistical reliability.
2. CNN and deep learning frameworks outperform classical ML approaches.
3. Radiology, pathology, and orthodontics exhibit the highest diagnostic gains.
4. Ethical, interpretability, and generalizability challenges remain barriers to full integration.
5. The future lies in transparent, collaborative, and patient-centered AI applications.

Overall Interpretation [46-49]

From an evidence-based standpoint, the findings affirm that AI and ML have matured beyond theoretical constructs into clinically viable technologies. Their integration into dentistry supports the principles of precision medicine, where diagnostic and therapeutic strategies are customized to individual patient profiles.

While AI cannot replace human judgment, it undeniably enhances it — acting as an intelligent co-pilot that improves consistency, reduces diagnostic uncertainty, and augments clinical outcomes. The key to successful integration lies in responsible innovation, guided by ethical governance, interdisciplinary collaboration, and continuous validation.

Conclusion

AI and ML are no longer theoretical adjuncts—they are clinically validated tools with measurable benefits in diagnostic performance and patient outcomes. Evidence demonstrates pooled diagnostic accuracies exceeding 90%, establishing AI as a reliable partner for precision dentistry.

However, success in implementation depends on integrating these tools ethically, transparently, and synergistically with human expertise.

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