ARTIFICIAL INTELLIGENCE–ASSISTED DENTAL CARIES DETECTION IN MODERN DENTISTRY: DIAGNOSTIC POTENTIAL, LIMITATIONS, AND CLINICAL INTEGRATION

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Abstract

Background: Artificial intelligence (AI) is increasingly used to assist the interpretation of dental images, particularly for detection and staging of carious lesions. However, technical diagnostic accuracy does not necessarily translate into better treatment decisions or patient outcomes. Objective: To critically examine the evidence for AI-assisted caries detection in contemporary dentistry and identify practical conditions for responsible clinical use. Methods: A focused narrative review was prepared using peer-reviewed systematic reviews, professional consensus documents and policy statements published between 2020 and 2026. Sources were selected for their relevance to caries detection, imaging, diagnostic validity and clinical governance; this was not a systematic review or a new clinical investigation. Results: A 2024 meta-analysis of five bitewing-based studies estimated summary sensitivity at 0.87 and specificity at 0.89, but identified substantial limitations in reporting and external validation. A 2026 review found high overall risk of bias in all 28 evaluated diagnostic-accuracy estimates and independent external validation in only five studies. Expert recommendations continue to place structured visual examination first, with indicated intraoral radiography and other adjunct methods used selectively. Conclusion: AI has potential as a second-reader and documentation-support technology, but requires population-relevant validation, transparent monitoring and clinician oversight. No original patient data or experimental outcomes are reported in this article. [2–7]

Keywords: artificial intelligence, digital dentistry, dental caries, bitewing radiography, deep learning, diagnostic accuracy, clinical decision support, oral health.

Introduction

Digital transformation has changed how dental information is acquired, reviewed and communicated. Intraoral cameras, digital radiography, optical scanning and electronic records are now parts of an increasingly connected clinical workflow. Within this environment, machine-learning and deep-learning models can identify visual patterns in images and highlight regions suspected of caries. Unlike conventional image-enhancement software, these models learn statistical relationships from annotated examples; their output is a probabilistic assessment rather than a direct biological measurement. The distinction is essential because a visually plausible algorithmic prediction can still be inaccurate for an individual patient. [1,6]

Caries diagnosis is more complex than marking a radiolucency on a radiograph. Clinicians need to consider lesion location and depth, surface activity, plaque retention, previous restorations, symptoms, the patient's caries-risk profile and whether intervention should be preventive or operative. A system that detects more suspicious image regions could improve case finding, yet it might also encourage unnecessary restorative treatment if false-positive predictions are accepted without examination. Consequently, AI-assisted interpretation should be evaluated not only by image-level statistics but also by its effect on clinical decisions. [2,5,8]

Recent international recommendations support an evidence-driven interpretation of new digital tools. The European Organisation for Caries Research and European Federation of Conservative Dentistry (ORCA–EFCD) recommend structured visual examination as the first-line method for accessible surfaces; intraoral radiography, preferably bitewing images when indicated, provides additional evidence. The FDI World Dental Federation similarly emphasizes human autonomy, professional competence and critical evaluation of AI applications. [2,6]

Aim of the Study

The aim of this narrative review is to summarize contemporary clinical applications of AI-assisted dental caries detection, compare available diagnostic evidence, distinguish algorithmic performance from patient benefit, and propose an evidence-informed framework for integration into dental practice and postgraduate training.

Materials and Methods

This manuscript is a focused narrative synthesis rather than an experimental or systematic study. Publications identified through PubMed-indexed records, journal websites and professional policy materials were consulted, with emphasis on the period 2020–2026. Priority was given to systematic reviews with explicit diagnostic endpoints, a caries-diagnosis expert consensus, dental-radiography recommendations and international guidance on AI ethics and education. The available evidence was examined across five domains: imaging input, diagnostic target, reference standard, validity of performance measures and applicability to clinical workflow. No patients were enrolled, no original imaging dataset was analyzed, and no new statistical calculations were performed. [1–10]

To avoid misleading comparisons, reported accuracy estimates were interpreted within the source study's imaging modality and diagnostic definition. The article does not claim an exhaustive literature search, independent risk-of-bias reassessment, pooled meta-analysis or locally validated diagnostic effectiveness. Numerical findings below are explicitly attributed to published evidence.

Results and Discussion

Clinical Applications and Imaging Modalities

AI-assisted caries detection has predominantly been evaluated using bitewing radiographs, although investigations also include periapical and panoramic radiographs, intraoral photographs and, less frequently, optical or three-dimensional imaging. Radiographic algorithms may outline areas of reduced mineral density and present confidence scores, whereas photograph-based tools typically focus on visually accessible surfaces. Because the two modalities detect different manifestations of disease, their performance estimates should not be treated as interchangeable. [3–5]

Bitewing radiographs can add information about posterior proximal surfaces that cannot be fully visualized clinically. Current dental-radiography recommendations recognize posterior bitewings for appropriate caries indications and do not support cone-beam computed tomography (CBCT) for routine caries detection. Artificial intelligence therefore does not justify additional radiation exposure; any image should be acquired on clinical grounds before the usefulness of automated interpretation is considered. [7]

What the Diagnostic Accuracy Literature Shows

Ammar and Kühnisch reviewed 14 studies of AI-assisted interpretation of bitewing radiographs published through early 2024. Five studies contributed to their diagnostic meta-analysis, which reported a summary sensitivity of 0.87 (95% confidence interval 0.76–0.94) and specificity of 0.89 (95% confidence interval 0.75–0.96). These values indicate encouraging discrimination within the analyzed datasets, but the authors noted unclear or high risk of bias and insufficient external validation. Reported sensitivity also differed between enamel and dentin lesions; in that review, sensitivity was 0.71 for enamel and 0.84 for dentin caries in the separate analyses. These numbers should not be generalized to every clinic or software product. [3]

A broader synthesis by Abbott and colleagues, published in 2025, confirmed research interest across dental photographs and radiographs, while highlighting variation in model architectures, evaluation datasets and quality of evidence. More recently, Chaple Gil and colleagues examined 29 reports representing 28 unique studies (2021–2026). They found that only five studies used independent external validation, and all 28 diagnostic-accuracy estimates had a high overall risk of bias. Among 12 reports with reconstructable two-by-two data, sensitivity ranged from 0.360 to 0.940 and specificity from 0.700 to 0.983. Because the underlying modalities and thresholds were heterogeneous, the authors did not combine these observations into a single clinical benchmark. [4,5]

These reviews illustrate why headline “accuracy” figures alone can mislead. Image-level classification, tooth-level detection, surface-level staging and lesion segmentation solve different tasks. An apparently high accuracy could also reflect the proportion of sound surfaces in the test set. More informative reporting should state sensitivity,

specificity, predictive values, calibration, confidence intervals, the exact decision threshold and the population to which the estimate applies. [3–5]

Table 1. Selected applications and limitations of AI-assisted caries detection

Input / target	Potential clinical contribution	Important limitation
Bitewing radiographs / proximal lesions	Flags suspicious approximal radiolucencies for clinician review.	Lesion-depth definitions, image quality and training-set bias vary.
Intraoral photographs / visible surfaces	May assist screening documentation and patient communication.	Lighting, saliva, restorations and surface visibility affect reliability.
Periapical or panoramic images / tooth findings	Can organize a secondary inspection of available images.	Lower relevance to some early proximal lesions; not equivalent to bitewings.
AI-assisted treatment planning	May help compare lesion records and follow-up observations.	Detection output alone cannot determine activity or whether drilling is indicated.

Source: conceptual synthesis of published reviews and clinical guidance [2–7]; not original clinical data.

AI as a Second Reader, Not an Autonomous Dentist

There is an important difference between a model's stand-alone accuracy and the benefit of using that model during clinical work. The latter depends on whether dentists correctly notice, verify and act on flagged findings. Controlled reader studies summarized in the 2026 review suggested improved sensitivity with AI support, but one study also found reduced specificity and another reported more invasive treatment choices. Thus, more detected lesions do not automatically mean better oral health. Patient-centered endpoints, including avoidance of unnecessary treatment, earlier appropriate prevention and long-term lesion outcomes, remain necessary. [5]

An appropriate workflow begins with risk assessment and clinical examination, followed by imaging when indicated. The clinician can then review an AI-assisted annotation as a second opinion, examine the original image without overlays, integrate other clinical findings and record the rationale for the final decision. When an algorithm and the clinical evaluation disagree, further verification is preferable to automatically accepting either conclusion. [2,6,7]

Data Quality, External Validity and Ethical Safeguards

Diagnostic models are sensitive to differences in detector type, acquisition settings, patient age, tooth anatomy, restorations, disease prevalence and image labeling. Randomly splitting images from the same patient into training and test partitions may create overly optimistic results if related images appear in both groups. Independent external evaluation across clinical sites is more informative than internal test accuracy alone. Before adoption, a dental service should verify performance in its patient population, monitor errors and review software updates that may change output. [1,5]

Ethical governance is equally important. Images and clinical records contain sensitive information and should be managed under applicable privacy and information-security requirements. Patients should understand when AI supports evaluation; clinicians must remain accountable for diagnosis and treatment. International work on dental AI ethics identifies fairness, transparency, accountability, autonomy and privacy as central safeguards. Costs, accessibility and potential bias against underrepresented patient groups also require attention. [6,8,10]

Implications for Postgraduate Dental Education

For a dental postgraduate trainee, the relevant competence is not simply the ability to operate software. Training should cover the difference between prediction and diagnosis, the meaning of true and false positives, the importance of a representative reference standard and the limitations of retrospective studies. A core curriculum proposed for oral and dental AI education includes model evaluation, clinical use cases, generalizability, explainability and governance. [9]

A practical teaching exercise can involve blinded review of a set of de-identified bitewing images, followed by AI-assisted review and structured discussion of discordant findings. Learners should record which observations changed and whether those changes would alter preventive advice, follow-up or restorative intervention. Such an exercise is an educational proposal; no student performance data or intervention effectiveness are claimed in the present article.

Practical Recommendations

On the basis of the reviewed guidance, a cautious introduction of AI-supported caries detection may follow four steps: (1) define the exact clinical question and imaging indication before selecting a tool; (2) review external validation evidence with attention to false positives and negatives; (3) retain clinician responsibility for examining original images and making patient-specific decisions; and (4) establish local quality assurance, patient-data protection, continuing education and a process for reporting algorithmic errors. These steps prioritize safe integration over unverified efficiency claims. [2,5–9]

Conclusion

AI-assisted interpretation of dental images is a promising component of modern dentistry, especially as a structured second reader for the assessment of carious lesions. Nevertheless, current studies differ substantially in lesion definitions, imaging modalities and methods of validation. Published diagnostic performance should not be interpreted as proof of safer treatment or improved patient outcomes. The most defensible approach is to integrate AI with visual examination, clinically indicated radiography, individualized risk assessment and independent professional judgment. Future studies should prioritize multicenter external validation and prospective evaluation of clinical decisions rather than algorithmic accuracy in isolation.

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