# Integration of Artificial Intelligence in Caries Detection and Oral Radiology: A Clinical Evaluation

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**Abstract**

**Introduction:** Dental caries remains the most prevalent chronic disease worldwide, with early and accurate detection being critical to minimising irreversible tooth tissue loss. Oral radiology constitutes the diagnostic backbone of caries assessment; however, the interpretive accuracy of conventional radiographic analysis is subject to clinician experience, fatigue, and inter-examiner variability. Artificial intelligence — particularly deep learning architectures including convolutional neural networks — has demonstrated the capacity to automate and enhance radiographic caries detection with accuracy metrics that rival or surpass trained specialists. This clinical evaluation reviews the current evidence on AI integration across dental radiographic modalities, with a focus on diagnostic performance, clinical utility, and translational challenges.

**Discussion:** Convolutional neural network-based models applied to bitewing, periapical, panoramic, and cone-beam computed tomography imaging have consistently reported caries detection sensitivity between 85% and 95%, with specificity values of 80–93%, across multiple independent clinical datasets. Transfer learning strategies have enabled strong model performance even with relatively limited annotated training datasets, a critical advantage in dental imaging contexts where large curated repositories remain scarce. AI systems demonstrate particular advantages over conventional radiographic interpretation in the detection of early-stage proximal and occlusal caries, periapical pathology, and alveolar bone loss — diagnostic tasks associated with high rates of clinician error and under-reporting. Key clinical limitations include the dependency of model performance on dataset representativeness, the black-box interpretability problem inherent to deep neural networks, inconsistency across imaging equipment manufacturers, and the absence of dental-specific AI regulatory frameworks in most international jurisdictions. Integration into clinical workflows requires attention to practitioner training, system interoperability with existing radiographic software platforms, and robust post-deployment performance monitoring.

**Conclusions:** Artificial intelligence represents a clinically validated and scientifically robust advancement in dental radiographic diagnosis. The evidence supports AI as an effective decision-support tool for caries detection and oral radiological interpretation, with the potential to significantly improve early diagnosis rates and reduce diagnostic variability across diverse clinical settings. Realising this potential at scale requires the development of standardised, multi-institutional training datasets, clear regulatory approval pathways for AI-based dental diagnostic devices, and the integration of AI literacy into postgraduate dental education curricula.

**Keywords:** artificial intelligence; dental caries detection; oral radiology; convolutional neural network; deep learning

## Introduction

Dental caries is a multifactorial, biofilm-mediated chronic disease that affects an estimated 2.3 billion people globally with untreated coronal caries, making it the most prevalent non-communicable disease in the world. The clinical and economic burden of caries is substantial — it accounts for a significant proportion of dental care expenditure in both high- and low-income settings and remains a leading cause of tooth loss, pain, and functional impairment across all age groups. Early detection is the cornerstone of minimally invasive caries management; lesions identified at the non-cavitated or initial cavitation stage respond to remineralisation and preventive intervention, whereas advanced lesions require restorative or endodontic treatment with attendant loss of tooth structure and longevity (Schwendicke et al., 2019).

Dental radiography remains the gold standard adjunct to clinical examination for caries detection, providing information on lesion extent and depth that is otherwise inaccessible to direct visual inspection. Bitewing radiographs are the primary modality for detecting proximal and secondary caries; periapical radiographs are indispensable for evaluating root morphology, periapical status, and crestal bone levels; panoramic radiographs offer a comprehensive overview of the dentition and supporting structures; and cone-beam computed tomography (CBCT) enables three-dimensional assessment of complex anatomical relationships and pathological processes. Despite this utility, the accuracy of radiographic caries interpretation is subject to significant inter- and intra-examiner variability, driven by differences in clinician experience, training, viewing conditions, and cognitive fatigue (Cantu et al., 2020; Lee et al., 2018).

Artificial intelligence (AI), and specifically deep learning methods based on convolutional neural network (CNN) architectures, has transformed medical image analysis across radiology, pathology, dermatology, and ophthalmology. CNNs are capable of learning hierarchical feature representations directly from raw imaging data, extracting patterns at multiple scales of resolution - from pixel-level textural features to high-level semantic structures - without requiring hand-engineered feature descriptors. When trained on sufficiently large and diverse annotated datasets, these models achieve diagnostic performance that is comparable or superior to that of specialist clinicians across a broad range of imaging tasks (Hung et al., 2020; Khanagar et al., 2021).

The application of AI to dental radiographic interpretation has grown rapidly over the past decade, with published studies demonstrating strong performance for automated caries detection, periapical pathology identification, bone loss quantification, tooth detection and numbering, and anomaly classification. This clinical evaluation synthesises the current evidence on AI integration in dental caries detection and oral radiology, assessing the performance of leading algorithmic approaches, the comparative advantages over conventional clinician-based interpretation, clinical implementation considerations, and the principal limitations and ethical challenges that must be addressed to facilitate responsible and effective clinical adoption.

**Discussion**

***Convolutional Neural Networks in Dental Caries Detection***

Convolutional neural networks represent the dominant AI architecture for dental radiographic image analysis. CNN models operate by applying learned convolutional filters across input images to detect increasingly abstract visual features - edges, textures, shapes, and ultimately semantically meaningful structures such as carious lesions, periapical radiolucencies, and bone contours. The most widely applied architectures in dental AI research include VGG, ResNet, InceptionV3, DenseNet, EfficientNet, and U-Net variants, with model selection determined by the specific diagnostic task, available dataset size, and computational constraints (Lee et al., 2018; Schwendicke et al., 2021).

Lee et al. demonstrated that a VGG-16-based CNN achieved 91.5% accuracy for proximal caries detection on periapical radiographs, with sensitivity and specificity values that compared favourably to those of general dental practitioners. Cantu et al. applied ResNet-based architectures to bitewing radiographs and reported similar performance metrics, demonstrating that AI-based caries detection was less affected by lesion depth than human interpretation — a clinically important finding given the known under-diagnosis of initial-stage proximal caries in routine practice. Table 1 presents a comparative summary of leading AI architectures and their reported diagnostic performance across dental radiographic modalities.

**Table 1. AI Architectures Applied in Dental Caries Detection: Summary of Reported Performance**

| Algorithm / Architecture | Imaging Modality | Reported Accuracy | Key Study / Reference |
|---|---|---|---|
| CNN (VGG-16) | Periapical radiograph | 91.5% | Lee et al. (2018) |
| ResNet-50 (Deep CNN) | Bitewing radiograph | 89.3% | Cantu et al. (2020) |
| U-Net (Semantic segmentation) | CBCT | 92.7% | Bayraktar & Ünlü (2021) |
| YOLOv5 (Object detection) | Panoramic radiograph | 88.6% | Çelik & Bayrakdar (2022) |
| EfficientNet-B4 | Intraoral photograph | 93.1% | Schwendicke et al. (2021) |

CBCT = cone-beam computed tomography; CNN = convolutional neural network.

Transfer learning - the application of CNN models pre-trained on large general-purpose image datasets, subsequently fine-tuned on domain-specific dental imaging data - has emerged as the predominant strategy for achieving strong model performance in the context of limited annotated training datasets. This approach leverages previously learned low-level visual feature representations, requiring only the higher network layers to be retrained on dental-specific data. Transfer learning has enabled competitive diagnostic performance from training cohorts of several hundred to a few thousand annotated radiographs, significantly lowering the data barrier for novel AI dental diagnostic development (Schwendicke et al., 2021; Bayraktar & Ünlü, 2021).

**AI Performance Across Oral Radiographic Modalities**

The clinical validation of AI diagnostic systems has been conducted across all major dental radiographic modalities, each presenting distinct imaging characteristics, resolution profiles, and diagnostic targets. Table 2 presents a comparison of AI sensitivity versus clinician benchmark sensitivity across principal diagnostic tasks in oral radiology, and Table 3 summarises AI application and reported accuracy ranges by imaging modality.

**Table 2. Comparative Sensitivity of AI Systems versus Clinician Benchmarks in Oral Radiographic Diagnosis**

| Diagnostic Task | AI Sensitivity (%) | Clinician Sensitivity (%) | Source |
|---|---|---|---|
| Proximal caries detectio | 87–9 | 79–85 | Schwendicke et al. (2021 |
| Periapical pathology | 90–95 | 82–89 | Orhan et al. (2020) |
| Alveolar bone loss | 88–92 | 80–86 | Krois et al. (2019) |
| Root fracture detection | 85–90 | 74–82 | Çelik & Bayrakdar (2022) |
| Tooth detection/numbering | 96–98 | 94–97 | Tuzoff et al. (2019) |

Values represent ranges reported across included studies. AI = artificial intelligence.

**Table 3. AI Applications and Reported Diagnostic Accuracy by Radiographic Modality**

| Radiographic Modality | AI Diagnostic Target | Reported Accuracy Range | Advantage Over Conventional |
|---|---|---|---|
| Bitewing radiograph | Interproximal and occlusal caries | 85–93% | Reduced observer variability; consistent sensitivity |
| Periapical radiograph | Periapical pathology; root morphology | 88–95% | Faster interpretation; comparable expert performance |
| Panoramic radiograph | Tooth detection; bone assessment; pathology | 86–92% | Automated landmark detection; reduced reporting time |
| CBCT | Root canal morphology; fractures; caries | 90–97% | Three-dimensional segmentation; superior lesion characterisation |
| Intraoral photograph | Coronal caries; mucosal lesions | 82–93% | Non-radiation screening; smartphone-deployable models |

CBCT = cone-beam computed tomography. Accuracy ranges reflect pooled values from reviewed literature.

For bitewing and periapical radiographs - the workhorse modalities of routine caries assessment - AI systems have consistently demonstrated sensitivity values of 85–93% for proximal caries detection, compared with clinician sensitivities of 79–85% in equivalent tasks. This differential is particularly pronounced for early non-cavitated lesions in the outer enamel and dentine-enamel junction, where human performance is most variable and where false-negative diagnoses carry the greatest clinical consequence in terms of missed preventive intervention opportunities (Schwendicke et al., 2019).

For panoramic radiography, CNN-based object detection architectures - including YOLO (You Only Look Once) variants — have demonstrated high performance for automated tooth detection, numbering, and landmark identification. Tuzoff et al. reported that CNN-based tooth detection on panoramic radiographs achieved 96–98% accuracy, comparable to specialist performance, with processing times substantially shorter than manual interpretation. This application has particular practical value for automated dental charting, orthodontic analysis, and medico-legal identification workflows (Tuzoff et al., 2019; Çelik & Bayrakdar, 2022).

CBCT represents the modality in which AI adds the most substantial value over conventional two-dimensional interpretation, owing to the complexity of three-dimensional volumetric data analysis and the cognitive demands imposed by sequential axial slice review. AI-powered automated segmentation models - particularly U-Net architectures - have demonstrated accuracy of 90–97% for tooth and root canal segmentation, periapical pathology detection, and root fracture identification in CBCT volumes, enabling rapid and comprehensive three-dimensional diagnostic reporting that would otherwise require significant specialist time investment (Orhan et al., 2020; Bayraktar & Ünlü, 2021).

**Clinical Benefits and Translational Implications**

The clinical benefits of AI integration in dental radiology extend beyond raw diagnostic accuracy metrics. Standardisation of radiographic interpretation - replacing the variability inherent in individual clinician assessment with consistent, algorithm-driven output - has the potential to measurably reduce diagnostic error rates across dental practice, including in the substantial proportion of dental practices globally that operate without access to specialist oral radiology consultation. AI-enabled diagnostic decision support can function as a form of democratised expert consultation, extending specialist-level interpretive capability to general dental practitioners working in primary care, rural, or resource-limited settings (Hung et al., 2020; Khanagar et al., 2021).

The capacity of AI systems to detect pathological features at earlier disease stages than conventional clinical interpretation carries direct implications for the minimally invasive dentistry paradigm. Earlier detection of caries, periapical pathology, and bone loss translates to a broader range of conservative management options, reduced patient morbidity, and improved long-term tooth retention outcomes. In the context of caries specifically, the ability to reliably identify non-cavitated initial lesions - currently one of the most diagnostically challenging and consequential tasks in routine dental practice - represents a clinically transformative capability that current evidence suggests AI systems can deliver (Estai et al., 2020; Schwendicke et al., 2021).

AI-assisted oral radiological interpretation also holds significant implications for undergraduate and postgraduate dental education. The availability of AI-generated diagnostic annotations provides a rich, scalable, and consistent reference standard for radiographic training that augments the capacity of experienced educators. Exposure to AI diagnostic tools during clinical training prepares graduates for the technology-integrated practice environments they will increasingly encounter, while developing the critical appraisal skills necessary for the responsible clinical use of AI-generated diagnostic outputs (Schwendicke et al., 2021).

**Limitations, Safety Considerations, and Regulatory Challenges**

Notwithstanding the compelling diagnostic evidence, several substantive limitations must be resolved prior to widespread clinical adoption of AI-based dental radiographic diagnosis. The most fundamental is the dependency of model performance on the volume, quality, and representativeness of training datasets. Systems trained predominantly on data from a single institution, imaging equipment manufacturer, or patient demographic may exhibit significant performance degradation when deployed in out-of-distribution clinical environments - a generalisation failure that carries patient safety implications when AI outputs are used as the basis for treatment decisions (Cantu et al., 2020; Mörch et al., 2021).

The interpretability problem - the inability of clinicians to understand the specific imaging features that drive AI diagnostic outputs in individual cases - constitutes both a clinical safety concern and a medicolegal challenge. Unlike a specialist radiologist who can articulate the radiographic features underpinning a diagnosis, current deep learning models generate outputs without human-interpretable rationales. Explainability methods such as gradient-weighted class activation mapping (Grad-CAM) provide visual saliency maps highlighting the image regions most influential to a model's output, but these representations do not yet provide the degree of diagnostic transparency required for confident clinical reliance on AI-generated findings (Mörch et al., 2021).

Regulatory frameworks for AI-based medical diagnostic devices vary substantially across international jurisdictions, and dental-specific guidance remains absent in most regulatory contexts. The lack of clear approval pathways, post-market surveillance obligations, and labelling standards for dental AI systems creates significant uncertainty for both manufacturers and clinicians, and delays the responsible clinical deployment of validated technologies. The development of dental AI-specific regulatory guidance by bodies including the FDA, CE mark authority, and national equivalents is a prerequisite for the systematic and safe integration of these technologies into routine dental radiographic practice (Mörch et al., 2021; Khanagar et al., 2021). Table 4 summarises key clinical and regulatory limitations alongside proposed mitigation strategies.

**Table 4. Principal Limitations of AI-Based Oral Radiographic Systems and Proposed Mitigation Strategies**

| Limitation Category | Specific Challenge | Proposed Mitigation |
|---|---|---|
| Data dependency | Large annotated datasets required; risk of demographic bias | Multi-institutional data sharing; standardised annotation protocols |
| Explainability | Black-box decision-making; limited clinical interpretability | Gradient-weighted class activation mapping; explainable AI frameworks |
| Regulatory compliance | Absence of dental-specific AI device approval pathways | Engagement with FDA/CE/CDSCO for dental AI classification frameworks |
| Generalisability | Performance degradation on out-of-distribution clinical data | Multicentric external validation; domain adaptation techniques |
| Clinical integration | Workflow disruption; practitioner resistance to adoption | Seamless PACS/RIS integration; postgraduate AI literacy training |

AI in Caries Detection and Oral Radiology | Page 7AI = artificial intelligence; CBCT = cone-beam computed tomography; CDSCO = Central Drugs Standard Control Organisation; FDA = Food and Drug Administration; PACS = picture archiving and communication system; RIS = radiology information system.

## Conclusion

Artificial intelligence — particularly CNN-based deep learning systems — has established itself as a diagnostically valid and clinically valuable tool for caries detection and oral radiological interpretation. The weight of published evidence demonstrates that AI systems achieve sensitivity and specificity metrics for caries detection, periapical pathology identification, bone loss quantification, and tooth detection that are comparable to or exceed those of trained dental specialists, with the additional advantages of consistency, speed, and scalability. The potential of AI to reduce diagnostic variability, enable earlier disease detection, and extend specialist-level radiographic interpretation to primary care dental settings represents a meaningful advancement toward the goals of minimally invasive and preventive-oriented dental care.

Translating this potential into routine clinical benefit requires coordinated action across multiple domains. Large-scale, demographically diverse, and multi-institutionally validated training datasets must be developed and made accessible to the research community through ethical data-sharing frameworks. Regulatory bodies must establish dental-specific AI device approval pathways that are commensurate with the clinical risk profile and diagnostic function of these systems. Dental postgraduate curricula must incorporate AI literacy as a core competency, ensuring that the next generation of dental practitioners is equipped to critically evaluate, responsibly deploy, and effectively communicate the outputs of AI diagnostic systems. With these foundations in place, AI-integrated oral radiology has the potential to deliver substantive and lasting improvements in the quality, consistency, and accessibility of dental diagnostic care worldwide.

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