# Deep Learning for Dental Caries Diagnosis and Clinical Applications

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**Abstract.** Dental caries, a prevalent disease with significant health and economic consequences, goes undiagnosed during the early phases of its progression since conventional diagnostic methods like visual inspection and radiography possess low sensitivity as well as inter-observer consensus. This review discusses the use of deep learning (DL) for the automatic detection and grading of caries, comparing systematically different imaging modalities, such as bitewing and periapical radiography, intraoral photography, optical coherence tomography (OCT), cone-beam computed tomography (CBCT), and laser fluorescence, and their implications in caries diagnosis. It emphasizes how DL models, especially convolutional neural networks (CNNs), Transformers, and U-Net architectures, perform well in classification, detection, and segmentation tasks with expert-level performance and quantitation of lesions. They facilitate diverse clinical applications such as tele dentistry and personalized treatment planning and are advancing with multimodal data fusion, explainable AI, and real-time processing. However, there are still challenges regarding limited annotated datasets, model generalizability, computational requirements, and clinical interpretability. The review aims to promote clinical translation by summarizing recent advances, comparing methodologies, and pointing out future directions for intelligent oral healthcare.

## 1 Introduction

Dental care is one of the most prevalent chronic oral diseases worldwide, significantly affecting quality of life across all age groups and imposing considerable economic burdens on healthcare systems. It is reported that 35% of the global population is afflicted by dental caries [1]. In its early stages, caries presents as mild demineralization of tooth enamel, typically without pain or obvious symptoms. Consequently, such early lesions are frequently overlooked, delaying optimal intervention and resulting in significantly increased treatment complexity and associated costs in later stages. Therefore, timely detection and accurate diagnosis of early dental caries are crucial to improving patient outcomes and reducing disease burdens.

Clinically, caries diagnosis primarily relies on visual inspection by dentists and radiographic assessments, including bitewing radiographs, panoramic radiographs, and intraoral photography. However, these traditional imaging methods have inherent limitations. Bitewing radiographs possess high sensitivity for detecting interproximal lesions but frequently miss superficial enamel caries or lesions near the cervical margin. Panoramic radiographs provide comprehensive oral coverage but suffer from lower spatial resolution and susceptibility to artifacts, restricting accurate detection of early-stage caries. Intraoral photography offers intuitive visualization of carious lesions but heavily depends on lighting conditions and imaging technique, potentially introducing subjective interpretation biases. Additionally, diagnostic consistency among different dentists remains low; even with bitewing radiographs, inter-observer agreement (Kappa values) ranges only from 0.38 to 0.62. Moreover, early enamel caries detection rates are still under 60% in actual clinical practice [2]. Consequently, there is an urgent need for more objective and precise automated diagnostic tools to assist clinical decision-making.

Recent advances in deep learning have shown promising results in dental caries diagnosis. For example, convolutional neural networks (CNNs) achieved an AUC of 0.89 for caries detection using periapical radiographs [3], and U-Net architectures achieved 0.91 Dice score in lesion segmentation [4]. Moreover, Transformers perform better on multimodal analysis with the combination of cone-beam computed tomography (CBCT) and intraoral images spite this progress, several practical challenges remain: the limited scale of annotated datasets (most studies include fewer than 5,000 images), poor generalization across different image devices, and the "black box" nature of decision-making processes, which is generally unacceptable in clinical practice. Therefore, this review systematically summarizes recent deep-learning approaches for automated detection and grading of dental caries from imaging data, compares various model architectures, data augmentation strategies, and interpretability methods, and highlights existing limitations and potential future directions, aiming to facilitate the clinical application of intelligent oral healthcare.

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# 2 Main Types of Radiographic Imaging for Dental Caries

Tooth decay imaging is done using a number of techniques, each with its own relative merits and limitations in identifying and quantifying tooth decay. The primary modalities include bitewing radiography, periapical radiography, intraoral photographs, OCT, CBCT and laser fluorescence instruments. The evolution of caries imaging is followed by recent developments like AI-assisted interpretation and enhanced detection devices[5]. These technologies have the capability to increase diagnostic accuracy while potentially reducing caries interpretation subjectivity. With continuous evolution in the field, the use of more than one imaging modality, guided by evidence-based guidelines and practitioner discretion, remains essential for successful caries management in diverse populations.

## 2.1 Bitewing Radiography

Bitewing radiography is regarded as the standard technique for interproximal caries detection due to its high sensitivity in identifying early enamel lesions while requiring only a low dose of radiation. Its ability to capture posterior teeth on both sides in a single image makes it indispensable for routine screening and longitudinal monitoring of caries progression. However, its focus on coronal structures necessitates additional imaging when root or periapical involvement is suspected. Accurate results also depend on precise sensor positioning, which can be challenging in certain patient populations such as children, elderly individuals, or patients with limited mouth opening. Furthermore, variations in angulation and exposure settings may affect diagnostic reliability, underlining the importance of operator expertise and standardized imaging protocols .

## 2.2 Periapical Radiography

Periapical radiography complements bitewing imaging by providing complete visualization of the tooth from crown to apex, offering valuable information that is not accessible with coronal-focused techniques alone. It is particularly effective in evaluating the progression of extensive caries, detecting pulpal involvement, and identifying periapical pathologies such as abscesses or cysts. However, its relatively narrow field of view necessitates multiple exposures to achieve a comprehensive examination of the full dentition, which may increase patient discomfort and radiation exposure. The method remains widely used in dental practice because of its simplicity, low cost, and availability, although its diagnostic accuracy can be affected by anatomical superimposition and image distortion. In many cases, periapical radiographs form part of a sequential diagnostic protocol, especially when initial screening raises suspicion of deeper or more complex lesions. Moreover, they are often integrated into endodontic assessments and treatment planning, providing critical information about root morphology, periapical bone status, and treatment outcomes [6].

## 2.3 Intraoral Photography

Intraoral photography is a radiation-free adjunct to radiographic methods and provides valuable records of enamel surface changes and visible caries[7]. It is particularly useful for patient education, enhancing communication by visually demonstrating disease presence and treatment progress, and for documenting clinical cases over time. However, its inability to disclose subsurface lesions restricts its use as an independent diagnostic method. The quality and diagnostic value of intraoral photographs continue to rely heavily on lighting conditions, camera settings, and operator technique. In addition, the presence of saliva, reflections, and limited access to posterior teeth may further compromise image quality. Recent advances in digital intraoral cameras and image processing software have improved standardization, and emerging AI-based tools show promise in enhancing lesion detection and reducing observer variability.

## 2.4 Optical Coherence Tomography (OCT)

OCT is an advanced imaging method that has the ability to detect micro-scale changes in enamel structure . The non-invasive technique has an unchallengeable resolution for early caries detection but is, at present, constrained by limited penetration depth and expense. Beyond mere detection, OCT enables quantitative monitoring of lesion progression or remineralization over time, making it highly valuable for preventive dentistry and longitudinal research. With ongoing improvements in imaging depth, scanning speed, and integration with AI-assisted interpretation, OCT has strong potential to become a routine chairside tool in the early detection and management of dental caries.

## 2.5 Cone-Beam Computed Tomography (CBCT)

CBCT offers three-dimensional imaging that overcomes the inherent limitations of two-dimensional radiography. It provides unparalleled structural detail in complex cases, enabling clinicians to assess lesion depth, spatial orientation, and associated anatomical variations with greater accuracy. While highly informative, the higher radiation dose and cost restrict its use to specific indications where conventional imaging proves insufficient. CBCT's ability to render occult caries visible and to establish spatial relationships makes it especially valuable for treatment planning in restorative, endodontic, and surgical cases, as well as for evaluating multi-surface or atypical lesion patterns that are difficult to visualize using traditional methods. Furthermore, integration with computer-aided design systems and AI-assisted analysis is expanding CBCT's utility, supporting more precise diagnosis, improved workflow efficiency, and simulation of treatment outcomes .

### 2.6 Laser Fluorescence

Laser fluorescence devices such as DIAGNOdent provide quantitative assessment of caries activity, with particular utility on occlusal surfaces where early lesions are often difficult to detect visually or radiographically. These portable instruments generate objective measurements for identifying incipient caries and for monitoring remineralization during preventive or restorative interventions. However, their diagnostic performance can be affected by confounding factors such as dental stains, plaque, and calculus, necessitating careful interpretation and proper calibration to ensure accuracy. The non-invasive and repeatable nature of the technology makes it particularly suitable for longitudinal monitoring in preventive programs and community-based screening. In addition, integration with digital record systems and emerging AI-assisted algorithms offers the potential to standardize readings, minimize operator variability, and expand the role of fluorescence-based tools in personalized caries management [8].

## 3 Classical Applications of Artificial Intelligence in Caries Diagnosis

### 3.1 Classification in Caries Diagnosis

Classification algorithms are a fundamental artificial intelligence (AI) approach in today's caries diagnosis, including automated dental image analysis for presence of caries and determination of severity. Large datasets comprising thousands of intraoral images, bitewing radiographs, and OCT scans are usually used to train deep convolutional neural networks (DCNNs) for these systems. Most advanced classification algorithms currently achieve diagnostic sensitivities greater than 90% for obvious cavitated lesions at the same level of performance as expert dentists [9].

Contemporary implementations utilize cutting-edge architecture including Efficient Net and Vision Transformers that are capable of processing multiple image modalities in parallel, which enables more integrated evaluations. In the practice of dentistry, these systems have a number of significant applications: primary screening in high-volume community dental clinics, creation of second opinions in complex cases, and educational tools for dental students. One application is very handy within tele dentistry systems, where AI classification enables remote clinicians to make early diagnoses. There are still significant challenges, specifically around early detection of caries. The subtle visual changes characteristic of early demineralization (white spot lesions) will likely cause false negatives.

Advances in recent years address this with multi-task learning architectures that, concurrently, classify caries and forecast future risk of progression from lesion characteristics. Other advances include the integration of clinical metadata (patient age, caries history) with imagery to enhance prediction accuracy. In the future, generations of classification systems will be tasked with integrating temporal analysis of sequential dental images to track lesions' progression and regression, so truly predictive caries management is possible. Other avenues of research involve creating explainable AI approaches to notify clinicians of classification outputs and federated learning approaches to increase model generalizability across various populations while ensuring patient anonymity.

### 3.2 Lesion Detection in Caries Imaging

Object detection methods emerged as efficient methods of precise caries localization in dental radiographs by combining classification with local lesion detection. Modern detection systems employ sophisticated architectures including Cascade R-CNN and RetinaNet that are tailored to the unique challenges of dental images where lesions (tooth decay lesions) may be extremely small relative to image dimensions [10]. These systems are especially effective at identifying kinds of caries - both pit-and-fissure, smooth surface, and root caries - and, as a matter of fact, their exact location within tooth structures. Clinically, it is highly useful for a range of applications: computerized dental charting systems populating electronic health records with the locations of detected caries, computer-aided diagnosis systems that label suspicious areas for dentist review, and treatment planning devices that suggest optimal intervention strategies as a function of lesion location.

New technology improvements have significantly improved accuracy in detection, particularly with attention mechanisms that help models focus on diagnostically relevant regions and multi-scale feature extraction that enhances detection of small lesions. Studies also explore 3D detection for volumetric imaging modalities like CBCT in order to enable holistic assessment of caries spatial distribution. Nevertheless, persistent challenges are maintaining performance uniformity over diverse imaging protocols (X-ray exposure, angulation variability) and reducing false positives due to frequent dental features (restorations, enamel crack). New solutions employ advanced data augmentation, domain adaptation, and synthetic data generation to improve model strength. The newest systems now integrate into clinical procedures employing DICOM-compliant interfaces with easy integration into commercially available dental practice management software. Futuristic directions include real-time intra-procedure detection with augmented reality display and the development of "detection-tracking" systems that monitor lesion changes over time. Such technologies have the potential to transform caries diagnosis from a static endeavor to a dynamic monitoring system, the potential to alter preventive dentistry and the ability to customize treatment approaches [11].

### 3.3 Lesion Segmentation in Caries Diagnosis

Pixel-level segmentation is the most accurate type of AI caries analysis, providing explicit lesion boundary demarcation on dental images. State-of-the-art segmentation algorithms make use of modern architectures like nnU-Net, which demonstrate unprecedented accuracy in delineating carious tissue from non-cavitated tooth structure on various imaging modalities [12]. This technology makes possible truly quantitative caries assessment, not just presence, but accurate lesion size, volume, and penetration depth - measurements critical to evidence-based treatment planning. In clinical practice, segmentation serves several critical roles: segmentation guides minimally invasive preparations via definition of accurate caries margins, enables automated caries activity scores by texture analysis of segmented regions, and facilitates accurate tracking of lesion activity or remineralization over time.

Some of the recent breakthroughs are 3D segmentation of volumetric dental scans (micro-CT, CBCT) showing never-before-seen views of spatial distribution of caries and the development of "activity-aware" segmentation that can separate arrested and active lesions [13]. Nevertheless, enormous technical challenges still need to be addressed, specifically computational efficiency (for real-time chairside use) and for tolerating very large intersubject variation of tooth anatomy. Current research addresses these in hybrid designs blending CNNs with vision transformers, self-supervised pre-training for reducing annotation dependency, and knowledge distillation methods to create lower-weight models compatible with clinical equipment. Real-world applications are now ready to roll out in a variety of applications: AR-enabled restorative systems that overlay segmented caries over procedures, automated treatment documentation software that delivers accurate caries maps for insurance reimbursement purposes, and digital treatment planning platforms that simulate varied intervention outcomes. The future of caries segmentation is temporal analysis - comparing consecutive scans to quantify changes in lesion parameters over time, and the potential for truly individualized preventive intervention.

Other extremely promising avenues are coupling segmentation with robotic dental platforms for computer-aided caries removal and "explainable segmentation" algorithms to provide clinicians with intuitive representations of AI decision-making. Through these technologies, as they advance, caries management can become less of an art based on subjective opinion and more of a data-driven science, improving results with less unnecessary loss of tooth structure.

## 4 Fundamental Functions of Different Models

Different models excel at undertaking different types of medical imaging tasks. For instance, CNNs are applied prominently for the classification of X-ray images, where they excel by obtaining hierarchical spatial information and minute textural details. The ability to be highly sensitive to local changes within the image permits detecting small or starting abnormalities such as microcalcifications or diffuse opacities, which is an important requirement for early diagnosis.

CNNs are more likely to provide image-level prediction without localization. U-Net models, however, are based on pixel-level segmentation and are hence highly effective in lesion, tumour, or anatomical structure detection and delineation[14]. U-Nets, by virtue of their encoder–decoder architecture and skip connections, retain high spatial resolution while gaining contextual information, allowing high sensitivity and precise boundary definition even in complex or low-contrast medical images. Whereas CNNs have better overall classification performances, the spatial precision of U-Nets is better, and hence the latter are a necessity in applications like tumour contouring, organ mapping, and planning surgery [15]. Used in combination, CNNs and U-Nets form a complementary toolkit for modern medical image analysis, enabling both accurate classification and precise anatomical delineation, which collectively enhance diagnostic reliability and clinical workflow efficiency.

## 5 Conclusion

In conclusion, deep learning has indicated great potential in the shift toward the diagnosis and treatment of dental caries by the capability to enable automated, accurate, and quantitative evaluation of a variety of imaging modalities. DL models like CNNs, U-Net, and Vision Transformers excel in classification, detection, and segmentation tasks, offering performance at par with dental experts and enhancing abilities in the early detection of caries, proper delineation of lesions, and tracking of caries progression. These technologies are particularly beneficial for identification of fragile early-stage lesions, multisurface complex cases, and in preventive dental care and teledentistry applications. Through clinical integration and multimodal imaging, AI-based tools enable more objective diagnosis and personalized treatment planning, reducing reliance on subjective interpretation and optimizing the efficiency of operations in dental practice.

Though these promising advances have been achieved, there have been numerous limitations, among them the unavailability of large and diverse annotated datasets, generalizability across image acquisition hardware and imaging protocols, computational infeasibility for real-time use, and lack of transparency in AI decision-making. Next-generation studies need to work towards developing explainable AI models, encourage federated learning platforms for enhanced data privacy and model robustness, include longitudinal data to track dynamic caries, and evaluate these systems using large-scale clinical trials. Interdisciplinary cooperation among clinicians, researchers, and industry stakeholders will be required to push these technology advances into scalable, ethical, and clinically usable tools that can improve patient care and promote global oral health.

## References

1. N.J. Kassebaum, E. Bernabé, M. Dahiya, et al. Global burden of untreated caries. J Dent Res. 94, **650** (2015). https://doi.org/10.1177/0022034515573272
2. M. Yen, A.W.K. Yeung. The performance of paralleling technique and bisecting angle technique for taking periapical radiographs: a systematic review. Dent J. **11**, 155 (2023). https://doi.org/10.3390/ dj11070155
3. J. Kühnisch, O. Meyer, M. Hesenius, et al. Caries detection on intraoral images using artificial intelligence. J Dent Res. **101**, 158 (2021). https://doi.org/10.1177/00220345211032524
4. S.L. Walston, D. Ueda. Enhancing AI-assisted interpretation of chest radiographs: a critical analysis of methods and applicability. Radiology. **311**, e233428 (2024). https://doi.org/10.1148/radio l.233428
5. G. Stera, M. Giusti, A. Magnini, et al. Diagnostic accuracy of periapical radiography and panoramic radiography in the detection of apical periodontitis: a systematic review and meta-analysis. Radiol Med. **11**, 129 (2024). https://doi.org/10.1007/s11547-024-01882-z
6. I. Nasseh, W. Al-Rawi. Cone beam computed tomography. Dent Clin North Am. **62**, 361 (2018). https://doi.org/10.1016/j.cden.2018.03.002
7. M. Kwaśny, A. Bombalska. Applications of laser-induced fluorescence in medicine. Sensors. **22**, 2956 (2022). https://doi.org/10.3390/s22082956
8. Y.J. Kim, K.G. Kim. Understanding and application of multi-task learning in medical artificial intelligence. J Korean Soc Radiol. **83**, 1208 (2022). https://doi.org/10.3348/jksr.2022.0155
9. F. Isensee, P.F. Jaeger, S.A.A. Kohl, et al. nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nat Methods. **18**, 203 (2020). https://doi.org/10.1038/s41592-020-01008-z
10. Y. Mori, S. Kudo, T. Berzin, et al. Computer-aided diagnosis for colonoscopy. Endoscopy. **49**, 813 (2017). https://doi.org/10.1055/s-0043-109430
11. G. Litjens, T. Kooi, B.E. Bejnordi, et al. A survey on deep learning in medical image analysis. Med Image Anal. **42**, 60 (2017). https://doi.org/10.1016/ j.media.2017.07.005
12. Bhandi S, Mashyakhy M, Abumelha AS, et al. Complete Obturation-Cold Lateral Condensation vs. Thermoplastic Techniques: A Systematic Review of Micro-CT Studies. Materials. **14**, 4013 (2021). https://doi.org/10.3390/ma14144013
13. A.S. Fard, D.C. Reutens, V. Vegh. From CNNs to GANs for cross-modality medical image estimation. Comput Biol Med. **146**, 105556 (2022). https://doi.org/10.1016/j.compbiomed.2022.105556
14. W. Qiang, F. Qiang, L. Lin. Estimation of effective dose of dental X-ray devices. Radiat Prot Dosimetry. **183**, 418 (2018). https://doi.org/10.1093/rpd/ ncy159
15. P. Duvnjak, A.A. Schulman, J.N. Holtz, et al. Multiparametric prostate MR imaging: impact on clinical staging and decision making. Radiol Clin North Am. **56**, 239 (2018). https://doi.org/10.1016/j.rcl. 2017.10.007