## **Quality Resource Guide**

**First Edition** 

# An Introduction to Artificial Intelligence and Dental Caries Detection

## **Author Acknowledgements**

### MOHAMED M. SHABAYEK, BDS MDS PHD

Associate Professor
Department of Preventive & Restorative Dentistry
Arthur Dugoni School of Dentistry
University of The Pacific
San Francisco, California

#### **AHMED S. SULTAN. BDS PHD**

Assistant Professor

Division of Artificial Intelligence Research
Department of Oncology and Diagnostic Sciences
University of Maryland School of Dentistry
University of Maryland Marlene and Stewart Greenebaum
Comprehensive Cancer Center
Baltimore, Maryland

## **Educational Objectives**

Following this unit of instruction, the learner should be able to:

- Define artificial intelligence and its role in dental caries detection.
- 2. Explain how Al-based dental caries detection systems work, including training, validation, and implementation.
- 3. Describe the ICDAS classification system and its relationship to AI-based detection.
- 4. Evaluate the current evidence for Al applications in dental caries detection.
- 5. Identify key limitations and challenges of AI implementation in dental practice.
- 6. Discuss future trends and developments in Al-based dental caries detection.

Drs. Shabayek and Sultan have no relevant financial relationships to disclose.

MetLife designates this activity for 1.0 continuing education credits for the review of this Quality Resource Guide and successful completion of the post test.

The following commentary highlights fundamental and commonly accepted practices on the subject matter. The information is intended as a general overview and is for educational purposes only. This information does not constitute legal advice, which can only be provided by an attorney.

© 2025 MetLife Services and Solutions, LLG. All materials subject to this copyright may be photocopied for the noncommercial purpose of scientific or educational advancement.

Published October 2025. Expiration date: October 2028.

The content of this Guide is subject to change as new scientific information becomes available.

## ADA C-E-R-P® | Continuing Education Recognition Program

Accepted Program Provider FAGD/MAGD Credit 05/01/25 - 06/30/29.

MetLife is an ADA CERP Recognized Provider. ADA CERP is a service of the American Dental Association to assist dental professionals in identifying quality providers of continuing dental education. ADA CERP does not approve or endorse individual courses or instructors, nor does it imply acceptance of credit hours by boards of dentistry. Concerns or complaints about a CE provider may be directed to the provider or to ADA CERP at https://ccepr.ada.org/en/ada-cerp-recognition.

#### Address comments or questions to:

DentalQuality@metlife.com - or -MetLife Dental Continuing Education 501 US Hwy 22 Bridgewater, NJ 08807

#### Cancellation/Refund Policy:

Any participant who is not 100% satisfied with this course can request a full refund by contacting us.



## Introduction to Artificial Intelligence Applications for Dental Caries Detection

Artificial intelligence (AI) refers to the capability of machines to perform tasks that typically require human intelligence. Al is firmly embedded in society and influences how we work, shop, travel, communicate, and even make decisions. With it has come a new set of new terms which are summarized in Appendix – 1. Al has revolutionized how we live, from the apps on our mobile devices to the services that keep our cities running.1 In dental radiography, AI uses computer vision methods and computational algorithms to analyze dental images or augment human-like decisionmaking. In dentistry, Al applications, especially those involving machine learning (ML) or deep learning (DL), have been developed to assist in diagnosing various dental diseases. Al-powered clinician decision support systems (CDSS) aim to augment, not replace, clinician expertise. These tools integrate diagnostic algorithms into practice management software or imaging platforms to flag potential lesions and recommend next steps. For instance, certain AI tools provide real-time annotations on digital radiographs, highlighting areas with suspected dental caries for review.2 Decision support systems can also incorporate risk assessment data, patient histories, and caries activity trends to create personalized treatment plans, potentially improving care quality. The potential for using AI for caries detection in radiographs and other imaging modalities, such as clinical photographs, optical coherence tomography images, and near-infrared light transillumination images, has been proposed in numerous studies.3 Of note, bitewing radiographs (BWRs) are the most extensively studied imaging modality with AI methods as they are the most widely used radiographs in clinical practice. However, commercially available AI tools are not limited to caries detection only. They can aid in tooth segmentation and in detecting periapical and periodontal lesions. 4,5 Importantly, AI models using DL-based convolutional neural networks (CNNs)6 have shown promise for identifying dental caries. particularly in its early stages.7 The integration of Al in dental practice may ultimately reshape how general dentists approach caries diagnosis and treatment planning. This QRG outlines essential considerations for general dentists on incorporating Al in their dental practices, specifically focusing on dental caries detection.

## A Brief History of Al in Dentistry

Al in dentistry has evolved over the past few decades, but its adoption has accelerated in recent years.

- 1980 1999: Early research explored computer-aided design (CAD) for dental restorations and basic image analysis.
- 2000 2010: Machine learning algorithms emerged for tasks such as caries detection and cephalometric analysis.
- 2010 2020: Deep learning (a subset of Al) revolutionized image recognition, enabling Al to analyze X-rays, CBCT scans, and intraoral images with high accuracy.
- 2020 present: Al-powered tools became commercially available, with FDA-cleared devices entering the market. Today, Al is used as an adjunct for diagnosis, treatment planning, patient communication, and practice management.

## FDA-cleared Al Devices for Dentistry

Al in dentistry can be classified based on its application and functionality:

- 1. Diagnostic Al: Detects conditions (e.g., caries, periodontal disease, oral cancer).
- Predictive AI: Predicts treatment outcomes or disease progression (e.g., orthodontic treatment planning).
- Generative AI: Creates treatment plans or designs restorations (e.g., CAD/CAM for crowns and bridges).
- Administrative AI: Assists with practice management, scheduling, and patient communication.

The FDA has cleared several Al-powered dental devices. As of December 2024, per the FDA Artificial Intelligence and Machine Learning (Al/ML)-Enabled Medical Devices (https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices), there are four "Dental" approved devices and several more dental Al devices that fall under "Radiology." Overall, there were 16 applications involving dental Al on the FDA list. These devices are designed to augment diagnostic accuracy and streamline workflows; they are meant to assist, not replace, human decision-making.

## How Do Dental Caries Detection Al Applications Work?

Al in dentistry typically works through ML and DL algorithms.<sup>8</sup> A simplified breakdown is presented below:

- 1. Data Collection: Al systems are trained on large datasets of annotated dental images (e.g., BWRs, panoramic radiographs, intraoral photographs, CBCT scans) and clinical data. To ensure robustness, these datasets must be diverse and accurately labeled by experts. They are then divided into training, validation, and test sets to develop and evaluate the model's performance.
- 2. Training: During training, supervised learning algorithms are employed, where models learn to classify images as "carious" or "non-carious" by recognizing patterns in pixel intensities and textures (Figure 1). The labeled dataset may consist of radiographs and/or intraoral images annotated by expert dentists, serving as the ground truth (Gold Standard). The model learns to map input images to corresponding caries labels through an iterative process of adjusting its internal parameters. Techniques such as data augmentation, transfer learning, and cross-validation are employed to enhance model robustness and generalizability.

- 3. Testing and Inference: Testing involves exposing the trained model to unseen datasets to evaluate its performance in sensitivity (the ability of a test to correctly identify individuals/surfaces who have a disease), specificity (the ability of a test to correctly identify individuals/surfaces who do not have a disease), and overall diagnostic accuracy. Cross-validation techniques and external validation using datasets from diverse image capture types and different demographic patient groups are critical for ensuring generalizability and real-world applicability.3,10-12 These datasets must be diverse and accurately labeled by experts to ensure robustness and to prevent model overfitting. Continuously updating the model with new training data and expert feedback helps improve its performance over time. Once tested on unseen data, the AI can analyze new patient data and provide insights, such as detecting abnormalities or suggesting treatment options.
- **4. Integration:** Al tools are integrated into dental software, allowing you to use them seamlessly in your practice.

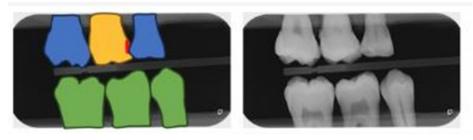
## What is Ground Truth Determination in Dental AI?

"Ground truth" or "Gold Standard" refers to the reference standard or the actual, verified diagnosis. In dental caries AI, ground truth is derived from expert annotations on radiographs, clinical diagnoses, or, in some cases, histological validation. Therefore, ground truth determination involves establishing a reliable reference standard against which AI model predictions are compared (e.g., the confirmed presence or absence of dental caries versus the AI output). Establishing a reliable ground truth is crucial for training AI models that can accurately detect caries.

Ground truth determination in caries detection faces several challenges:

 Subjectivity: Expert annotations can vary significantly, introducing bias. Importantly, annotators may have vastly different years of experience, leading to inconsistencies in labeling. Moreover, the subtle nature of early caries lesions can make them difficult to detect and annotate consistently.

Figure 1



**Left image**: Training label annotations on BWR with a color-coded setup -yellow: tooth of interest, red: carious lesion, blue: adjacent tooth, green: antagonistic tooth. **Right image**: Unannotated bitewing radiograph. Images modified and adapted from Boldt et al., 2024<sup>9</sup>

- Insufficient Standards: There is no universally accepted protocol for determining ground truth. Furthermore, obtaining a histological validation of caries diagnosis is often impractical, making it challenging to establish a definitive ground truth.
- Lack of Longitudinal Data: Ground truth often relies on cross-sectional snapshots, not lesion progression over time.

Future advancements in dental caries AI to optimize ground truth determination include the following:

- Consensus Annotation: The process of using multiple experts to reduce variability, including an e-Delphi process involving several rounds of blinded consensus review.
   Developing standardized annotation protocols and providing training to expert annotators can help reduce inter-examiner variability.
- Al-Assisted Ground Truthing: Iterative refinement of ground truth through Al feedback. Incorporating other diagnostic modalities, such as micro-CT, transillumination, fluorescence, or histological validation (when feasible), can provide additional information to support the annotation process.
- Validation with Clinical Outcomes: Linking Al predictions to long-term outcomes to refine accuracy. Continuously updating and refining the ground truth based on new evidence and

expert feedback can help improve the quality of training data over time. By improving ground truth determination, AI systems can achieve higher reliability and clinical applicability, ensuring safer integration into dental practices.

# An Overview of the Etiology, Diagnosis and Management of Dental Caries

Dental caries is caused by the acid-driven loss of minerals from hard tooth structure due to plaque microorganisms' metabolism of fermentable carbohydrates. During the tooth's life span, it is subjected to cycles of demineralization and remineralization. When the cycles of demineralization predominate over those of remineralization, the tooth surface will incur a net loss of minerals, manifested by clinical signs of dental caries.13 The carious lesion starts at a subclinical microscopic level. As demineralization continues, a visual color change can be detected only upon dryness. If unreversed through remineralization, the mineral loss will continue, and lesion detection will become easier and appear as a noticeable change of color in the enamel. That will continue as a greyish-black shadow in the underlying dentin. As more minerals are lost, enamel becomes undermined and weakened, and ultimately becomes cavitated. A classification schema (Table 1) that describes the clinical

stages of caries is the ICDAS classification.<sup>14</sup> Cavitated lesions, extending into dentin (ICDAS 5 & 6), are easily detected visually using a dental probe (visual-tactile methods). On the other hand, non-cavitated or minimally cavitated lesions (ICDAS 2, 3 & 4) may be challenging to identify, especially when located on proximal surfaces where direct access to the lesion is not possible because of the presence of an adjacent tooth. In addition, estimating the lesion depth of those minimally/non-cavitated lesions is challenging.

During the past two decades, modern caries management has shifted from cavity management to disease management through caries prevention and early intervention. Consequently, early detection of the lesions before cavitation is considered pivotal in modern caries management. Clinicians usually resort to additional diagnostic tools to aid in detecting lesions and estimating

the lesion depth. BWRs are widely used tools to detect the presence of caries and assess the lesion depth and extension in occlusal and proximal lesions. The ICDAS radiographic scoring system (Table 1) provides a classification for the radiographic image of caries.

When evaluating the accuracy of radiographic caries detection, Schwendicke and colleagues found that dentists had low sensitivity, equaling 0.24, and higher specificity, equaling 0.97, for the same task.<sup>16</sup> Studies demonstrated that adding BWRs to the visual-tactile examination, when at least one of the diagnostic tests is positive, will increase the sensitivity of the combined diagnostic test but will also diminish the specificity. Thus, more cavities are correctly detected, but this occurs at the expense of an increase in the number of false-positive diagnoses. Therefore, adding diagnostic test methods also means increasing the rate of diagnostic errors.<sup>17</sup>

BWRs are prone to errors due to superimposition formed on the image sensor.<sup>18,19</sup> Although BWRs may be reproducible in assessing the depth of demineralization, they cannot definitively confirm the presence of a cavity or lesion activity. That is a significant limitation for treatment decision-making. Accordingly, not every dentinal lesion that appears on a radiograph requires restoration. Too much reliance on radiographic diagnosis inevitably leads to overtreatment, since it suffers from a high falsepositive rate. Visual-tactile caries examination and activity assessment circumvent this problem by identifying most lesions indicated for treatment.13 Nascimento and colleagues studied the distribution of carious lesions by radiographic depth and surface cavitation status as determined before and after tooth separation.20 They found that 66% of lesions located radiographically in outer dentin (RA 3) are clinically non-cavitated when examined after teeth separation.

Table 1 - ICDAS Classification & Radiographic scores of the corresponding clinical score (CONTINUED ON NEXT PAGE) (adapted from Pitts, et al.<sup>14</sup> and de Carvalho, et al.<sup>21</sup>)

ICDAS Score	Criteria	Clinical	ICDAS Radiographic Score	Criteria	Radiographic
0	Sound surfaces show no evidence of visible caries (no or questionable change in enamel translucency) when viewed clean and after prolonged air-drying (5 seconds)		None	Normal	
1	First or distinct visual changes in enamel seen as a carious opacity or visible discoloration (white spot lesion and/or brown carious discoloration) upon dryness only		RA1	Radiolucency in the outer ½ of the enamel	

Table 1 - ICDAS Classification & Radiographic scores of the corresponding clinical score (CONTINUED FROM PREVIOUS PAGE) (adapted from Pitts, *et al.*<sup>14</sup> and de Carvalho, *et al.*<sup>21</sup>)

ICDAS Score	Criteria	Clinical	ICDAS Radiographic Score	Criteria	Radiographic	
2	Distinct visual changes in enamel seen as a carious opacity or visible discoloration (white spot lesion and/or brown carious discoloration) without dryness.  No evidence of surface breakdown or underlying dentin shadowing		RA2	Radiolucency in the inner ½ of the enamel ± EDJ		
3	A white or brown spot lesion with localized enamel breakdown, without visible dentin exposure		RA3	Radiolucency limited to the outer 1/3 of dentin		
4	An underlying dentin shadow, which obviously originated on the surface being evaluated		RB4	Radiolucency reaching the middle 1/3 of dentin		
5	A distinct cavity in opaque or discolored enamel with visible dentin		RC5	Radiolucency reaching the inner 1/3 of dentin, clinically cavitated		
6	An extensive cavity into dentin probably extending towards the pulp		RC6	Radiolucency into the pulp, clinically cavitated		

## Current Evidence for Al-Based Caries Diagnostic Tools

Mertens and colleagues conducted a randomized trial investigating a commercially available Al software product that utilized a DL-CNN for caries detection, which was employed randomly by 22 dentists.<sup>22</sup> The results showed increased sensitivity for enamel lesions, but not early or advanced dentin lesions. They concluded that Al could increase dentists' diagnostic accuracy. mainly by increasing their sensitivity for detecting enamel lesions, but may also increase the decision to recommend invasive therapies. Schwendicke and colleagues investigated the cost-effectiveness of using AI for proximal caries detection.<sup>23</sup> They determined that utilizing AI to support proximal caries detection on BWRs was more cost-effective than detection without AI. This was attributed to a higher likelihood of detecting early caries lesions, which can be managed with non-invasive therapies, thereby avoiding costly invasive treatments. Not surprisingly, this outcome only held true for early lesions that were treated noninvasively. They concluded that Al-associated early caries detection may potentially lower healthcare costs.

When using AI for caries risk assessment, a systematic review concluded that Al models used for dental caries prediction, detection, and diagnosis have demonstrated excellent performance and can be used in clinical practice for identifying patients with higher caries risk.24 Al models can also enhance diagnostic accuracy, treatment quality, and patient outcomes. The authors added that these models can assist dentists as a supportive tool in clinical practice and assist non-dental professionals in detecting and diagnosing dental caries more accurately in schools and rural health centers. However, there are limitations related to the size and heterogeneity of the datasets reported in most of the studies reviewed. Hence, these models need additional training and validation for better performance.24

A recent systematic review and meta-analysis investigated the diagnostic accuracy of AI for approximal carious lesions on BWRs.<sup>25</sup> The review showed a moderate capacity for identifying true positives among decayed teeth and a high ability to exclude healthy teeth, with a strong overall diagnostic performance. It was concluded that AI models demonstrate clinically acceptable diagnostic accuracy for approximal caries on BWRs, which may prove valuable for preliminary screening. However, the dentist should verify positive findings to prevent unnecessary treatments and ensure timely diagnosis.<sup>25</sup>

Some studies employ a man versus machine comparative design whereby the Al prediction is compared to human prediction. In their study, Tichý and colleagues compared the detection of caries in BWRs performed by experienced and novice dentists versus an automated DL-CNN method.<sup>26</sup> They found that repeatable and accurate caries detection in BWRs is challenging even for experienced dentists, which was confirmed by the marked differences between expert annotators. The tested AI model consistently outperformed novices, and its performance was similar to or superior to that of highly experienced experts. They concluded that the tested AI model could provide a useful second opinion for dentists, especially those with limited clinical experience, and help improve the accuracy and repeatability of caries detection.

## Limitations of Al for General Dental Practice

Despite its promoted promise, AI in caries detection faces several limitations. These include:

Dataset Bias: Training datasets often lack diversity regarding patient demographics and imaging equipment, adversely affecting model generalizability. For instance, AI models trained on data from one population or imaging system may not generalize well to others, limiting their broad applicability.

- Over-reliance on Al: Clinicians may blindly trust Al outputs without applying critical judgment.
- Regulatory and Ethical Challenges: The lack of standardized protocols and regulatory frameworks for AI in dentistry prevents widespread adoption. Informed consent and data privacy issues should be important considerations before implementation in dental practice.
- 4. Limited Access: High costs and technical barriers can prevent smaller practices from implementing AI solutions. Additionally, integrating AI seamlessly into existing dental practice workflows and ensuring user acceptance remains a challenge.
- 5. False Positives/Negatives: Another limitation is the potential for AI to produce false positive or false negative results, leading to over- or under-treatment. While improving, AI still generates diagnostic errors that require clinician oversight.

## What Does the Future Hold for Al in Dentistry?

Future advancements in AI for dental caries detection aim to address the limitations mentioned above through:

- 1. Larger and More Diverse Datasets: Multicenter collaborations to create global image repositories will improve model performance across populations.
- 2. Integration of Multimodal Data: Combining radiographic, clinical, and patient history data could enhance Al-driven diagnostics.
- 3. Real-Time Al Applications: Innovations like chairside Al tools integrated into intraoral scanners or handheld imaging devices may improve usability.
- **4. Standardized Evaluation Metrics:** Cross-study standardization will ensure uniform research reporting and generalizability of results, as well as a benchmark to assess new AI dental devices.<sup>27</sup>

#### 5. Explainable Al and Regulatory Frameworks:

Explainable AI (XAI) techniques that provide insights into the model's decision-making process can enhance trust and interpretability for clinicians (showing how and why decisions were made).<sup>28</sup> Establishing clear guidelines for the validation, approval, ethical, and responsible use of AI in dentistry should be at the core of dental AI development and planning.<sup>11,27,29</sup> Dento-legal perspectives involving more routine and widespread use of AI in dental practice are in the nascent stages. Issues about liability and insurance remain unanswered. Case law addressing AI in related areas of healthcare may further inform dentistry

As AI evolves and improves, it may become a valuable tool for delivering high-quality, patient-centered care. Some potential future uses of AI in dentistry include:

- Personalized Treatment: Al may assist the clinician in developing more tailored treatment plans based on individual patient data.
- Diagnostic adjunct for diagnosis: Al assessment tools may flag dental disease and generate a differential diagnosis for the clinician to consider.
- Robotics: Al-powered robots may assist in surgeries and other procedures.
- Teledentistry: Al has the potential to expand remote monitoring and virtual consultations.
- Integration with electronic health records (EHRs): All systems can seamlessly integrate with EHRs to improve holistic decision-making.

 Education: New chatbots and Large Language Learning Models (LLMs) may provide additional avenues for patient and student education.

### **Conclusions**

Most studies and reviews stress three essential points for the effective use of AI in caries management:

**First:** Al aims to support clinical judgment, **not to replace it**. The final interpretation of Al findings and decision-making should be correlated with a clinical examination performed by the clinician.

**Second**: To maximize the cost-effectiveness of using AI and achieve maximum preservation of the natural tooth structure, early (non-cavitated) lesions should be managed non-restoratively. Otherwise, AI use will lead to overtreatment.

Third: While numerous studies attest to the potential of Al-augmented caries detection, confirmatory validation studies are lacking. Due to the wide variability between the numerous Al models and protocols addressing their training, more well-designed and standardized clinical trial studies are needed to confirm and recommend their use in everyday clinical practice.

Accordingly, dental clinicians considering incorporating Al-augmented caries detection tools into their practice should understand their limitations. Finally, dental clinicians should refer to the American Dental Association's Artificial Intelligence in Dentistry website for additional information (<a href="https://www.ada.org/resources/practice/dental-standards/artificial-intelligence-indentistry">https://www.ada.org/resources/practice/dental-standards/artificial-intelligence-indentistry</a>).

## Appendix 1

## **Fundamental AI Terminology**

Term	Definition
Accuracy	Percentage of correct diagnoses made by the AI system on dental images
Al (Artificial Intelligence)	Computer systems that can perform tasks typically requiring human intelligence, such as identifying dental caries from radiographs
Algorithm	A set of rules or instructions that a computer follows to solve problems
Annotation	Process of labeling dental images with diagnostic information for AI training
Classification	Al task of categorizing dental images into predefined classes (e.g., healthy, carious, restored)
CNN (Convolutional Neural Network)	A deep learning architecture particularly effective for image analysis, commonly used for dental X-ray interpretation
Cross-validation	Technique to assess AI model performance by testing on different subsets of data
DL (Deep Learning)	A subset of ML using neural networks with multiple layers to automatically extract features from dental images
Ensemble Methods	Combining multiple AI models to improve diagnostic performance
Feature Extraction	Process of identifying relevant characteristics in dental images (e.g., bone density, tooth boundaries)
Ground Truth	Verified diagnoses from dental experts used as the standard for training and testing Al
ML (Machine Learning)	A subset of AI where algorithms learn patterns from data without being explicitly programmed, used for tasks like caries detection
Neural Network	A computing system inspired by biological neural networks, consisting of interconnected nodes that process dental image data
Object Detection	Al technique to locate and identify specific structures in dental images (e.g., implants, fractures)
Overfitting	When an AI model performs well on training data but poorly on new dental images
Postprocessing	Refinement of AI results to improve diagnostic accuracy or presentation
Precision	Proportion of positive AI predictions that are actually correct
Preprocessing	Steps to prepare dental images for Al analysis (e.g., noise reduction, contrast enhancement)
Recall	Proportion of actual positive cases that the AI system correctly identifies
ROC Curve	Graph showing Al model performance across different diagnostic thresholds
Segmentation	Process of dividing dental images into distinct regions (e.g., teeth, bone, soft tissue, pathology)
Sensitivity	Al system's ability to correctly identify positive cases (e.g., detecting actual caries)
Specificity	Al system's ability to correctly identify negative cases (e.g., confirming healthy teeth)
Supervised Learning	ML approach using labeled dental images to train models for specific diagnostic tasks
Test Data	Final dataset of dental images used to evaluate the trained model's real-world performance
Training Data	Collection of dental images with known diagnoses used to teach Al systems to recognize patterns
Transfer Learning	Using pre-trained AI models and adapting them for specific dental imaging tasks
Underfitting	When an AI model is too simple to capture important patterns in dental images
Unsupervised Learning	ML approach that finds hidden patterns in dental images without labeled examples
Validation Data	Separate set of dental images used to test Al model training performance during development

## References

- Science News Today. Al in Everyday Life: 20
  Real-World Examples. 2025. Available at: https://
  www.sciencenewstoday.org/ai-in-everydaylife-20-real-world-examples. Accessed 14 July
  2025.
- Qayyum A, Tahir A, Butt MA, et al. Dental caries detection using a semi-supervised learning approach. Sci Rep. 2023;13(1):749. doi: 10.1038/ s41598-023-27808-9.
- Mohammad-Rahimi H, Motamedian SR, Rohban MH, et al. Deep learning for caries detection: A systematic review. J Dent. 2022;122:104115. doi: 10.1016/j.jdent.2022.104115.
- Alam MK, Alftaikhah SAA, Issrani R, et al. Applications of artificial intelligence in the utilisation of imaging modalities in dentistry: A systematic review and meta-analysis of in-vitro studies. Heliyon. 2024;10(3):e24221. doi: 10.1016/j.heliyon.2024.e24221.
- Scott J, Biancardi AM, Jones O, Andrew D. Artificial Intelligence in Periodontology: A Scoping Review. Dent J (Basel). 2023;11(2):43. doi: 10.3390/dj11020043.
- Schwendicke F, Golla T, Dreher M, Krois J. Convolutional neural networks for dental image diagnostics: A scoping review. J Dent. 2019;91:103226. oi: 10.1016/j.jdent.2019.103226.
- Lee S, Oh SI, Jo J, Kang S, Shin Y, Park JW. Deep learning for early dental caries detection in bitewing radiographs. Sci Rep. 2021;11(1):16807. doi: 10.1038/s41598-021-96368-7.
- Sultan AS, Elgharib MA, Tavares T, Jessri M, Basile JR. The use of artificial intelligence, machine learning and deep learning in oncologic histopathology. J Oral Pathol Med. 2020;49(9):849-856. doi: 10.1111/jop.13042.
- Boldt J, Schuster M, Krastl G, et al. Developing the Benchmark: Establishing a Gold Standard for the Evaluation of Al Caries Diagnostics. J Clin Med. 2024;13(13).3846. doi: 10.3390/ jcm13133846.
- Frenkel E, Neumayr J, Schwarzmaier J, et al. Caries Detection and Classification in Photographs Using an Artificial Intelligence-Based Model-An External Validation Study. Diagnostics (Basel). 2024;14(20).2281. doi: 10.3390/diagnostics14202281.

- Ducret M, Wahal E, Gruson D, et al. Trustworthy Artificial Intelligence in Dentistry: Learnings from the EU AI Act. J Dent Res. 2024;103(11):1051-1056. doi: 10.1177/00220345241271160.
- Schwarzmaier J, Frenkel E, Neumayr J, et al. Validation of an Artificial Intelligence-Based Model for Early Childhood Caries Detection in Dental Photographs. J Clin Med. 2024;13(17).5215. doi: 10.3390/jcm13175215.
- Fejerskov O, Nyvad B. Dental Caries: The Disease and its Clinical Management. 4th ed. Hoboken, NJ: Wiley-Blackwell; 2024.
- Pitts N, Ismail A, Martignon S, Ekstrand K, Douglas G, Longbottom C. ICCMSTM Guide for Practitioners and Educators. In: ICDAS Foundation; 2014. Available at: https://www.iccms-web.com/uploads/ asset/59284654c0a6f822230100.pdf Accessed 14 July 2025.
- Fontana M, Gonzalez-Cabezas C, Tenuta LMA. Evidence-based approaches and considerations for nonrestorative treatments within modern caries management: Integrating science into practice. J Am Dent Assoc. 2024;155(12):1000-1011. doi: 10.1016/j.adaj.2024.09.007.
- Schwendicke F, Tzschoppe M, Paris S. Radiographic caries detection: A systematic review and meta-analysis. J Dent. 2015;43(8):924-933. doi: 10.1016/j.jdent.2015.02.009.
- Baelum V, Hintze H, Wenzel A, Danielsen B, Nyvad B. Implications of caries diagnostic strategies for clinical management decisions. Community Dent Oral Epidemiol. 2012;40(3):257-266. doi: 10.1111/j.1600-0528.2011.00655.x.
- Secgin C, Gulsahi A, Arhun N. Diagnostic Challange: Instances Mimicking a Proximal Carious Lesion Detected by Bitewing Radiography. Oral Health Dent Manag. 2016;0-0.
- Schwendicke F, Göstemeyer G. Conventional bitewing radiography. Clinical Dentistry Reviewed. 2020;4. Available at: https://doi. org/10.1007/s41894-020-00086-8. Accessed 14 July 2025.
- Nascimento MM, Ribeiro AP, Delgado AJ, et al. Temporary Tooth Separation to Improve Assessment of Approximal Caries Lesions: A School-Based Study. Oper Dent. 2020;45(6):581-588. doi: 10.2341/19-221-C.

- Carvalho RN, Letieri ADS, Vieira TI, et al. Accuracy of visual and image-based ICDAS criteria compared with a micro-CT gold standard for caries detection on occlusal surfaces. Braz Oral Res. 2018;32:e60. doi: 10.1590/1807-3107bor-2018.vol32.0060.
- Mertens S, Krois J, Cantu AG, Arsiwala LT, Schwendicke F. Artificial intelligence for caries detection: Randomized trial. J Dent. 2021;115:103849. doi: 10.1016/j. jdent.2021.103849.
- Schwendicke F, Rossi JG, Göstemeyer G, et al. Cost-effectiveness of Artificial Intelligence for Proximal Caries Detection. J Dent Res. 2021;100(4):369-376. doi: 10.1177/0022034520972335.
- Khanagar SB, Alfouzan K, Awawdeh M, Alkadi L, Albalawi F, Alfadley A. Application and Performance of Artificial Intelligence Technology in Detection, Diagnosis and Prediction of Dental Caries (DC)-A Systematic Review. Diagnostics (Basel). 2022;12(5):1083. doi: 10.3390/diagnostics12051083.
- Carvalho BKG, Nolden EL, Wenning AS, et al. Diagnostic accuracy of artificial intelligence for approximal caries on bitewing radiographs: A systematic review and meta-analysis. J Dent. 2024;151:105388. doi: 10.1016/j. ident.2024.105388.
- Tichý A, Kunt L, Nagyová V, Kybic J. Automatic caries detection in bitewing radiographs-Part II: experimental comparison. Clin Oral Investig. 2024;28(2):133. doi: 10.1007/s00784-024-05528-2.
- Rokhshad R, Ducret M, Chaurasia A, et al. Ethical considerations on artificial intelligence in dentistry: A framework and checklist. J Dent. 2023;135:104593.doi: 10.1016/j. jdent.2023.104593.
- Noor Uddin A, Ali SA, Lal A, et al. Applications of Al-based deep learning models for detecting dental caries on intraoral images - a systematic review. Evid Based Dent. 2025;26(1):71-72. doi: 10.1038/s41432-024-01089-1.
- Khoury ZH, Ferguson A, Price JB, Sultan AS, Wang R. Responsible artificial intelligence for addressing equity in oral healthcare. Front Oral Health. 2024;5:1408867. doi: 10.3389/ froh.2024.1408867.

### **POST-TEST**

Internet Users: This page is intended to assist you in fast and accurate testing when completing the "Online Exam." We suggest reviewing the questions and then circling your answers on this page prior to completing the online exam.

(1.0 CE Credit Contact Hour) Please circle the correct answer. 70% equals passing grade.

- 1. What is the primary aim of Al-powered clinician decision support systems (CDSS) in dentistry?
  - a. To replace clinician expertise
  - b. To augment clinician expertise
  - c. To automate all dental procedures
  - d. To eliminate the need for radiographs
- 2. In the context of dental Al training, what does "ground truth" refer to?
  - a. The actual tooth structure
  - b. The reference standard or verified diagnosis
  - c. The Al's final prediction
  - d. The patient's self-reported symptoms
- 3. Which imaging modality has been most extensively studied with AI methods for caries detection?
  - a. CBCT scans
  - b. Intraoral photographs
  - c. Bitewing radiographs
  - d. Panoramic radiographs
- Studies have shown that \_\_\_ percent of the lesions detected radiographically within outer dentin are clinically non-cavitated.
  - a. 66
  - b. 77
  - c. 55
  - d. 33
- 5. What is considered the main risk of Al implementation in dental practice?
  - a. High implementation costs
  - b. Patient privacy concerns
  - c. Over-reliance on AI outputs without critical judgment
  - d. Increased treatment time

- 6. Which of these approaches is required to ensure optimal results when integrating AI in dental practice?
  - a. Complete reliance on Al diagnostics
  - b. Elimination of traditional diagnostic methods
  - c. Use of AI findings in conjunction with clinical examination
  - d. Replacement of radiographic imaging
- 7. What is the best method to improve ground truth determination in dental Al?
  - a. Single expert annotation
  - b. Consensus annotation using multiple experts
  - c. Annotation by non-experts
  - d. Automated annotation without human input
- 8. Which of the following is identified as a key component of "Explainable AI" (XAI) in dentistry?
  - a. Faster processing speeds
  - b. Lower cost implementation
  - c. Automated treatment planning
  - d. Insights into the model's decision-making process
- 9. When combining BWR with visual-tactile diagnosis, the combined diagnostic outcome will show:
  - a. Higher sensitivity and specificity
  - b.. Higher sensitivity and lower specificity
  - c. Lower sensitivity and specificity
  - d. Lower sensitivity and higher specificity
- 10. When a clinician detects cavitation into outer- mid dentin on a surface, this lesion is coded as ICDAS\_\_ lesion:
  - a. 2
  - b. 3
  - c. 5
  - d. 4

Registration/Certification Information (Necessary for proper	certification)							
Name (Last, First, Middle Initial):								
Street Address:						ND.		
City: State:	Zip:				FC			
Telephone: Email:					)FF	ICE		
tate(s) of Licensure: License Number(s):					US	SF		
Preferred Dentist Program ID Number: Check Box If Not A PDP Member								
AGD Mastership:  Yes No					ON	LY		
AGD Fellowship:  Yes  No Date:								
Please Check One: General Practitioner Specialist Dental Hygienist Other								
Evaluation - An Introduction to Artificial Intelligence and Dental Caries Detection  Providing dentists with the opportunity for continuing dental education is an essential part of MetLife's commitment to helping dentists improve the oral health of their patients through education. You can help in this effort by providing feedback regarding the continuing education offering you have just completed.								
Please respond to the statements below by checking the appropriate box, using the scale on the right.	1 = POOR 1	2	3	4	= Excelle			
1. How well did this course meet its stated educational objectives?								
2. How would you rate the quality of the content?								
3. Please rate the effectiveness of the author.								
4. Please rate the written materials and visual aids used.								
5. The use of evidence-based dentistry on the topic when applicable.						□ N/A		
6. How relevant was the course material to your practice?								
7. The extent to which the course enhanced your current knowledge or skill?								
8. The level to which your personal objectives were satisfied.								
9. Please rate the administrative arrangements for this course.								

What is the primary reason for your 0-10 recommendation rating above?

11. Please identify future topics that you would like to see:

9

Thank you for your time and feedback.

10. How likely are you to recommend MetLife's CE program to a friend or colleague? (please circle one number below:)

neutral

6



10

extremely likely

2

**0** not likely at all