ARTIFICIAL INTELLIGENCE IN DENTAL CARIES DIAGNOSIS: A NARRATIVE REVIEW

Georgiana-Andreea Frumuzache[1], Antonia -Theodora Vrabie[1*], Sorin Andrian[2], Gianina Iovan[2], Irina Nica[2], Alice-Teodora Rotaru-Costin[2], Simona Stoleriu[2]

[1]Department of Odontology-Periodontology and Fixed Prosthodontics, Faculty of Dental Medicine, Grigore T. Popa University of Medicine and Pharmacy Iasi, 16 Universitatii Street, 700115 Iasi, Romania; PhD student
[2]Department of Odontology-Periodontology and Fixed Prosthodontics, Faculty of Dental Medicine, Grigore T. Popa University of Medicine and Pharmacy Iasi, 16 Universitatii Street, 700115 Iasi, Romania

*Corresponding author: Antonia-Theodora Vrabie e-mail: antonia-theodora.vrabie@d.umfiasi.ro

ABSTRACT

Background: Dental caries is one of the most prevalent chronic disease worldwide. It is essential to use fast and accurate methods for caries detection. In this context, increased interest was recorded in using artificial intelligence (AI) deep learning techniques for dental images analysis in order to detect and evaluate dental caries. **Objective:** The aim of this narrative review is to evaluate the applications of artificial intelligence in the diagnosis of dental caries and to highlight the limitations of these technologies. **Methods:** Analysis of the scientific literature was conducted by consulting the PubMed/MEDLINE, Scopus, Web of Science and ScienceDirect databases. Articles investigating the use of AI in the detection and classification of dental caries published from 2021 to 2026 were included. **Results:** Studies analysis showed that artificial intelligence–based systems, especially based on convolutional neural networks (CNN), can establish caries diagnosis very simmilar to experienced clinicians. In the studies the main investigated data source was bitewing radiography. However, factors such as the annotation method, image quality, and the size and diversity of datasets have an impact on model performance. Regarding external validation, most studies rely on retrospective datasets. **Conclusions:** Artificial intelligence is a promising tool for the diagnosis of dental caries, improving the efficiency and accuracy of this process. However, the validation in clinical practice requires prospective studies, standardization of methodologies and it addressing ethical and regulatory aspects.

Key words: *artificial intelligence, deep learning, dental caries, caries detection, bitewing radiograph, dental radiology.*

1. INTRODUCTION

Dental caries is one of the most common chronic conditions worldwide. Dental caries affects various populations and represents a major public health problem due to the impact on quality of life. According to data published by the World Health Organization (WHO), oral diseases affect approximately 3.5 billion people worldwide (1). Dental caries of permanent teeth is the most prevalent of these conditions (1). The high prevalence highlights the need for early and accurate diagnosis, as well as the need to implement global strategies for prevention and treatment. Advanced technologies and screening programs can be used to prevent lesion progression and to reduce the need for invasive treatments (1,2).

Visual clinical and imaging examination, especially the use of bitewing and periapical radiographs, are essential for the diagnosis of dental caries, for caries progression, and for caries activity assessment. Proximal caries lesion or occlusal dental caries extended into the dentin that cannot be identified or evaluated using direct visual inspection can be assessed using radiographic imaging. The interpretation of radiographic images highly varies with the experience of dental practioner. Studies have shown that image quality, lesion severity, and clinician experience can significantly affect the interpretation of radiographs, which may

DOI : 10.62610/RJOR.2025.1.18.10

affect the accuracy of caries diagnosis and treatment (3).

In the last decade, the automatic analysis of medical and dental images has been developed by using artificial intelligence (AI) technologies, especially deep learning methods in this process. These modern methods provide more efficient and accurate results when comparing to traditional visual evaluation (4). Convolutional neural network (CNN) algorithms have the ability to learn to identify relevant patterns and features directly from images in the same way as human brain recognizes shapes and objects. As a result, there is no longer a need to manually define features. Numerous studies evaluated the use of AI for automatic detection of caries on dental radiographic images and have demonstrated higher accuracy and shorter time for diagnosis (3,5,6).

In the scientific literature, studies have shown that AI-based systems can have the performance in caries diagnosis comparable to experienced clinicians under certain controlled conditions, especially in identifying approximal dental caries on bitewing radiographs (7). However, a number of variations such as image quality and dataset size, affect the performance of these systems and can have a significant impact on the accuracy and clarity of detection. For example, the size and diversity of training data can influence model accuracy by providing an adequate representation of clinical variability; image quality can affect detection clarity by reducing noise and improving contrast; and lesion labeling techniques can determine identification precision by standardizing evaluation criteria. In addition, an increased number of studies rely on retrospective data and require further external validation to confirm clinical relevance in real-world situations (8–10).

In this context, present study aims to evaluate the potential of these technologies to support clinical diagnosis, to improve image interpretation, and to facilitate the early identification of dental caries .

2. MATERIALS AND METHODS

The present paper represents a narrative review of the literature regarding the use of artificial intelligence in the diagnosis of dental caries. A descriptive analysis of published studies was conducted, with the aim of synthesizing clinical applications, reported performance, and methodological limitations.

2.1. Study Design

This paper is a narrative review of the scientific literature regarding the use of artificial intelligence.

2.2.Search Strategy

Literature search was conducted in scientific databases (PubMed/MEDLINE, Scopus, Web of Science, and ScienceDirect), using combinations of terms such as: “artificial intelligence”, “deep learning”, “dental caries”, “caries detection”, “bitewing radiograph”, “dental radiology”.

The following types of studies were included: systematic reviews, meta-analyses, controlled clinical studies, relevant observational studies, and articles on the regulation of AI in healthcare.

A total of 58 records were identified through database searching. After removing 6 duplicate records, 52 articles remained for screening. Following title and abstract screening, as well as full-text assessment based on the inclusion and exclusion criteria, 40 studies were included in the final analysis.

2.3. Inclusion criteria

The following articles were included: articles published in English within the last 5 years (2021-2026), with the exception of

DOI : 10.62610/RJOR.2025.1.18.10

key studies, which evaluated the use of artificial intelligence in the detection, classification, or identification and outlining of dental caries using dental images (bitewing, periapical, panoramic radiographs, or other relevant imaging methods).

2.4. Methodological limitations

A selection according to the PRISMA guidelines was not performed, and no quantitative meta-analysis was conducted. The data synthesis is descriptive and interpretative.

3. LITERATURE REVIEW

3.1.Imaging used for AI-based detection of dental caries

Widely used dental imaging provides a standardized representation of hard structures. It is the basis for studies that evaluate artificial intelligence in the detection of dental caries. The main data source is dental radiography, especially bitewing radiographs (11). Bitewing radiographs are the most commonly used for training and testing AI models. This is due to their relevance for proximal lesions detection, when direct visual examination has limitation (3,5,8).

3.1.1. Bitewing radiographs (BW) – the dominant standard for proximal dental caries

Bitewing radiographs are essential in AI research for the dental caries diagnosis because:
• they allow the visualization of posterior and interproximal areas, frequently associated with proximal dental caries onset;
• they facilitate the early detection of dental lesions by capturing critical areas for the onset of proximal caries;
• they are frequently used in screening and monitoring, generating large datasets that are essential for training and validating AI algorithms;
• they enable the definition of clear AI tasks (e.g., classification: caries vs. no caries; lesion segmentation; depth estimation).

According to some systematic analyses and studies which evaluated the diagnostic accuracy, AI can be considered at least “clinically acceptable” for approximal dental caries identification on bitewing radiographs. Although this aspect indicates a high potential for AI to improve caries diagnosis, it also highlights the need of clinicians to verify the results in order to avoid overdiagnosis (5,8,9,12).

3.1.2. Periapical radiographs – good local resolution, frequently used in specific clinical settings

Application of AI on periapical radiographs for caries detection are also investigated in some studies. Periapical radiographs are mostly used when clinical protocol requires the investigation of periapical area to establish the diagnosis. AI models were developed for caries detection on periapical radiographs, sometimes in addition to other radiological evaluation, such as the identification of bone loss or periapical infection (10,13,14).

3.1.3. Panoramic radiographs (OPG) – wide coverage, but with limitations for dental caries

Panoramic radiographs provide an overall view of the dental arches and due to their wide availability and possibility to provide large amount of data for training algorithms are attractive for AI (15). However, when comparing to bitewing radiographs, which are more precise for these details, they have limitations in caries detection, such as overlaps and distortions, and offer lower resolution on proximal

DOI : 10.62610/RJOR.2025.1.18.10

surfaces. Nevertheless, research on caries detection and segmentation on panoramic radiographs using deep learning (DL) models has highlighted the potential of these technologies to improve diagnostic accuracy (16,17).

3.1.4.Near-Infrared Transillumination (NILT/NIR TI) – a non-ionizing radiation alternative

Near-infrared transillumination (NILT), has been studied as a promising method for caries detection, including early dental caries, without exposure to X-rays. NILT models have been analyzed in pilot studies and in studies evaluating model generalization, demonstrating their ability to identify and localize severe dental caries (18,19).

3.1.5. Optical Coherence Tomography (OCT) – microstructural detail, predominantly in research

OCT provides high-resolution images of dental structures, allowing detailed identification of subsurface changes, such as enamel demineralization. This makes it useful for identifying early lesions and for accurately assessing their depth. In the deep learning (DL) literature regarding dental caries, OCT is mentioned as an alternative method that has been investigated in methodological studies. However, the clinical use of OCT is limited in comparison to radiographs and the evidence regarding its clinical applicability is heterogeneous (8,20,21).

3.2. Artificial intelligence algorithms

In the scientific literature, convolutional neural networks (CNNs) are the most frequently used baseline algorithm for dental image analysis in AI-assisted detection of dental caries, as they have the capacity to efficiently analyze complex images (22). This trend was highlighted in review and meta-analysis studies which showed that most of the included studies used CNN architectures (or derived variants) for tasks as detection, classification, and segmentation of dental caries. These studies emphasize the efficiency and accuracy of these techniques when comparing to conventional visual inspection and radiographic interpretation (8,23,24).

3.2.1. Relevance of CNNs in the detection of dental caries

CNNs are suited for images evaluation due to their capacity to learn hierarchical representations, a process that involves first of all the identification of simple features such as edges and textures, then the progression to more complex structures using raw pixel data. In practice, it means that the model has the capacity to automatically extract features from images, which significantly reduces the need for manual feature design. This process is known as „feature engineering” (25,26).

3.2.2. Types of tasks and commonly used CNN architectures

In studies regarding the detection of dental caries, CNNs were used in several standard formulations, depending on the expected output of the system (27, 28). A summary of these tasks, along with their corresponding architectures and clinical relevance, is presented in Table 1.

3.2.3. Non-CNN algorithms (less commonly used, but existing)

Although CNNs dominate image-based applications, the literature also includes other types of algorithms (28). These approaches, along with their main characteristics and applications, are summarized in Table 2.

DOI : 10.62610/RJOR.2025.1.18.10

Table 1. CNN-based tasks for dental caries detection and their clinical relevance

Task type	Description	Common architectures	Output type	Clinical relevance
Classification	Caries vs. no caries; severity grading (24)	ResNet, VGG, Inception, DenseNet; fine-tuned pre-trained models	Binary / multi-class label	Supports screening and decision-making
Detection / Localization	Identifies the location of the lesion; bounding boxes for suspicious areas (29)	YOLO (You Only Look Once) family	Bounding boxes	Highlights suspicious regions for clinician review
Segmentation	Defines the exact contour of the lesion; pixel-level mapping (3,8)	U-Net and encoder–decoder variants	Pixel-level mask	Enables precise lesion assessment and depth estimation

Table 2. Non-CNN Approaches in caries detection

Algorithm type	Description	Typical use case
Classical machine learning	SVM, Random Forest; often used on structured/tabular data (30,31)	Risk prediction; hybrid models
Transformers/ViT	Deep learning models based on attention mechanisms (32,33)	Image-based detection (e.g., panoramic)

3.3. Diagnostic performance

Available evidence (particularly from experimental/retrospective studies on labeled radiographic datasets and from systematic reviews with meta-analysis) suggests that AI systems can detect with high performance advanced dental caries. In addition, when using certain predefined settings, they might be comparable to clinical evaluation or might improve sensitivity when used as decision-support tools. However, the literature showed significant variability between studies, making difficult the generalization of a single “standard” level of accuracy for all clinical scenarios (5,8,34,35).

3.3.1. Variability of diagnostic performance

Approximal dental caries analyzed on bitewing radiographs showed a summary sensitivity of ~0.94 and a summary specificity of ~0.91, suggesting “clinically acceptable” accuracy for screening/triage, with the recommendation that positive results must be verified by an

DOI : 10.62610/RJOR.2025.1.18.10

expert to reduce the risk of overtreatment (5).

The literature explicitly highlights that the variation in diagnostic performance is influenced by several methodological factors. These factors are summarized in Table 3.

Table 3. Methodological factors influencing AI diagnostic performance

Factor	Description	Impact on performance
Dataset size and diversity	Datasets vary considerably in size, from a few hundred to several thousand radiographs; both size and diversity influence model performance and generalizability (34,36)	Affects model robustness and ability to generalize
Image quality and acquisition heterogeneity	Differences in resolution, contrast, artifacts, overlaps, and acquisition protocols can significantly affect lesion detectability (3,8)	Leads to variability in detection accuracy
Annotation methodology and reference standard	Labeling process (number of annotators, consensus vs. individual labeling, severity criteria) and the chosen ground truth can substantially alter perceived model performance (6,34)	Influences reported accuracy and evaluation reliability

3.3.2.Limitations in the interpretation of results

A large proportion of the available evidence comes from studies conducted under controlled conditions, frequently using retrospective data, selected images, caries prevalences different from those in clinical practice, and varying protocols. For this reason, literature reviews emphasize the need for external validation and evaluation in real-world practice settings before the performance of these models can be considered stable across different clinics or populations (5,8,37).

The level of evidence regarding AI performance and influencing factors is summarized in Table 4.

Table 4. Level of evidence on AI diagnostic performance and influencing factors

Topic	Summary of evidence	Level of evidence
Diagnostic performance of AI	AI systems can achieve high diagnostic performance and in some cases performance comparable to clinical evaluation under controlled conditions; however, variability between studies is observed (5,8,34)	High
Methodological influencing factors	Dataset size and diversity, image quality, and annotation methodology are major factors influencing model performance, as highlighted in reviews and methodological studies (6,34,36)	High

DOI : 10.62610/RJOR.2025.1.18.10

3.4. Methodological bias

A recurrent limitation in the literature on AI-based caries detection is that most studies use retrospective datasets (archived images), which increases the risk of selection bias (e.g., case–control design, caries distributions different from real clinical practice) and may overestimate performance when comparing to the use in general population. Reviews and meta-analyses frequently highlight this predominance of retrospective design and the need for prospective/clinical studies (34,24,38).

In addition, many studies use expert consensus on radiographs as the reference standard (ground truth), since histological/clinically invasive confirmation is not routinely available. This may introduce reference bias and inter-observer variability, especially for early lesions or for severity delineation. Methodological reviews emphasize that differences in labeling criteria and in the way consensus is achieved directly influence the reported performance (24,39).

Major issues that complicate the interpretation of AI performance are summarized in Table 5.

Table 5. Key issues affecting the interpretation of AI diagnostic performance

Issue	Description	Impact on interpretation
Limited external validation	Many models are tested on data from the same source as the training data (or internal splits); lack of validation across different centers, devices, and populations reduces confidence in generalizability (24,38)	Limits applicability to real-world clinical settings
Dataset heterogeneity	Variations in image type (bitewing/periapical/panoramic), acquisition parameters, image quality, prevalence, and labeling criteria make direct comparison between studies difficult(34,40)	Leads to inconsistent and non-uniform results

4. DISCUSSION

The present narrative review highlights that artificial intelligence, particularly deep learning methods based on convolutional neural networks, represents a promising direction for dental caries diagnosis , having an increased potential for integration into clinical practice. This is supported by multiple reviews that emphasize the increasing role of AI in dental imaging and diagnostics (3,8,23). The included studies suggest that AI systems can achieve high levels of diagnostic performance. Sometimes the performance is comparable to experienced clinicians, especially in the diagnosis of interproximal caries using bitewing radiographs, as demonstrated in recent meta-analyses (5,24,34). These findings support the role of AI as a decision-support tool rather than a substitute for clinical examination.

The performance of AI models showed significant variability, mainly influenced by the characteristics of the datasets used for training and validation. As highlighted in the literature, studies that include large,

DOI : 10.62610/RJOR.2025.1.18.10

diverse, and well-annotated datasets tend to report superior performance and better ability to generalize (34,36). In contrast, the use of limited and homogeneous datasets may lead to poor generalization to new data and reduced performance in real clinical settings, a limitation frequently discussed in systematic reviews (8,40).

Another factor to consider is the quality of radiographic images. Variability in technical equipment, and consequently in the resulting images and the presence of artifacts can significantly affect the ability of algorithms to identify dental caries, especially in early stages. Previous studies and reviews describe image heterogeneity as a major source of inconsistency in AI performance (3,8,40). In this regard, the standardization of imaging protocols and the development of algorithms robust to technical variations are essential for clinical implementation.

Annotation methodology (ground truth) also represents a major source of heterogeneity. Most studies use clinician consensus as reference standard, which introduces a certain degree of subjectivity and variability. Researches have shown that annotation strategies and choosing the reference standard can significantly influence reported model performance (6,39). This limitation affects both model training and evaluation, highlighting the need for standardized labeling protocols and for correlation with clinical or histological data when possible.

Moreover, most studies are retrospective and were conducted under controlled conditions. This aspect can limit the applicability of AI in clinical practice with increased variability in patients, images, working conditions, and clinical scenarios . Reviews and umbrella analyses consistently emphasize the lack of external validation and prospective clinical studies as major barriers to clinical translation (24,37,38). Therefore, rigorous, multicenter clinical studies are needed to evaluate AI performance under real-world conditions.

In clinical practice, the use of AI can bring various benefits, including optimization of analysis time and increased diagnostic sensitivity, as suggested by several recent studies (9,10,16). However, potential risks such as overdiagnosis and consequently overtreatment must also be considered, especially in the context of early lesions or false-positive results. Thus, AI integration should be carried out in a controlled manner, preserving the central role to the clinician in the decision-making process.

Furthermore, regulation is needed regarding ethical aspects, patient data protection, algorithm transparency (black box), and responsibility in the case of diagnostic errors, as highlighted in recent literature on AI implementation in healthcare (31,38).

5. CONCLUSION

Artificial intelligence, particularly deep learning methods based on convolutional neural networks, represents a significant innovative method for imaging diagnosis of dental caries. The articles analyzed in this narrative review indicate that artificial intelligence systems can achieve high diagnostic performance, especially in the detection of interproximal caries using bitewing radiographs and may be comparable to clinician evaluation in certain situations.

Bitewing radiographs remain the gold standard for training and evaluating these models, while other imaging methods such as periapical and panoramic radiographs or non-ionizing techniques are currently under investigation for future AI applications.

However, the performance of AI systems is significantly influenced by factors such as dataset size, image quality, and annotation techniques. The variability of these factors, along with the predominance of retrospective studies with

DOI : 10.62610/RJOR.2025.1.18.10

lack of external validation limit the results generalisation and the possibility of immediate clinical integration.

In this context, artificial intelligence should be considered as a supportive tool that can complement, but not replace, clinical examination and diagnosis. AI integration into dental practice requires methodological standardization, rigorous clinical validation, and the implementation of ethical standards and regulations.

In the future, research should focus on the development of models using multicenter datasets and on the evaluation of real impact of AI on clinical outcomes. The responsible implementation of these technologies has the potential to improve early detection of dental caries and can contribute to the optimization of patient management in dental medicine.

REFERENCES

1. WHO. Global oral health status report: towards universal health coverage for oral health by 2030 [Internet]. 2022. Available from: https://www.who.int/publications/i/item/9789240061484?utm_source=chatgpt.com
2. Abdelaziz M. Detection, Diagnosis, and Monitoring of Early Caries: The Future of Individualized Dental Care. Diagnostics (Basel). 2023 Dec 12;13(24):3649. doi:10.3390/diagnostics13243649 PubMed PMID: 38132233; PubMed Central PMCID: PMC10742918.
3. Al-Khalifa KS, Ahmed WM, Azhari AA, Qaw M, Alsheikh R, Alqudaihi F, et al. The Use of Artificial Intelligence in Caries Detection: A Review. Bioengineering. 2024 Sep 18;11(9):936. doi:10.3390/bioengineering11090936
4. Khattak O, Hashem AS, Alqarni MS, Almufarrij RAS, Siddiqui AY, Anis R, et al. Deep Learning Applications in Dental Image-Based Diagnostics: A Systematic Review. Healthcare. 2025 Jun 18;13(12):1466. doi:10.3390/healthcare13121466
5. Carvalho BKG, Nolden EL, Wenning AS, Kiss-Dala S, Agócs G, Róth I, et al. Diagnostic accuracy of artificial intelligence for approximal caries on bitewing radiographs: A systematic review and meta-analysis. Journal of Dentistry. 2024 Dec;151:105388. doi:10.1016/j.jdent.2024.105388
6. Gonzalez-Valenzuela RE, Mettes P, Loos BG, Marquering H, Berkhout E. Accuracy of deep learning-based AI models for early caries lesion detection: the influence of annotation quality and reference choice. Clin Oral Invest. 2025 Dec 4;29(12):598. doi:10.1007/s00784-025-06672-z
7. Kwiatek J, Leśna M, Piskórz W, Kaczewiak J. Comparison of the Diagnostic Accuracy of an AI-Based System for Dental Caries Detection and Clinical Evaluation Conducted by Dentists. JCM. 2025 Feb 26;14(5):1566. doi:10.3390/jcm14051566
8. Mohammad-Rahimi H, Motamedian SR, Rohban MH, Krois J, Uribe SE, Mahmoudinia E, et al. Deep learning for caries detection: A systematic review. Journal of Dentistry. 2022 Jul;122:104115. doi:10.1016/j.jdent.2022.104115
9. Piipari L, Anttonen V, Lussi A, Laitala ML, Tanner T, Karki S. Reliability of an Artificial Intelligence Software in the Detection of Approximal Caries Lesions Using Bitewing Radiographs. Caries Res. 2025 Jul 4;1–8. doi:10.1159/000547245
10. Li S, Liu J, Zhou Z, Zhou Z, Wu X, Li Y, et al. Artificial intelligence for caries and periapical periodontitis detection. Journal of Dentistry. 2022 Jul;122:104107. doi:10.1016/j.jdent.2022.104107
11. Boldt J, Schuster M, Krastl G, Schmitter M, Pfundt J, Stellzig-Eisenhauer A, et al. Developing the Benchmark: Establishing a Gold Standard for the Evaluation of AI Caries Diagnostics. JCM. 2024 Jun 29;13(13):3846. doi:10.3390/jcm13133846
12. Bayati M, Alizadeh Savareh B, Ahmadinejad H, Mosavat F. Advanced AI-driven detection of interproximal caries in bitewing radiographs using YOLOv8. Sci Rep. 2025 Feb 7;15(1):4641.

DOI : 10.62610/RJOR.2025.1.18.10

doi:10.1038/s41598-024-84737-x PubMed PMID: 39920198; PubMed Central PMCID: PMC11806056.
13. Shujaat S, Aljadaan H, Alrashid H, Aboalela AA, Riaz M. FDA-Approved AI Solutions in Dental Imaging: A Narrative Review of Applications, Evidence, and Outlook. Int Dent J. 2026 Feb;76(1):109315. doi:10.1016/j.identj.2025.109315 PubMed PMID: 41421004; PubMed Central PMCID: PMC12775797.
14. Aloufi AS. Detection of Periapical Lesions Using Artificial Intelligence: A Narrative Review. Diagnostics. 2026 Jan 17;16(2):301. doi:10.3390/diagnostics16020301
15. Hung M, Yevseyevich D, Khazana M, Schwartz C, Lipsky MS. Charting New Territory: AI Applications in Dental Caries Detection from Panoramic Imaging. Dentistry Journal. 2025 Aug 12;13(8):366. doi:10.3390/dj13080366
16. Pornprasertsuk-Damrongsri S, Vachmanus S, Papasratorn D, Kitisubkanchana J, Chaikantha S, Arayasantiparb R, et al. Clinical application of deep learning for enhanced multistage caries detection in panoramic radiographs. Sci Rep. 2025 Sep 29;15(1):33491. doi:10.1038/s41598-025-16591-4
17. Turosz N, Chęcińska K, Chęciński M, Sielski M, Sikora M. Evaluation of Dental Panoramic Radiographs by Artificial Intelligence Compared to Human Reference: A Diagnostic Accuracy Study. J Clin Med. 2024 Nov 14;13(22):6859. doi:10.3390/jcm13226859 PubMed PMID: 39598002; PubMed Central PMCID: PMC11595016.
18. Mohamed Nur M, Vazquez L, Anton Y Otero C, Giacobino C, Krejci I, Abdelaziz M. Near-Infrared Transillumination for Occlusal Carious Lesion Detection: A Retrospective Reliability Study. Diagnostics (Basel). 2022 Dec 23;13(1):36. doi:10.3390/diagnostics13010036 PubMed PMID: 36611328; PubMed Central PMCID: PMC9818492.
19. Asma Alatawi. DEEP LEARNING FOR CARIES DETECTION IN DIAGNOCAM IMAGES: A SYSTEMATIC REVIEW OF CURRENT EVIDENCE AND CHALLENGES. ijam. 2025 Oct 15;38(6s):1452–62. doi:10.12732/ijam.v38i6s.801
20. Huang YP, Lee SY. Deep Learning for Caries Detection using Optical Coherence Tomography [Internet]. 2021 [cited 2026 Mar 4]. Available from: http://medrxiv.org/lookup/doi/10.1101/2021.05.04.21256502 doi:10.1101/2021.05.04.21256502
21. Janjua OS, Jeelani W, Khan MI, Qureshi SM, Shaikh MS, Zafar MS, et al. Use of Optical Coherence Tomography in Dentistry. Int J Dent. 2023;2023:4179210. doi:10.1155/2023/4179210 PubMed PMID: 38111754; PubMed Central PMCID: PMC10727803.
22. Yang L, Chen GY. Evaluation of Deep Learning for Caries Detection With Fine-Grained Classification and Postprocessing Improvements. International Dental Journal. 2025 Oct;75(5):100898. doi:10.1016/j.identj.2025.100898
23. Negi S, Mathur A, Tripathy S, Mehta V, Snigdha NT, Adil AH, et al. Artificial Intelligence in Dental Caries Diagnosis and Detection: An Umbrella Review. Clin Exp Dent Res. 2024 Aug;10(4):e70004. doi:10.1002/cre2.70004 PubMed PMID: 39206581; PubMed Central PMCID: PMC11358700.
24. Luke AM, Rezallah NNF. Accuracy of artificial intelligence in caries detection: a systematic review and meta-analysis. Head Face Med. 2025 Apr 4;21(1):24. doi:10.1186/s13005-025-00496-8
25. Fan CL. Multiscale Feature Extraction by Using Convolutional Neural Network: Extraction of Objects from Multiresolution Images of Urban Areas. IJGI. 2023 Dec 21;13(1):5. doi:10.3390/ijgi13010005
26. Krichen M. Convolutional Neural Networks: A Survey. Computers. 2023 Jul 28;12(8):151. doi:10.3390/computers12080151
27. Ghaffari M, Zhu Y, Shrestha A. A review of advancements of artificial intelligence in dentistry. Dentistry Review. 2024 Jun;4(2):100081. doi:10.1016/j.dentre.2024.100081
28. ForouzeshFar P, Safaei AA, Ghaderi F, Hashemikamangar SS. Dental Caries diagnosis from bitewing images using convolutional neural networks. BMC Oral Health. 2024 Feb 10;24(1):211. doi:10.1186/s12903-024-03973-9 PubMed PMID: 38341526; PubMed Central PMCID: PMC10858561.

DOI : 10.62610/RJOR.2025.1.18.10

29. Mao YC, Lin YJ, Hu JP, Liu ZY, Chen SL, Chen CA, et al. Automated Caries Detection Under Dental Restorations and Braces Using Deep Learning. Bioengineering. 2025 May 15;12(5):533. doi:10.3390/bioengineering12050533
30. Kang IA, Ngnamsie Njimbouom S, Lee KO, Kim JD. DCP: Prediction of Dental Caries Using Machine Learning in Personalized Medicine. Applied Sciences. 2022 Mar 16;12(6):3043. doi:10.3390/app12063043
31. Marwaha J, Singla M, Nath A, Arya A. Revolutionizing the diagnosis of dental caries using artificial intelligence-based methods. Journal of Conservative Dentistry and Endodontics. 2025 May;28(5):401–5. doi:10.4103/JCDE.JCDE_172_25
32. Felek T, Tercanlı H, Gök RŞ. Evaluating vision transformers and convolutional neural networks in the context of dental image processing: a systematic review. BMC Oral Health. 2025 Oct 15;25(1):1626. doi:10.1186/s12903-025-07036-5
33. Wang L, Li Z. Transformer-based intelligent detection model for early dental caries in panoramic radiographs. Sci Rep. 2026 Jan 23;16(1):3507. doi:10.1038/s41598-025-33391-y
34. Ammar N, Kühnisch J. Diagnostic performance of artificial intelligence-aided caries detection on bitewing radiographs: a systematic review and meta-analysis. Japanese Dental Science Review. 2024 Dec;60:128–36. doi:10.1016/j.jdsr.2024.02.001
35. Dashti M, Londono J, Ghasemi S, Zare N, Samman M, Ashi H, et al. Comparative analysis of deep learning algorithms for dental caries detection and prediction from radiographic images: a comprehensive umbrella review. PeerJ Comput Sci. 2024;10:e2371. doi:10.7717/peerj-cs.2371 PubMed PMID: 39650341; PubMed Central PMCID: PMC11622875.
36. Faizan Ahmed SM, Ghori MH, Khalid A, Nooruddin A, Adnan N, Lal A, et al. Annotated intraoral image dataset for dental caries detection. Sci Data. 2025 Jul 25;12(1):1297. doi:10.1038/s41597-025-05647-9
37. Arzani S, Karimi A, Iranmanesh P, Yazdi M, Sabeti MA, Nekoofar MH, et al. Examining the diagnostic accuracy of artificial intelligence for detecting dental caries across a range of imaging modalities: An umbrella review with meta-analysis. Vu GT, editor. PLoS One. 2025 Aug 13;20(8):e0329986. doi:10.1371/journal.pone.0329986
38. Araidy S, Batshon G, Mirochnik R. Artificial Intelligence Applications in Dentistry: A Systematic Review. Oral. 2025 Nov 7;5(4):90. doi:10.3390/oral5040090
39. Ndiaye AD, Gasqui MA, Millioz F, Perard M, Leye Benoist F, Grosgogeat B. Exploring the Methodological Approaches of Studies on Radiographic Databases Used in Cariology to Feed Artificial Intelligence: A Systematic Review. Caries Res. 2024;58(3):117–40. doi:10.1159/000536277
40. Albano D, Galiano V, Basile M, Di Luca F, Gitto S, Messina C, et al. Artificial intelligence for radiographic imaging detection of caries lesions: a systematic review. BMC Oral Health. 2024 Feb 24;24(1):274. doi:10.1186/s12903-024-04046-7

DOI : 10.62610/RJOR.2025.1.18.10

DOI : 10.62610/RJOR.2025.1.18.10