ARTIFICIAL INTELLIGENCE IN DENTAL CARIES DIAGNOSIS: A NARRATIVE REVIEW

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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

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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

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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

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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.

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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

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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

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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,

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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

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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.

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