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Artificial Intelligence in Periodontal Diagnosis: Current Evidence and Future Clinical Integration (Narrative Review)

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Abstract

Periodontitis, a chronic inflammation that affects the supporting structures of teeth, can result in the loss of alveolar bone and potentially tooth loss. Traditional diagnostic techniques of periodontitis rely heavily on clinical and radiographic evaluations, which are subject to human variability and limited predictive capability. Advances in artificial intelligence (AI) have given rise to potential tools for achieving better and more efficient diagnosis in periodontology. The diagnosis of periodontitis is addressed in this mini-review using machine learning (ML) and deep learning algorithms implemented in artificial intelligence. Convolutional neural networks (CNNs) are the primary focus of research due to their demonstrated capacity for achieving high diagnostic sensitivity and specificity in detecting periodontal bone loss from radiographic inputs. Moreover, this review notes that "Hybrid models" are being developed to better reflect the predictive power of these models by integrating clinical risk factors such as smoking and diabetes with radiographic features. The integration of the 2017 classification system with AI models enables automated staging and diagnosis to meet modern clinical criteria resulting in accurate diagnostic outputs. Recent work shows that AI, particularly convolutional neural networks, can accurately interpret radiographs for periodontal diagnosis. However, challenges remain, including inconsistent datasets, absence of unified standards, and limited use in daily clinical practice. Future progress will depend on developing large multi-center databases, more transparent AI models, and systems linked to electronic dental records for real-time decision support.

Keywords: Artificial Intelligence, periodontal disease, machine learning, deep learning, diagnosis.

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1. Introduction

Periodontitis, a prevalent chronic inflammatory disease, leads to progressive destruction of the supporting structures of the teeth, including the alveolar bone. While periodontal disease includes various conditions affecting the periodontium, periodontitis is defined as the most severe manifestation of detrimental effects. Progressive bone loss and tooth movement are caused by periodontitis, the most severe form. The study of periodontal inflammation is of critical importance because chronic periodontal infection has been linked to systemic conditions such as type 2 diabetes mellitus and cardiovascular disease; epidemiological and mechanistic research shows that periodontitis worsens glycemic control and promotes atherogenic inflammation. [1]. Global Burden of Disease Study estimates that between 10-15% of the world's adult population is affected by periodontitis [2]. In Egypt, periodontitis is notably widespread, with cross-sectional research indicating that 50% to 70% of adults are affected. Factors such as economic challenges, limited availability of dental services, and insufficient public awareness about oral hygiene contribute to this high prevalence. These findings underscore the urgent need for improved prevention strategies and diagnostic tools in Egypt [3].

2. Diagnosis of Periodontal Diseases

The nature of periodontitis being a multifactorial disease necessitates the importance of establishing accurate and early diagnosis. Conventionally, diagnosis relied on clinical parameters and radiographic parameters such as probing depth (PD), clinical attachment loss (CAL), bleeding on probing (BOP), and gingival indices such as Gingival Index (GI), Bleeding on Probing (POB) and Plaque Index (PI), and radiographic bone loss which are highly dependent on clinician expertise and consistency [4]. The classification of periodontitis has long been essential for guiding diagnosis, treatment, and prognosis in clinical practice. Early systems, such as the 1977 American Academy of Periodontology (AAP) classification, aimed to standardize case definitions by categorizing diseases based on clinical features and etiology. However, these early frameworks struggled to distinguish between disease severities and forms, especially in younger patients, and did not fully address complexity of periodontal conditions [4]. Subsequent revisions, including the 1989 World Workshop and 1999 AAP classification, introduced distinctions between destructive and non-destructive diseases and recognized the influence of systemic factors.

The 1999 system was a significant step forward, offering more detailed categories and acknowledging the role of systemic diseases and genetic predispositions. Despite these improvements, limitations remained, such as insufficient integration of new scientific insights into host-microbiome interactions and a lack of individualized treatment planning [5-6]. The most recent classification, developed jointly by the AAP and the European Federation of Periodontology, introduced a staging and grading approach, incorporated risk factors like smoking and diabetes in periodontitis, and emphasized personalized patient management. The new system reflects advances in understanding the interplay between host factors and the microbiome. While this classification offers a more comprehensive and tailored framework, the ongoing evolution of periodontal science highlights the need for innovative diagnostic tools to further enhance accuracy and patient outcomes [7]. The staging of periodontitis focuses on describing the severity, extent, and complexity of the disease using the CAL and radiographic bone loss (RBL).

It categorizes the disease into a stage of four stages, stage I being the initial status and stage IV as advanced. The criteria of staging depend on three main parameters. The severity of periodontitis is assessed through CAL, radiographic bone loss (RBL), and the number of teeth lost due to periodontitis. In stage I and II no teeth are lost due to periodontitis but in stage III 4 or more teeth have been lost and 5 or more in stage IV. The complexity of management is influenced by factors such as deep probing depths, furcation involvement, ridge defects, and mobility. Additionally, the extent and distribution of the disease classify it as localized (affecting ≤30% of teeth), generalized (affecting >30% of teeth), or following a molar/incisor pattern [7]**.** Grading, conversely, aims to estimate the rate of progression and the potential risk of future progression, categorizing patients into Grade A (slow rate), Grade B (moderate rate), or Grade C (rapid rate), often informed by a patient's risk factors such as smoking or uncontrolled systemic diseases like diabetes. The grading of the periodontitis is based on both direct and indirect evidence.

Direct evidence includes longitudinal data of CAL or RBL, which can be assessed when previous clinical examination records are available. In cases where such data is not available, indirect evidence is used, which considers bone loss relative to the patient's age and case phenotype [8]. Although notable advancements have been made in the understanding and classification of periodontal diseases, current diagnostic approaches still rely heavily on clinicians' subjective assessments and traditional radiographic evaluations. The manual evaluation of multiple variables, such as radiographic bone loss, clinical attachment levels, and systemic modifiers, introduces the potential for human error and inconsistency across clinicians. Therefore, the integration of automated tools and AI based decision support systems can significantly simplify this process. These technologies can standardize assessments, enhance diagnostic accuracy, and reduce the time required for clinical documentation, thereby making the classification framework more practical for everyday periodontal diagnosis and management [9].

3. Artificial Intelligence

Artificial intelligence (AI) is a branch of computer science that is defined as the ability for a computer to mimic the cognitive abilities of a human being. AI corresponds to a large array of techniques. It can perform tasks that include learning from experience, decision making, visual perception, voice recognition, pattern recognition, understanding different languages, and problem solving. In 1995, John McCarthy, an American computer scientist and one of the pioneers of AI, was the first to define the term artificial intelligence as follows: The goal of AI is to develop machines that behave as though they were intelligent [10]. Artificial intelligence (AI) is categorized based on its capabilities into three levels: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI). ANI, or Weak AI, is the most common form, designed for specific, goal-oriented tasks within limited constraints, such as diagnostic analytics in medical applications, yet it lacks human flexibility and cannot generalize beyond its programming.

AGI, also called Strong AI, is currently theoretical but aims to achieve human level cognitive abilities to understand, learn, and apply knowledge across a wide range of tasks, featuring flexible thinking and reasoning. ASI is a hypothetical future stage where AI would surpass human intelligence entirely, exhibiting superior cognitive abilities across all domains [11-12]. Machine learning (ML), a subset of AI, allows computers to learn from data using algorithms, creating models classified by approach: supervised learning uses labeled data for classification (e.g., annotated radiographs for periodontitis detection), while unsupervised learning finds patterns in unlabeled data. Deep learning (DL) is a more advanced technique employing multi-layered neural networks, with Convolutional Neural Networks (CNNs) being highly effective in medical imaging like analyzing radiographs, by extracting hierarchical features to detect intricate patterns [11-13].

4. Artificial Intelligence and Medical Practice

In different medical fields, AI algorithms significantly aid doctors and radiologists by analyzing medical images to detect subtle abnormalities that are difficult to identify with the naked eye, leading to rapid and accurate diagnoses and report generation. A general workflow for the application of AI in medical practice is summarized in figure (1). Playing a key role in precision medicine, AI enhances oncology by identifying unnoticed radiological patterns, predicting disease progression, and optimizing treatment regimens. For example, deep learning models can detect mammographic lesions with accuracy rivaling certified screening radiologists and accurately classify prostate cancer based on digitized tissue slides (Gleason score). AI is also effective in diagnosing and classifying skin cancer from clinical pictures and holds promise for developing more clinically successful anticancer therapies [13-15]. AI applications are rapidly advancing in various medical specialties, including cardiology, where machine learning models use cardiovascular imaging and clinical data to predict major adverse clinical cardiac events (MACE). In neurology, diverse algorithms have been successfully developed to diagnose significant disorders such as brain tumors, epilepsy, dementia, Alzheimer's Disease, and Parkinson's Disease using imaging techniques like MRI for accurate understanding of brain function. Importantly, AI can also diagnose Alzheimer's Disease with high accuracy solely from retinal photographs, demonstrating its diagnostic reach beyond traditional x-rays and specialized brain scans [16-18].

5. Artificial Intelligence and Dentistry

In dentistry, AI has emerged as a transformative tool, with applications ranging from caries detection and orthodontic analysis to oral cancer screening and dental radiograph interpretation. The most significant AI subfields in dental diagnostics are ML and deep learning. ML is a type of artificial intelligence that can predict or make decisions without user input, using data as source code [14-19]. AI and machine learning models, particularly deep learning algorithms like convolutional neural networks (CNNs), have been employed to automate identification of dental caries, apical lesions, and periodontal bone loss in radiographic images. These technologies enhance diagnostic consistency, reduce examiner variability, and support clinicians in differentiating b/w disease stages a type. However, clinical impact of these models depends on their alignment with current classification frameworks and quality of annotated datasets used for training [20-21]. The application extends to prosthodontics, implantology, and endodontics, where AI systems streamline digital workflows, optimize CAD/CAM fabrication, predict implant longevity by evaluating bone morphology, and improve detection of subtle root pathologies. Furthermore, AI has notably improved treatment planning in orthodontics via automated cephalometric analysis and aligner customization, while achieving diagnostic accuracy comparable to expert clinicians in oral and maxillofacial radiology for identifying cysts, tumors, and fractures. Even in pediatric dentistry, AI supports early-stage caries recognition and growth prediction, collectively marking a paradigm shift toward enhanced diagnostic precision and therapeutic efficacy across the field [22-25].

6. Artificial Intelligence and Periodontal diagnosis

Recent advancements in machine learning have facilitated the automated assessment of intraoral photographs to detect variations in key periodontal parameters, such as inflamed gingival margins, plaque accumulation, and gingival recession. These models support the creation of standardized digital periodontal charts by objectively quantifying visual parameters, thereby minimizing examiner subjectivity. Such AI systems provide a valuable adjunct to clinical examination and are pivotal for future development of real-time chairside periodontal evaluation tools.

6.1. Artificial Intelligence and Clinical parameters for Periodontal diagnosis

Artificial intelligence assisted systems have recently been introduced to automate the recording of periodontal parameters and minimize operators' variability. Convolutional neural networks (CNNs) are capable of identifying teeth and delineating gingival contours in intraoral photographs by employing image segmentation and feature extraction algorithms that differentiate gingival margins, plaque accumulation, and sulcular depths based on pixel intensity and color gradients. These networks are trained on large annotated image datasets, where ground-truth labels for gingival landmarks and probing sites are provided by expert periodontists, enabling the model to learn spatial and morphological relationships associated with periodontal tissue boundaries. The processed outputs are then translated into quantitative estimates of probing depth and bleeding indices through geometric calibration of segmented regions. Such automated analysis supports standardized digital charting & facilitates longitudinal monitoring of periodontal health with improved objectivity and reproducibility [26].

Machine learning approaches have also been applied to the assessment of visible periodontal parameters, including plaque accumulation, calculus deposits, and gingival inflammation. Using clinical intraoral images, Ramirez-Pedraza et al, (2025) tested a YOLOv11m that demonstrated the highest detection performance (mAP@50 = 0.713), with older plaque being more readily identified than newly formed deposits. Notably, over half of the examined population exhibited severe plaque accumulation based on the O'Leary index, emphasizing the potential clinical value of AI-assisted plaque assessment in periodontal evaluation [27]. In a complementary investigation, a convolutional neural network (CNN) trained on intraoral scanning images. The model achieved an accuracy of 89.6% and an Area Under the Curve (AUC) of 0.93 in identifying gingival inflammation, confirming that deep learning applied to 3D surface data can reliably differentiate inflamed from healthy gingival tissues. These models provide objective quantification of soft-tissue alterations and could serve as standardized digital tools for chairside evaluation and patient motivation in oral hygiene reinforcement [28-29].

6.2. Artificial Intelligence and Radiographic Interpretation for Periodontal diagnosis

Convolutional neural networks developed, have demonstrated substantial capability in detecting and measuring alveolar bone loss from two-dimensional radiographs. Krois et al. (2019) trained a CNN that achieved an AUC of 0.92 in distinguishing the presence and extent of bone loss, with performance comparable to experienced examiners. Similarly, Chang et al. (2020) proposed a hybrid model integrating clinical and radiographic parameters that achieved a diagnostic accuracy of 93.2%. These findings confirm that CNN-based systems can enhance diagnostic consistency and contribute to the automated staging of periodontitis [30-31]. The incorporation of three-dimensional imaging into periodontal diagnostics has been further advanced through AI-based analysis of cone-beam computed tomography (CBCT) data. Cui et al. (2022) demonstrated that deep learning systems could accurately detect and quantify alveolar bone resorption patterns in CBCT images [32]. Tan et al. (2025) developed *PerioAI*, a CNN-based system that integrates intraoral scans and CBCT with an overall accuracy of 94.4% and sensitivity of 100%, exceeded performance of expert periodontists (≈91.1% accuracy). These approaches provide volumetric insight into periodontal architecture and may facilitate the transition toward fully automated, quantitative assessment of periodontal breakdown [33].

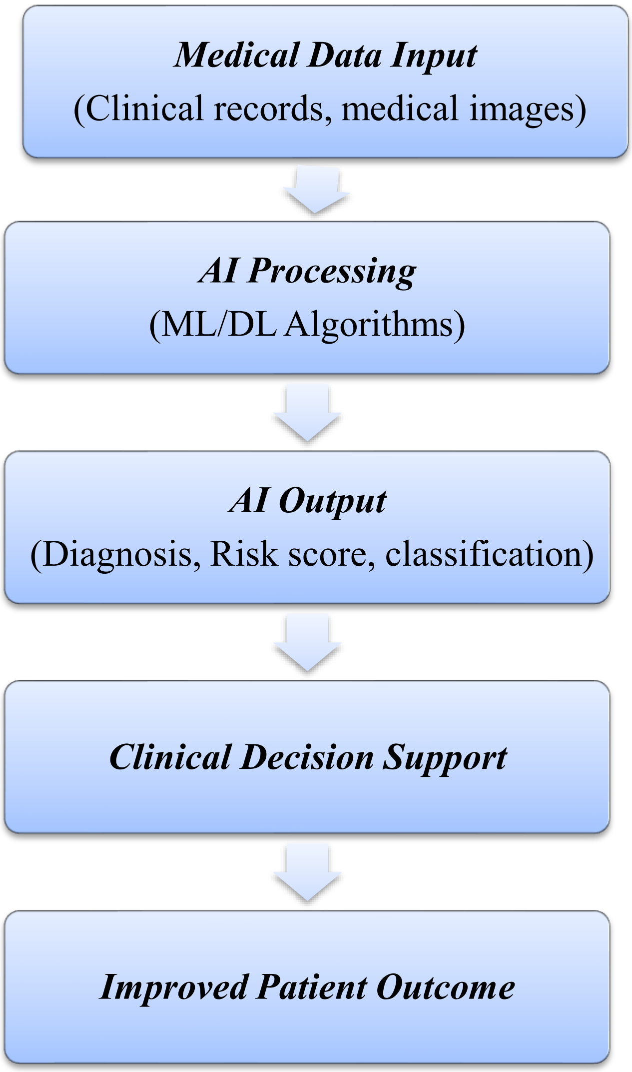

Figure (1): Flow Chart of Artificial Intelligence Application in Medical Practice. This diagram illustrates the general process of integrating AI into a medical workflow, from the acquisition of diverse data (e.g., medical imaging, clinical records) to its analysis by machine learning (ML) or deep learning (DL) models. The resulting objective output supports clinicians in making accurate decisions, ultimately leading to enhanced patient care and outcomes.

Table (1): Summary of AI applications in Dentistry and Periodontology including diagnostic, risk assessment, and treatment planning models.

Author (year)	Study design	Population / dataset	Imaging / data type	AI model / technique	Comparative reference	Performance measures	Key findings / conclusions
Basu et al. (2020)	Review	—	Medical and dental applications overview	General AI and ML frameworks	—	—	Summarized the transformative potential of AI in medical sciences, highlighting diagnostic accuracy and data-driven decision making.
Krois et al. (2019)	Experimental	Dental radiographs	2D periapical & bitewing radiographs	CNN	Expert examiners	AUC = 0.92	AI accurately detected periodontal bone loss with comparable performance to clinicians.
Chang et al. (2020)	Experimental	Panoramic radiographs	2D radiographs	Hybrid CNN model integrating clinical data	Expert examiners	Accuracy = 93.2%	Hybrid model enhanced staging of periodontitis by combining radiographic and clinical parameters.
Cui et al. (2022)	Cross-sectional	4,215 CBCT scans	3D CBCT	Deep learning segmentation network	Manual annotation	Dice coefficient > 0.9	Fully automated segmentation of teeth and alveolar bone; accurately quantified bone resorption patterns.
Tan et al. (2025)	Developmental	Multi-source dataset	CBCT + intraoral scans	CNN-based PerioAI	Expert periodontists	Accuracy = 94.4%; Sensitivity = 100%	Integrated 3D and surface data for automated periodontal diagnosis surpassing expert performance.
Lee et al. (2025)	Cross-sectional	Panoramic radiographs	2D panoramic	CNN	Manual staging	Accuracy = 89.7%; Sensitivity = 87.4%; Specificity = 90.5%	Automated classification of periodontitis severity using CNN models.
Do et al. (2025)	Validation study	Panoramic radiographs	2D panoramic	Deep learning CNN	Expert-labeled staging and grading	Accuracy > 95%	Automated staging and grading system matched 2017 classification criteria and expert performance.
Ertaş et al. (2022)	Retrospective	Panoramic + clinical data	2D panoramic & clinical features	Hybrid ResNet50 + SVM, RF, KNN	Expert diagnosis	Accuracy up to 98.6%	Integrated radiographic and systemic factors for AI-based grading and risk prediction; demonstrated superior accuracy.
Santana (2024)	Developmental	Clinical + demographic data	Clinical and radiographic features	Supervised ML (feature selection + classification)	Manual risk scoring	—	AI framework categorized patients into risk strata using systemic, demographic, and clinical predictors.
Sarakbi et al. (2025)	Retrospective cohort	3347 teeth (10-year follow-up)	Clinical + radiographic data	Random Forest	Clinical records (expert prognosis)	AUC = 0.91; Accuracy = 0.93	Predicted tooth-loss risk and optimized treatment planning by integrating clinical and radiographic indicators.
Mao et al. (2025)	Systematic review	Intraoral photographs	2D photographs	CNN	Manual periodontal charting	—	Validated CNNs for gingival margin detection, plaque and inflammation quantification.
Ramírez-Pedraza et al. (2025)	Experimental	Intraoral photographs	2D clinical images	YOLOv11m	Manual O'Leary index scoring	mAP@50 = 0.713	AI achieved reliable plaque detection, identifying severe accumulation in >50% of subjects.
Li et al. (2025)	Cross-sectional	3D intraoral scans	Surface imaging	CNN	Expert-labeled inflammation maps	Accuracy = 89.6%; AUC = 0.93	Detected gingival inflammation accurately using 3D surface data.
Moharrami et al. (2025)	Systematic review	Oral photographs	2D clinical images	Deep learning review	—	—	Reported strong potential of CNNs for plaque and gingivitis detection across multiple datasets.

6.3. Artificial Intelligence Models for Staging, Grading, and Risk Prediction

Lee et al. developed a CNN-based approach for classifying periodontitis severity using panoramic radiographs, achieving an accuracy of 89.7%, with 87.4% sensitivity and 90.5% specificity [22]. Similarly, Do et al. (2025) designed a deep learning system that directly estimated bone loss percentages from radiographic images and successfully assigned both stage and grade according to the 2017 classification, achieving an overall accuracy exceeding 95%, thereby establishing the potential of AI to perform automated staging and grading in clinical settings [34]. For grading and risk assessment, hybrid models were developed to integrate radiographic features with systemic and modifying factors to detect the periodontitis progression rate. In 2022, Ertaş et al. proposed a hybrid framework combining the ResNet50 architecture with a support vector machine (SVM) using clinical and panoramic radiographic data, which yielded an accuracy of 97.2%, while the random forest and k-nearest neighbor models achieved up to 98.6%.

Collectively, these studies underscore the capability of AI-driven systems to enhance diagnostic consistency and accuracy, supporting their integration into routine periodontal diagnostic workflows [35]. Santana explored the application of machine-learning algorithms for individualized periodontitis progression risk scoring. In the study, "Artificial Intelligence (AI) and Periodontal Risk Assessment," the model integrated a comprehensive dataset, including demographics, systemic health status, clinical periodontal parameters, and radiographic bone loss. Through a feature-selection process, the system identified the most predictive variables and subsequently utilized supervised learning to classify patients into distinct risk strata. This automated approach provides an objective and the reproducible alternative to conventional manual scoring tools, ultimately enabling clinicians to implement more precisely tailored monitoring and preventive strategies [36]. In a separate retrospective longitudinal cohort study, an AI model was developed to assist in periodontal therapy decision-making.

Analyzing data from 3,347 teeth tracked over a minimum of ten years, the study incorporated crucial variables such as probing pocket depths, bone-loss measurements, furcation involvement, and systemic disease status. Analyzing teeth over ten years, the model incorporated key variables like probing depths, bone loss, and systemic status, ultimately selecting a Random Forest algorithm (AUC = 0.91, Accuracy = 0.93). This established algorithm can thus support the treatment-planning workflow by accurately predicting tooth-loss risk and guiding the selection of optimal intervention strategies, thereby integrating AI into the clinical management of periodontitis [37]. A summary of representative studies implementing artificial intelligence in dental and periodontal diagnostics is presented in table 1, highlighting key methodologies, datasets, AI models, and performance metrics.

7. Future Directions

To fully integrate AI into periodontal diagnostics, future work should focus on the development of large-scale, publicly available annotated datasets. Furthermore, prospective clinical trials are necessary for validating AI model performance in diverse settings. Explainable AI (XAI) to provide interpretable results to clinicians and operational integration with electronic dental records and clinical workflows. Finally, ethical frameworks must be established to address data sharing, patient consent, and accountability.

8. Conclusions

Artificial intelligence has demonstrated strong potential in aiding the diagnosis of periodontitis, offering high accuracy and consistency. Despite its promise, practical deployment in clinical settings requires further validation, ethical oversight, and user-centered design. With collaborative efforts between researchers, clinicians, and developers, AI can become an integral component of modern periodontics. Artificial intelligence, particularly deep learning and convolutional neural networks, has demonstrated promising performance in detecting periodontal bone loss, quantifying clinical parameters, and even automating staging and grading according to the 2017 classification. Reported accuracies frequently exceed those of experienced clinicians, indicating that AI can significantly enhance diagnostic consistency and reduce subjectivity. However, despite this progress, most models remain at an experimental or pilot stage rather than full clinical deployment. The current evidence also reveals several critical gaps. Many studies rely on small, single-center datasets with limited demographic diversity, which restricts the generalizability of trained models. In addition, labeling of radiographs or photographs is often performed by a small group of specialists, introducing potential annotation bias.

A lack of external validation, prospective clinical trials, and standardized imaging protocols further limits translation into real-world dental practice. Although CNNs show strong technical performance, they are not yet suitable for routine clinical use or regulatory approval. FDA acceptance requires reproducible results, transparent model behavior, and proven safety across diverse populations. Current models still function as “black boxes,” lack seamless integration into clinical workflows, and face unresolved issues in data privacy, ethics, and accountability. In conclusion, artificial intelligence has the potential to become a powerful diagnostic tool in periodontology, but further work is needed. The future of clinically accepted AI will depend on large, standardized datasets, explainable model architectures, external validation, and regulatory pathways that ensure reliability and patient safety. With collaboration between clinicians, data scientists, and industry stakeholders, AI-assisted periodontal diagnosis may move from experimental research to routine dental care in the near future.

Declaration of Conflicting Interest

The authors declare that there is no conflict of interest.

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