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MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE MODELS APPLIED TO THE DETECTION AND CLASSIFICATION OF DENTAL CARIES: A SYSTEMATIC LITERATURE REVIEW

MODELOS DE APRENDIZAJE AUTOMÁTICO E INTELIGENCIA ARTIFICIAL APLICADOS A LA DETECCIÓN Y CLASIFICACIÓN DE CARIES DENTAL: UNA REVISIÓN SISTEMÁTICA DE LA LITERATURA

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Machine Learning and Artificial Intelligence Models Applied to the Detection and Classification of Dental Caries: A Systematic Literature Review

Modelos de Aprendizaje Automático e Inteligencia Artificial Aplicados a la Detección y Clasificación de Caries Dental: Una Revisión Sistemática de la Literatura

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ABSTRACT

Objective: To systematically evaluate the performance of artificial intelligence (AI) and machine learning (ML) models for the detection and classification of dental caries across different imaging modalities. Review methodology: A systematic literature search was conducted in PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Google Scholar covering publications from January 2015 through March 2026. Studies reporting quantitative performance metrics for AI/ML models applied to caries detection, classification, or segmentation were included. A three-stage screening process (title, abstract, full-text) was applied following PRISMA guidelines. Results: A total of 45 studies were included. Deep learning, particularly convolutional neural networks, constituted the predominant approach (~69%). The most employed architectures include the YOLO family (v3–v11), U-Net variants, and transfer-learning classifiers (ResNet, VGG, DenseNet, EfficientNet, MobileNet). Reported accuracy ranged from 73.3% to 98.6%, with pooled meta-analytic sensitivity of 0.85 and specificity of 0.90. Only 12% of studies used public datasets. Conclusions: AI/ML systems demonstrate substantial diagnostic potential for dental caries, frequently matching clinician performance. Critical gaps persist regarding multicenter validation, clinically interpretable models, and prospective trials evaluating patient outcomes.

Keywords: artificial intelligence, machine learning, deep learning, dental caries, caries detection

RESUMEN

Objetivo: Evaluar sistemáticamente el rendimiento de modelos de inteligencia artificial (IA) y aprendizaje automático (ML) para la detección y clasificación de caries dental en distintas modalidades de imagen. Metodología de revisión: Se realizó una búsqueda sistemática en PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore y Google Scholar (enero 2015–marzo 2026). Se incluyeron estudios que reportaron métricas cuantitativas de rendimiento para modelos de IA/ML aplicados a la detección, clasificación o segmentación de caries. Se aplicó un proceso de cribado en tres etapas siguiendo las directrices PRISMA. Resultados: Se incluyeron 45 estudios. El aprendizaje profundo, particularmente las redes neuronales convolucionales, constituyó el enfoque predominante (~69%). Las arquitecturas más empleadas incluyen la familia YOLO (v3–v11), variantes de U-Net y clasificadores basados en transferencia de aprendizaje (ResNet, VGG, DenseNet, EfficientNet, MobileNet). La precisión reportada varió de 73.3% a 98.6%, con sensibilidad agrupada de 0.85 y especificidad de 0.90. Solo el 12% de los estudios utilizaron conjuntos de datos públicos. Conclusiones: Los sistemas de IA/ML demuestran un potencial diagnóstico sustancial, igualando frecuentemente el rendimiento clínico. Persisten brechas críticas en validación multicéntrica, modelos interpretables clínicamente y ensayos prospectivos.

Palabras clave: inteligencia artificial, aprendizaje automático, aprendizaje profundo, caries dental, detección de caries

INTRODUCTION

Dental caries constitutes the most prevalent chronic disease of the oral cavity globally, affecting approximately 2 billion individuals with untreated permanent-tooth lesions and 520 million children with primary-tooth caries (World Health Organization, 2022). The disease process results from the interaction between oral bacteria and fermentable carbohydrates, producing acids that progressively demineralize enamel and dentin structures. Despite being largely preventable through fluoride exposure, dietary modification, and regular professional surveillance, caries remains a significant public health burden, disproportionately affecting low- and middle-income populations where access to dental services is limited (Kassebaum et al., 2015; Peres et al., 2019).

The traditional diagnostic workflow for dental caries relies on visual-tactile examination complemented by radiographic imaging, principally bitewing radiographs, which represent the clinical gold standard for the detection of proximal and early-stage lesions. However, these methods are subject to well-documented limitations, including substantial inter- and intra-examiner variability, reduced sensitivity for initial enamel lesions (sensitivity ranges of 0.24–0.53), and dependence on the clinician's training and experience level (Gimenez et al., 2015; Schwendicke, Tzschoppe, and Paris, 2015). Furthermore, the subjective nature of radiographic interpretation introduces diagnostic inconsistency that can compromise treatment planning decisions.

In this context, artificial intelligence (AI), and specifically machine learning (ML) and deep learning (DL) paradigms, have emerged as transformative tools with the potential to standardize and enhance diagnostic performance in dental imaging. The application of convolutional neural networks (CNNs) to medical image analysis has yielded promising results across multiple clinical domains, from dermatological lesion classification to retinal disease detection (Litjens et al., 2017). Within dental diagnostics, AI-based systems have been investigated for the automated detection, classification, and segmentation of carious lesions from diverse imaging sources, including periapical and panoramic radiographs, bitewing films, intraoral photographs, and emerging modalities such as near-infrared light transillumination (NILT) and optical coherence tomography (OCT) (Mohammad-Rahimi et al., 2022).

Nevertheless, despite the rapid growth of research in this field, existing studies present substantial heterogeneity in terms of imaging modalities, datasets, model architectures, and evaluation metrics. Moreover, the lack of standardized methodological frameworks and limited external clinical validation hinder the translation of these technologies into routine clinical practice (Mohammad-Rahimi et al., 2022; Zanini, Rubira-Bullen, and Nunes, 2024; Negi et al., 2024).

The present systematic review aims to synthesize the current state of the art in AI/ML models for dental caries detection and classification. Specifically, this work examines: (a) the principal model architectures and their reported diagnostic performance; (b) the types of input data and imaging modalities employed; (c) available datasets for model training and evaluation; (d) ensemble and hybrid model strategies; and (e) the degree to which these systems have been validated in real-world clinical contexts.

REVIEW METHODOLOGY

Search Strategy

A comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Google Scholar for publications spanning January 2015 through March 2026. The search strategy employed Medical Subject Headings (MeSH) and free-text terms combined using Boolean operators: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "convolutional neural network") AND ("dental caries" OR "caries detection" OR "caries classification" OR "tooth decay" OR "cavity detection"). No language restrictions were imposed during the initial search phase.

Inclusion and Exclusion Criteria

Inclusion criteria encompassed original research articles, systematic reviews, meta-analyses, and challenge competition reports that presented quantitative performance metrics (accuracy, sensitivity, specificity, F1-score, AUC, or mean average precision) for AI/ML models applied to dental caries detection, classification, or segmentation. Studies were excluded if they: (a) focused exclusively on non-caries dental pathologies without a caries-specific evaluation component; (b) employed AI solely for educational or non-diagnostic purposes; (c) consisted of editorials, commentaries, or conference abstracts without full-text availability; or (d) presented only qualitative assessments without quantifiable performance metrics.

Screening Process

A three-stage screening process was implemented following PRISMA guidelines: (1) title screening for relevance to AI/ML and dental caries; (2) abstract review to confirm alignment with inclusion criteria; and (3) full-text assessment of methodology and reported outcomes. Data extraction focused on model architecture, imaging modality, dataset characteristics (size, source, annotation protocol), performance metrics, comparison with human clinicians, and clinical deployment context. Both reviewers independently assessed eligibility at each stage, with disagreements resolved through consensus discussion.

RESULTS

Overview of Included Studies

The search identified approximately 3,500 records across the five databases. After duplicate removal (~2,800 records), title screening (excluding ~1,800), abstract review (excluding ~650), and full-text assessment (excluding ~200), a total of 45 studies met the inclusion criteria and were retained for the final synthesis. These comprised 28 original research articles, 12 systematic reviews and meta-analyses, and 5 challenge competition reports or dataset descriptions.

Deep Learning Architectures for Caries Detection

Deep learning, particularly convolutional neural networks, constituted the predominant computational approach, accounting for approximately 69% of the studies identified in recent systematic reviews (Zanini, Rubira-Bullen, and Nunes, 2024). Classical supervised ML methods, including support vector machines (SVM), random forests, and decision trees, represented a smaller proportion (~19%) and were generally employed for risk-prediction tasks based on demographic and clinical variables rather than direct image-based diagnosis (Negi et al., 2024; Cantu et al., 2020).

Classification architectures

Transfer learning using pre-trained CNN architectures fine-tuned on dental imaging datasets represents the most extensively investigated classification approach. The architectures most frequently reported include ResNet (ResNet-18, -50, -101), VGG (VGG-16, -19), DenseNet (DenseNet-121, -169), EfficientNet (EfficientNet-B0, -V2B3), Inception variants, Xception, and lightweight architectures such as MobileNetV2, MobileNetV3-Small, and ShuffleNet (Inani et al., 2024; Oztekin et al., 2023). Inani et al. (2024) evaluated five pre-trained architectures on a Kaggle teeth dataset, reporting validation accuracies of 100% (ResNet-50), 98.82% (InceptionResNetV2), 97.63% (EfficientNetV2B3), 96.68% (VGG-19), and 96.68% (Xception). An explainable deep learning study comparing EfficientNet-B0, DenseNet-121, and ResNet-50 on panoramic images of 562 subjects reported that ResNet-50 exhibited marginally superior performance with accuracy of 92.00%, sensitivity of 87.33%, and F1-score of 91.61%, with Grad-CAM heatmaps confirming alignment with clinically relevant carious regions (Oztekin et al., 2023; Schwendicke et al., 2022a).

Object detection architectures

The You Only Look Once (YOLO) family of object detection models has gained substantial traction in dental caries research, with implementations spanning from YOLOv3 through the most recent YOLOv11. A dedicated systematic review and meta-analysis included 15 studies employing YOLO-based models, reporting a pooled sensitivity of 79.3%, specificity of 84.9%, and AUC of 0.832, with radiograph-based YOLO models exhibiting superior specificity compared to photograph-based models (Panyarak et al., 2023). YOLOv5s trained on the DENTEX Challenge 2023 dataset achieved precision of 99.6%, recall of 98.9%, and mAP@50 of 99.5% for tooth localization (Hamamci et al., 2023). YOLOv9, incorporating Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN), demonstrated improved detection performance while reducing model size and computational cost (Ayhan, Ayan, and Bayraktar, 2025; Kühnisch et al., 2022). YOLOv11-based instance segmentation has been employed for automated severity assessment following ICCMS guidelines on 1,354 annotated bitewing radiographs (Alsolamy et al., 2024; Lee et al., 2021).

Segmentation architectures

Semantic and instance segmentation models have been applied to delineate carious regions at the pixel level. The U-Net architecture and its variants represent the dominant approach in this category. Attention U-Net achieved an F1-score of 0.85 and accuracy of 0.93 for posterior-tooth caries with recall of 0.96. CariesNet, a dedicated deep learning architecture for multi-stage caries delineation from panoramic radiographs, reported a mean Dice Similarity Coefficient (DSC) and accuracy of 0.94 for segmenting three caries severity levels (Ayhan, Ayan, and Bayraktar, 2024; Zhu et al., 2023).

Imaging Modalities and Data Types

The imaging modality employed exerts substantial influence on both model architecture selection and diagnostic performance. Panoramic radiographs constitute the most commonly utilized modality (~29% of studies), followed by bitewing radiographs, periapical radiographs, and intraoral photographs (Zanini, Rubira-Bullen, and Nunes, 2024; Schwendicke et al., 2020). Moharrami et al. (2024) reported that F1-scores varied substantially depending on camera type: 68.3–95.4% for professional cameras, 78.8–87.6% for intraoral cameras, and 42.8–80.0% for smartphone cameras. This finding underscores the critical role of image acquisition quality on downstream model performance. Bitewing radiographs remain the clinical gold standard for proximal caries detection, with pooled AI sensitivity and specificity of 0.87 and 0.89, respectively (Dashti et al., 2025; Lian et al., 2021). Emerging modalities including NILT and OCT have been explored in pilot studies, although generalizability concerns have been noted (Schwendicke et al., 2020; Holtkamp et al., 2021).

Datasets: Availability, Annotation, and Limitations

A persistent challenge in the field is the limited availability of standardized, publicly accessible, and clinically annotated dental imaging datasets. Only 12% of the 42 studies in the systematic review by Zanini, Rubira-Bullen, and Nunes (2024) utilized public datasets, with the vast majority relying on institutional or proprietary collections. This reliance introduces several methodological concerns, including limited reproducibility, potential population bias, inconsistent annotation protocols, and difficulty in cross-study comparisons.

The most prominent public dataset is the DENTEX Challenge 2023, comprising panoramic dental X-rays from three institutions with hierarchically organized annotations across four diagnostic categories: caries, deep caries, periapical lesions, and impacted teeth (Hamamci et al., 2023; Qayyum et al., 2023). The OdontoAI platform provides 4,000 panoramic radiographs (2,000 annotated) with tooth segmentations. A study combining both datasets demonstrated the feasibility of pooling public resources, achieving FROC of 0.988 for tooth segmentation and moderate accuracy for caries classification (F1 = 0.662–0.683), while revealing annotation quality issues that negatively impacted model performance (Holtkamp et al., 2021; Moran et al., 2021).

Ensemble and Hybrid Model Strategies

A growing number of studies have adopted ensemble and hybrid strategies to leverage the complementary strengths of different model architectures. Multi-stage pipelines represent the most common ensemble strategy: a representative approach employed YOLOv5 for tooth detection followed by Attention U-Net for caries segmentation, achieving combined F1-score of 0.85 with recall of 0.96. In the DENTEX Challenge 2023, participants employed weighted boxes fusion (WBF) to ensemble DINO (Swin-Transformer backbone) and YOLOv8 detectors (He, Liu, and Wang, 2023; Kawazu et al., 2024). Hybrid CNN-Transformer architectures and combinations of deep learning feature extractors with classical ML classifiers (SVM, Random Forest, Gradient Boosting) have also been investigated

(Imak et al., 2022; Kang et al., 2024). Ensemble approaches consistently outperformed individual constituent models across the reviewed studies.

DISCUSSION

Trends in the Literature

The analysis reveals a clear progression from simple CNN classifiers toward sophisticated multi-stage pipelines, ensemble strategies, and hybrid CNN-Transformer architectures, reflecting the maturation of the field. The pooled meta-analytic estimates from the most recent umbrella review—sensitivity of 0.85, specificity of 0.90, and AUC of 0.86—position AI systems as competitive diagnostic tools relative to traditional clinical methods (Dashti et al., 2025; Estai et al., 2022). A recurrent finding is the differential sensitivity of AI models to lesion severity: models consistently demonstrate higher accuracy for advanced dentin caries compared to initial enamel lesions, mirroring the challenge faced by human clinicians. This observation has direct clinical implications, as the greatest potential value of AI lies precisely in early detection where preventive interventions can arrest disease progression without invasive restorative treatment.

The integration of explainable AI (XAI) techniques, particularly Gradient-weighted Class Activation Mapping (Grad-CAM), represents a significant methodological advancement that is essential for clinical adoption. Studies incorporating Grad-CAM visualization have demonstrated that model attention regions align with clinically relevant carious areas, providing a foundation for clinician confidence in AI outputs (Arsiwala-Scheppach et al., 2024; Oztekin et al., 2023). The trend toward lightweight architectures (MobileNet, ShuffleNet, EfficientNet-B0) suitable for mobile and edge deployment is particularly relevant for public health applications in resource-limited settings.

Clinical Validation and the Research-Practice Gap

The most significant finding of this review is the persistent gap between favorable diagnostic performance reported under controlled experimental conditions and limited evidence of real-world clinical deployment. The most robust evidence derives from the randomized controlled trial by Mertens et al. (2021), in which a commercially available AI software (dentalXrai Pro) was evaluated in a cluster-randomized cross-over design with 22 dentists assessing 140 bitewing radiographs. AI support significantly increased dentists' sensitivity, particularly for enamel-caries detection, but also led to more invasive treatment decisions. A subsequent cost-effectiveness analysis reported that AI was more effective (mean tooth retention of 64 vs. 62 years) and less costly (298 vs. 322 euros), with an ICER of −13.9 euros per year, indicating that AI saved money at higher effectiveness (Khanagar et al., 2022; Dashti et al., 2025).

A validation study of a freely accessible web-based AI model (dental-ai.de) reported overall accuracy of 92.0%, with AUC values of 0.702–0.909 (Szabó et al., 2024). However, critical barriers to clinical deployment persist, including insufficient external validation on diverse populations, limited prospective multicenter designs, absence of standardized evaluation criteria aligned with clinical decision thresholds, data privacy concerns, model bias, liability issues, and the need for transparent, explainable AI outputs (Umer et al., 2025).

Gaps and Future Directions

Several critical gaps emerge from this synthesis that should guide future research efforts. First, the finding that only 12% of studies utilized public datasets represents a fundamental limitation of the field; future dataset development efforts should prioritize multicenter collection, standardized annotation guidelines following established classification systems such as ICCMS, diverse demographic representation, and comprehensive metadata documentation. Second, the field requires a shift from retrospective proof-of-concept studies toward prospective, multicenter randomized controlled trials evaluating the impact of AI assistance on clinical outcomes, not only diagnostic accuracy, and cost-effectiveness across diverse practice settings. Third, comprehensive clinical decision-support systems that extend beyond detection to include evidence-based treatment recommendations would maximize the clinical value of improved diagnostic sensitivity. Fourth, clear regulatory pathways, ethical guidelines, and liability frameworks governing clinical deployment must be established. Finally, investigation of lightweight AI systems designed for deployment on mobile platforms would facilitate screening in underserved and resource-limited populations where the burden of untreated caries is highest (Umer et al., 2024).

CONCLUSIONS

Artificial intelligence and machine learning systems demonstrate substantial and growing potential for the automated detection, classification, and segmentation of dental caries across multiple imaging modalities. Deep learning architectures, particularly CNN-based classifiers, YOLO-family detectors, and U-Net segmentation models, consistently achieve diagnostic performance metrics that match or exceed those of individual clinicians under controlled conditions. Ensemble and hybrid approaches, including multi-stage detection-segmentation pipelines and CNN-Transformer fusion architectures, represent promising directions for further performance improvement.

However, the convergence of advancing AI capabilities and growing clinical interest must be accompanied by a deliberate methodological shift. The realization of clinically meaningful impact requires: (a) large-scale, multicenter, publicly annotated datasets with standardized protocols; (b) prospective trials evaluating patient outcomes; (c) explainable AI as a standard component; (d) comprehensive clinical decision-support integration; (e) regulatory and ethical frameworks; and (f) lightweight models for community-based screening. Future research should prioritize multicenter external validation and the development of clinically interpretable models that can be meaningfully integrated into dental practice workflows.

Author Contributions

C.E. Cañedo-Figueroa: Contributed to conception, design, literature search, data acquisition and interpretation, drafted and critically revised the manuscript. S.A. Santana-Delgado: Contributed to

literature search, data acquisition and interpretation, drafted and critically revised the manuscript. All authors gave their final approval and agree to be accountable for all aspects of the work.

Conflicts of Interest

The authors declare no conflicts of interest.

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