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Application of Artificial Intelligence in Dental Caries Detection: A Comprehensive Scientific Review

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ABSTRACT

This review examines the application of artificial intelligence (AI), specifically deep learning (DL) and convolutional neural networks (CNNs), in the detection, classification, and diagnosis of dental caries across diverse imaging modalities. Dental caries remains one of the most prevalent chronic diseases worldwide, and early detection is critical for timely treatment and prevention of complications.
Methods: A systematic literature search was conducted across PubMed, Scopus, Web of Science, and IEEE Xplore for studies published between 2018 and 2025. Only studies utilizing machine learning and deep learning algorithms for caries detection were included. Radiographic images, intraoral photographs, and cone beam computed tomography (CBCT) were considered suitable sources. Findings: AI-based caries detection systems have demonstrated sensitivity ranging from 73% to 96%, specificity from 84% to 97%, and accuracy from 86% to 99%, depending on the imaging modality and model architecture. CNN models such as ResNet, VGG, U-Net, EfficientNet, and YOLO variants have shown considerable promise across multiple clinical scenarios.
Conclusions: AI technologies represent an innovative advancement in dental caries diagnosis, offering greater objectivity and reduced observer variability. However, challenges including dataset standardization, model generalizability, and regulatory frameworks require further attention to facilitate clinical integration.

1. Introduction

Dental caries is a chronic, multifactorial disease that affects populations across the globe. According to the World Health Organization, untreated caries in permanent teeth constitutes the most prevalent health condition, affecting approximately 2.3 billion people worldwide [1]. The pathogenesis of dental caries involves demineralization of tooth hard tissues—

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enamel and dentin—by acidic metabolic products of cariogenic bacteria within dental biofilms if left undetected and untreated, caries can progress to involve the dental pulp, resulting in pain, infection, and eventual tooth loss, with substantial impacts on quality of life and healthcare expenditure.

Early identification of carious lesions is fundamental to the implementation of minimally invasive treatment and preventive strategies. Conventional methods for caries detection include visual inspection, tactile examination using explorers or probes, and various radiographic techniques such as panoramic radiography, bitewing radiographs, and periapical radiographs. Despite their widespread use, these methods suffer from inherent limitations, including inter-examiner variability and difficulty in detecting early-stage lesions . [3].

Dentistry has emerged as one of the most promising fields for the application of artificial intelligence (AI) in medical diagnosis, offering the potential for enhanced accuracy, objectivity, and efficiency in clinical practice [4], [14]. Machine learning (ML) and its subset, deep learning (DL), are among the most important AI techniques applied to dental caries diagnosis. These algorithms can be trained on large volumes of data to extract diagnostic patterns. Convolutional neural networks (CNNs), a class of deep learning architectures designed specifically for image analysis, are capable of processing diverse imaging modalities including radiographs and cone beam computed tomography (CBCT) scans [10].The objective of this review is to synthesize current evidence on AI applications in dental caries detection, critically evaluate the performance of different deep learning models across imaging modalities, identify methodological limitations and biases in existing studies, and outline future directions for research and clinical practice.

2. Background and Fundamentals

2.1 Artificial Intelligence in Medical Imaging

Artificial intelligence refers to computational systems designed to perform tasks that typically require human intelligence, such as visual perception, pattern recognition, and decision-making. In the context of medical imaging, AI systems are trained to identify patterns in images that are associated with specific pathological conditions [21].

Machine learning, a branch of AI, enables systems to learn from datasets without explicit programming. Deep learning extends this capability through artificial neural networks with multiple hidden layers that automatically extract hierarchical features from raw data. The foundational architecture for deep learning in image analysis is the convolutional neural network (CNN) [10].

CNNs are specifically designed for image processing, employing convolutional layers to extract spatial features from images. Deep convolutional neural networks (DCNNs) represent an advanced extension of CNNs, utilizing multiple layers of convolution and pooling to capture complex image patterns. These models have been successfully applied to various dental imaging modalities, including bitewing and panoramic radiography, for caries detection and diagnosis, demonstrating high accuracy and reliability [26].

2.2 Deep Learning Architectures and Imaging Modalities

This section provides an integrated overview of both the deep learning architectures and the imaging modalities employed in AI-based caries detection, as these two dimensions are inherently interconnected in determining system performance.

2.2.1 Key Architectures

Several CNN architectures have been adapted for dental caries detection. VGGNet employs stacked 3×3 filters with increasing depth and has demonstrated high accuracy in dental image classification tasks. GoogLeNet/Inception architectures utilize parallel convolutions with varying kernel sizes, enabling multi-scale feature extraction that is particularly useful for identifying dental lesions of different sizes [10].

YOLO (You Only Look Once) models perform detection in a single forward pass, achieving high computational speed while maintaining accuracy. Recent versions, including YOLOv7, YOLOv8, and YOLOv11, have demonstrated impressive performance in caries localization, with F1 scores exceeding 0.80 in several studies. U-Net, originally developed for biomedical image segmentation, has proven highly capable at delineating carious lesion boundaries [16]. DenseNet and EfficientNet architectures offer superior parameter efficiency, making them suitable for resource-constrained environments such as mobile-based detection systems [23].

2.2.2 Imaging Modalities

Bitewing radiography is the preferred modality for detecting proximal caries, offering quality visualization of interproximal surfaces with relatively low radiation exposure [11]. Periapical radiographs provide complete images of teeth, including roots and surrounding alveolar bone, and are particularly valuable for identifying caries associated with periapical lesions [5].

Panoramic radiography provides a comprehensive view of the dental arches and surrounding tissues, serving as a valuable tool for initial examination and general diagnosis. However, AI applications analyzing panoramic images face challenges related to image distortion and superimposition of anatomical structures, which may limit the accuracy of computational models [8].

Cone beam computed tomography (CBCT) offers high-resolution volumetric data with multi-planar reconstruction capabilities, enabling detection of occlusal caries and recurrent caries beneath restorations that two-dimensional radiographs may miss. However, the increased radiation dose necessitates careful consideration of usage criteria [18]. Intraoral photographs and smartphone-captured images represent emerging modalities with particular significance for teledentistry and patient self-assessment outside clinical settings [6].

3- Literature Review Methodology

3.1 Search Strategy

A comprehensive literature search was conducted across multiple electronic databases, including PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and the Directory of Open Access Journals. The search encompassed articles published from January 2018 to December 2025, reflecting the period of intensive development in AI-based dental diagnostics. Search terms included combinations of: “artificial intelligence,” “machine learning,” “deep learning,” “convolutional neural network,” “dental caries,” “caries detection,” “tooth decay,” “radiograph,” “bitewing,” “CBCT,” and “intraoral photograph.”

3.2 Inclusion and Exclusion Criteria

Studies were included if they employed AI/ML/DL algorithms for caries detection or classification, utilized dental radiography, CBCT scans, or intraoral photographs, reported quantitative performance metrics (accuracy, sensitivity, specificity, F1-score, or AUC), and were published in peer-reviewed journals or conference proceedings in English within the specified timeframe.

Studies were excluded if they investigated dental conditions other than caries, applied AI for purposes other than diagnosis (e.g., treatment planning only), or provided insufficient methodological information for quality evaluation. Study quality was assessed using the QUADAS-2 tool for diagnostic accuracy studies and the CLAIM checklist for AI studies in medical imaging [7].

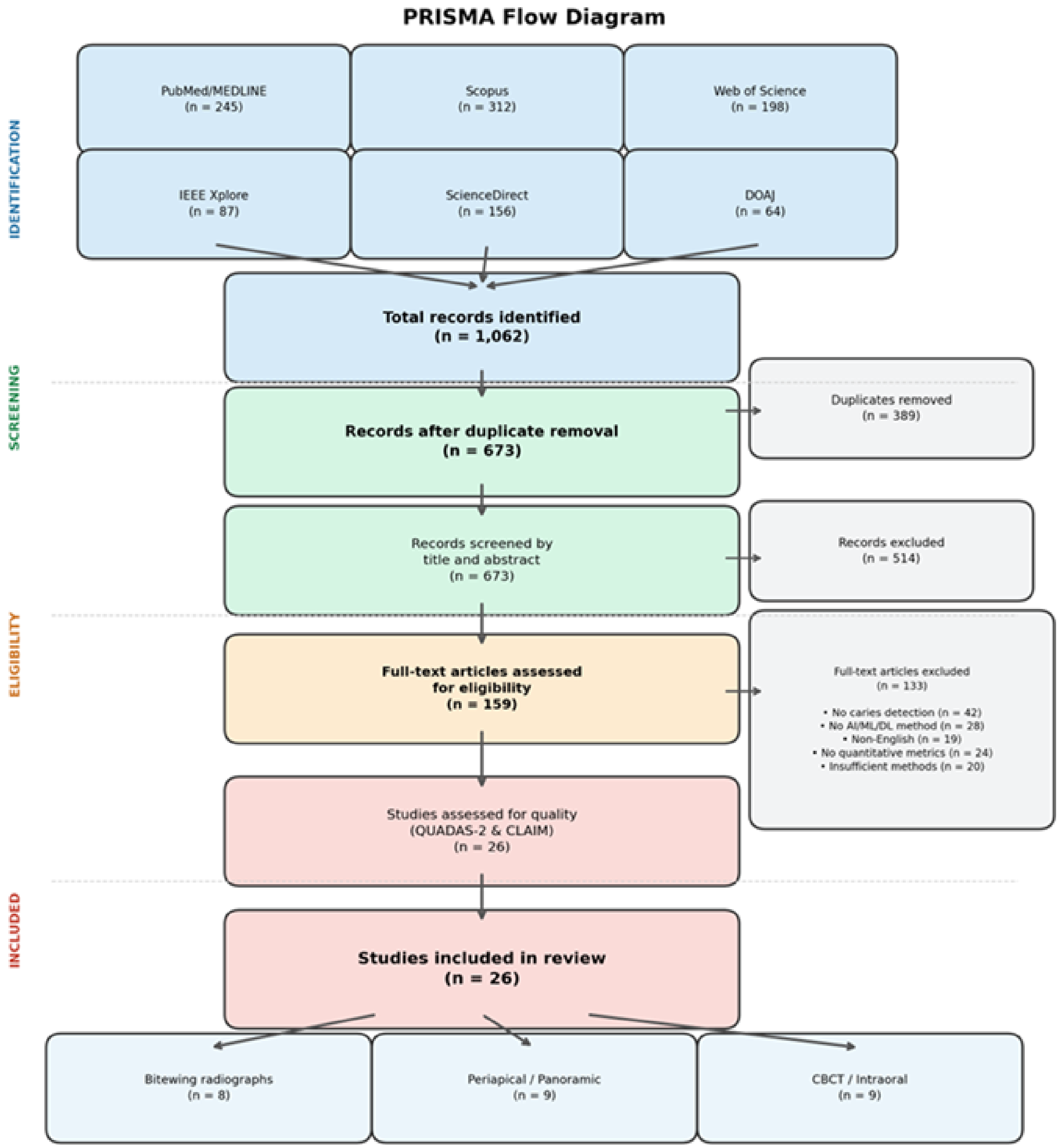

Figure 1. The design of the systematic review methodology.

4. AI Performance across Imaging Modalities

4.1 Bitewing Radiographs

The most researched caries detection modality based on AI is bitewing radiography. Experiments using ResNet-50 architectures on datasets of around 5,000 annotated images have reported accuracy, sensitivity, and specificity levels of 92.5%, 89.3%, and 94.1%, respectively [11].

Convolutional neural network (CNN) models have proven to be highly effective in detecting early stages of tooth decay, outperforming practitioners [10]. The VGG-16 model combined with U-Net achieved a sensitivity and precision of 0.84. Both detection and segmentation performance levels are equal in terms of precision and recall, indicating consistent results. The combination of VGG-16 and U-Net showed a high accuracy of 0.84, with the F-measure also reaching 0.84, demonstrating reliable detection and recall capabilities [16].

The YOLOv7 model and its versions with Attention Mechanisms (CBAM) demonstrated an evident increase in the detection of dental caries. YOLOv7+CBAM attained a recall rate of 0.827, an accuracy of 0.834, a mean average precision (mAP) of 0.846, and F1 of 0.830 [8]. These results verify that the inclusion of attention mechanisms can make the model concentrate on relevant information, thus enhancing the detection performance, particularly in less obvious instances, where the lesions are small. Also, the analysis of the performance of AI systems and the quality of their interpretation indicates that deep learning models can match, or even exceed, the accuracy of novice dentists, while experienced dentists still have an edge in complex cases [5].

4.2 Periapical Radiographs

The use of artificial intelligence in periapical radiographs has already demonstrated highly promising outcomes, namely, the detection of dental caries and periapical pathology simultaneously. Models of modern diagnostics, when trained using data on over 4000 annotated images and implemented based on ResNet with a spatial attention module (ResNet+SAM), scored F1 of 0.886, accuracy of 0.885, and AUC of 0.954 [5].

Such findings point to the high potential of artificial intelligence regarding the overall and simultaneous diagnosis of various medical conditions. Comparative analyses revealed that the implementation of AI-based decision support positively affected the quality of diagnoses of physicians and that the F1 scores improved from 0.592–0.610 to 0.706–0.723 [5]. These results affirm that artificial intelligence needs to be adopted to supplement, rather than substitute, clinical decision-making. In addition, the fact that the rate of concurrence among viewers is increased in the case of AI demonstrates the viability of this form of participatory format [20].

4.3 Panoramic Radiographs

Despite challenges related to distortion, varying magnifications, and overlapping anatomical structures, CNN models trained using VGG-16 and EfficientNet-B0 architectures have achieved AUC values of 0.95 on datasets comprising 10,000 panoramic radiographs, outperforming traditional computer-aided detection (CAD) software [19].

YOLOv7 models applied to the detection of caries beneath fixed dental prostheses (FDPs) achieved precision of 0.966 and recall of 0.947, with F1-scores of 0.813–0.830 [8]. Hybrid approaches combining CNN-based feature extraction with traditional machine learning classifiers (SVM, random forest, gradient boosting) have also shown promise, with a CNN+Random Forest model achieving 90.6% accuracy and ROC-AUC of 0.987 for multi-category dental classification [19].

4.4 Cone Beam Computed Tomography (CBCT)

Three-dimensional CBCT imaging addresses several limitations of two-dimensional radiography, particularly in detecting occlusal and recurrent caries [18]. CNN architectures that process axial, coronal, and sagittal slices simultaneously have proven effective for identifying and classifying dental lesions by depth and location. Studies report sensitivity of 89.7% and specificity of 92.3% for CBCT-based caries detection, with performance varying according to lesion location and the presence of metallic restorations [25].

CBCT-enhanced modes demonstrated superior diagnostic capabilities for recurrent caries detection compared to standard modes. However, performance decreased substantially in the presence of amalgam restorations compared with composite materials, highlighting persistent challenges related to beam hardening and streak artifacts in AI-based CBCT analysis [18]. Semi-supervised learning approaches have also shown effectiveness in caries classification when annotated data are limited [25].

4.5 Intraoral Photographs

AI-driven intraoral photography systems are particularly significant for enabling self-examination, remote monitoring, and caries detection in resource-limited settings. Multi-stage deep learning systems trained on datasets of over 50,000 intraoral photographs achieved sensitivity of 89.78% and specificity of 91.67% for identifying white spot lesions (ICDAS 1–2) in anterior teeth, and sensitivity of 97.06% and specificity of 99.79% for cavitated lesions (ICDAS 3–6) [6]. For posterior teeth, sensitivity and specificity were somewhat lower, at 90.25% and 86.96%, respectively [7].

Lightweight architectures such as MobileNetV2, enhanced through mixup augmentation, fine-tuning, and quantization-aware training, have been specifically optimized for mobile deployment [23].

A meta-analysis comparing AI performance on clinical images versus bitewing radiographs demonstrated the superiority of AI in detecting caries from clinical images, highlighting the complementary roles of different imaging modalities [7].

5. Comparative Analysis of Deep Learning Architectures

Table 1 provides a comparative overview of the most significant deep learning architectures implemented to detect dental caries, their main features, the metrics of reported performance, and their main applications.

Table 1: Comparison of Deep Learning Architectures for Dental Caries Detection

Architecture	Key Features	Performance Metrics	Primary Applications	References
ResNet-50/101	Skip connections, deep architecture (50–152 layers)	Accuracy: 92–95%, F1: 0.83–0.89	Classification, feature extraction for bitewing/periapical	[5, 11]
VGG-16/19	3×3 convolutions, high classification accuracy	Sensitivity: 0.84, Precision: 0.84–0.86	Detection in bitewing, panoramic radiographs	[10, 16, 19]
U-Net	Encoder-decoder with skip connections for segmentation	F1: 0.84, Precision: 0.70–0.81	Caries segmentation, lesion boundary delineation	[16]
YOLOv7/v8/v11	Single-pass detection, real-time performance	mAP: 0.80–0.85, F1: 0.81–0.83	Object detection, localization, caries under FDPs	[8, 17]
Inception/GoogLeNet	Multi-scale feature extraction, parallel convolutions	Accuracy: 73–93%	Multi-class classification, severity assessment	[10, 19]
EfficientNet	Compound scaling, parameter efficient	AUC: 0.95, Accuracy: 95–96%	Panoramic analysis, mobile deployment	[19, 23]
MobileNetV2	Lightweight, inverted residuals, linear bottlenecks	Validation Accuracy: 91%	Smartphone-based detection, teledentistry	[23]
DenseNet	Dense connections, feature reuse, gradient flow	DSC: 0.94 (segmentation)	CBCT analysis, tooth condition classification	[18, 25]

6. Critical Discussion and Evidence Synthesis

While the preceding sections have summarized the reported performance of AI models across imaging modalities, a critical evaluation of the underlying methodologies, potential biases, and overall strength of evidence is essential for interpreting these findings within a clinical context. This section addresses the gaps identified in the descriptive reporting by providing a comparative analysis of study methodologies, an assessment of bias, and an evaluation of evidence strength.

6.1 Comparison of Study Methodologies

The studies reviewed exhibit considerable methodological heterogeneity across several dimensions. First, dataset sizes vary dramatically, ranging from fewer than 500 images in some studies [22] to over 50,000 in others [6], with the majority utilizing datasets of 1,000–5,000 images. This variation significantly affects model training adequacy and the reliability of reported metrics. Studies with smaller datasets are more susceptible to overfitting, and their performance estimates may not generalize to broader clinical populations.

Second, ground truth labeling methods differ substantially across studies. Some employ a single annotator [22], while others use consensus-based annotation by multiple experts [5], [11]. The use of different caries classification systems (e.g., ICDAS versus binary carious/non-carious categorization) further complicates direct comparison of sensitivity and specificity values. Studies using finer-grained classification systems tend to report lower overall accuracy due to the increased difficulty of distinguishing between adjacent severity levels.

Third, validation strategies vary considerably. While some studies employ rigorous k-fold cross-validation [10], [11], others rely on simple train-test splits without external validation [22], [24]. Only a minority of the reviewed studies performed external validation on independent datasets from different institutions or imaging equipment, which is essential for establishing clinical applicability. The absence of standardized evaluation protocols limits the comparability of results across studies and undermines the reliability of aggregate performance estimates.

6.2 Risk of Bias Analysis

Applying concepts from the QUADAS-2 framework for diagnostic test accuracy studies, we can identify a number of biases in the literature. Selection bias is common with most studies reporting datasets from a single centre [13], [24], which limits the variability of patients and imaging conditions that may be encountered in clinical practice. The geographical bias in datasets (mostly from East Asia and Europe) also limits the generalizability of the models to other populations [3].

Verification bias also exists, with varying diagnostic methods used as the reference standard for caries diagnosis. Although histology is the gold standard, the majority of studies use the consensus of expert clinicians' interpretation of radiographs, which is prone to variability [9]. This circular process, in which human judgment is used to train the AI and then validate its performance, creates a "best case" outcome for AI performance and may hide systematic diagnostic bias. Reporting bias is due to variable reporting of performance. While most studies report accuracy, sensitivity, and specificity, fewer studies report full performance metrics such as F1-score, the area under the curve (AUC) and confidence intervals. The absence of confidence intervals in many studies makes it difficult to assess the statistical significance of reported performance differences between models. Finally, publication bias may lead to bias in the reporting of positive studies, overestimating the performance of AI-based caries detection systems.

6.3 Strength of Evidence Evaluation

The strength of evidence supporting the use of AI for dental caries detection can be described as moderate to promising, with major caveats. There are various lines of evidence that support the field: the reported accuracy of multiple research groups for bitewing and periapical radiograph analysis consistently exceeds 85% [5], [10],and [11],and the superiority of CNN-based approaches over traditional CAD systems has been demonstrated across imaging modalities [19].

However, there are a number of caveats. A lack of prospective clinical trials is the most important factor. Almost all studies reviewed are retrospective and use existing image data sets rather than test the performance of AI in clinical practice. The limited number of studies that have evaluated AI in a clinical environment may suggest lower accuracy when compared to retrospective studies [20]. Furthermore, the absence of standardized benchmark datasets analogous to ImageNet for dental imaging prevents fair and reproducible comparisons across studies.

Lacking in the literature is the comparative performance of different architectures on the same dataset with identical conditions. Although performance metrics are reported in Table 1, these metrics were generated under different experimental settings and cannot be compared directly. Multicenter prospective validation studies using consistent protocols should be a priority for future work to determine the clinical value of AI systems for detection of dental caries.

7. Challenges and Limitations

7.1 Dataset-Related Challenges

The development of robust AI models for caries detection depends critically on the quality and diversity of training datasets. The reviewed literature reveals several persistent challenges: insufficient dataset sizes (frequently fewer than 1,000 images), which undermine model generalizability; inconsistencies in expert annotation that introduce label noise; and the absence of uniform protocols that impede cross-study comparison and benchmark development [9].

Class imbalance, where healthy teeth substantially outnumber carious teeth, leads to inflated accuracy values while masking reduced sensitivity [22]. Although data augmentation, synthetic data generation, and balanced sampling have been employed to address this issue, optimal solutions remain under investigation. Furthermore, most published datasets originate from limited geographic regions, raising concerns about the applicability of trained models across diverse populations and imaging equipment [3].

7.2 Technical Limitations

Overfitting remains a persistent concern, particularly when deep networks are trained on small datasets [14]. While transfer learning from models pre-trained on large natural image collections (e.g., ImageNet) provides a partial solution, the domain gap between natural and medical images can constrain performance gains. Cross-institutional generalizability remains poorly established, as most evaluations are conducted on data from single institutions [13].

Image quality parameters, including exposure, contrast, patient positioning, and artifacts from metallic restorations, significantly affect model performance [24]. Additionally, barriers to clinical adoption include concerns about the replacement of human judgment, limited familiarity with AI technologies among practitioners, and infrastructure requirements such as computational resources, network connectivity, and integration with existing practice management systems [21].

7.3 Clinical Implementation Barriers

The translation of AI systems from research settings to clinical practice faces multifaceted challenges. Regulatory frameworks for AI-assisted diagnostics vary across jurisdictions and remain in the early stages of development. Data privacy concerns associated with cloud-based processing of patient images require compliance with regulations such as HIPAA and GDPR [4].

Legal liability for AI-assisted diagnoses remains unresolved, with ongoing debate regarding the allocation of responsibility among developers, AI systems, and clinicians. The opacity of certain deep learning models, often characterized as “black boxes,” may impede clinical acceptance and regulatory approval, underscoring the importance of explainable AI approaches discussed in Section 8.1.

8. Future Directions

8.1 Explainable AI (XAI)

The integration of interpretability techniques into AI diagnostic models is essential for building clinician trust and facilitating regulatory approval [21]. Gradient-weighted Class Activation Mapping (Grad-CAM), attention mechanisms, and saliency maps provide visual explanations of model decision-making by highlighting the image regions most influential in the diagnostic output. These techniques enable clinicians to verify that models are attending to clinically relevant features rather than spurious correlations, thereby supporting appropriate integration of AI outputs into clinical decision-making.

8.2 Clinical Decision Support Systems

The deployment of AI as a clinical decision support system, rather than as an autonomous diagnostic tool, represents the most pragmatic implementation pathway in the near term [20]. Such systems can augment clinician capabilities by providing second opinions and flagging potential findings for confirmation. The development of standardized clinical validation protocols and regulatory frameworks specifically designed for AI-assisted diagnosis will be critical for responsible clinical implementation [12].

8.3 Mobile and Teledentistry Applications

Mobile-based AI applications have the potential to transform dental care delivery, particularly in underserved communities and remote areas. These systems enable patient self-examination and remote consultation, facilitating early diagnosis and timely referral for treatment. Integration of mobile AI applications with electronic dental records and health information systems is necessary to maximize their clinical benefit and ensure continuity of care.

9. Conclusions

This review demonstrates that deep learning has achieved measurable progress in automating caries detection across multiple imaging modalities. AI systems, particularly CNNs, have achieved accuracy rates of 73–96%, sensitivity rates of 84–97%, and specificity rates of 86–99%, depending on the imaging modality and architectural configuration

Different architectures offer distinct advantages suited to specific clinical requirements: VGG for classification tasks, U-Net for segmentation, lightweight networks such as MobileNet for mobile deployment, and YOLO for real-time detection and localization. However, the critical analysis presented in this review reveals that the strength of existing evidence is tempered by significant methodological heterogeneity, prevalent risk of bias, and a near-complete absence of prospective clinical validation studies.

The path toward responsible clinical integration requires addressing several priorities: the development of large-scale, diverse, and standardized benchmark datasets; the design of regulatory frameworks appropriate for AI-assisted diagnostics; resolution of liability concerns; and the advancement of explainable AI methodologies. Collaborative efforts among researchers, clinicians, regulatory bodies, and industry partners are essential to realize the potential of AI-assisted caries detection.

Ultimately, AI in dental caries detection should be understood as a complementary technology that empowers clinicians with enhanced diagnostic capabilities rather than a replacement for clinical expertise. As these technologies mature, their integration into routine clinical practice holds the potential to reduce diagnostic variability, enable earlier intervention, and promote improved oral health outcomes at both individual and population levels.

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