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DEEP LEARNING FOR CARIES DETECTION IN DIAGNOCAM IMAGES: A SYSTEMATIC REVIEW OF CURRENT EVIDENCE AND CHALLENGES

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Abstract:

Dental caries remains a widespread chronic disease, with early detection being vital to prevent lesion progression and tooth loss. Conventional diagnostic methods, such as visual-tactile examination and bitewing radiographs, have limited sensitivity for early lesions, particularly in children. Near-infrared light transillumination (NILT), as used in the DIAGNOcam system, provides a radiation-free and non-invasive alternative for detecting occlusal and proximal caries. Recently, deep learning approaches, especially convolutional neural networks (CNNs), have shown great promise in automating dental image analysis and improving diagnostic accuracy.

This systematic review analyzed studies published from 2012 to 2025 on caries detection using DIAGNOcam images. A total of six clinical and three deep learning studies met the inclusion criteria. Primary outcomes included diagnostic accuracy, sensitivity, and specificity. Clinical studies confirmed DIAGNOcam's reliability for early lesion detection, while AI-based approaches achieved comparable or superior performance to traditional methods.

However, limited datasets, small sample sizes, and inconsistent annotation standards restrict generalization. Future work should emphasize larger, standardized datasets and interpretable AI models. Combining DIAGNOcam imaging with deep learning may enable earlier, more objective, and patient-friendly caries diagnosis.

Keyword: DIAGNOcam, Near-infrared light transillumination, Artificial intelligence, Deep Learning, Caries detection

1. Introduction:

Dental caries remains one of the leading chronic health conditions globally, affecting both children and adults [1], [2]. It is a multifactorial condition initiated by acid production from bacterial fermentation of dietary carbohydrates, particularly sugars. If not diagnosed and managed at an early

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stage, carious lesions may progress rapidly, leading to extensive structural damage, pain, and even tooth loss a major cause of extractions in patients under 44 years of age [3], [4]. Several risk factors contribute to caries progression, including excessive sugar intake, poor oral hygiene, fluoride deficiency, and reduced salivary flow, while preventive strategies such as patient education, dietary modification, and fluoride application remain essential [5]. The earliest phase of dental caries involves subsurface enamel demineralization without visible cavitation. Progression toward the enamel–dentin junction (EDJ) and into dentin accelerates due to its tubular structure and higher organic content [6].

Conventional caries lesion diagnostic methods such as visual-tactile inspection are limited in detecting early caries [7] [8], prompting the use of adjunctive imaging techniques. Bitewing radiographs are widely employed to evaluate proximal caries but are restricted by two-dimensional imaging, overlapping structures, and radiation exposure, limiting repeated use in children [9], [10]. Alternative approaches such as Digital Imaging Fiber-Optic Transillumination (DIFOTI) and Near-infrared light transillumination (NILT) are radiation-free and effective for early detection [11] [12] [13]. NILT has emerged as a promising non-invasive, radiation-free diagnostic modality. The DIAGNOcam (KaVo, 2012) applies NILT at a wavelength of approximately 780 nm, enabling visualization of occlusal and proximal caries by capturing light transmission differences between healthy and demineralized tissues [14]. A CCD camera records the resulting images, which can reveal early lesions not visible through conventional methods. DIAGNOcam is particularly advantageous for children and adolescents, offering high sensitivity, comfort, and radiation-free diagnosis. Studies have demonstrated its effectiveness in detecting proximal lesions adjacent to restorations and in pediatric patients [15] [16] [17].

The integration of artificial intelligence (AI) into diagnostic imaging represents a major advancement in medical and dental healthcare [18]. A foundational component of many modern AI detection systems is the convolutional neural network (CNN). CNNs are a class of deep learning models specifically designed to process and analyze visual data. These networks consist of multiple layers, including convolutional, pooling, and fully connected layers, that work hierarchically to extract image features. Early layers typically detect simple patterns such as edges, while deeper layers learn more abstract and complex features necessary for classification tasks [19]. In dentistry, CNNs have gained significant attention due to their ability to analyze radiographic images and other forms of dental imaging data. Recent studies have demonstrated the successful application of CNNs in various dental tasks, including tooth classification, detection of dental caries [20], localization of anatomical structures [21] [22] [23], and bounding box prediction [24] [25] [26] [27]. These applications help automate diagnostic workflows and reduce subjectivity in interpretation, contributing to more consistent and efficient clinical assessments [28].

A comprehensive literature search was conducted to identify relevant studies on the application of deep learning techniques for the detection and classification of dental caries using DIAGNOcam images. Electronic databases including Google Scholar, PubMed, Web of Science, and IEEE Xplore were systematically searched for articles published between 2012 (the year DIAGNOcam was introduced) and September 2025. The search strategy combined keywords and Boolean operators such as “DIAGNOcam,” “near-infrared light transillumination,” “dental caries detection,” “deep learning,” “artificial intelligence,” and “machine learning.” Additional studies were identified

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through manual screening of the reference lists of included articles. Only peer-reviewed articles written in English and focusing on human subjects were considered. Studies were excluded if they involved other imaging technique, or traditional diagnostic methods without deep learning integration. After removing duplicates, titles and abstracts were screened, followed by full-text review to ensure relevance to the scope of this review.

More recently, DIAGNOcam images have been integrated with deep learning approaches for automated caries detection. While systematic reviews of artificial intelligence in dentistry have highlighted promising applications across radiographs and photographs, they also emphasize the scarcity of DIAGNOcam-specific studies [29]. This gap underscores the need for a focused review. This article therefore aims to summarize and critically evaluate published studies that have applied deep learning to DIAGNOcam images, highlighting current achievements, limitations, and future research directions.

2. Literature review

2.1. Clinical case study in DIAGNOcam:

Several in vitro and clinical studies have established the diagnostic performance of the DIAGNOcam and near-infrared light transillumination (NILT) in detecting dental caries. Elhennawy et al. (2018) [30] demonstrated high sensitivity of DIAGNOcam for detecting proximal caries adjacent to composite restorations, while Lederer et al. (2019) [31] validated NILT at 780 nm for proximal lesions, confirming its value as a radiation-free alternative. Litzenburger et al. (2020) [32] enhanced this approach by integrating high dynamic range imaging, which improved visualization of occlusal lesions, particularly at early stages. Clinical experiences reported by Söchtig et al. (2014) [33] highlighted DIAGNOcam as a reliable adjunctive tool for early proximal and occlusal caries, whereas Russotto et al. (2021) [34] confirmed its feasibility in large private practice populations, showing strong agreement with radiographs without radiation exposure. More recently, Schulz-Weidner et al. (2022) [35] demonstrated superior sensitivity of NILT compared to intraoral scanners in detecting occlusal caries in children, underscoring its particular advantage in pediatric dentistry. Collectively, these findings validate DIAGNOcam as a robust, radiation-free diagnostic modality across both experimental and clinical contexts, laying the groundwork for its integration with deep learning applications.

Generally, these studies confirm that DIAGNOcam and related NILT approaches provide reliable, radiation-free caries detection in both in vitro and clinical settings. They demonstrate strong performance for proximal and occlusal lesions, even adjacent to restorations, and have shown particular advantages in pediatric dentistry. This body of evidence establishes DIAGNOcam as a validated diagnostic tool and provides a foundation for subsequent applications of deep learning methods.

2.2. Deep learning with DIAGNOcam:

Several studies have applied deep learning methods to DIAGNOcam images in both in-vitro and clinical settings. Schwendicke et al. (2019) [36] evaluated convolutional neural networks (ResNet18 and ResNet50) on an in-vitro dataset of 226 extracted teeth and reported moderate diagnostic performance for ResNet50 is Area Under Curve (AUC) was 0.74, sensitivity and specificity were 0.59 and 0.76, Positive Predictive Value (PPV) was 0.63, Negative Predictive Value (NPV) 0.73,

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though limited by small sample size and annotation bias. Holtkamp et al. (2021) [37] expanded this work by testing CNNs on both in-vitro and in-vivo DIAGNOcam datasets, demonstrating that models trained on clinical data achieved superior generalizability, F1 was 0.56, AUC was 0.66, sensitivity was 0.49, specificity was 0.83, PPV was 0.67 and NPV was 0.71, underscoring the importance of real-world images for robust model development. Complementing these diagnostic approaches, Casalegno et al. (2019) [38] introduced a segmentation model based on U-Net and VGG16 to localize carious lesions in 217 DIAGNOcam images, achieving a mean IoU of 72.7% and 49.5%, 49.0% for proximal and occlusal lesions. Collectively, these studies highlight the potential of deep learning to enhance DIAGNOcam image interpretation, while also emphasizing the limitations of small datasets and the need for clinically diverse training samples to ensure reliable diagnostic performance.

Table 1: Summary of deep learning studies applying DIAGNOcam (NILT) images for caries detection and segmentation, highlighting datasets, caries types, model approaches, and result.

Study	Dataset	Caries Type	Approach	Model	Result
Falk Schwendicke (2020)	226 dummy head images	Occlusal proximal	Classification	ResNet18 ResNet50	For ResNet50 AUC 0.74, sensitivity 0.59, specificity 0.76, PPV 0.63, NPV 0.73
Holtkamp (2021)	226 in vitro, 1319 in vivo	Proximal caries	Classification	ResNet	Trained in vivo and tested in vitro F1 0.56, AUC 0.66, sensitivity 0.49, specificity 0.83, PPV 0.67, NPV 0.71
F. Casalegno (2019)	217 images	Background, enamel, dentin, proximal, occlusal	Semantic segmentation	U-Net with VGG16-inspired encoder	IoU 72.7%, proximal 49.5% occlusal 49.0%

Deep learning studies applying DIAGNOcam images for caries detection and segmentation have adopted different optimization strategies, loss functions, and model designs to enhance performance see Table.1. Schwendicke et al. (2020) trained ResNet18 and ResNet50 models using the Adam optimizer with a low learning rate (5×10^{-5}) and small batch size (10), allowing stable convergence on a small in-vitro dataset of 226 images. Although the loss function was not explicitly reported, the use of Adam was intended to improve gradient stability and adapt learning across layers, which is critical for limited data. Holtkamp et al. (2021) extended this work by applying binary cross-entropy loss with Adam, which is well-suited for binary classification tasks such as caries presence/absence. Their study showed that training on in-vivo datasets improved generalizability, suggesting that loss

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choice combined with clinical data was more effective than in-vitro training alone. In contrast, Casalegno et al. (2019) implemented a U-Net with a VGG16 encoder for semantic segmentation, optimized using mini-batch stochastic gradient descent (SGD) and categorical cross-entropy loss. The combination of SGD with cross-entropy was appropriate for handling their five-class segmentation problem (background, enamel, dentin, proximal caries, and occlusal caries), supporting multi-class pixel-level classification. Together, these studies demonstrate that optimizer selection, learning rate, batch size, and loss functions directly shaped the models' ability to learn robust caries representations from DIAGNOcam images, with binary cross-entropy favoring classification tasks and categorical cross-entropy enabling detailed multi-class segmentation.

3. Evaluation metrics

In caries detection and segmentation, a wide range of evaluation metrics have been reported see Table.2. Pixel-level spatial metrics such as the Intersection over Union (IoU) are commonly used to quantify the overlap between predicted masks and ground truth annotations, defined as Equation.1. F1 combines precision and recall into a single metric, reflecting how well a model identifies positive cases while avoiding false alarms, see Equation.2.

$$IOU = \frac{TP}{(TP + FP + FN)} \tag{1}$$

$$F1 = \frac{2 \cdot (Precision \times Recall)}{(Precision + Recall)} \tag{2}$$

Sensitivity (recall) measures the ability to correctly identify carious regions, while specificity reflects the ability to exclude sound regions, is defined as Equation. 3, 4.

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{3}$$

$$Specificity = \frac{TN}{(TN + FP)} \tag{4}$$

Positive Predictive Value (PPV) and Negative Predictive Value (NPV) provide information about the reliability of positive and negative predictions, respectively see Equation. 5, 6.

$$PPV = \frac{TP}{(TP + FP)} \tag{5}$$

$$NPV = \frac{TP}{(TN + FN)} \tag{6}$$

Where:

TP (True Positives) are correctly identified positive pixels, FP (False Positives) are pixels incorrectly predicted as positive, FN (False Negatives) are positive pixels missed by the model and TN (True Negatives) are correctly identified negative pixels.

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These metrics collectively provide a comprehensive evaluation of the model's ability to accurately segment dental structures while minimizing false detections, particularly important for assessing model reliability across imbalanced classes in dental datasets.

Table 2: Performance evaluation metrics reported in deep learning studies using DIAGNOcam (NILT) images for caries detection and segmentation.

	AUC	PPV	NPV	sensitivity	specificity	F1-score	IOU
Schwendicke et al. (2019) [24]	√	√	√	√	√		
Holtkamp et al. (2021) [37]	√	√	√	√	√	√	
Casalegno et al. (2019) [38]	√						√

4. Discussion

4.1. Clinical interpretation

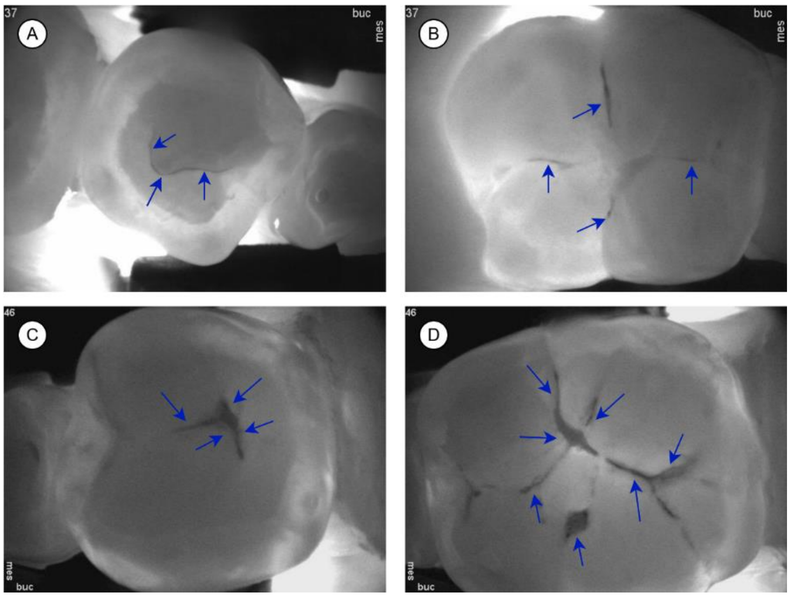

Figure 1: DIAGNOcam images illustrating occlusal caries lesions at different stages. (A, B) Early occlusal caries lesions, visible as low-density thin dark lines. (C, D) Advanced occlusal caries lesions, characterized by thickened dark lines and pronounced shadowing.

From a clinical perspective, the high sensitivity achieved by DIAGNOcam is promising, as undetected lesions pose a significant risk in caries progression and management. However, the trade-off of lower specificity suggests that some lesions may be over-diagnosed, leading to possible overtreatment. The use of DIAGNOcam provides a clear advantage, as it enables radiation-free visualization of early carious lesions, making it particularly suitable for children and young adults. As illustrated in Figure 1, DIAGNOcam effectively captures early and advanced occlusal lesions,

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with early stages appearing as thin, low-density dark lines and advanced lesions presenting as thicker, more pronounced shadows. Similarly, Figure 2 demonstrates the progression of proximal lesions, where early lesions are confined to enamel, while advanced lesions extend beyond the enamel–dentin junction into dentin. These distinct image patterns highlight the anatomical differences between occlusal and proximal caries, emphasizing the need for lesion-specific deep learning models. Overall, AI-assisted DIAGNOcam imaging has the potential to enhance early detection, but clinical judgment remains essential to interpret ambiguous findings and reduce unnecessary interventions.

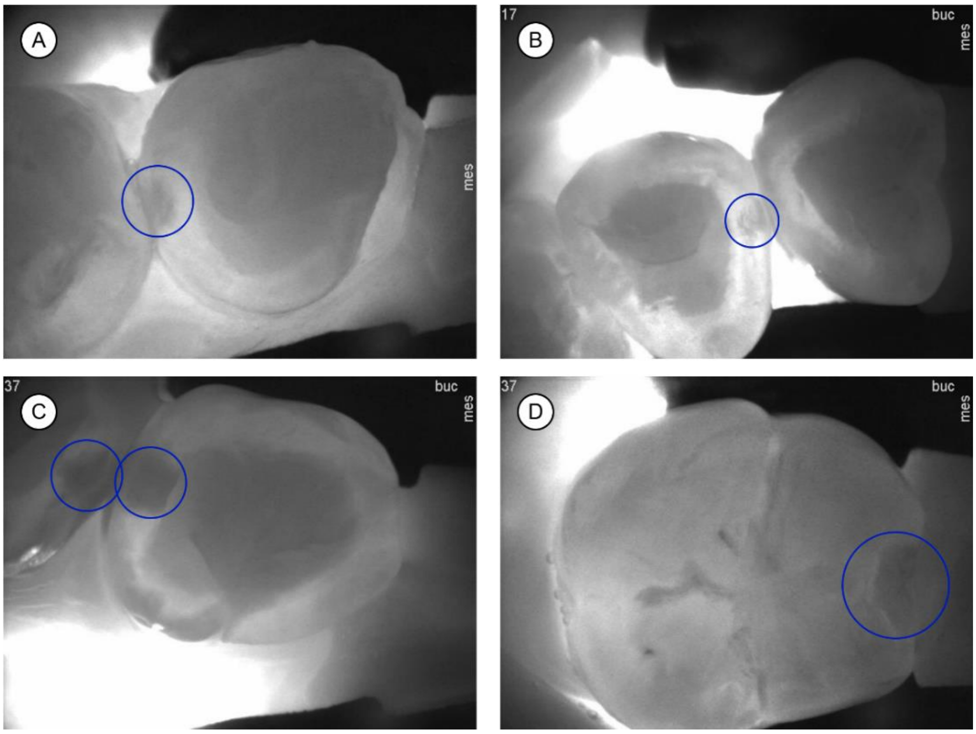

Figure 2: DIAGNOcam images illustrating proximal caries lesions at different stages. (A, B) Early proximal caries lesions, visible as localized dark areas within the enamel. (C, D) Advanced proximal caries lesions, with darker regions extending across the enamel. (C, D) Advanced proximal caries lesions, with darker regions extending across the enamel–dentin junction (EDJ) into dentin.

4.2. Deep learning

The application of deep learning to DIAGNOcam images for caries detection has primarily followed two directions: classification and segmentation. In their pilot study, Schwendicke et al. (2020) demonstrated that convolutional neural networks (ResNet18 and ResNet50) could classify caries lesions in posterior teeth with reasonable accuracy, even with a relatively small in vitro dataset. This early work established the feasibility of classification models, which are computationally efficient and can provide rapid diagnostic support. Holtkamp et al. (2021) expanded on this by incorporating both in vitro and in vivo DIAGNOcam images, demonstrating that training on real-world clinical data significantly improved generalizability. These findings suggest that classification networks,

particularly residual CNNs, are well-suited for lesion-level diagnosis and may serve as effective adjuncts for chairside caries detection.
However, classification approaches offer only binary or categorical outcomes without localizing lesions, which can limit clinical interpretation. Casalegno et al. (2019) addressed this gap by applying a segmentation model (U-Net with VGG-inspired encoder) to DIAGNOcam images. Their model achieved strong performance across multiple classes, including enamel, dentin, and proximal/occlusal caries, highlighting the added value of pixel-level localization. For clinicians, segmentation provides more actionable information by delineating lesion boundaries, supporting treatment planning and monitoring of progression.

Comparing the two approaches, classification models appear best suited for screening and rapid diagnosis, where sensitivity is prioritized to avoid missed lesions. Segmentation models, by contrast, are preferable for detailed lesion characterization, enabling a more precise understanding of lesion. Given the complementary strengths, future research may benefit from hybrid models that combine classification for initial detection with segmentation for localization. Larger, multicenter datasets and advanced architectures such as transformers or self-supervised learning could further enhance performance and clinical applicability.

4.3. Limitation and challenging

Despite the encouraging results of deep learning for caries detection using DIAGNOcam images, several limitations must be acknowledged. Most existing studies were pilot investigations with relatively small and homogeneous datasets, often acquired under in vitro conditions. This restricts the generalizability of the findings to real clinical practice. The establishment of ground truth relied on a limited number of expert annotations, without extensive validation against histology or larger panels of examiners, which introduces potential bias. Furthermore, classification models were mainly restricted to binary outcomes, oversimplifying the clinical complexity of caries diagnosis, while segmentation models struggled with small or early lesions and demonstrated variable performance across classes. Importantly, no study to date has conducted large-scale, multicenter, or real-time clinical validation, limiting translation into routine workflows. These factors highlight the need for larger, more diverse datasets, standardized annotation protocols, and integration into prospective clinical trials.

5. Conclusion

Deep learning applied to DIAGNOcam images offers a promising pathway toward more accurate and non-invasive caries detection. Current evidence suggests that classification networks achieve strong diagnostic sensitivity, while segmentation models provide lesion localization but remain challenged by early or small lesions. Despite these advances, existing studies are limited by small datasets and pilot designs, underscoring the need for larger, clinically diverse investigations. Future work should focus on multicenter validation, robust annotation strategies, and integration into clinical workflows to realize the full potential of AI-enhanced NILT imaging in dentistry.

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