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Review
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ADVANCES IN ARTIFICIAL INTELLIGENCE-AIDED INTRAORAL IMAGING ANALYSIS IN PERIODONTICS

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Abstract: Artificial intelligence has increasingly influenced the field of periodontology by enhancing diagnostic accuracy and treatment planning through advanced data-driven techniques. It was aimed to examine the integration of artificial intelligence, particularly deep learning and machine learning, in analyzing intraoral photographs for periodontal conditions in this review. Periodontal assessments rely on clinical and radiographic evaluations, but artificial intelligence introduces a transformative approach by analyzing large datasets to improve clinical decision-making. The review investigates the effectiveness of artificial intelligence-enhanced intraoral photograph analysis, focusing on methodologies for dataset creation, model development, training, and performance evaluation. A thorough search of databases such as PubMed, Scopus, Google Scholar, and IEEE Xplore identified 338 articles, with 16 meeting the inclusion criteria. These studies primarily utilized convolutional neural networks and architectures like DeepLabv3+ and U-Net, demonstrating high accuracy in detecting conditions such as gingivitis, dental plaque, and other periodontal issues. The dataset sizes ranged from 110 to 7220 images, affecting the models' generalizability. Most studies employed supervised learning, with models trained on labeled datasets to achieve precise diagnostic outcomes. The review highlights that while artificial intelligence and machine learning techniques, including convolutional neural networks and U-Net, offer significant improvements in periodontal diagnostics, the choice of model and the quality of the dataset are crucial for performance. Hybrid approaches that combine automated and expert-driven methods might provide a balance between efficiency and accuracy. The successful integration of artificial intelligence into clinical practice requires continuous validation and adaptation to ensure that these technologies remain accurate and relevant. Future research should focus on enhancing model robustness, expanding dataset diversity, and refining clinical applications to fully exploit the potential of artificial intelligence in periodontology.

Keywords: Artificial intelligence, Periodontics, Photograph

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1. Introduction

Artificial intelligence (AI) is a broad discipline focused on creating machines that can replicate human cognitive abilities (Sharifani and Amini, 2023). The advancement of AI has significantly influenced various fields within healthcare, enhancing areas from diagnostics to personalized medicine. The integration of AI is likely to lead to notable advancements in various aspects of periodontology, including diagnosis, treatment planning, and patient management (Scott et al., 2023). In the last ten years, AI, particularly deep learning (DL) and machine learning (ML) has emerged as a transformative tool for precision and efficiency in diagnosing and managing periodontal diseases (Pitchika et al., 2024). Periodontal diseases are generally initiated as gingival inflammation by a host response to oral microorganisms colonizing the subgingival area and might lead to periodontal tissue destruction (Löe et al., 1965; Tonetti et al., 2018). Plaque-induced gingivitis may exhibit various patterns of observable signs and symptoms of inflammation localized to the gingiva and initiated by accumulating a microbial biofilm on teeth. Gingival inflammation is considered a prerequisite for the subsequent development of periodontitis and progressive attachment loss around teeth. Management of gingivitis is a key preventive strategy for periodontitis (Murakami et al., 2018). Periodontology focuses on the prevention, diagnosis, and treatment of periodontal diseases. It is a complex field that requires precise clinical decision. Periodontal assessments have been reliant on the clinician's experience and clinical examinations, which have often been supplemented by radiographic evaluations. However, the advent of AI has introduced a more data-driven approach, whereby algorithms are used to analyze large datasets and generate insights that can enhance clinical decision-making.

Most AI research in periodontics focuses on diagnosing, staging and grading periodontitis using radiographic images, based on the 2017 classification (Tonetti et al., 2018). However, identifying gingival inflammation and gingivitis, which are early and reversible signs of periodontal disease, is also critical (Löe et al., 1965). Besides, it is equally crucial to identify dental biofilm, the primary cause of gingivitis, to effectively manage and prevent the progression of periodontal diseases. These early detections are essential for preventive dentistry, emphasizing the importance of early intervention to prevent more severe periodontal diseases (Löe and Silness, 1963). Nowadays, teledentistry has become an effective way to interact remotely with patients to provide dental consultations and instructions to reach patients who would otherwise not have access to dental care (such as in rural areas, patients in nursing facilities, or during a pandemic). As these applications grow in popularity, digital images have also become increasingly vital for monitoring and facilitating diagnosis and treatment planning for patients. Over the past 10 years, research on detecting periodontal structures and oral disease and conditions through intraoral photographs has evolved significantly. Initially leveraging machine learning techniques, these studies have advanced with the development of deeper AI algorithms, mainly through the adoption of sophisticated deep learning models.

The aim of this review is to summarize research using intraoral photographs in periodontics, outline advancements, and highlight future research directions in this field.

2. Review

The focused question used for the current review was "What is the effectiveness of AI-enhanced intra-oral photograph analysis in periodontics?" The secondary questions focused on identifying the methodologies employed in these studies for dataset creation, model development, training, testing, and performance reporting. Additionally, in instances where the models were evaluated against human performance, the questions sought to determine which metrics were used for comparison and what the resulting outcomes were.

A detailed search was conducted using a range of databases, including PubMed, Scopus, Google Scholar and IEEE Xplore, using the keywords according to Boolean search strategy "Periodontics" AND "Artificial Intelligence" OR "Machine Learning", "Periodontitis" OR "Gingivitis" OR "Gingiva" AND "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" AND "intraoral photograph", "Deep Learning OR ML AND dental plaque AND intraoral imaging", "Artificial Intelligence" AND "intraoral photograph" OR "dental image" and demonstrated in Table 1. The publication period was set at 20 years. This review included original articles, clinical trials and conference proceedings that utilized AI and intraoral images for periodontal diagnosis and detection of periodontal tissues or dental plaque, as well as study designs in which AI was used as the independent variable. Studies published in languages other than English, studies utilizing software other than AI-based tools, and studies employing AI for purposes other than periodontology or not evaluated with intraoral images were excluded from the review.

Table 1. Description of included studies

Study	Year	Brief Description	Image Total	ML Architecture	Performance Comparison	CNN Performance Comment
Alalharith	2020	An evaluation of the effectiveness of deep learning based CNNs for the pre-emptive detection and diagnosis of periodontal disease and gingivitis by using intraoral images.	134	Faster R-CNN	Previously published outcomes	Faster R-CNN had 77.12% accuracy to detect inflammation.
Andrade	2023	Assessed the U-Net neural network's ability to detect dental biofilm on tooth images automatically.	480	U-Net	Not comparative	The U-Net model achieved an accuracy of 91.8%. The accuracy was higher in the presence of orthodontic appliances (92.6%).
Aykol-Sahin	2024	Assessed different CNNs in deep learning algorithms to detect keratinized gingiva based on intraoral photos and evaluated the ability of networks to measure keratinized gingiva width.	600	Res-Net 50, Mobilenettv2, ResNet 18, UNet	Periodontists	Among the compared networks, ResNet50 distinguished keratinized gingiva at the highest accuracy rate of 91.4%. The measurements between deep learning and clinicians were in excellent agreement according to jaw and phenotype.
Chau	2023	An assessment of a novel AI system to detect gingivitis from intraoral photographs	567	DeepLabv3+built on Keras (v2.12,GoogleLLC) with Tensor Flow2	Dentist	The accuracy of this method was above 90% in diagnosing gingivitis

Table 1. Description of included studies (continue)

Study	Year	Brief Description	Image Total	ML Architecture	Performance Comparison	CNN Performance Comment
Chen	2020	Visual recognition of gingivitis testing a novel ANN for binary classification exercise—gingivitis or healthy.	180	ANN (no description)	Not comparative	ANN accuracy of 75% for presence of gingivitis from photographs.
Joo	2019	Descriptive analysis of preliminary data for imaging analysis concepts, employing a method that confirms the presence of periodontal disease by photographs with a CNN.	451	CNN encoder + 1 dense layer	Not comparative	Reported CNN accuracy of 70–81% for validation data
Khaleel	2021	Assessment of different algorithms' efficacy in recognizing gingival and oral diseases.	120	BAT algorithm, PCA, SOM	Not comparative	BAT method provided 95% accuracy against ground truth
Kurt-Bayrakdar	2023	Evaluated the effectiveness of the deep learning algorithm YOLOv5 in identifying key periodontal conditions such as frenulum attachments, gingival hyperplasia, and gingival inflammation from digital dental photographs.	1296	YOLOv5	Not comparative	In this detection analysis, frenulum accuracy was 71%, gingival hyperplasia accuracy was 56%, and gingival inflammation accuracy was 64%.
Li.GH	2021	Different CNNs trialed for RGB assessment of gingival tissues to assess inflamed gingiva detection on photographs.	110	DeepLabv3+	Not comparative	MobileNetV2 performed in a similar manner to Xception65; however, Mob, was 20× quicker.
Li	2021	CNN was used for gingivitis, its irritants, calculus, and soft deposit detection by photographs.	3932	Multi-Task Learning CNN (FNet, CNet and Lnet)	Not comparative	The model achieved a classification AUC of 87.11% for gingivitis, 80.11% for dental calculus, and 78.57% for soft deposits.
Li	2024	Evaluated deep convolutional neural networks, particularly ResNet and GoogLeNet, using ensemble learning to effectively identify gingivitis from intraoral images.	683	ResNet and GoogLeNet	Not comparative	Among the four models, the ResNet and GoogLeNet models performed well with high recognition accuracy. GoogLeNet detected gingivitis from oral images, achieving the highest diagnostic accuracy, 97%.
Moriyama	2019	CNN was used to establish if there is a correlation between pocket depth probing and images of the diseased area.	820	AlexNet with GAN-based augmentation	Not comparative	Changes in ROC curves significantly affected outcomes. The sensitivity was 74.0%, and the specificity was 88.7%.
Rana	2017	The machine learning classifier provided pixel-wise inflammation segmentations for the gingival index scores from photographs of color-augmented intraoral images.	405	CNN Autoencoder	Not comparative	AU ROC curve of 0.746 for classifier to distinguish between inflamed and healthy gingiva.
Shang	2021	Comparison of U-Net vs. comparison between U-Net and DeepLabv3/PSPNet architecture for image recognition on intraoral photos for wear, decay, calculus, and gingivitis.	7220	U-Net	Dentists	U-Net to have a 10% increased recognition of calculus, wear facets, gingivitis, and decay
You	2020	CNN used to assess plaque presence in primary teeth	886	DeepLabv3+	Orthodontists	MIoU of the AI model was 72%. No statistically significant difference in the ability to discern plaque on photographs compared to clinician.
Yüksel	2024	Evaluated deep learning to diagnose dental plaque from photographs of permanent teeth.	168	DeepLabv3+	Dentist	DeepLabv3+ detected dental plaque with 87% accuracy and showed significantly higher performance than the dentist.

The author comprehensively analyzed the titles and abstracts, identifying the most relevant papers aligned with the current topic. Any articles deemed irrelevant were excluded. The full texts were then reviewed to ascertain their eligibility for studies that met the established inclusion criteria.

3. Results

3.1. Study Selection and Data Compilation

The search strategy led to the identification 338 studies from the selected databases: 140 from Google Scholar, 110 from Pubmed, 68 from Scopus and 20 from IEEE Xplore. 338 records were screened for titles and abstracts, leading to the selection of 21 studies potentially eligible for this systematic review. 5 studies were excluded due to exclusion criteria. These studies were evaluated for eligibility by full-text assessment. The flowchart of the study selection was shown in Figure 1. Finally, 16 articles were included in the analysis. The included articles were evaluated based on a set of predefined criteria, with the key findings summarized in Table 1. A total of ten studies assessed the detection of gingivitis and inflammation, while four studies evaluated dental plaque. Additionally, two studies evaluated calculus. There was one study each evaluating keratinized gingiva, frenulum attachment, gingival hyperplasia, and periodontal pocket.

3.2. Publication Year

Figure 2 illustrates the year in which the studies were published. The first was released in 2017, and the frequency of publication increased over the subsequent seven years, with the exception of 2022.

3.3. ML Architectures

The included studies used a wide range of convolutional architectures (n=16). The most common architectures were different CNN algorithms of DeepLabv3+ series network (n=6). ML architectures of the studies were presented in Table 1.

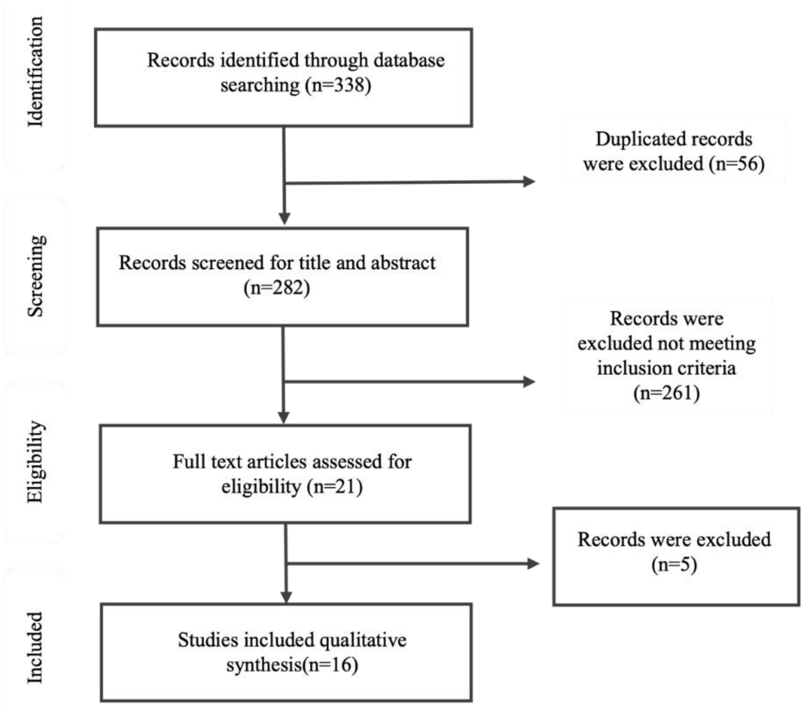

Figure 1. Flow diagram of the review strategy.

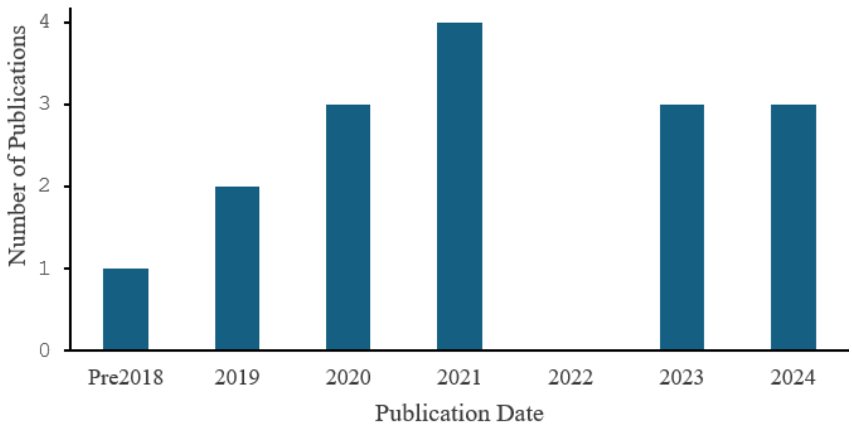

Figure 2. Distribution of publications according to years.

3.4. Datasets and Training

In the context of image data processing, CNNs are designed to emulate human cognitive processes, necessitating a training phase to enable them to perform their intended functions. Datasets for image processing studies ranged from 110 to 7220. The distribution of image dataset numbers was presented in the Figure 3. In the included studies, the majority of labeling methods involved manually annotating by drawing or labelling the external pixels of the desired features.

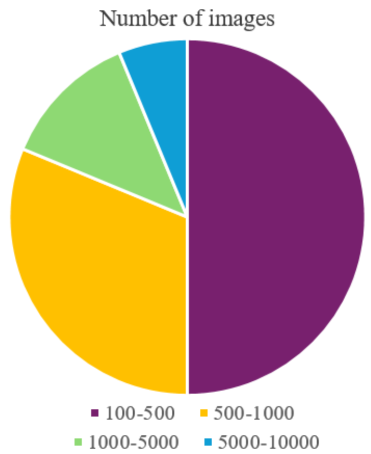

Figure 3. Numbers of images used in training datasets.

4. Discussion

Machine learning, a subfield of artificial intelligence, entails the construction of statistical models for the classification of data or images and the prediction of risks or outcomes (Sharifani and Amini, 2023). This is achieved through the utilization of techniques such as regression, k-nearest neighbours, decision trees, random forests, support vector machines (Sharifani and Amini, 2023). In essence, ML is a field of study that aims to enable computers to recognize patterns and make decisions based on data. Machine learning can be classified into supervised and unsupervised learning. In supervised learning, models are developed using training data that includes known outcome labels or classification variables. In contrast, unsupervised learning does not provide models with outcome labels, necessitating the independent identification of structures and patterns within the data (Pitchika et al., 2024). Irrespective of the approach employed, the trained model is validated using an independent dataset, and its performance is evaluated with metrics such as sensitivity, specificity, accuracy, balanced accuracy, and F1-score (the harmonic mean of precision and recall), among others (Hicks et al., 2022). Deep learning, a subset of ML, employs algorithms inspired by the structure and function of the human brain, namely artificial neural networks (ANNs). These consist of interconnected neurons capable of processing information and learning from data. CNNs, a subclass of DL models, are particularly adept at analyzing complex image modalities (Pitchika et al., 2024). This is achieved by employing convolutional layers to process data in small, overlapping sections, thereby enabling the recognition of local patterns within an image (Huang et al., 2023). While few of the included studies (Joo et al., 2019; Chen and Chen, 2020; Khaleel and Aziz, 2021) used unsupervised learning, supervised learning where models are trained on labeled datasets was opted in most studies. These labels assist the algorithm in identifying the patterns associated with specific outputs. Chen and Chen (2020) used unsupervised learning algorithms (Gray-Level Co-occurrence Matrix, Artificial Neural Network and Genetic Algorithm) for detecting gingivitis. They added Genetic algorithm to solve the binary classification problem in their previous studies. Their accuracy improved to 75% from 68%. Another unsupervised learning study was by Khaleel and Aziz (2021). Unlike Chen and Chen (2020) which distinguished the health gingiva and gingivitis, Khaleel and Aziz (2021) assessed recognizing different gingival and oral diseases. They used the BAT algorithm with a self-organization feature map. With this method, they detected different gingival and oral diseases with 95% accuracy against ground truth. On the other hand, while slower and more resource-intensive, labeling provides high-quality data crucial for training accurate supervised learning models (Peng and Wang, 2021). Labeling involves manually or automatically assigning labels to data points so that a machine learning algorithm can learn to predict these labels from the features of the data. It is particularly effective when high diagnostic precision is required. In practice, a hybrid approach that combines automated methods for initial analysis and data reduction, followed by expert-driven labeling for final model training, could potentially offer a balance between efficiency and accuracy (Das et al., 2017). Alalharith et al. (2020) indicated that they utilized Padilla and Silva's implementation, which compares the ground truths to the model's detections to evaluate the object detection model accurately and unbiasedly for the detection of early signs of gingivitis. They reported that their model has achieved an accuracy that is 10% higher than that of models using traditional machine learning methods, thus proving the current technique to be more advantageous than traditional methods. Unlike traditional machine learning techniques, deep CNN algorithms have the capability to efficiently learn representations and extract features that may hold great predictive capabilities due to their deep multi-layer architecture (Alalharith et al., 2020). Rana et al. (2017) used a machine learning classifier, CNN-encoder, to provide pixel-wise inflammation segmentations for the gingival index scores from photographs of color-augmented intraoral images and compared the results with dentists. Three dentists validated the classifier segmentation and the agreement between the experts and the classifier. CNN-encoder can learn from unlabeled data, making them useful when explicit annotations are scarce or expensive to obtain. However, while they can generalize well, this is contingent on having a diverse training dataset that captures all variations of gingivitis. CNNs recognize and segment the images, and to capture local patterns, they utilize filters such as edges, shapes, and textures in images. The ability of these networks to learn such features layer by layer (moving from simple to complex structures) is fundamental to their success (Huang et al., 2023).

DeepLabv3+ is used for semantic image segmentation, which is critical for accurately delineating object boundaries. DeepLabv3+ employs atrous convolutions to capture multi-scale context, which involves recognizing local and broader patterns to improve segmentation accuracy (Chen et al., 2018). In the included studies, the most common architectures were different CNN algorithms of the DeepLabv3+ series network (You et al., 2020; Li et al., 2021; Chau et al., 2023; Aykol-Sahin et al., 2024; Li et al., 2024; Yüksel et al., 2024). If the goal is simultaneously identifying gingivitis while also recognizing related conditions like dental calculus or plaque levels, CNNs with Multi-task Learning present advantages. Li et al. (2021) used Multi-task CNN to detect gingivitis and its irritants, calculus, and soft deposits. It achieved a classification AUC of 87.11 for gingivitis, 80.11% for dental calculus, and 78.57% for soft deposits (Li et al., 2021). Shang et al. (2021) used U-Net to detect wear, decay, calculus, and gingivitis from intraoral photos. U-Net recognized calculus, wear facets, gingivitis, and decay 10% more effectively than DeepLabv3/PSPNet architecture, with an average mIou of 50.41% (Shang et al., 2021). On the other hand, Kurt-Bayrakdar et al. (2023) assessed the detection of different gingival diseases and anatomical structures using a different CNN model, YOYOv5. YOYOv5 is fine-tuned for high accuracy across various object detection tasks. They found the frenulum accuracy was 71%, gingival hyperplasia accuracy was 56%, and gingival inflammation accuracy was 64%. Unlike Shang et al. (2021), Andrade et al. (2023) had higher accuracy at 91.8%, in detecting dental biofilm using U-Net. Due to its specialization in segmentation, U-Net is likely more suited to detect and precisely delineate one specific situation in dental images. YOLOv5 would be more advantageous in scenarios requiring broader object detection within dental photos, such as quickly identifying various conditions or anomalies within a broader diagnostic context. DeepLabv3+ and U-Net are both strong in segmentation tasks. DeepLabv3+ is optimized for more generalized tasks, with its atrous convolution allowing an adaptable field of view, making it suitable for varied image resolutions. U-Net, with its specific design for medical segmentation, might provide better results in medical contexts where high precision in small-scale segmentation is required. Yüksel et al. (2024) evaluated DeepLabv3+ to diagnose dental plaque from photographs of permanent teeth. DeepLabv3+ detected dental plaque with 87% accuracy and showed significantly higher performance than the dentist. Aykol-Sahin et al. (2024) compared the efficiency of different CNN models in distinguishing keratinized gingiva from nonkeratinized gingiva. Among the compared networks, ResNet50 with the DeepLabv3+ architecture distinguished keratinized gingiva at the highest accuracy rate of 91.4%. However, U-Net showed the lowest accuracy value compared to other DeepLabv3+ models. They also evaluated the efficiency of measuring keratinized tissue wide from the results of ResNet50 and compared it with two clinicians. The measurements between deep learning and clinicians agreed according to jaw and phenotype. Chau et al. (2023) assessed a novel AI system, DeepLabv3+built on Keras with Tensor Flow2 to detect gingivitis from intraoral photographs. The accuracy of this method was above 90% in diagnosing gingivitis. The novel AI system was able to identify specific sites with and without gingival inflammation with sensitivity and specificity that was almost on par with human dentists.

Datasets for image processing studies in the present review ranged from 110 to 7220. The amount of data directly influences a model's ability to generalize well to new, unseen data. With insufficient data, models are more prone to overfitting, where they perform well on training data but poorly on any new data. A larger dataset provides a more diverse range of examples from which the model can learn, allowing it to capture a wide array of features and nuances that might be missed with a smaller dataset (Kufel et al., 2023). Augmentation models are typically effective in making datasets larger and more varied for training robust machine learning models (Sharifani and Amini, 2023). Five studies in the current review used augmentation methods in their study (Moriyama et al., 2019; Li et al., 2021; Andrade et al., 2023; Aykol-Sahin et al., 2024; Li et al., 2024). In their study, Chen and Chen (2020) stated their intention to collect a larger number of images of gingivitis and employ data augmentation techniques to construct a valid dataset for future studies. Furthermore, Joo et al. identified the overfitting problem as a limitation, noting that additional data or the application of data augmentation and data regularization techniques not utilized in their paper would be beneficial in addressing this issue. Moriyama et al. (2019) presented an approach to enhancing the accuracy of periodontal pocket detection by utilizing a MapReduce-like model integrated with advanced neural network techniques. This approach, specifically tailored to estimate pocket depth from enhanced pocket region images, improved the estimation accuracy from 78.3% to 84.5% and sensitivity from 50.4% to 74.0%, with a specificity of around 90%, compared to the MapReduce-like model without the augmentation.

The integration of AI in periodontology offers significant potential to improve clinical practice by enhancing early detection and diagnostic accuracy. However, successful implementation requires addressing several practical considerations, such as training clinicians to effectively interpret AI insights and integrating AI tools into existing workflows without disruption. Challenges include ensuring data quality, addressing regulatory and ethical concerns, managing costs, and facilitating clinician acceptance and adaptation.

Limitations of this review may include a limited focus on specific AI techniques or applications, potentially overlooking other relevant AI advances or methods in periodontology. The review may have relied on a few studies with varying dataset sizes and quality, which may affect the generalizability of findings and the effectiveness of AI models. In addition, potential biases in AI models and their impact on diagnostic accuracy may not be fully addressed, affecting the reliability of AI systems in different patient populations.

5. Conclusion

The application of artificial intelligence has the potential to significantly enhance periodontics and preventive dentistry, particularly through the analysis of intraoral photographs, which could facilitate more accurate detection and decision-making. Selecting the appropriate deep learning model, such as CNNs for spatial analysis or U-Net for precise segmentation, is critical to effectively interpreting dental images. Training these models on diverse datasets that include various dental conditions might ensure better generalization and diagnostic accuracy. Integrating these technologies into clinical workflows might enhance usability for dental professionals, allowing them to apply AI insights in patient care easily.

Author Contributions

The percentage of the author(s) contributions is presented below. All author(s) reviewed and approved the final version of the manuscript.

	G.A.Ş.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declare that there is no conflict of interest.

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