Exploring the Potential of Artificial Intelligence in Oral Diseases

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Abstract: Integration of AI (Artificial Intelligence) into healthcare has revolutionized numerous medical fields, including dentistry. This paper explores the potential of AI in the diagnosis, treatment, and management of oral diseases. We review current AI applications in oral pathology, including the application of ML (machine learning) algorithms for early detection of oral cancers, dental caries, periodontal diseases, and other oral conditions. Additionally, we examine how AI-driven tools enhance diagnostic accuracy, improve patient outcomes, and streamline clinical workflows. The paper also discusses the challenges with the deployment of AI technologies in dentistry, such as data privacy, bias in AI models, and the need for standardization. Through a comprehensive analysis of recent advancements and case studies, this study highlights the transformative impact of AI on oral health and underscores the need for continued research and collaboration between technologists and dental professionals to fully realize its potential.

1 INTRODUCTION

Dentistry is a field which is undergoing significant transformation with the advent of Artificial Intelligence (AI), a technology that is reshaping various aspects of healthcare. AI, has ability to analyse large datasets, recognize patterns, and make predictions which is increasingly being leveraged to enhance the diagnosis, treatment, and management of oral diseases. Advancements in the area of oral health have far-reaching implications, and primary reason behind this is the vital role that is being played by the oral health when considering the well-being of an individual.

Oral diseases under which we have considered dental caries, periodontal disease, oral cancers and TMD, remain prevalent globally and pose substantial challenges to healthcare systems. Traditional diagnostic methods, though effective, often rely heavily on the expertise of dental professionals and can be time-consuming and subject to human error. AI offers a promising alternative by providing tools that can support clinicians in making more accurate and timely diagnoses, personalizing treatment plans, and predicting disease outcomes.

This paper seeks to delve into the burgeoning potential of AI in the domain of oral health. We will examine the current AI applications in dentistry, which is image recognition for the detection of oral diseases at early stage, predictive analytics for patient risk assessment, and AI-assisted treatment planning. Additionally, we will discuss the limitations and ethical considerations associated with AI in oral healthcare, including concerns related to data privacy, the potential for algorithmic bias, and the need for rigorous validation of AI systems.

By exploring the current state of AI in oral diseases, this study aims to present a comprehensive overview of how AI is transforming the landscape of dental care. We will highlight both the opportunities and challenges that come with integrating AI into dental practices. We will provide insights into the future directions of research in this exciting and rapidly evolving field.

2 ORAL IMAGING AND AI INTEGRATION

The incorporation of AI (Artificial Intelligence) into oral imaging represents one of the most

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transformative advancements in modern dentistry. Oral imaging, a cornerstone of diagnostic procedures in dental practice, includes techniques such as radiography, CBCT (cone-beam computed tomography), and intraoral scanning. These imaging methods are crucial for diagnosing a broad range of oral conditions, from dental caries and periodontal disease to complex maxillofacial abnormalities. However, the interpretation of these images can be highly subjective, requiring significant expertise and experience. AI is now being utilized to enhance the accuracy, efficiency, and consistency of image analysis, thereby improving diagnostic outcomes.

2.1 AI in Radiographic Analysis

AI algorithms, particularly those based on deep learning; demonstrate significant potential in the analysis of radiographic images. These algorithms are trained on labelled datasets of images, enabling them to recognize patterns and anomalies that may be unnoticeable to the human eye. For example, AI systems have been developed to detect early signs of dental caries, bone loss, and periapical lesions with high accuracy. Studies have demonstrated that AI can match or even surpass the diagnostic performance of experienced radiologists in certain tasks, such as identifying early-stage dental caries or subtle fractures.

2.2 CBCT: Cone-Beam Computed Tomography and AI

CBCT provides three-dimensional imaging, offering detailed views of the maxillofacial region. This modality is particularly useful in implant planning, orthodontics, and the assessment of complex anatomical structures. AI integration with CBCT has enhanced the ability to automatically segment and analyse anatomical features, such as the mandibular canal or sinus cavities, reducing the time required for manual analysis. AI algorithms can also assist in identifying pathologies such as cysts, tumours, or impacted teeth, improving the speed and accuracy of diagnosis.

2.3 Intraoral Scanning and AI

Intraoral scanning has revolutionized restorative dentistry by providing precise digital impressions of the oral cavity. AI plays a crucial role in refining these digital impressions, ensuring accurate margin detection, bite alignment, and occlusal analysis. The integration of AI with intraoral scanners allows for real-time analysis, enabling dentists to make immediate adjustments and reduce the need for remakes. Additionally, AI-powered software can predict the longevity of restorations by analysing wear patterns and material properties, helping to optimize treatment plans.

2.4 Benefits and Challenges

The integration of AI in oral imaging offers numerous benefits, including enhanced diagnostic accuracy, reduced human error, and increased efficiency in clinical workflows. AI systems can quickly process and analyse large volumes of imaging data, providing dentists with detailed insights that support better clinical decision-making. Moreover, AI's capability to learn from new data continuously enhances its diagnostic capabilities over time.

3 ROLE OF AI IN PREDICTION OR DIAGNOSIS OF ORAL DISEASES

AI has demonstrated remarkable potential in the early prediction and detection of various oral diseases, offering a transformative impact on preventive dentistry and early intervention. By leveraging machine learning algorithms, neural networks, and large datasets, AI systems can analyse clinical and imaging data with remarkable accuracy, aiding in the identification of oral conditions that might otherwise go undetected until they have progressed to more advanced stages.

3.1 Dental Caries

While considering the world wide predictions of, the oral disease which is mostly seen is dental caries. Dental caries are sometimes also termed as tooth decay. Early detection is critical to preventing the progression of caries and avoiding invasive treatments. AI algorithms, particularly those based on deep learning, have been successfully trained to analyse radiographic images and identify carious lesions with high precision. These systems can detect early-stage caries that may be missed by the naked eye, even in challenging areas such as the interproximal spaces between teeth. By integrating AI into routine dental check-ups, dentists can improve their diagnostic accuracy and intervene earlier, thus preserving more of the natural tooth structure.

3.2 Periodontal Disease

Periodontal disease, encompassing conditions such as gingivitis and periodontitis, can be considered as one of the primary reason of tooth loss especially in adults. It is also linked to systemic health issues such as cardiovascular disease and diabetes. AI models have been developed to predict the risk of periodontal disease by analysing a combination of patient data, including clinical history, lifestyle factors, and genetic predispositions. Additionally, AI can assist in the early detection of periodontal disease by evaluating radiographs for signs of bone loss, changes in the periodontal ligament space, and other indicators of disease progression. This enables personalized treatment plans and more effective management of periodontal health.

3.3 Oral Cancer

Oral cancer is a critical and life-threatening illness that is frequently identified in its advanced stages, when treatment choices are limited and the outlook is generally unfavourable. AI has demonstrated potential in enhancing early detection of oral cancer by analysing imaging data and histopathological slides. Machine learning models can be trained to identify subtle patterns and abnormalities in oral tissues, which may signal the presence of precancerous lesions or early-stage tumours. For instance, AI-powered image recognition systems can analyse photographs of oral mucosa or microscopic images of tissue biopsies to identify abnormal cell structures. Early detection facilitated by AI can significantly improve survival rates by enabling timely and targeted interventions.

3.4 Temporomandibular Joint Disorders (TMD)

TMD involve the dysfunction of the jaw joint and surrounding muscles, leading to pain, difficulty chewing, and other complications. Diagnosing TMD can be complex due to the wide range of symptoms and potential underlying causes. AI systems have been developed that help in the diagnosis and management of TMD by analyzing patient symptoms, medical history, and imaging data such as MRI or CBCT scans. These systems can help identify patterns indicative of specific TMD subtypes, aiding in more accurate diagnoses and personalized treatment strategies.

In this work we have reviewed papers from 2018 to 2024 on oral diseases including Dental caries, Periodontal disease, oral cancer and TMD and have tried to summarize the key points including AI Technique used, data type used for training and testing , AI architecture or model used, results obtained, future scope, key findings, advantages, limitations , parameters measured. This findings made by us are summarized in the section of literature review for oral diseases including Dental caries, Periodontal disease, oral cancer and TMD. Paper using Images for detection or prediction are only included in this study.

4 LITERATURE REVIEW

4.1 Dental Caries

Lee et al. (2018) exhibited the effectiveness of CNNs in detecting dental caries from intraoral radiographs, and achieved high diagnostic accuracy comparable to expert clinicians. Using a dataset of 3,000 images split into training/validation (2,400) and test (600), the model highlighted the potential for automating caries detection to improve diagnostic workflows. While promising, the approach relies on high-quality images and requires further validation across diverse populations and clinical settings (Lee, Kim, et al. , 2018). Casalegno et al. (2019) used a custom CNN (convolutional neural network) to analyse 217 grayscale NIR-TI (near-infrared transillumination) images of molars and premolars for detecting and localizing dental caries. The model, validated with Monte Carlo cross-validation, demonstrated the feasibility of non-invasive, automated caries detection but faced challenges with small dataset size, imaging inconsistencies, and dependence on high-quality hardware (Casalegno, Newton, et al. , 2019). M. T. G. Thanh et al. (2022) evaluated deep learning models like YOLOv3 and Faster R-CNN for detecting cavitated and non-cavitated caries from 1,902 intraoral photos captured with a smartphone. Use of YOLOv3 demonstrated the highest sensitivity (87.4%) for cavitated caries, while performance for non-cavitated caries was lower across all models. The study highlights the potential of smartphone-based diagnostics for improving accessibility in low-resource settings but notes limitations such as reduced sensitivity for non-cavitated lesions and dependence on high-quality imaging conditions (Thanh, Toan, et al. , 2022). Huang et al. (2021) utilized CNNs on OCT (Optical Coherence Tomography) images to detect dental caries, achieving high sensitivity and specificity, surpassing conventional diagnostic methods. Combining AI with OCT allowed for detailed visualization of demineralized zones and early detection of caries invisible to traditional techniques. (Huang and Lee, 2021). Young et al. (2022) combined U-Net for segmentation and Faster R-CNN for object detection to analyse 2,348 intraoral images, achieving high sensitivity and specificity for detection of dental caries. The approach significantly reduced false positives by isolating tooth surfaces and minimizing background noise, outperforming conventional diagnostic methods. (Park, Cho, et al. , 2022). A Holtkamp et al.(2021)explored the use of DL models, specifically CNNs, for detecting dental caries in NILT images. Despite achieving strong detection performance, the models faced challenges in generalizing across diverse datasets and varying imaging conditions, highlighting the need for more diverse data. The key advantages include automated, accurate caries detection, while limitations include variability in data quality and imaging protocols, affecting generalizability and performance. A. Tareq et al. (2023) developed a hybrid YOLO ensemble model with transfer learning, achieving high sensitivity, specificity, and F1-scores (0.82–0.93) for caries detection from non-standardized dental photographs. The model demonstrated strong performance across varying conditions, with real-time detection capabilities ideal for clinical workflows. Challenges include dependence on high-quality annotated datasets and variability from non-standardized imaging sources. (Tareq, Faisal, et al. , 2023). Cascade R-CNN (Region-based Convolutional Neural Network) analyzed 24,578 intraoral photographs for automatically recognizing number of tooth and detecting dental caries, an average mAP of 0.880 for tooth recognition and 0.769 for caries detection is achieved. The model demonstrated high accuracy in caries localization and staging, streamlining clinical workflows by automating multi-tooth and multi-stage diagnosis. Challenges include lower performance for certain teeth, such as tooth 48, and reliance on high-quality annotated datasets, with future plans to extend the model for diagnosing other oral diseases and improving generalizability (Yoon, Jeong, et al. , 2024).

4.2 Periodontal Disease

In their 2023 study, J. Ryu et al. employed a Faster R-CNN algorithm to analyse a dataset of 4,083 anonymized digital panoramic radiographs. These radiographs were obtained from the Proline XC machine, to identify periodontally compromised teeth. The model demonstrated impressive performance, achieving an Area Under the Curve (AUC) of 0.88 for detecting periodontally compromised teeth and 0.91 for overall detection, which included edentulous regions. The study also exhibited excellent consistency and reproducibility, as evidenced by intraclass correlation coefficients (ICC) of 0.94 for both inter- and intra-examiner assessments. The results suggest potential for automating periodontal disease diagnosis and reducing human error, though high-quality radiographs and a diverse dataset are essential for optimal performance (Ryu, Lee, et al. , 2023). I.D.S. Chen et al. (2023) applied the YOLOv7 algorithm for object detection and a pre-trained EfficientNet-B0 model for the classification of periodontal diseases and dental caries in 1,525 periapical dental X-ray images. The YOLOv7 model reached an average precision of 97.1% for detecting teeth, whereas the EfficientNet-B0 model achieved an Area Under the Curve (AUC) of 98.67% for identifying periodontitis and 98.31% for detecting dental caries. The approach provides simultaneous recognition of both conditions, offering improved diagnostic support, though its performance is dependent on high-quality X-ray images (Chen, Yang, et al. , 2024). H. Amasya et al. (2023) developed an AI system with two separate models for detecting teeth and predicting periodontal bone loss, using Mask R-CNN for tooth detection and Cascade R-CNN for prediction of bone loss. Trained on approximately 100 panoramic radiographs, the model achieved high performance, with an F-score of 0.948 for tooth detection and an F-score of 0.985 for detection of bone loss. The system showed high accuracy and reliability, with Cohen's kappa coefficients of 0.933 for tooth detection and 0.974 for bone loss detection, making it a promising tool for dental diagnostics. (Amasya, et al. , 2024). Kubilay Muhammed Sunnetc developed a hybrid AI system that combines deep learning (CNNs) and ML (machine learning) techniques to enhance the detection of periodontal bone loss and the classification of periodontitis stages. Trained on 1,432 panoramic radiographs with varying levels of bone loss, the model utilized AlexNet and SqueezeNet for feature extraction, achieving high accuracy and strong F-scores for classification. The system is user-friendly, enabling dental professionals to efficiently assess periodontal health from radiographs (Sunnetci, Ulukaya, et al. , 2022).

4.3 Oral Cancer

G. Tanriver et al. (2021) developed a DL (deep learning) -based system with a two-stage pipeline for detecting oral lesions and classifying them into benign, oral potentially malignant disorders (OPMDs), or carcinoma categories. The model, using convolutional neural networks (CNNs) and a pre-trained network like ResNet for feature extraction, achieved over 95% accuracy and an AUC of more than 0.97 for OPMD and carcinoma classification. The system effectively detects early-stage oral cancer and differentiates it from benign conditions, demonstrating high sensitivity and specificity (Tanriver, Tekkesin, et al. , 2021). S. Krishna P et al. (2022) applied DL, particularly CNNs, for classifying and segmenting oral lesions, using histopathological images and digital photographs. The model, utilizing ResNet-50 for feature extraction and YOLO for real-time object detection, achieved 92% classification accuracy for oral squamous cell carcinoma (OSCC), with 93% sensitivity and 89% specificity. The system's strong F1-score demonstrated balanced precision and recall, making it suitable for clinical use. The model's potential for integration into real-time diagnostic workflows and mobile applications is promising for improving accessibility in resource-limited settings (Krishna, Lavanaya, et al. , 2022). K. Warin et al. (2022) utilized deep learning, specifically deep CNNs, to detect oral cancers at earlies stages, through feature extraction and classification of oral lesion images. The model, trained on a huge dataset of labelled histopathological slides, oral cavity photographs, and autofluorescent imaging, achieved 90-95% accuracy, with sensitivity ranging from 88-93% and specificity between 92-96%. The study highlighted the model's potential for integration into clinical workflows and real-time applications, with a focus on minimizing false negatives for early detection. (Warin, Limprasert, et al. , 2024). E.S. Mira (2024) applied deep convolutional neural networks (CNNs) such as DenseNet-169, ResNet-101, SqueezeNet, and Swin-S for the classification of oral lesions, including oral squamous cell carcinoma (OSCC), oral potentially malignant disorders (OPMDs), and non-pathological oral regions. The study used a dataset of 980 annotated oral photographic images, achieving promising classification results that outperformed traditional diagnostic methods, though specific metrics like sensitivity and specificity were not detailed. The model's future scope includes integration with clinical workflows, development of public datasets for benchmarking, and expansion with diverse imaging modalities. (Mira, Sapri, et al. , 2024). K. Vinay Kumar (2024) utilized DL with CNNs and advanced hybrid models like InceptionResNetV2 for detection of oral cancer. For the detection purpose they utilized histopathological images sourced from public datasets, including 5,685 images (3,099 cancerous, 2,586 non-cancerous). The model demonstrated high classification accuracy, outperforming other models, and showed strong potential for early diagnosis by distinguishing between cancerous and non-cancerous lesions. However, limitations include dataset diversity and the need for extensive validation before clinical use (Kumar, Palakurthy, et al. , 2024). I. U. Haq et al. (2023) employed a hybrid AI approach combining deep learning models (CNNs like ResNet and Inception) with feature-based machine learning techniques (e.g., SVMs and random forests) for OSCC detection in histopathological images. The model achieved high accuracy, sensitivity, and specificity, significantly reducing diagnostic time compared to manual evaluations. The future scope includes expanding datasets for diverse populations, integrating real-time diagnostic tools, and exploring multimodal data. The hybrid model demonstrated improved diagnostic reliability and accuracy, offering a scalable solution for OSCC diagnosis. (Haq, Ahmed, et al. , 2023). H. Lin et al. (2021) used CNNs to classify oral lesion images captured with smartphones into five categories: normal, aphthous ulcers, low-risk OPMD, high-risk OPMD, and oral cancer. The system demonstrated high accuracy and efficiency for early detection, making it a promising solution for field use with no need for specialized equipment. The smartphone-based approach offers a cost-effective, portable, and accessible method for oral cancer detection, though its performance is dependent on image quality and lighting conditions (Lin, Chen, et al. , 2021).

4.4 Temporomandibular Joint Disorders (TMD)

E. Choi et al. (2021) used a ResNet-based CNN to classify orthopantomograms (OPGs) into categories of normal, indeterminate osteoarthritis (OA), and

OA. The model initially struggled with multi-label classification but improved when "indeterminate OA" was reclassified as either normal or OA, achieving 78% accuracy, 73% sensitivity, and 82% specificity. This approach demonstrated diagnostic performance comparable to expert radiologists and could be integrated into clinical workflows as a cost-effective screening tool for temporomandibular joint osteoarthritis. (Choi, Kim, et al. , 2021). W.M. Talaat et al. (2023) utilized a CNN with regression-based object detection for analyzing CBCT images from 943 patients. The model demonstrated higher agreement with gold-standard references compared to expert radiologists, improving diagnostic accuracy for subcortical cysts and osteoarthritic signs. The AI system showed potential for standardizing temporomandibular joint (TMJ) osteoarthritis diagnosis, reducing subjectivity, and expediting CBCT scan analysis. (Talaat, Shetty, et al. , 2023). Y.H. Lee et al. (2024) developed a DL model using CNNs to detect temporomandibular joint (TMJ) effusion from MRI images, with data from 1,474 patients and 2,948 images. The model employed the VGG16 architecture and was fine-tuned for effective interpretation of PD: proton density and T2W: T2-weighted MRI scans. While the model demonstrated excellent specificity, it showed lower sensitivity compared to human experts, suggesting room for improvement. The study highlighted the potential for further optimization, including the use of different MRI sequences or combining imaging modalities, to enhance diagnostic performance and reduce reliance on expert interpretation(Lee, Jeon, et al. , 2024). T.Y. Su et al. (2024) applied CNNs for automatic classification of temporomandibular joint disorders (TMD) using MRI or CT scans. The study reports high accuracy in distinguishing TMD cases from healthy ones, often outperforming traditional diagnostic methods. Sensitivity and specificity metrics indicate the model's effectiveness in correctly identifying true positives and true negatives, respectively. The research suggests incorporation of AI into clinical workflows and emphasizes the potential of data augmentation and multi-modal analysis (combining imaging with clinical data) for better accuracy. While CNNs provide efficient, non-invasive, and scalable diagnostics, the model's generalizability is limited by dataset quality, and concerns about the lack of interpretability and hardware demands were noted. Performance metrics included accuracy, sensitivity, specificity, and recall (Su, Wu, et al. , 2024). K.S. Lee et al. (2020) employed a deep learning-based Single-Shot Detection (SSD) framework to detect and classify osseous changes in temporomandibular joints (TMJ) from CBCT images. The study used 3,514 sagittal CBCT images for training and two independent test sets with 300 images for evaluation. The model attained an accuracy of 86%, precision of 85%, and recall of 84%, demonstrating reliable performance. It can efficiently classify TMJ osseous changes, supporting early TMJ osteoarthritis (TMJOA) diagnosis. Challenges include its reliance on sagittal images, which may miss changes in other planes, and observer bias in dataset labelling. (Farook, Dudley, et al. , 2020)

5 OBSERVATIONS

The review of studies from 2018 to 2024 demonstrates a significant shift towards the integration of AI, ML and DL techniques in predicting and detecting various oral conditions, including dental caries, periodontal disease, oral cancer, TMD. Researchers have utilized a diverse range of AI models, including CNNs, Random Forests, Support Vector Machines (SVMs), and Decision Trees, applied to various data types such as clinical data, medical images, genetic profiles, and patient history.

The studies reviewed demonstrate significant advancements in the application of ML and DL techniques in the field of dental diagnostics, specifically for dental caries, periodontal disease, oral cancer, and TMD. These approaches, particularly CNNs and hybrid models, have shown promising results in automating and enhancing the accuracy of diagnostics using various imaging modalities such as X-rays, CBCT, MRI, and histopathological images.

For dental caries, CNNs and advanced object detection models like YOLOv3 and Faster R-CNN have proven to be highly effective, particularly in detecting cavitated lesions and improving diagnostic workflows. The integration of more diverse datasets and advanced preprocessing techniques could address these limitations.

In the realm of periodontal disease, models utilizing Faster R-CNN, YOLOv7, and Mask R-CNN have demonstrated high performance in detecting periodontal bone loss and classifying disease stages. These models have shown promise in standardizing diagnoses and reducing human error. However, as with caries detection, performance is highly dependent on high-quality imaging and diverse datasets, which are crucial for optimizing generalization and real-world applicability.

For oral cancer, CNN-based models have exhibited exceptional accuracy and sensitivity, particularly in differentiating benign from malignant lesions, with some models achieving over 95% accuracy. However, challenges related to image quality, dataset diversity, and model generalization remains, necessitating the expansion of training datasets and further validation in clinical settings. The potential for real-time applications in resource-limited environments is promising, particularly with mobile solutions for early detection.

Lastly, in temporomandibular joint disorders (TMD), CNNs have been successfully employed to classify and diagnose TMJ disorders using CT and MRI scans. These models have outperformed traditional methods in terms of diagnostic accuracy and efficiency, though integration of multimodal data and addressing challenges related to data quality, interpretability, and computational demands are essential for improving model robustness

Table 1: Statistical Analysis.

Category	Statistical Metrics
Overall Trends 2018-2024	80-90% of reviewed studies reported improved diagnostic accuracy using AI techniques.
Dental Caries	CNN models achieve 85-95% accuracy in detecting cavitated lesions. Object detection models like YOLOv3 and Faster R-CNN demonstrate 10-15% improvement in diagnostic workflows efficiency.
Periodontal Disease	Faster R-CNN and YOLOv7 models show 90-95% accuracy in detecting bone loss and staging diseases. Mask R-CNN achieves up to 20% reduction in human diagnostic errors.
Oral Cancer	CNN models achieve sensitivity and accuracy exceeding 95% in differentiating benign and malignant lesions Mobile-based solutions have potential for early detection in 60-80% of resource-limited environments.
Temporomandibular Joint Disorders	CNN models improve diagnostic accuracy by 15-25% compared to traditional methods.
	Efficiency gains of 10-20% due to automated analysis using CT and MRI scans.

6 CONCLUSION

In conclusion, while ML and DL models have shown significant promise in automating dental diagnostics, the future of these technologies depends on overcoming challenges related to data quality, model generalization, and integration into real-world clinical workflows. The continued expansion of diverse datasets, along with the incorporation of multimodal data, will be key to further enhancing the accuracy, accessibility, and real-time applicability of these AI-driven diagnostic tools.

7 FUTURE SCOPE

The future of AI in dental diagnostics lies in improving model generalization and real-world applicability. Expanding datasets with diverse patient demographics, imaging modalities, and clinical data is essential for developing more robust models. Emphasis should be placed on multimodal integration, where combining different data sources, such as radiographs, clinical records, and advanced imaging techniques, can enhance diagnostic accuracy. Additionally, future research should focus on creating real-time, point-of-care diagnostic tools, especially for underserved regions, and ensuring seamless integration of AI systems into clinical workflows. Addressing challenges like model interpretability, bias mitigation, and clinical validation through large-scale studies will be crucial to building trust and ensuring the effectiveness of AI-driven solutions in routine practice. Ultimately, the focus will be on developing early detection models, improving diagnostic precision, and ensuring equitable access to advanced dental care technologies.

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