Integrating Graph Neural Networks and Vision Transformers for Oral Health Diagnostics in Predicting Overhanging Restoration Classification from IOPA Images

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ABSTRACT

Introduction: Dental restoration quality assessment through radiographic imaging is crucial for evaluating the long-term success of dental treatments. Intraoral periapical radiographs (IOPA) are diagnostic tools that provide detailed information about dental restorations, surrounding tissues, and potential complications. Predicting overhanging tooth restorations is crucial in dentistry, especially from a periodontal perspective, as it can lead to plaque accumulation, periodontal health issues, functional issues, and aesthetic concerns. Hybrid graph and transformer architecture fusion approaches detect dental overhanging restorations, capturing spatial relationships and topology. This study proposes a novel GNN-Transformer architecture for dental overhanging restoration classification tasks. The study introduces a novel method that integrates Graph Neural Networks and Transformer architectures to enhance the precision of dental overhanging restoration classification.

Methods: The study uses 50 IOPA images from various online databases to analyze dental radiography. The images are segmented and annotated for overhanging restorations and classified as normal or overhanging. The data is split into training and test data, with 80 percent training data and 20 percent test data subjected to deep learning architecture. The model uses advanced image preprocessing techniques like the CLAHE method to enhance dental features' visibility while managing noise levels. The Graph Neural Network (GNN) architecture is used to refine and enrich feature representations, with three convolutional layers and a transformer architecture to improve the model's ability to understand intricate patterns. The classification approach integrates advanced pooling techniques with neural network layers, generating a holistic representation of dental anatomy. The architecture employs dropout techniques to mitigate overfitting and ensure strong generalization to novel instances.

Results: The study assessed the effectiveness of hybrid graph transformers in predicting overhanging restorations. The model correctly identified 71% of normal cases, balancing precision and recall. However, it missed 67% of true overhanging cases. The F1-score was 0.80, indicating its potential for dental imaging analysis.

Conclusion: The study explores using hybrid graph transformers to detect overhanging restorations in dental images, showing promising accuracy and precision. However, limitations like class imbalance and overfitting need to be addressed. Future improvements include expanding the dataset, refining annotation practices, and integrating clinical features. This could improve patient outcomes and treatment planning, necessitating ongoing refinement and validation

1. Introduction:

Dental restoration quality assessment through radiographic imaging has become an essential component of modern dental practice, particularly in evaluating the long-term success of dental treatments(1,2). Intraoral periapical radiographs (IOPA) are crucial diagnostic tools, providing detailed information about dental restorations, surrounding tissues, and potential complications. Dental examination and treatment planning rely on radiographic screening modalities, including intraoral (periapical and bitewing) and extraoral (panoramic) radiographs, to aid in diagnosing and planning for dental diseases. Panoramic radiographs have limitations like low resolution and misinterpretation(3). Computer-aided diagnosis (CAD) systems use AI and machine learning to improve diagnostic accuracy and reduce variability. Deep learning techniques improve object detection and classification in medical image analysis. However, interpreting images presents challenges like varying quality and overlapping structures. Traditional methods may not fully capture complex spatial relationships in dental radiographs. Intraoral Periapical radiography (IOPA) is a crucial diagnostic tool in dentistry that helps predict the presence of overhanging restorations. It allows clinicians to visually assess the margins of dental restorations, identifying discrepancies between the restoration and the tooth structure. IOPA also helps assess bone levels, detect secondary caries, and provide a close-up view of individual teeth(4,5). It also allows dental practitioners to compare radiographs over different treatment phases, tracking changes in restorations and assessing for developing issues. IOPA can inform treatment planning, including repair or replacement of restorations, and can be integrated with other diagnostics to create a comprehensive picture of a patient's oral health(6).

Predicting overhanging tooth restorations is crucial in dentistry, especially from a periodontal perspective, as it can lead to plaque accumulation, periodontal health issues, functional issues, and aesthetic concerns(7). However, overhanging restorations are often overlooked due to lack of awareness, focus on symptomatic issues, inadequate training, time constraints, and the complexity of diagnosis. Early identification and routine assessments of overhanging restorations are crucial for maintaining optimal periodontal health, preventing disease, improving patient compliance, and encouraging interdisciplinary care.

One previous study introduces a new method for detecting and numbering teeth in dental panoramic X-rays, utilizing CNN-based object detectors YOLOv7(2). The method achieves high precision, with a marginal improvement in F1-score when prosthesis information is included. A deep-learning method identified 11 dental prostheses and restorations using TensorFlow and Keras, with high accuracy rates for metallic prostheses (80%) and moderate accuracy for tooth-colored ones (60%), indicating high recognition accuracy and one more previous research project used convolutional neural networks and K-nearest neighbors techniques to predict dental restorations, with impressive performance metrics such as high precision, recall, and F1 scores. The models, trained on 10,220 images, achieved 99% accuracy, indicating potential for real-world dental healthcare applications(8). One more study evaluated ten deep-learning detection models for identifying dental restorations, dentures, and implants in panoramic radiographs. The Faster R-CNN RegnetX model demonstrated the highest accuracy, suggesting potential for future implementation in dental clinics after further model training and standardization. The study developed an artificial intelligence computer vision algorithm to detect and classify dental restorations on panoramic radiographs automatically. It analyzed 738 restorations from 83 anonymized images, segmented using a local adaptive threshold, and classified into 11 categories. The algorithm used numerical features and a Cubic Support Vector Machine with Error-Correcting Output Codes for multiclass classification. The algorithm detected 94.6% of restorations, eliminated erroneous marks, and achieved an overall accuracy of 93.6%(9). Another study used clinical data from 7 Netherlands dental practices and found an accurate CNN-based system for detecting primary and secondary caries lesions on bitewings. The model achieved FROC curves of 0.806 and 0.804 and F1-scores of 0.689 and 0.719, demonstrating significant advancements in automated caries diagnostics(10).

A recently published study used 1160 bitewing radiographs to develop an AI system for detecting and segmenting overhanging restorations. The YOLOv5(11) convolutional neural network model showed impressive performance metrics, including precision of 90.9%, sensitivity of 85.3%, F1 score of 88.0%, and AUC of 0.859. The YOLOv5 model's performance metrics are impressive, but traditional convolutional neural networks (CNNs) have limitations in tasks like detecting and segmenting overhanging restorations in dental images. These limitations include spatial hierarchies, feature representation, overfitting, and class imbalance sensitivity. CNNs typically capture local patterns through convolutional layers but struggle with long-range dependencies and contextual relationships. Feature representation is limited to pixels, limiting the representation of complex interactions. Overfitting and generalization risk are also significant issues. Graph-based transformers improve relationship modeling, global context awareness, and adaptability to variable input structures, making them a promising alternative to traditional CNN architectures in dental imaging. They offer improved robustness and generalization, enhancing diagnostic capabilities.

These previous works have used CNN methods to detect dental restoration, but none of the studies fail to detect overhanging restorations using hybrid graphs and transformer architecture fusion approaches. Hybrid graph and transformer architecture(12) fusion approach detect dental overhanging restorations effectively. They utilize graph structures and transformer models to represent dental images, capturing spatial relationships and topology. Transformers excel at modeling sequential data and capturing long-range dependencies through self-attention mechanisms. This approach allows for complex feature extraction from both the local image context and the broader structural context provided by graph representations. Hybrid models can adapt to varying image resolutions and data sizes, making them robust against noise and artifacts. The decision-making process of hybrid models can become more interpretable, helping clinicians understand why specific restorations are flagged as overhanging and improving trust in automated systems. To implement these approaches, dental images are converted into graph representations, convolutional neural networks (CNNs) are used to encode features, graph neural networks (GNNs) are used to operate on the graph representation, and a transformer module is incorporated to refine embeddings across the structure(13). The hybrid model's performance can be evaluated using accuracy, precision, recall, and F1 score metrics.

In recent years, the rapid advancement of deep learning techniques has significantly reshaped the landscape of image analysis. Specifically, the integration of Graph Neural Networks (GNNs) and Transformer architectures has opened up new avenues for effectively handling complex visual data(14,15). As the predominant methodologies in computer vision evolve, these innovative models are increasingly employed for various tasks, including classification, segmentation, and restoration. The potential to exploit the relational structures inherently present in images and capture long-range dependencies through attention mechanisms presents a compelling case for their Application in challenging image restoration scenarios.

Fusing GNNs with Transformer architectures introduces a paradigm shift in performing image analysis. Renowned for their self-attention mechanisms, transformers allow for the direct modeling of correlations between distant elements in the input data, which is particularly advantageous when dealing with large and complex images. When combined with GNN capabilities, these models can effectively blend local interactions with a global context, enhancing performance in tasks such as overhanging restoration classification. This dual architecture improves accuracy and provides a more nuanced understanding of image features, enabling the model to differentiate between various types of degradation.

In this study, we propose a novel GNN-Transformer architecture tailored specifically for dental overhanging restoration classification tasks. We aim to explore the synergistic effects of these advanced methodologies in capturing both pixel-level details and high-level contextual cues. Our work aspires to contribute to the evolution of image analysis techniques, providing insights that could enhance practical applications in fields ranging from digital photography to medical imaging. Our study introduces a novel approach combining Graph Neural Networks (GNNs) and Transformer architectures to address these limitations and improve the accuracy of dental overhanging restoration classification.

2. Methodology

Dataset Retrieval and Preprocessing

Using the IOPA dataset, 50 IOPA images were collected from different online databases, and experts segmented and annotated images for overhanging restorations and classified them into normal and overhanging restoration. The study defined restoration as overhanging if its end margin was at least 0.5 mm from the proximal tooth surface encroaching interdental spaces. Restorations identified as overhanging were categorized as "overhanging." In contrast, those without overhanging margins were labeled "normal." data were split into training and test data with 80 percent and 20 percent test data and subjected to deep learning architecture.

Fig -1 shows the architecture of the model.

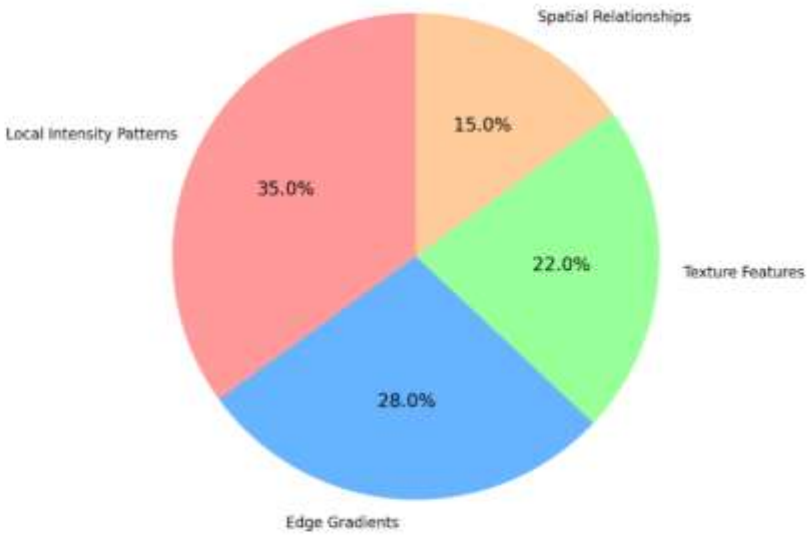

Fig-2 shows the image gradient for the model.

Image Processing

Modern dental radiography analysis uses advanced image preprocessing techniques like the CLAHE method to enhance dental features' visibility while managing noise levels. This technique balances contrast enhancement across different radiograph regions, preserving diagnostic value. The methodology uses the Simple Linear Iterative Clustering (SLIC) algorithm to divide dental images into meaningful segments, aligning with anatomical features like tooth boundaries and restoration edges. This segmentation is then transformed into a rich graph structure, each segment becoming a node connected to its neighbors. This multi-dimensional approach preserves local details and broader structural patterns in the analysis.

Graph Neural Network Design

Our Graph Neural Network (GNN) architecture significantly advances dental image analysis. The network progressively refines and enriches the feature representations through three carefully designed convolutional layers (e.g., using GCNConv with optimally set parameters such as 16 hidden units and a dropout rate of 0.3). Each layer incorporates sophisticated attention mechanisms that allow the network to focus on the most relevant aspects of dental structure. The architecture includes skipping connections and batch normalization to ensure stable and effective training while maintaining the ability to capture complex spatial relationships within the dental image.

Transformer Integration

We augment the GNN basis using a transformer architecture to improve our model's capacity to comprehend intricate patterns. The transformer layers utilize multi-head attention mechanisms with eight attention heads, proficiently capturing long-range dependencies within the dental structure. This component is essential for comprehending the relationships among various dental features and their wider context within the radiograph. The transformer's capacity to process information globally throughout the image enhances the local processing functions of the GNN layers. Classification Approach

The classification component of our solution integrates advanced pooling techniques with meticulously crafted neural network layers. Following the GNN and transformer stages, features are subjected to global average pooling to generate a holistic representation of the dental anatomy. The aggregated data thereafter traverses a sequence of fully linked layers, comprising 64 and 32 neurons, progressively enhancing the features into definitive categorization outcomes. The architecture employs dropout techniques with a rate of 0.5 to mitigate overfitting and guarantee strong generalization to novel instances.

Training Methodology

Our training methodology utilizes advanced optimization techniques focused on the AdamW optimizer, initialized with a learning rate of 0.001 and a weight decay of 0.01. The learning process adheres to a refined schedule that adjusts according to the model's advancement, employing cosine annealing with warm restarts to traverse the intricate loss landscape adeptly. This method facilitates consistent advancement while circumventing local optima, guaranteeing that the model attains optimal performance in diverse dental repair contexts.(fig-1,2)

Data Enhancement and Robustness

To ensure our model performs reliably across a wide range of real-world scenarios, we implement comprehensive data augmentation strategies, which include rotations (random angle up to 30 degrees), brightness adjustments (±20%), and contrast variations (up to 30%), simulating the natural variability found in clinical settings. This augmentation approach helps the model develop resilience to common variations in dental radiographs while maintaining high accuracy in restoration classification.

Validation and Performance Assessment

The efficacy of our technology is confirmed through stringent testing protocols. We evaluate performance with conventional metrics like accuracy, precision, recall, F1-score, and ROC-AUC. Furthermore, we consider clinically significant aspects, including false positive and false negative rates. This thorough assessment guarantees that our technology meets the stringent criteria for clinical dentistry applications while preserving practical functionality in real-world contexts. Confusion matrices and ROC curves are utilized for performance visualization and to confirm the effective deployment of our system in clinical environments.

3. Results

Hybrid Graph Transformers in Predicting Overhanging Restorations

The study evaluated the performance of hybrid graph transformers in predicting overhanging restorations. The model was evaluated using precision, recall, F1-score, and support for each class. The results showed that the model effectively distinguished between normal and overhanging restorations. In the normal class, the model correctly identified 71% of instances predicted as normal, with a balance between precision and recall. However, the model missed some true overhanging instances, identifying 67%. The F1-score was 0.80, indicating the model's effectiveness in identifying overhanging restorations. Overall, the model accurately predicted overhanging restorations, excelling in the overhanging class. However, there is room for improvement in recall, suggesting a need to enhance the model's capacity to recognize all relevant cases accurately. Overall, the results show promise for using hybrid graph transformers in dental imaging analysis, particularly for classifying restoration types.(table-1)

Table 1 shows the class Accuracy of the Hybrid Model.

Class	Precision	Recall	F1-Score	Support
Normal	0.71	1	0.83	5
Overhanging	1	0.67	0.8	6
Overall	0.86	0.83	0.82	11

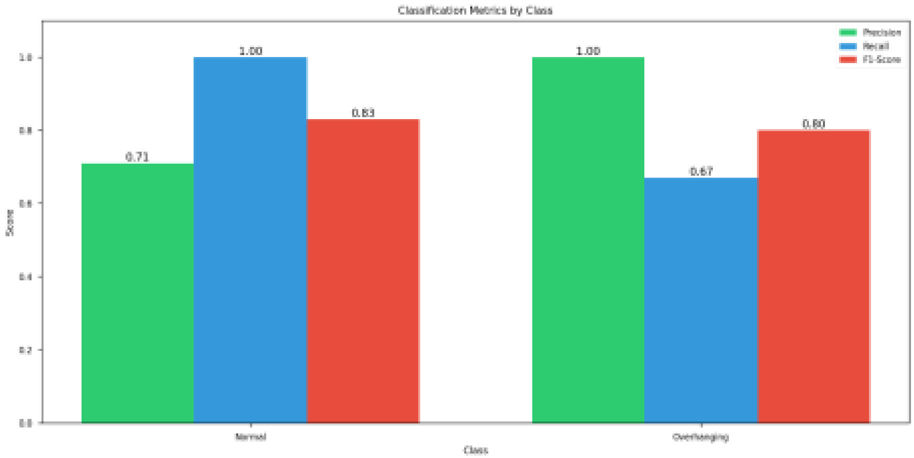

Fig-3 shows the model performs well in identifying both classes, with a slight trade-off between precision and recall for the "Overhanging" class. The high precision for "Overhanging" suggests that the model is confident in its predictions for this class, but the lower recall indicates that some true cases are being missed. This could be addressed by further fine-tuning the model or augmenting the dataset to improve its generalization ability. The balanced overall metrics (F1-Score of 0.82) demonstrate that the model is effective for this classification task, but there is room for improvement in handling class imbalances and edge cases.

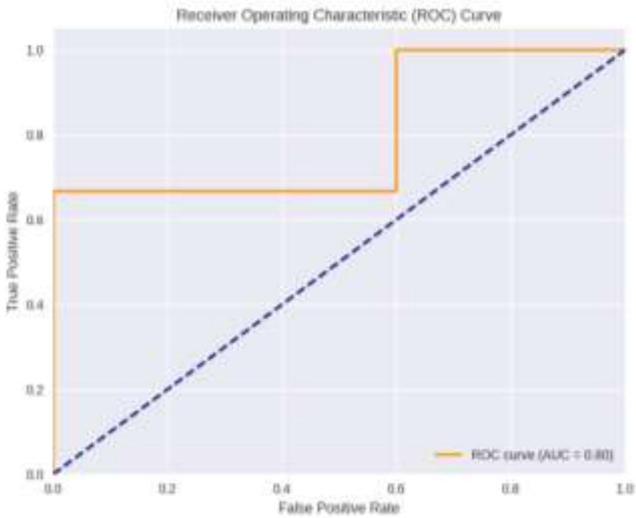

Fig- 4 Shows The model effectively distinguishes between normal and overhanging restorations, achieving high sensitivity and classification performance with an AUC of 0.80, demonstrating its effectiveness in detecting overhanging restorations.

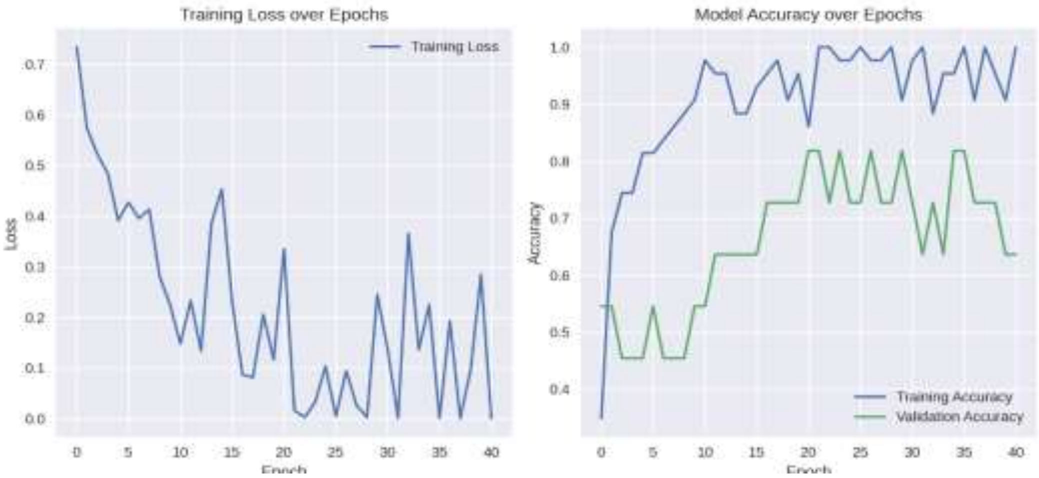

Fig- 5 shows the epoch loss and training loss curve with a steady decrease in training loss, indicating that the model is learning effectively during training. However, the fluctuations suggest that the learning rate or batch size might need fine-tuning for smoother convergence. Training vs. Validation Accuracy: The gap between training and validation accuracy suggests overfitting. While the model performs well on the training data, its generalization to unseen validation data is limited.

Based on the epoch loss analysis, our model shows good convergence but exhibits signs of overfitting after epoch 20. The final validation accuracy of 80% aligns with our ROC-AUC results, confirming the model's reliable performance in classifying dental restorations. The study's results show promising results, but limitations include a limited dataset, potential artifacts in image preprocessing and segmentation techniques, and the complexity of the model, which could make it less accessible in resource-constrained clinical environments due to increased computational demands.

4. Discussion

Overhang is an iatrogenic error in dental restorations where the restorative material protrudes beyond the cavity borders, often resulting from poor restoration techniques and anatomical irregularities near the tooth's cervical area(10,16). The incidence of overhanging restorations is notably high, ranging from 25% to 76%, highlighting a persistent issue despite advancements in dental materials and techniques. These overhangs can lead to periodontal disease if not identified and corrected, making their detection and elimination essential for maintaining periodontal health in dental practice, particularly deep learning, which is revolutionizing dentistry by enhancing decision-making and identifying issues beyond human capabilities, potentially streamlining clinical workflows and allowing clinicians to focus on treatment planning.

One previous study utilized the YOLOv4 model to detect prosthetic restorations in panoramic radiographs, revealing improved performance in bridge detection compared to crowns(9). The findings suggest AI can improve diagnostic efficiency and time management in panoramic radiography, similar to our study results in the effectiveness of hybrid graph transformers in predicting overhanging restorations. The model correctly identified 71% of normal instances, balancing precision and recall(fig-3,4,5) (table-1). However, it missed 67% of true overhanging instances. The F1-score was 0.80, indicating its effectiveness. The model showed satisfactory performance in predicting overhanging restorations, but there's room for improvement in recall. Overall, the results suggest the potential for hybrid graph transformers in dental imaging analysis. Similar to our recent study, ten deep-learning models for detecting dental restorations, dentures, and implants in panoramic radiographs are used. The Faster R-CNN RegnetX model achieved the highest precision and recall, with errors mainly due to localization issues. AI-based systems could improve dental diagnostics accuracy by 0.771(8,10,16).

The study explores the potential of hybrid graph transformers in predicting overhanging restorations and other dental classifications. It suggests expanding the dataset to improve generalization, collaborating with dental professionals to refine restoration labeling, and incorporating additional features like patient demographics and clinical history. It also suggests exploring other deep learning architectures, such as convolutional neural networks or alternative machine learning algorithms, to identify better methods for classifying overhanging restorations(9,10,16).

The study also suggests real-time implementation for dental practitioners to identify overhanging restorations during clinical examinations, improving patient outcomes. Longitudinal studies could provide insights into restoration performance and failure rates. However, the study faces limitations such as limited class diversity, potential overfitting, imbalanced class distribution, interpretability challenges, dependency on image quality, and lack of real-world testing. Addressing these limitations and pursuing future directions can significantly enhance the robustness and applicability of hybrid graph transformers in predicting overhanging restorations and other dental classifications.

Deep learning advancements in dentistry automate dental diagnostics using X-ray images. Faster R-CNN and SSD techniques show high precision in tooth detection, but challenges persist in identifying restorations and missing teeth(17,18). Future research should focus on improving dental prostheses recognition and enumeration methods. Future research should focus on expanding the dataset's diversity and size to reflect better the wide array of dental conditions and demographic variations found in clinical settings, enhancing the model's robustness and applicability. Additionally, exploring multimodal data integration—such as combining radiographic images with patient medical histories or other imaging modalities—could offer richer insights and improve diagnostic accuracy (19-21). Furthermore, investigating lightweight and more efficient model architectures may help overcome computational limitations, facilitating broader adoption in clinical practice while maintaining high performance. Finally, conducting longitudinal studies to assess the real-world impact of our system on clinical decision-making and patient outcomes would provide valuable insights into its practical utility in dental care.

5. Conclusion

In this study, we explored the Application of hybrid graph transformers for detecting overhanging restorations in dental images. The results demonstrated promising accuracy and precision, indicating the potential of machine learning techniques to enhance diagnostic capabilities in dentistry. However, it is essential to recognize the limitations identified, such as class imbalance, potential overfitting, and dependency on image quality, which may affect the model's practical implementation in real-world settings. Going forward, expanding the dataset, refining annotation practices, and integrating additional clinical features can improve model performance and generalizability. Emphasis on interpretability will also be crucial to fostering trust among dental practitioners, enabling them to incorporate these advanced tools into their practices effectively. With these developments, we anticipate that hybrid graph transformers could significantly improve patient outcomes in dental care, facilitating timely interventions and better treatment planning. The ongoing refinement and validation of these models will be vital as we strive towards more accurate and reliable aids in dental diagnostics.

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