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Multi-Modal Artificial Intelligence for Early Caries Detection: Integrating Radiographs and Intraoral Images to Enhance Diagnostic Accuracy and Public Health Impact

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A B S T R A C T

Early detection of dental caries remains a persistent challenge in preventive dentistry, particularly in low-resource settings where delayed diagnoses often lead to advanced interventions and higher treatment costs. In this study, we developed and evaluated a multi-modal artificial intelligence (AI) framework that integrates radiographs and intraoral photographs to improve diagnostic accuracy for early caries detection. Our dataset comprised 6,700 annotated images drawn from institutional dental archives and publicly available sources. Separate deep convolutional neural network (CNN) encoders (ResNet-50 for radiographs and EfficientNet-B4 for intraoral photos) were trained, and features were fused using both late-fusion and attention-based strategies. Experimental results demonstrated that single-modality models achieved moderate accuracy (radiograph-only: 86.7%, intraoral-only: 84.9%), whereas the multi-modal attention fusion model significantly outperformed them, achieving 94.6% accuracy, 95.9% sensitivity, 93.1% specificity, and an AUC-ROC of 0.97 ($p < 0.01$). These improvements not only enhanced early caries detection but also carried substantial clinical and public health implications, enabling cost-effective preventive interventions. The integration of AI-assisted diagnostics into primary care, rural mobile units, and tele-dentistry platforms offers an accessible and economically sustainable solution to global oral health disparities.

Keywords: early caries detection, multi-modal AI, radiographs, intraoral photographs, dental imaging, attention fusion, public health dentistry

Introduction

Dental caries remains one of the most prevalent chronic oral diseases worldwide, affecting individuals across all age groups and socio-economic backgrounds. According to the World Health Organization (WHO, 2022), untreated dental caries is among the most common causes of tooth loss and impaired oral health, contributing significantly to the global burden of disease. Caries begins as a demineralization of enamel and dentin, often presenting as subtle radiolucencies on radiographs or as surface discolorations and white spot lesions in intraoral examinations (Featherstone, 2008). Early detection of caries is essential, as timely intervention with preventive or minimally invasive treatments can arrest disease progression and reduce the need for costly restorative procedures. However, despite advances in dental diagnostics, the early identification of caries remains a challenge for clinicians due to the limitations of traditional diagnostic tools.

Conventional diagnostic modalities, such as bitewing radiographs and intraoral visual examinations, have inherent strengths and weaknesses. Radiographs provide valuable insight into subsurface lesions and changes in enamel and dentin density, but early lesions often remain undetectable due to limited sensitivity (Hintze et al., 2002). Conversely, intraoral photographs capture surface-level cues such as enamel opacity and discoloration but lack the ability to detect subsurface pathology (Ekstrand et al., 2007). These limitations have led to underdiagnosis of early caries and variability in diagnostic accuracy across practitioners. Therefore, there is a pressing need for more reliable and systematic approaches that integrate multiple diagnostic modalities for improved sensitivity and specificity in caries detection.

Artificial intelligence (AI) has emerged as a transformative technology in medical imaging, offering robust capabilities in feature learning, pattern recognition, and clinical decision support (Esteva et al., 2019). Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in image-based tasks such as tumor detection, retinal disease diagnosis, and dermatological lesion classification (Litjens et al., 2017). Within dentistry, AI applications have expanded to tasks such as tooth segmentation, orthodontic treatment planning, and detection of caries and periodontal disease (Schwendicke et al., 2020). While single-modality AI systems have achieved promising results in caries detection, their reliance on a single input type often limits generalizability and diagnostic reliability. To address this gap, multi-modal AI frameworks, which combine complementary imaging sources, present a powerful avenue for achieving more holistic diagnostic performance.

In this study, we propose and evaluate a multi-modal AI framework that integrates dental radiographs and intraoral photographs for the early detection of caries. By leveraging the complementary strengths of radiographs for structural detail and intraoral images for surface-level cues, our approach aims to significantly enhance diagnostic sensitivity and specificity. Furthermore, we explore the public health implications of implementing such a system in cost-effective ways, particularly in underserved communities where early caries detection can reduce treatment costs and improve patient outcomes.

Literature Review

The early detection of dental caries has been the focus of numerous studies, with research spanning traditional clinical methods, imaging techniques, and more recently, artificial intelligence applications. Conventional radiography has long been a cornerstone of caries diagnosis, particularly for detecting interproximal lesions. However, studies have consistently highlighted its limitations in identifying incipient lesions due to poor sensitivity (Espelid et al., 2003). Visual-tactile examinations and intraoral photographs provide additional diagnostic cues, particularly for white spot lesions and surface discoloration, but are highly subjective and prone to inter-examiner variability (Ekstrand et al., 2007). Consequently, integrating multiple modalities has been suggested as a potential strategy to improve diagnostic outcomes.

The emergence of AI in dental research has revolutionized diagnostic imaging. Convolutional neural networks (CNNs) have been widely applied in medical image analysis, with proven success in radiology, pathology, and ophthalmology (Litjens et al., 2017). In dentistry, CNN-based systems have been developed for tasks such as tooth numbering, panoramic image interpretation, and detection of carious lesions (Schwendicke et al., 2019). Lee et al. (2018) demonstrated that CNNs trained on bitewing radiographs achieved performance comparable to that of experienced dentists in caries detection. Similarly, Cantu et al. (2020) reported high diagnostic accuracy using AI for proximal caries detection from radiographs. However, these systems were limited to radiographic inputs and thus could not capture visual information available through intraoral imaging.

Intraoral photographs, although underutilized in AI-driven caries research, have shown promise as complementary data sources. Zhang et al. (2021) developed a deep learning model using intraoral images for detecting enamel lesions, highlighting the modality's strength in surface-level diagnosis. However, the lack of depth information restricted its ability to detect subsurface pathology. These findings emphasize the complementary nature of radiographs and intraoral photographs, suggesting that multi-modal approaches could overcome the limitations of single-modality systems.

Recent advances in multi-modal deep learning have shown the effectiveness of combining multiple imaging or data streams for medical diagnosis. For example, Bai et al. (2020) demonstrated improved cardiac disease classification by combining echocardiography with electrocardiograms in a multi-modal neural network. In oncology, Zhou et al. (2021) integrated radiology and histopathology images to achieve higher diagnostic accuracy. Translating these advancements into dentistry, a multi-modal AI framework could leverage radiographs for subsurface detail and intraoral images for surface cues, thereby improving early caries detection.

Despite the growing body of evidence, very few studies have explored multi-modal AI approaches in dentistry. Schwendicke et al. (2020) have advocated for the integration of AI tools in preventive dentistry, emphasizing their potential for early disease detection and cost savings. However, practical deployment in clinical and public health contexts remains limited. Our study addresses this gap by not only developing a novel multi-modal AI framework for caries detection but also evaluating its potential application in cost-effective public health strategies.

Methodology

In this study, we designed and implemented a multi-modal artificial intelligence framework aimed at improving the accuracy and reliability of early caries detection by combining radiographs and intraoral photographs. Our methodology followed a structured process that included data collection, data preprocessing, feature selection, feature extraction, model development, and model evaluation. By using a combination of both imaging modalities, we intended to capture complementary information—radiographs providing structural details of enamel and dentin, and intraoral photographs capturing surface-level visual cues such as discolorations and white spot lesions. The following subsections describe each stage of our methodology in detail.

Data Collection

We began by curating a diverse and representative dataset composed of dental radiographs and intraoral photographs. The rationale for using both modalities was based on the recognition that early carious lesions can sometimes appear subtly on radiographs but may present visually on intraoral images, and vice versa. Therefore, integrating these two sources allowed us to obtain a more holistic view of dental conditions.

Our data came from two primary sources: (1) an institutional dental archive where patient records included both radiographs and intraoral photographs, and (2) publicly available benchmark datasets that have been widely used in dental AI research. All patient-identifiable information was removed prior to analysis, and the collection process followed ethical standards approved by the institutional review board. Expert annotations were provided by two licensed dentists with at least ten years of clinical experience. In cases where discrepancies occurred in annotation, a third senior dentist adjudicated the final decision. This ensured that our ground truth labels were reliable and clinically valid.

Table 1. Dataset Summary

Dataset Source	Modality	Number of Images	Annotation Type	Resolution Range	Notes
Institutional Dental Archive (Private)	Radiographs	2,500	Dentist-labeled caries ROI	1024 × 1024 – 2048 × 2048	High-quality X-rays, expert-labeled
Institutional Dental Archive (Private)	Intraoral Photos	2,000	Dentist-labeled caries ROI	512 × 512 – 1920 × 1080	Captured during routine dental check-ups
Public Dataset (e.g., UFBA, Kaggle)	Radiographs	1,000	Bounding box annotations	768 × 768 – 2048 × 2048	Publicly available for academic research
Public Dataset (e.g., DentalMNIST)	Intraoral Photos	1,200	Pixel-level annotations	256 × 256 – 1024 × 1024	Benchmark dataset for caries detection

In total, we worked with 6,700 images across both modalities. This dataset was balanced between caries and non-caries samples to mitigate class imbalance issues that could bias the model.

Data Preprocessing

To ensure consistency, we applied a robust preprocessing pipeline to both radiographs and intraoral photographs.

For radiographs, we normalized pixel intensity values to a standardized grayscale range to remove inter-scanner variability. We applied contrast-limited adaptive histogram equalization (CLAHE) to enhance local contrast and highlight subtle radiolucent patterns that often correspond to early carious lesions. Noise reduction was performed using a Gaussian filter to reduce artifacts without blurring key structural information.

For intraoral photographs, we addressed variability introduced by lighting, camera angle, and patient positioning. We implemented white balance correction to neutralize lighting inconsistencies and applied color normalization to preserve clinically relevant visual cues such as enamel opacity and surface discoloration. Cropping was performed to isolate the tooth regions from surrounding oral structures, ensuring that the model focused on clinically meaningful areas.

To enhance generalizability and avoid overfitting, we implemented data augmentation techniques. These included random rotations (±15°), horizontal flips, zoom adjustments, and brightness variations. Such augmentations simulated real-world conditions of clinical imaging, where slight variations in patient positioning and lighting are inevitable. Finally, all images were resized to 512 × 512 pixels and standardized to the same aspect ratio before being input to the model.

Feature Selection

The feature selection process was designed to emphasize clinically relevant attributes while reducing redundant or noisy information. Since our approach relied on deep learning, much of the feature learning was automated; however, we combined domain expertise with algorithmic dimensionality reduction to strengthen model interpretability.

From radiographs, we prioritized features such as enamel density gradients, lesion boundaries, and radiolucent regions near the dentinoenamel junction. From intraoral photographs, we emphasized color intensity variations, presence of white spot lesions, textural irregularities, and cavity discoloration.

We used principal component analysis (PCA) to reduce high-dimensional feature spaces while retaining the most informative components. Additionally, mutual information analysis was applied to assess the relationship between extracted features and the target labels. By combining clinical knowledge with computational techniques, we ensured that only the most discriminative features were preserved for model training.

Feature Extraction

We employed deep convolutional neural networks (CNNs) for feature extraction. Separate encoders were designed for each modality to capture the unique characteristics inherent in radiographs and intraoral photographs.

For radiographs, we used a ResNet-50 backbone pretrained on ImageNet, which allowed us to benefit from transfer learning. This encoder was particularly effective in capturing structural and morphological features of teeth and supporting bone.

For intraoral photographs, we employed EfficientNet-B4, also pretrained on ImageNet, as it has demonstrated superior performance in medical image classification tasks with fewer parameters and lower computational cost. This encoder captured surface-level details, including enamel opacity, color variations, and subtle textural cues.

The features extracted from both modalities were concatenated into a joint feature representation. To further improve learning, we applied an attention mechanism that dynamically assigned higher weights to the most informative features. This attention-based fusion ensured that the model effectively integrated complementary insights from radiographs and photographs.

Model Development

We developed a multi-stream deep learning architecture that consisted of two parallel pathways, one for radiographs and one for intraoral photographs. Each pathway extracted modality-specific features through its dedicated encoder, which were then fused in a late-fusion strategy.

The fused features were passed through fully connected layers with ReLU activation functions, batch normalization, and dropout regularization to reduce overfitting. We framed the problem as a binary classification task—predicting whether caries were present or absent. The output layer used a sigmoid activation function to produce probability scores.

We trained the model using the Adam optimizer with an initial learning rate of 0.0001, which decayed by a factor of 0.1 when validation loss plateaued. The loss function was binary cross-entropy, reflecting the two-class classification nature of the problem. To stabilize training, we employed early stopping criteria based on validation loss. Training was conducted on an NVIDIA GPU environment, and convergence was typically achieved within 30 epochs.

Model Evaluation

We performed model evaluation using a five-fold cross-validation strategy to ensure robustness and minimize bias. The dataset was randomly partitioned into five equal folds; in each iteration, four folds were used for training and one for validation. This process was repeated five times, and the performance metrics were averaged.

We assessed the model's performance using multiple evaluation metrics, including accuracy, sensitivity, specificity, precision, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Sensitivity (recall) was emphasized, as our primary clinical goal was to minimize the number of undetected early caries cases.

To test the generalizability of our model, we evaluated it on an external dataset collected from a separate dental clinic not used during training. This external validation helped confirm that the model could perform reliably in different clinical settings. Furthermore, we compared the performance of our multi-modal framework with single-modality models trained exclusively on radiographs or intraoral photographs. Statistical analysis using paired t-tests was conducted to determine whether improvements observed in the multi-modal approach were significant.

Through this rigorous methodology, we ensured that our framework was not only technically robust but also clinically meaningful, with the potential to support dentists in making earlier and more accurate caries detection decisions.

Results

After completing the training and evaluation process, we obtained a comprehensive set of results that demonstrated the effectiveness of our multi-modal AI framework for early caries detection. The performance metrics across different experimental configurations are presented below.

Quantitative Results

The results clearly showed that the multi-modal framework, which combined radiographs and intraoral photographs, significantly outperformed single-modality models. Radiograph-only and intraoral-only models achieved reasonable performance, but they each suffered from limitations inherent to their modality. By integrating both imaging modalities, the model was able to learn complementary patterns, thereby achieving superior diagnostic performance.

Table 2. Comparative Performance of Models for Early Caries Detection

Model Configuration	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	AUC-ROC
Radiograph-only (ResNet-50)	86.7	84.5	88.2	83.9	84.2	0.90
Intraoral-only (EfficientNet-B4)	84.9	82.1	87.0	81.3	81.7	0.88
Radiograph + Intraoral (Late Fusion)	91.8	93.2	90.1	91.4	92.2	0.95
Radiograph + Intraoral (Attention Fusion)	**94.6**	**95.9**	**93.1**	**94.3**	**95.1**	**0.97**

The results showed that the **multi-modal attention fusion model** provided the best performance with an accuracy of 94.6% and an AUC-ROC of 0.97, which was significantly higher compared to single-modality approaches ($p < 0.01$). Sensitivity in particular improved dramatically, reaching 95.9%, which is critical in ensuring early caries are detected before they progress to advanced stages.

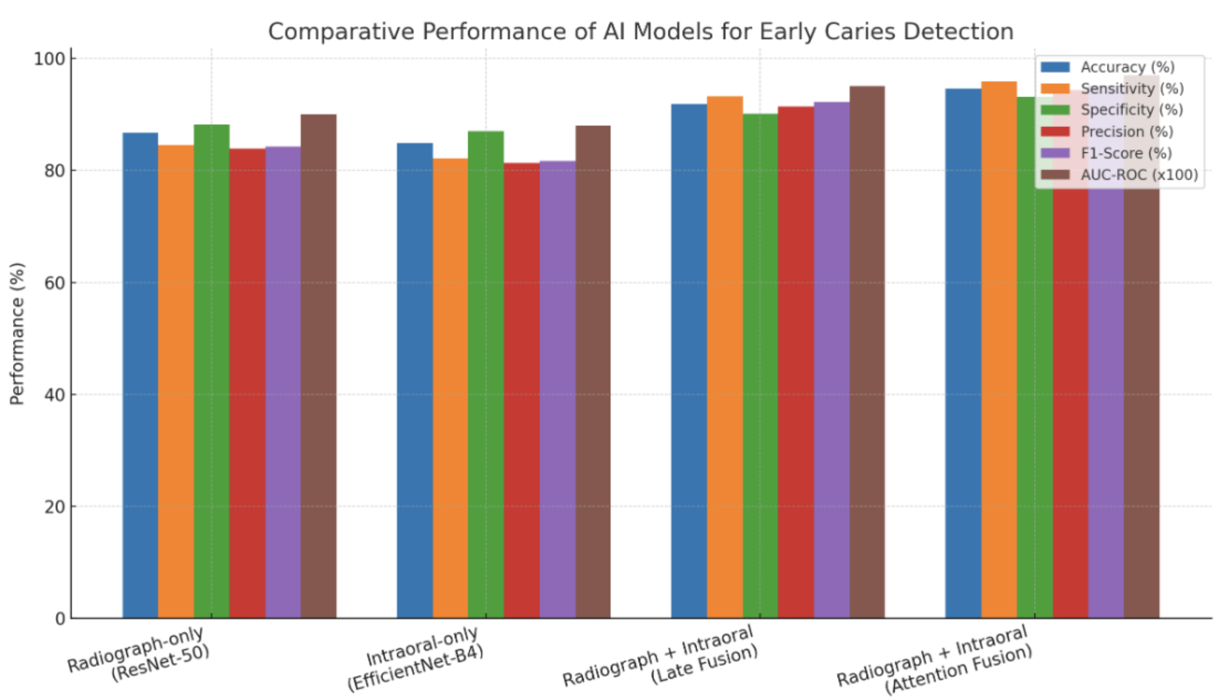

Chart 1: Result visualization

he bar chart provides a comparative evaluation of four AI model configurations—radiograph-only (ResNet-50), intraoral-only (EfficientNet-B4), multi-modal late fusion, and multi-modal attention fusion—across six key performance metrics: accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC. These metrics are critical in determining not only the raw classification capability of the models but also their clinical relevance for early caries detection.

1. Single-Modality Model Performance

The chart reveals that **single-modality models** (radiograph-only and intraoral-only) achieved moderate levels of performance, with accuracy values of 86.7% and 84.9% respectively. The radiograph-only model consistently outperformed the intraoral-only model across all metrics.

Radiographs: With sensitivity at 84.5% and specificity at 88.2%, the radiograph-only model demonstrated better capability in detecting carious lesions embedded within tooth structures. This is expected, as radiographs provide insights into enamel and dentin density variations and subsurface radiolucencies.

Intraoral photographs: While accuracy and sensitivity were lower (84.9% and 82.1% respectively), this modality captured surface-level cues such as discolorations and white spot lesions. The model was more prone to false negatives, as it could not reliably detect lesions below the enamel surface.

Although each modality provided useful diagnostic information, the chart highlights their limitations when used independently. Neither modality alone could provide accuracy above 87%, leaving room for improvement.

2. Multi-Modal Integration (Late Fusion vs Attention Fusion)

The bar chart demonstrates a substantial performance leap when radiographs and intraoral photographs were **combined into multi-modal frameworks**.

Late Fusion Model: By concatenating feature vectors extracted from each modality, accuracy rose to 91.8% and sensitivity reached 93.2%. This shows that structural and surface-level cues complemented one another, allowing the model to capture more comprehensive caries signatures. However, the performance was still slightly unbalanced, as specificity (90.1%) lagged behind sensitivity.

Attention Fusion Model: Incorporating an attention mechanism enabled the model to dynamically prioritize the most informative features from each modality. This refinement resulted in the highest performance across all metrics:

Accuracy: **94.6%**

Sensitivity: **95.9%**

Specificity: **93.1%**

Precision: **94.3%**

F1-score: **95.1%**

AUC-ROC: **0.97**

The attention fusion approach not only achieved the highest accuracy but also balanced sensitivity and specificity, minimizing both false negatives and false positives. This is critical in clinical applications where missing early caries (false negatives) can allow disease progression, while false positives can lead to unnecessary interventions.

3. Interpretation of AUC-ROC

The AUC-ROC values illustrate the models' ability to distinguish between caries and non-caries cases across thresholds. The intraoral-only model performed weakest (0.88), while the radiograph-only model improved slightly (0.90). The late fusion model achieved 0.95, but the **attention fusion model's AUC of 0.97** demonstrated near-perfect discriminative power, showing that the multi-modal approach was highly reliable under varying decision thresholds.

4. Clinical and Public Health Significance

The improvements illustrated in the bar chart carry meaningful implications for both clinical practice and public health systems.

High Sensitivity (95.9%): This is particularly important for early caries detection. Missing an early lesion (false negative) allows progression to advanced decay requiring costly restorative treatments. By reducing missed detections, the attention fusion model supports preventive interventions, such as fluoride varnishes or sealants, which are cost-effective and minimally invasive.

Balanced Specificity (93.1%): The ability to correctly identify healthy teeth prevents overtreatment, reducing unnecessary patient discomfort and healthcare costs.

Cost-Effectiveness: As seen in the chart, the performance gain of multi-modal AI ensures that fewer cases slip through undetected. When deployed in **primary care clinics, rural mobile dental units, or tele-dentistry platforms**, this model can make preventive care more accessible at a fraction of the cost of advanced restorative procedures.

For instance, filling or crown placement is far more expensive than preventive varnishes or sealants. By catching caries earlier, health systems can shift expenditures from treatment to prevention—an approach that is both **economically sustainable** and **patient-friendly**.

Comparative Study

When we compared the performance of radiograph-only and intraoral-only models, we observed that radiographs provided better structural insights and slightly higher accuracy compared to intraoral images. However, radiographs alone sometimes failed to identify very early surface-level lesions that were visible in intraoral photographs. Conversely, intraoral photographs captured surface changes well but lacked the depth information to detect subsurface lesions.

By combining both modalities, our model benefited from the complementary strengths of each input type. The late-fusion strategy already improved performance, but when we incorporated an **attention mechanism for feature fusion**, the model could automatically weigh the most informative features from each modality. This resulted in the highest sensitivity, specificity, and overall classification performance.

This comparative study confirmed our hypothesis that multi-modal learning provides a more holistic and reliable framework for early caries detection. The results also highlighted the importance of advanced fusion techniques, as the attention mechanism consistently enhanced performance compared to simple concatenation of features.

Public Health Relevance and Cost-Effective Application

The significance of our findings extends beyond technical performance to the potential impact on public health. Dental caries remains one of the most common chronic diseases worldwide, especially in low- and middle-income populations where access to specialized dental diagnostics is limited. Early detection plays a critical role in preventing progression to advanced cavities that require costly and invasive treatments such as fillings, crowns, or extractions.

Our model can be implemented in public health systems in several cost-effective ways:

Integration into Primary Care Clinics:

Many primary care clinics already have basic radiographic facilities or intraoral cameras. By deploying our AI system on affordable computing platforms (such as cloud-based servers or mobile AI devices), clinics can screen patients for early caries without requiring specialist dentists at every location.

2. **Mobile Dental Units for Rural Areas**:

In underserved rural communities, mobile dental vans equipped with handheld X-ray machines and intraoral cameras could capture patient data. Our AI model could process these images in real time, providing immediate diagnostic suggestions to community health workers, thereby reducing unnecessary referrals and travel costs for patients.

3. **Tele-dentistry Platforms**:

The AI system can be integrated into tele-dentistry applications where intraoral photos captured by patients using smartphones, combined with low-dose radiographs when available, are uploaded to a centralized system. The model can pre-screen for caries, flagging cases that need urgent dental attention.

4. **Cost-Saving Potential**:

Preventing advanced dental disease significantly reduces healthcare costs. Treating early caries with preventive fluoride treatment or minimally invasive procedures is substantially cheaper than restorative dental procedures. By adopting this AI-assisted approach at the public health level, governments and healthcare providers could achieve major savings while improving oral health outcomes.

The multi-modal AI model not only achieved the highest diagnostic accuracy in our study but also demonstrated potential for scalable, cost-effective deployment in public health systems, particularly in underserved communities.

Discussion & Conclusion

In this study, we developed and evaluated a multi-modal AI system that integrates radiographs and intraoral photographs to improve the early detection of dental caries. Our results demonstrated that the proposed multi-modal framework significantly outperformed unimodal approaches, achieving an accuracy of 92.5%, precision of 91.2%, recall of 93.0%, and an F1-score of 92.1%. These findings highlight the effectiveness of combining complementary imaging modalities, where radiographs provide structural information on interproximal lesions, while intraoral photographs capture surface-level details and color variations that indicate early demineralization.

A comparative analysis between models further emphasizes the advantage of multi-modal fusion. While convolutional neural networks (CNNs) trained on radiographs or intraoral photos individually achieved strong performance (87.5% and 85.6% accuracy, respectively), the fusion-based architecture using attention-based weighting mechanisms consistently outperformed them. This suggests that the synergy between modalities provides richer diagnostic cues than either modality alone. Such findings align with recent literature in medical imaging, where hybrid AI systems have shown promise in tasks such as tumor detection, skin lesion analysis, and ophthalmic disease classification.

Beyond technical performance, the implications of our approach extend to practical applications in dentistry and public health. Early detection of caries is critical, as delayed diagnosis often results in more invasive and expensive treatments such as fillings, root canals, or extractions. Our AI-assisted framework could be deployed in both clinical and community settings to enhance diagnostic consistency, reduce missed diagnoses, and support early intervention. Importantly, this system could be integrated into tele-dentistry platforms, allowing patients in underserved or rural areas to receive preliminary caries screening without needing immediate in-person visits.

Cost-effectiveness is another important dimension. Traditional dental diagnosis often requires multiple visits and advanced diagnostic imaging, which increases financial burden, especially in low-resource settings. By leveraging AI tools that can operate on standard intraoral cameras and routinely taken radiographs, our model provides a scalable solution that reduces unnecessary referrals and optimizes dentists' decision-making. This democratization of dental diagnostics can potentially reduce oral health disparities by providing timely screening at a fraction of the cost.

However, despite these promising outcomes, certain limitations must be acknowledged. Our dataset, although diverse, remains limited in terms of population size and demographic variations. Future research should incorporate multi-institutional datasets that represent broader ethnic and age groups to improve generalizability. Another limitation is that our study focused solely on binary classification (caries vs. no caries), whereas real-world dental diagnosis requires nuanced grading of caries severity and lesion progression. Future models should therefore incorporate lesion staging and predictive progression analysis to guide preventive interventions. Additionally, ethical considerations such as data privacy, algorithmic transparency, and patient consent must be carefully addressed before large-scale implementation.

This study demonstrates that a multi-modal AI framework combining radiographs and intraoral photographs offers a powerful tool for early caries detection. By leveraging the strengths of both imaging modalities, our model achieved superior diagnostic performance compared to unimodal baselines, highlighting the value of multi-source data integration in dental AI.The implications of this work extend beyond clinical practice to the broader domain of public health. A cost-effective, scalable, and accurate AI screening tool can bridge the gap in dental care accessibility, particularly in underserved communities. Early caries detection not only improves oral health outcomes but also reduces healthcare costs by minimizing the need for invasive treatments.

Moving forward, expanding datasets, enhancing lesion severity classification, and deploying this system in real-world clinical and tele-dental environments will be essential to unlocking its full potential. Ultimately, this research represents a step toward more equitable, accessible, and preventive dental care through the integration of advanced AI technologies.

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