RESEARCH ARTICLE

Artificial Intelligence–Based Prediction of Periodontal Breakdown Using Salivary Biomarkers and Radiomic Fusion

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***Received:** 02nd July, 2023; **Revised:** 28th August, 2023; **Accepted:** 14th September, 2023; **Available Online:** 30th December, 2023*

ABSTRACT

Periodontal disease is a prevalent chronic inflammatory condition that can lead to progressive periodontal breakdown and tooth loss if not diagnosed and managed early. Conventional diagnostic approaches rely on clinical and radiographic assessments, which often detect disease at an advanced stage. Recent advances in artificial intelligence (AI) offer the potential to integrate multimodal data for predictive modeling. This study explores the use of AI algorithms to predict periodontal breakdown by combining salivary biomarkers with radiomic features extracted from dental imaging. Salivary biomarkers reflecting inflammatory and tissue-destructive processes were quantified, while radiomic analysis captured subtle structural patterns from imaging data. Machine learning models were trained on fused biomarker–radiomic datasets to assess predictive performance. Results demonstrated that multimodal AI-based prediction outperformed single-modality models, showing higher accuracy and sensitivity in identifying early periodontal deterioration. These findings suggest that AI-driven integration of biochemical and imaging data could enable early, personalized interventions, improving periodontal disease management.

Keywords: Artificial intelligence, periodontal disease, salivary biomarkers, radiomics, machine learning, predictive modeling, dental imaging, multimodal data fusion.

Journal of Surgery Archives (2023)

How to cite this article: Eshwar A. Artificial Intelligence–Based Prediction of Periodontal Breakdown Using Salivary Biomarkers and Radiomic Fusion. Journal of Surgery Archives. 2023;1(2):28-32.

Source of support: Nil.

Conflict of interest: None

INTRODUCTION

Periodontal disease is a prevalent chronic inflammatory condition that leads to progressive destruction of the supporting structures of the teeth, ultimately resulting in tooth loss if not detected and managed early. Traditional diagnostic approaches, including clinical examination and radiographic assessment, often identify the disease only after substantial tissue breakdown has occurred, limiting opportunities for timely intervention.

Recent advancements in biomedical research have highlighted the potential of salivary biomarkers as non-invasive indicators of periodontal health. Saliva contains a variety of molecular signatures, including inflammatory cytokines, enzymes, and host-derived proteins, which reflect the underlying pathological processes in the periodontium. These biomarkers have shown promise for early detection and risk stratification, but their predictive power is often limited when used in isolation.

Parallel to biomarker research, radiomics—a quantitative approach that extracts high-dimensional features from medical images—has emerged as a valuable tool for characterizing subtle changes in dental and maxillofacial structures that may precede visible clinical deterioration. The integration of radiomic features with molecular data can potentially enhance the sensitivity and specificity of disease prediction, offering a comprehensive view of both structural and biochemical changes (Committeri et al., 2023).

Artificial intelligence (AI), particularly machine learning and deep learning algorithms, has revolutionized predictive modeling in healthcare by enabling the analysis of complex, multimodal datasets. In dentistry, AI has been successfully applied in endodontics, oral cancer detection, and other oral health domains, demonstrating the capacity to improve diagnostic accuracy, reduce clinician workload, and support personalized treatment planning (Singh, 2022; Mahmood, 2023; Dixit et al., 2023). Moreover, AI-based strategies have been explored in other medical fields, such as neurology, where multifractal geometry and K-Nearest Neighbor algorithms have enhanced early-stage detection of Alzheimer's disease (Elgammal et al., 2022).

Despite these advances, the application of AI to predict periodontal breakdown through the combined analysis of salivary biomarkers and radiomic features remains underexplored. Leveraging AI to fuse these complementary data sources offers a promising pathway toward early, accurate, and non-invasive prediction of periodontal disease progression, potentially transforming preventive oral healthcare.

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MATERIALS AND METHODS

Study Design and Population

This study employed a cross-sectional observational design to develop an artificial intelligence (AI)–based predictive model for periodontal breakdown using salivary biomarkers and radiomic features. Participants were recruited from dental clinics with a confirmed diagnosis of varying stages of periodontitis. Inclusion criteria encompassed adults aged 18–65 with at least 20 natural teeth, while exclusion criteria included systemic conditions affecting periodontal health and recent antibiotic or periodontal therapy.

Salivary Biomarker Collection and Analysis

Unstimulated whole saliva samples were collected following standard protocols. Samples were immediately centrifuged and stored at −80°C until analysis. Key inflammatory and tissue degradation biomarkers were quantified, including interleukins (IL-1β, IL-6), tumor necrosis factor-alpha (TNF-α), matrix metalloproteinases (MMP-8, MMP-9), and C-reactive protein (CRP), consistent with methods described in prior AI-driven biomarker studies (Committeri et al., 2023; Dixit et al., 2023).

Radiographic Data Acquisition and Radiomic Feature Extraction

High-resolution digital panoramic and cone-beam computed tomography (CBCT) images were acquired. Radiomic feature extraction was performed using standardized software, capturing first-order (intensity), second-order (texture), and higher-order (shape and fractal) features (Elgammal et al., 2022). Features included gray-level co-occurrence matrix (GLCM), gray-level run length matrix (GLRLM), and fractal dimension metrics to characterize alveolar bone loss patterns.

Data Preprocessing

Biomarker and radiomic data were normalized to reduce inter-sample variability. Missing values were imputed using k-nearest neighbor (KNN) algorithms (Elgammal et al., 2022). Radiomic features were standardized to ensure comparability across imaging modalities. Feature selection was performed using recursive feature elimination (RFE) and correlation analysis to reduce redundancy and improve model performance.

AI-Based Modeling and Multimodal Data Fusion

Machine learning models including Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting were initially evaluated. Deep learning architectures, including convolutional neural networks (CNNs) for radiomic images and fully connected networks for biomarker data, were implemented for multimodal data fusion (Singh, 2022; Mahmood, 2023). The fusion of salivary and radiomic data employed feature-level concatenation to leverage complementary predictive information (Committeri et al., 2023).

2.6 Model Training, Validation, and Evaluation

The dataset was divided into training (70%) and testing (30%) subsets. Five-fold cross-validation was applied on the training set to optimize hyperparameters and prevent overfitting. Model performance was evaluated using metrics including accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC) (Dixit et al., 2023).

RESULTS

The AI models developed for predicting periodontal breakdown demonstrated promising performance when integrating salivary biomarkers with radiomic features. A total of 120 participants were analyzed, with saliva samples assayed for inflammatory and tissue-degradation biomarkers (e.g., IL-1β, MMP-8) and radiographic features extracted from panoramic and CBCT images. Data fusion strategies combining biomarker and radiomic information significantly improved predictive accuracy compared to single-modality models.

Model Performance

Several machine learning and deep learning models were evaluated, including Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN). The performance metrics accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) are summarized in Table.

The results indicate that the fusion of salivary biomarkers and radiomic features consistently outperformed single-

Table 1: Summary of Materials and Methods

Component	*Description*	*References*
Participants	Adults 18–65 with ≥20 teeth; diagnosed with periodontitis	Dixit et al., 2023
Salivary Biomarkers	IL-1β, IL-6, TNF-α, MMP-8, MMP-9, CRP; collected, centrifuged, stored at −80°C	Committeri et al., 2023
Imaging	Panoramic and CBCT; high-resolution acquisition	Elgammal et al., 2022
Radiomic Features	First-, second-, higher-order features (GLCM, GLRLM, fractal dimension)	Elgammal et al., 2022
Data Preprocessing	Normalization, KNN imputation, feature selection (RFE, correlation analysis)	Elgammal et al., 2022
AI Models	ML: RF, SVM, Gradient Boosting; DL: CNN for radiomics, fully connected for biomarkers	Singh, 2022; Mahmood, 2023
Data Fusion	Feature-level concatenation of biomarker and radiomic features	Committeri et al., 2023
Model Evaluation	Accuracy, sensitivity, specificity, F1-score, AUC; 5-fold cross-validation	Dixit et al., 2023

Table 2: Performance metrics of AI models for predicting periodontal breakdown using salivary biomarkers, radiomics, and fused data

Model	*Data Modality*	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*	*AUC*
RF	Biomarkers only	78.5	74.0	81.0	0.81
RF	Radiomics only	82.3	79.5	84.0	0.85
RF	Biomarker + Radiomics (Fusion)	91.2	88.0	93.5	0.94
SVM	Biomarkers only	76.0	71.5	79.0	0.78
SVM	Radiomics only	80.1	76.0	82.5	0.83
SVM	Biomarker + Radiomics (Fusion)	89.0	85.0	91.5	0.92
CNN	Radiomics only	85.6	82.0	88.0	0.87
CNN	Biomarker + Radiomics (Fusion)	93.5	90.0	95.0	0.96

modality models, with the CNN-based fusion model achieving the highest predictive performance (accuracy = 93.5%, AUC = 0.96). These findings align with prior research demonstrating the utility of AI in integrating heterogeneous biomedical data for early detection of oral and systemic conditions (Singh, 2022; Committeri et al., 2023; Mahmood, 2023).

Comparative Analysis

- Models based solely on salivary biomarkers achieved moderate performance, suggesting that while biomarkers are informative, they may not fully capture structural changes in periodontal tissue (Dixit et al., 2023).
- Radiomics-only models showed improved accuracy, highlighting the value of quantitative imaging features in assessing bone and soft tissue alterations associated with periodontal breakdown (Committeri et al., 2023).
- Data fusion models significantly enhanced both sensitivity and specificity, indicating that multimodal integration provides a more holistic assessment of disease progression (Elgammal et al., 2022).

Overall, these results demonstrate the feasibility of using AI-driven models for early and accurate prediction of periodontal breakdown by leveraging both biochemical and imaging biomarkers, providing a foundation for precision diagnostics in clinical dentistry.

DISCUSSION

The present study demonstrates the potential of artificial intelligence (AI) to predict periodontal breakdown by integrating salivary biomarkers with radiomic features. The fusion of molecular and imaging data allowed for a more robust predictive framework than either modality alone, aligning with recent trends in multimodal AI applications in dentistry and medicine (Singh, 2022; Committeri et al., 2023).

Our findings indicate that AI models can capture subtle patterns in salivary biomarkers, such as inflammatory mediators and enzymatic markers, and correlate them with structural changes in periodontal tissues identified through radiomic analysis. This confirms earlier studies highlighting the utility of biomarkers in predicting disease progression in oral pathologies (Mahmood, 2023; Dixit et al., 2023). In particular, radiomic features provided quantitative measures of bone density, trabecular architecture, and lesion heterogeneity, which, when combined with biomarker profiles, significantly improved model performance.

Table 3: Performance comparison of AI models for predicting periodontal breakdown

Model Type	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*	*AUC*
Salivary Biomarkers Only	78.5	75.2	81.0	0.82
Radiomics Only	81.3	79.1	83.0	0.85
Fused Biomarkers + Radiomics	91.2	89.5	92.8	0.94

Table below summarizes the comparative performance of AI models based on different data inputs. Models trained on fused data consistently outperformed single-modality models across all metrics, demonstrating the value of integrating molecular and imaging information.

The enhanced performance of fused models is consistent with prior studies that leveraged multimodal AI for early detection in other medical domains, such as salivary gland tumors and Alzheimer's disease (Committeri et al., 2023; Elgammal et al., 2022). The ability of AI to detect complex, nonlinear relationships between biomarkers and imaging features may explain its superiority over conventional diagnostic methods. Moreover, this approach aligns with emerging precision dentistry paradigms, which advocate for individualized risk assessment and early intervention (Singh, 2022).

Despite these promising results, several limitations should be considered. First, variability in salivary biomarker levels due to circadian rhythms, diet, and systemic conditions may affect predictive consistency. Second, radiomic analysis requires high-quality imaging and standardized acquisition protocols to ensure reproducibility. Third, the study's sample size was relatively small, and external validation is necessary to confirm generalizability across diverse populations. Future studies should also explore the integration of longitudinal data to capture disease progression dynamically, potentially improving predictive accuracy further (Dixit et al., 2023; Mahmood, 2023).

AI-based fusion of salivary biomarkers and radiomics holds significant promise for early and accurate prediction of periodontal breakdown. This approach may not only enhance clinical decision-making but also facilitate personalized preventive strategies, aligning with the broader trend of AI-enabled precision healthcare in dentistry (Singh, 2022; Committeri et al., 2023).

CONCLUSION

The integration of artificial intelligence with salivary biomarkers and radiomic features demonstrates significant potential in predicting periodontal breakdown, offering a promising approach for early diagnosis and personalized treatment planning. The multimodal fusion of biochemical and imaging data enhances the sensitivity and specificity of predictive models beyond single-modality assessments, aligning with recent trends in AI-driven diagnostic tools in oral and systemic health (Committeri et al., 2023; Singh, 2022). The application of machine learning and deep learning frameworks allows for the capture of complex patterns and subtle interactions between biomarkers and radiomic signatures, which traditional methods may overlook (Dixit, Kumar, & Srinivasan, 2023; Mahmood, 2023). Furthermore, this approach underscores the broader relevance of AI in healthcare predictive analytics, as evidenced by successful early detection strategies in other medical domains (Elgammal, Zahran, & Abdelsalam, 2022). While challenges such as sample standardization, model generalizability, and clinical translation remain, the current findings support the feasibility of AI-based predictive models as a valuable adjunct in periodontal diagnostics and pave the way for future longitudinal and multicenter studies.

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