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AI-Based Prediction of Periodontal Disease Reactivation Using Changes in Gingival Color, Bleeding Patterns and Patient Behavioral Data

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Abstract

Periodontal disease reactivation remains a significant challenge in maintaining long-term periodontal health, particularly among patients who have completed active treatment. Conventional monitoring methods may not consistently detect early changes occurring between scheduled dental visits. This paper explores an artificial intelligence (AI)-based approach for predicting periodontal disease reactivation through the integration of gingival color changes, bleeding patterns, and patient behavioral data. Digital gingival images can provide visual indicators of inflammation, while longitudinal bleeding records may reveal persistent or increasing inflammatory activity. Behavioral variables, including oral hygiene practices, smoking status, interdental cleaning, and adherence to periodontal maintenance appointments, provide additional information for individualized risk assessment. Machine-learning and deep-learning techniques could integrate these multimodal data sources to identify patterns associated with future disease reactivation and classify patients according to their predicted risk. Existing research on AI-assisted periodontal diagnosis and intelligent periodontitis classification provides a foundation for developing such predictive approaches. However, variations in image quality, clinical measurement consistency, data completeness, algorithmic bias, and patient privacy present important challenges. Prospective clinical validation is necessary to establish predictive accuracy and determine whether AI-assisted monitoring improves periodontal outcomes. This approach may support earlier clinical intervention, personalized maintenance planning, and more effective long-term periodontal disease management.

Keywords: Artificial intelligence; periodontal disease; disease reactivation; gingival color analysis; bleeding on probing; machine learning; behavioral data; periodontal risk prediction; digital dental monitoring.

I. Introduction

Periodontal disease is a chronic inflammatory condition affecting the supporting tissues of the teeth, including the gingiva, periodontal ligament, cementum, and alveolar bone. It commonly develops through interactions between pathogenic dental biofilms and the host inflammatory response. Although periodontal treatment can control inflammation and stabilize periodontal tissues, some patients experience recurrent disease activity after treatment. This reactivation may result from inadequate plaque control, persistent risk factors, irregular maintenance visits, smoking, metabolic disturbances, or changes in individual susceptibility. Early identification of patients at risk of periodontal disease reactivation is therefore important for preventing progressive tissue destruction, tooth mobility, and eventual tooth loss.

Traditional periodontal monitoring relies on clinical examination, including gingival appearance, bleeding on probing, probing pocket depth, clinical attachment level, and radiographic assessment of alveolar bone. These procedures remain essential for diagnosis and treatment planning. However, clinical assessments performed at widely spaced appointments may fail to identify subtle changes occurring between visits. Furthermore, variations in clinical presentation, patient compliance, and the interpretation of clinical findings can complicate the early recognition of recurrent inflammation.

Artificial intelligence (AI) offers opportunities to improve periodontal monitoring by identifying patterns across clinical images, bleeding records, and patient behavioral information. Machine-learning algorithms can analyze multiple variables simultaneously, identify combinations associated with increased risk, and estimate the probability of disease reactivation before substantial clinical deterioration becomes evident. Revilla-León et al. (2023) examined AI models for diagnosing gingivitis and periodontal disease, providing a relevant foundation for investigating automated periodontal assessment. Similarly, Ameli (2024) addressed the development of an intelligent model for predicting periodontitis stage and grade, supporting the broader application of computational methods to periodontal risk characterization.

The proposed approach focuses on three complementary information sources: changes in gingival color, bleeding patterns, and patient behavioral data. Gingival color may provide visual evidence of inflammatory changes, while bleeding observations can help characterize the frequency and

distribution of gingival inflammation. Behavioral information, including oral hygiene practices, smoking status, interdental cleaning, and attendance at periodontal maintenance appointments, can help explain why inflammation may recur despite previous treatment.

The central objective is to develop an AI-based prediction framework that combines these indicators to identify patients who may experience periodontal disease reactivation. Rather than replacing periodontal examination, the system would support clinical decision-making by identifying patients who may benefit from earlier assessment, individualized preventive advice, or more frequent maintenance appointments. Its effectiveness would depend on reliable data collection, appropriate outcome definitions, representative patient populations, and prospective clinical validation.

II. Clinical and Behavioral Indicators of Periodontal Disease Reactivation

2.1 Gingival Color Changes

Gingival color is an important clinical feature in periodontal assessment. Healthy gingiva commonly appears pale pink, although normal pigmentation varies according to ethnicity, individual characteristics, tissue thickness, vascularity, and anatomical location. Inflammation may produce redness or a darker erythematous appearance because of increased vascularity and other tissue changes. Swelling, altered surface texture, and loss of normal gingival contours may accompany these changes.

Digital imaging provides a potential method for tracking gingival appearance over time. Standardized photographs captured during routine examinations or suitable patient-assisted monitoring could be analyzed using computer-vision algorithms to identify changes in color distribution, redness, swelling, and gingival margin appearance. Instead of interpreting a single photograph in isolation, the AI system could compare images collected at different time points to detect deviations from a patient's established baseline.

Image-processing methods may quantify color characteristics, including red-green-blue values and perceptually meaningful color differences. Deep-learning models could additionally examine

spatial patterns across gingival regions and identify areas where visual changes coincide with other indicators of inflammation. These outputs could contribute to a composite risk estimate rather than serve as an independent diagnosis.

However, gingival color is influenced by lighting, camera settings, image compression, pigmentation, dehydration, and photographic angle. Consequently, reliable analysis requires standardized image acquisition and appropriate calibration. A change in apparent redness should not automatically be interpreted as periodontal disease reactivation. The system must account for normal variation and should interpret visual findings alongside bleeding patterns, clinical measurements, and relevant patient characteristics.

The systematic review by Revilla-León et al. (2023) provides relevant context for applying AI to gingivitis and periodontal disease diagnosis. Nevertheless, the use of AI for predicting future reactivation from serial gingival images represents a distinct task that requires its own validation.

2.2 Bleeding Patterns as Predictive Indicators

Bleeding on probing is an established clinical indicator of gingival inflammation. When assessed consistently, it helps clinicians evaluate periodontal status and monitor changes following treatment. Persistent or increasing bleeding across multiple visits may suggest inadequate inflammatory control and can provide useful information about future periodontal risk.

An AI-based system could analyze bleeding observations according to frequency, anatomical distribution, persistence, and changes over time. For example, a patient whose bleeding scores increase across successive maintenance visits may receive a higher predicted risk than a patient with consistently low bleeding levels, provided other relevant factors are considered.

Bleeding information could be recorded through periodontal charts, clinician-entered examination findings, and appropriately designed digital monitoring systems. A model might distinguish between isolated bleeding sites and a broader increase across several periodontal regions. It could also identify whether previously improved sites have developed renewed inflammatory signs.

Importantly, bleeding on probing does not independently establish progressive periodontitis. Gingival inflammation can occur without measurable attachment loss, and bleeding results may vary according to probing technique, force, and examiner consistency. Prediction models should

therefore incorporate periodontal pocket depth, clinical attachment level, and other clinical findings whenever available. Evidence of actual disease progression must be distinguished from inflammation alone.

2.3 Patient Behavioral Data

Patient behavior plays an important role in maintaining periodontal health after active treatment. Even when clinical treatment successfully reduces inflammation, inadequate plaque removal and inconsistent maintenance can contribute to renewed disease activity. Behavioral data can therefore complement clinical observations by identifying potentially modifiable risk factors.

Relevant variables include brushing frequency and technique, interdental cleaning, smoking or tobacco exposure, adherence to prescribed oral hygiene instructions, attendance at periodontal maintenance appointments, and reported barriers to accessing dental care. Medical and lifestyle information relevant to periodontal risk may also be included when appropriately collected and clinically justified.

For instance, a patient with increasing gingival redness, repeated bleeding observations, and declining adherence to interdental cleaning may exhibit a higher predicted risk than a patient with similar visual findings but stable oral hygiene practices. The model would estimate associations across these variables rather than assume that any single behavior inevitably causes reactivation.

Behavioral information could be obtained through patient questionnaires, electronic dental records, structured follow-up forms, or voluntary digital self-monitoring. Data quality is important because self-reported behavior may be affected by recall errors and socially desirable responses. Missing information, changes in circumstances, and differences in access to dental services must also be considered.

Tahir (2024), in research concerning AI-driven dental monitoring for clear aligner treatment, provides a related example of intelligent monitoring in dentistry. Although orthodontic monitoring is different from periodontal disease prediction, it illustrates the relevance of integrating digital observations with ongoing dental care. Application to periodontal reactivation would require disease-specific model development and validation.

III. AI-Based Prediction Model

3.1 Data Collection and Integration

An AI-based periodontal reactivation prediction model requires a structured dataset combining clinical observations, gingival photographs, bleeding records, and patient behavioral information. The first stage involves collecting longitudinal data from patients who have completed active periodontal treatment and are undergoing supportive periodontal care. Longitudinal data are particularly important because the objective is to predict future reactivation rather than merely classify the patient's current periodontal condition.

Clinical data may include periodontal pocket depth, bleeding on probing, clinical attachment level, plaque scores, previous periodontal treatment, and documented evidence of disease progression. Gingival photographs provide visual information, while behavioral records describe oral hygiene practices, smoking exposure, and attendance at maintenance appointments.

These variables should be integrated using consistent patient identifiers, examination dates, and standardized recording procedures. Missing values, inconsistent clinical measurements, duplicated records, and poor-quality photographs must be identified before model training. Data preprocessing should also address differences in image illumination, camera specifications, and clinical documentation practices.

The model should distinguish between predictors recorded before an outcome and information obtained after the outcome occurs. This separation prevents data leakage, which could produce misleadingly high performance during testing. Ameli (2024) provides a relevant foundation for intelligent prediction of periodontitis stage and grade, although a model designed to predict reactivation must specifically learn from changes over time and clearly defined follow-up outcomes.

3.2 Machine-Learning and Deep-Learning Techniques

Different AI techniques may be appropriate for different components of the proposed system. Convolutional neural networks can analyze gingival photographs to identify visual characteristics associated with inflammation. Conventional machine-learning algorithms, including logistic

regression, random forests, and gradient-boosting methods, can integrate clinical measurements and behavioral variables to estimate reactivation risk.

A temporal model could additionally examine changes between successive observations. For example, it could evaluate whether increasing redness, repeated bleeding, and declining oral hygiene adherence occur together before a documented episode of periodontal deterioration. Where sufficient longitudinal data are available, recurrent neural networks or other time-series approaches may be investigated.

The framework could operate through three principal stages:

1. Feature extraction: Identify relevant visual features, bleeding characteristics, clinical measurements, and behavioral indicators.
2. Risk prediction: Integrate the extracted information to estimate the probability of periodontal reactivation within a predefined period.
3. Clinical interpretation: Present the predicted risk, contributing indicators, and recommended need for professional reassessment.

Revilla-León et al. (2023) provide a relevant evidence base for AI applications in gingivitis and periodontal disease diagnosis. However, diagnostic classification and future-risk prediction are different tasks. A model that accurately recognizes existing periodontal disease may not necessarily predict recurrence after successful treatment.

Consequently, the proposed model should be trained using longitudinal outcomes, compared with appropriate clinical prediction methods, and tested on patients from independent clinical settings. Its predictions should be evaluated using discrimination, calibration, sensitivity, specificity, and clinically meaningful measures of predictive performance.

3.3 Risk Classification and Clinical Decision Support

The model could classify patients into low-, moderate-, and high-risk categories according to their estimated probability of reactivation. These categories should be established using validated thresholds rather than arbitrary scores.

Patients classified as low risk may continue their existing maintenance schedules, subject to routine clinical review. Those classified as moderate risk may benefit from reinforced oral hygiene education and closer monitoring. Patients classified as high risk may require earlier periodontal reassessment, professional plaque control, or individualized modification of their maintenance schedule.

The system should explain the main factors contributing to its predictions whenever possible. For example, it might indicate that increasing bleeding frequency and worsening gingival appearance contributed to an elevated risk estimate. Such explanations can help clinicians evaluate whether the prediction is consistent with the patient's actual condition.

The AI system must remain a decision-support tool. Final decisions should be made by qualified dental professionals after considering clinical findings, patient preferences, and other relevant information.

IV. Risk Assessment and Clinical Applications

4.1 Early Identification of High-Risk Patients

The principal clinical application of the proposed model is the early identification of patients who may experience periodontal disease reactivation. Conventional assessments generally depend on information available during scheduled visits, whereas appropriately designed digital monitoring could provide additional observations between appointments.

Combining gingival color changes, bleeding patterns, and behavioral information may reveal concerning trends that are less apparent when each indicator is evaluated independently. For example, a gradual increase in gingival redness accompanied by repeated bleeding and reduced adherence to interdental cleaning could prompt an earlier professional assessment.

Nevertheless, these findings should be interpreted as warning signals rather than definitive evidence of recurrent periodontitis. Confirmation requires appropriate clinical examination, including assessment of periodontal pockets, attachment levels, and other indicators of disease progression.

The approach may be particularly useful for organizing follow-up care, prioritizing appointments, and identifying patients who need additional preventive support. Its practical value would depend on whether earlier intervention improves outcomes compared with conventional monitoring.

4.2 Personalized Periodontal Maintenance

AI-based prediction could support individualized maintenance strategies by considering the differences between patients. Rather than applying identical follow-up schedules to everyone, clinicians could use validated risk estimates alongside clinical judgment to determine the intensity of preventive care.

Patients with persistently stable periodontal findings may continue routine supportive care, while those demonstrating increasing inflammatory indicators may require more frequent reviews. Behavioral information could also guide personalized education, such as improving interdental cleaning, addressing tobacco use, or identifying barriers to attending maintenance appointments.

Tahir (2024) examined AI-driven dental monitoring in orthodontic clear aligner treatment. Although the clinical objective differs from periodontal maintenance, this work provides related context for exploring digital monitoring and individualized dental care. The proposed periodontal framework would require evidence that its predictions improve the timing and effectiveness of periodontal interventions.

4.3 Relevance of Supporting Dental Research

Other dental studies can provide complementary biological and methodological context without directly establishing the effectiveness of periodontal prediction. Singh et al. (2025) investigated periapical healing in endodontic retreatment using nano-hydroxyapatite with and without platelet-rich fibrin. This study concerns periapical healing rather than periodontal disease reactivation, but it illustrates the wider importance of evaluating healing outcomes and treatment-related changes in dental tissues.

Similarly, Singh (2025) examined tensile bond strength between glass ionomer cements and composite resins in dental restorations. Its direct relevance to periodontal reactivation prediction is

limited, although it contributes to the broader restorative dentistry literature in which treatment outcomes and material performance are assessed.

Gamra (2022) investigated podoplanin immunohistopathological expression in oral squamous cell carcinoma and its associated stroma. This research concerns oral pathology rather than periodontal disease prediction. It may offer broader context for studying tissue-related biological markers, but it should not be interpreted as direct evidence that podoplanin predicts periodontal reactivation.

These distinctions are important when integrating diverse dental references into an AI research framework. Evidence from endodontics, restorative dentistry, orthodontics, and oral pathology may inform broader research methods, but periodontal-specific conclusions must be supported by appropriate periodontal evidence.

V. Challenges, Future Directions, and Conclusion

5.1 Challenges and Limitations

Several challenges must be addressed before AI-based periodontal reactivation prediction can be implemented reliably. First, differences in image quality, gingival pigmentation, lighting, and camera specifications may reduce the accuracy of automated color analysis. Standardized image acquisition and testing across different devices are therefore essential.

Second, bleeding observations and periodontal measurements may vary between clinicians. Consistent examination protocols, examiner training, and reliable outcome definitions are needed to minimize measurement errors. Models must also distinguish gingivitis from recurrent periodontitis, particularly when inflammation occurs without documented attachment loss or progressive bone destruction.

Third, behavioral data may be incomplete or inaccurate. Smoking exposure, oral hygiene practices, and appointment attendance can change over time, requiring repeated assessment. Patient privacy, informed consent, secure data storage, and responsible use of personal information must be addressed.

Another important concern is algorithmic bias. A model trained on a limited patient population may perform poorly in other populations with different gingival pigmentation, healthcare access, or behavioral characteristics. External validation and subgroup performance assessment are necessary to establish generalizability.

Finally, predictive accuracy alone does not demonstrate clinical usefulness. Prospective studies should establish whether using the model reduces disease progression, improves maintenance attendance, supports appropriate treatment decisions, and offers acceptable cost-effectiveness.

5.2 Future Directions

Future research should prioritize the development of multicenter longitudinal datasets that combine standardized gingival images, bleeding records, periodontal measurements, and repeated behavioral assessments. Investigators should establish clear definitions of reactivation and distinguish temporary gingival inflammation from objectively documented periodontal deterioration.

Comparative studies should evaluate whether multimodal AI models outperform approaches based on clinical measurements alone. External validation, calibration assessment, transparent reporting, and prospective clinical trials will be necessary before routine implementation.

Mobile dental monitoring tools may eventually enable patients and clinicians to track selected indicators between appointments. However, these tools should not encourage patients to self-diagnose periodontal disease or replace professional examination. Automated alerts should communicate uncertainty and direct patients toward appropriate dental assessment when concerns are detected.

5.3 Conclusion

AI-based prediction of periodontal disease reactivation offers a promising approach to integrating gingival color changes, bleeding patterns, and patient behavioral data into personalized periodontal monitoring. By identifying patterns across these information sources, machine-learning models may help clinicians recognize patients who require earlier assessment and targeted preventive care. Existing research on AI-based periodontal diagnosis (Revilla-León et al.,

2023) and intelligent periodontitis classification (Ameli, 2024) provides a relevant foundation for further investigation.

Nevertheless, the proposed framework should be considered a developing research approach rather than an established clinical solution. Its effectiveness will depend on reliable longitudinal data, appropriate outcome definitions, external validation, and evidence of improved patient outcomes. With rigorous development and clinical oversight, AI-assisted monitoring may strengthen supportive periodontal care and contribute to more timely, individualized management of periodontal disease.

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