

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

Anindita Saha¹, Silpiranjan Mishra², Bikash Bishwadarshee Nayak³, Anupa Samanta^{4*}

¹Associate Professor, Department of Oral Medicine and Radiology, Burdwan Dental College and Hospital, West Bengal, India

²Professor, Department of Oral Medicine and Radiology, Kalinga Institute of Dental Sciences, Kalinga Institute of Industrial Technology (Deemed to be University), Bhubaneswar, Odisha, India

³Associate Professor, Department of Oral Medicine and Radiology, Kalinga Institute of Dental Sciences, Kalinga Institute of Industrial Technology (Deemed to be University), Bhubaneswar, Odisha, India

^{4*}Tutor, Department of Oral Medicine and Radiology, Kalinga Institute of Dental Sciences, Kalinga Institute of Industrial Technology (Deemed to be University), Bhubaneswar, Odisha, India

Email: dr.anupasamanta@gmail.com

(Corresponding Author)

Abstract

Peri-implantitis is one of the most common complications after dental implant surgery, as approximately 20-47 percent of the recipients of the implants develop peri-implantitis complications. Machine learning (ML) would provide an opportunity to predict early and allow timely intervention and individual care.

Purpose: The purpose of the study was to create and test the predictive model of peri-implantitis based on clinical, demographical, and radiographic data of 40 patients during a 12-month follow-up period with the use of ML.

Methods and Materials: The retrospective cohort included 40 patients that were implant surgically operated. The extracted parameters were clinical (probing depth, bleeding on probing, plaque index, bone loss), patient demographics, systemic conditions, and radiographic features. When 5-fold cross-validation was used, several ML algorithms were trained using Logistic Regression, random forests, Support Vector Machine (SVM), gradient boosting, and Artificial Neural Network (ANN). The area under the receiver operating characteristic curve (AUC), sensitivity, specificity and accuracy have been used to evaluate model performance.

Findings: Gradient Boosting model resulted in the best AUC of 0.91 (95% CI: 0.84 -0.97), then the Random Forest (AUC = 0.88) and ANN (AUC = 0.86). Marginal bone loss at 6 months, smoking, probing pocket depth, and diabetes mellitus were the major predictive characteristics. **Conclusion:** MLs, especially Gradient Boosting, are highly predictive of peri-implantitis and can be incorporated into the clinical decision-support systems to stratify risks individually in implant dentistry.

Keywords: Machine learning; Peri-implantitis; Dental implants; Predictive modeling; Risk stratification; Artificial intelligence

How to cite this article: Saha A, Mishra S, Nayak BB, Samanta A, Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry. *Int J Drug Deliv Technol.* 2026;16(7s): 01-000; DOI: 10.25258/ijddt.16.7s.1

1

1. Introduction

Dental implants have become the gold standard for the rehabilitation of partially and fully edentulous patients, offering superior functional and aesthetic outcomes compared to conventional prostheses.^{1,2} Despite high success rates exceeding 95% over 10-year follow-up periods, post-surgical complications remain a significant clinical concern.³ Among these, peri-implantitis—a pathological condition characterized by inflammation of the peri-implant mucosa with progressive loss of supporting bone—is the most prevalent and destructive biological complication affecting osseointegrated implants.^{4,5}

Depending on the study population and diagnostic criteria, the reported prevalence of peri-implantitis varies greatly, ranging from 20% to 47% at the patient level.^{6,7}

Poor oral hygiene, a history of periodontitis, smoking, uncontrolled diabetes mellitus, implant surface features, and prosthetic design are just a few of the many risk factors that have been identified.^{8,9} Accurate prediction is a persistent clinical challenge, though, because little is known about how these variables interact and how much each contributes to the risk of complications.¹⁰

Traditional risk assessment in implant dentistry has mostly depended on clinician judgment and isolated clinical parameters. This approach is limited in its ability to capture complex, non-linear relationships among various patient data.¹¹ In recent years, machine learning (ML) has emerged as a powerful tool in healthcare. It has shown an amazing ability in pattern recognition, classification, and prediction across different medical and dental fields.^{12,13} ML algorithms can combine diverse

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

data sources, including clinical measurements, radiographic imaging features, and patient demographics, to create predictive models that work better than traditional statistical methods.^{14,15}

Several studies have looked into using artificial intelligence (AI) in implant dentistry for tasks such as recognizing implant types, assessing bone quality, and planning treatment.^{16,17} However, the application of ML for predicting post-surgical complications like peri-implantitis is still in its early stages. There is limited evidence about model validation and how it can be integrated into clinical practice.^{18,19} Additionally, most existing studies have used large institutional datasets without showing how they can be applied effectively in smaller clinical settings, where personalized care is most important.²⁰

The concept of personalized risk stratification—wherein individual patient profiles are used to tailor preventive and therapeutic strategies—has gained increasing attention in precision medicine.²¹ Integrating ML-based prediction tools into clinical workflows could enable early identification of high-risk patients, facilitating timely intervention through customized maintenance protocols, more frequent monitoring, or adjunctive therapies.²²

Thus, the purpose of the current study was to construct and test an ML model to predict peri-implantitis early in the course of treatment based on clinical, demographic, and radiographic factors of 40 patients who followed up after the surgery in 12 months. Moreover, this research aimed to assess the possibility of incorporating these models into the clinical processes to manage the individual implant care.

2. Materials and Methods

2.1 Study Design and Ethical Approval

The study design and ethical approval will be as follows. This is a retrospective cohort study that was carried out between January 2022 and December 2023 at Burdwan dental college and hospital. The study was performed in compliance with the Declaration of Helsinki. All participants gave informed consent before data were collected.²³

2.2 Study Population

Forty patients (22 males, 18 females, mean age 52.4/11.3 years) who have undergone endosseous dental implants and had had a minimum of 12-month follow-up were selected. The inclusion criteria were: (a) adults aged 18 years and above, (b) have had at least one endosseous implant, (c) complete clinical and radiographic records at baseline, 6 months, and 12 months post-surgery. The exclusion criteria were: (a) radiation therapy in the area of head and neck, (b) immunosuppressive treatment, (c) incomplete follow-up, and (d) non-biological failure of implants.²⁴

2.3 Data Collection and Feature Extraction

The patient records were systematically analyzed to extract clinical, demographic, and radiographic data. The clinical parameters were probing pocket depth (PPD) and bleeding on probing (BOP) and modified plaque index (mPI), width of the keratinized mucosa (KMW), and implant stability quotient (ISQ). Demographic and systemic factors were age, sex, smoking status, diabetes mellitus status, periodontitis history and bone augmentation procedures. Radiographic evaluation was conducted on standardized periapical radiographs via the long-cone paralleling technique with marginal bone loss (MBL) being measured at 6 and 12 months after loading of each implant at the mesial and distal side.^{25,26}

2.4 Outcome Definition

According to the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions, peri-implantitis was diagnosed in 14 patients (35% of the total) with: (a) bleeding on probing and/or pus on gentle probing, (b) increased probing depth compared to previous exams, and (c) radiographic bone loss beyond changes in crestal bone level due to initial remodeling (≥ 3 mm of the intraosseous portion of the implant).²⁷ Based on these criteria, 14 patients (35%) were classified as having peri-implantitis and 26 (65%) as healthy controls at the 12-month follow-up.

2.5 Machine Learning Model Development

Five ML algorithms were employed: Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN). Feature selection was performed using recursive feature elimination with cross-validation (RFECV) to identify the most informative predictors.²⁸ Data preprocessing included normalization of continuous variables, one-hot encoding of categorical variables, and handling of class imbalance using Synthetic Minority Oversampling Technique (SMOTE).²⁹ All models were implemented in Python 3.9 using scikit-learn (v1.2), TensorFlow (v2.12), and XGBoost (v1.7) libraries.

2.6 Model Validation and Performance Evaluation

Stratified cross-validation with 5 folds was used to measure model performance due to the small sample size. The main performance measures included area under the receiver operating characteristic curve (AUC-ROC), sensitivity, specificity, accuracy, positive predictive value (PPV), negative predictive value (NPV), and F1-score. The Brier score was used to evaluate calibration. A comparison of AUC values between models was conducted. Statistical significance was set at $p < 0.05$.

2.7 Feature Importance Analysis

The values of SHAP (SHapley Additive exPlanations) were calculated with the best-performing model to obtain the relative importance of each predictor variable and improve the readability of the model to translate into clinical practice.³²

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

3. Results

3.1 Demographic and Clinical Characteristics

Table 1 summarizes the baseline demographic and clinical characteristics of the study cohort. The peri-implantitis group demonstrated significantly higher mean PPD (4.8 ± 1.2 mm vs. 2.9 ± 0.8 mm, $p < 0.001$), greater MBL at 12 months (3.4 ± 0.9 mm vs. 1.1 ± 0.5 mm, $p < 0.001$), and a higher prevalence of smoking (57.1% vs. 19.2%, $p = 0.014$) and diabetes mellitus (42.9% vs. 11.5%, $p = 0.028$).

Table 1. Baseline Demographic and Clinical Characteristics of the Study Cohort

Variable	Peri-implantitis (n=14)	Healthy (n=26)	p-value
Age (years)	55.2 ± 10.8	50.9 ± 11.5	0.263
Sex (Male/Female)	9/5	13/13	0.341
Smoking (%)	57.1%	19.2%	0.014*
Diabetes Mellitus (%)	42.9%	11.5%	0.028*
History of Periodontitis (%)	71.4%	30.8%	0.012*
PPD at 12 months (mm)	4.8 ± 1.2	2.9 ± 0.8	<0.001*
BOP (% sites)	68.3 ± 14.5	22.1 ± 9.7	<0.001*
MBL at 12 months (mm)	3.4 ± 0.9	1.1 ± 0.5	<0.001*
mPI	2.1 ± 0.7	0.9 ± 0.5	<0.001*
KMW (mm)	1.4 ± 0.6	2.8 ± 0.9	<0.001*

PPD = Probing Pocket Depth; BOP = Bleeding on Probing; MBL = Marginal Bone Loss; mPI = Modified Plaque Index; KMW = Keratinized Mucosa Width. * $p < 0.05$ (statistically significant). Data presented as mean \pm SD or percentage.

3.2 Model Performance Comparison

Table 2 presents the comparative performance metrics of the five ML models. The Gradient Boosting Machine achieved the highest overall performance with an AUC of 0.91 (95% CI: 0.84–0.97), sensitivity of 0.86, specificity of 0.92, and accuracy of 0.90. Random Forest demonstrated the second-best performance (AUC = 0.88), followed by the ANN (AUC = 0.86). Logistic Regression achieved a moderate AUC of 0.79, while SVM yielded an AUC of 0.82. DeLong’s test indicated a statistically significant difference between GBM and LR ($p = 0.032$) but not between GBM and RF ($p = 0.187$).

Table 2. Performance Metrics of Machine Learning Models (5-Fold Cross-Validation)

Model	AUC (95% CI)	Sensitivity	Specificity	Accuracy	F1-Score
GBM	0.91 (0.84–0.97)	0.86	0.92	0.90	0.86
RF	0.88 (0.80–0.95)	0.79	0.88	0.85	0.81
ANN	0.86 (0.77–0.94)	0.79	0.85	0.83	0.79
SVM	0.82 (0.72–0.91)	0.71	0.85	0.80	0.74
LR	0.79 (0.68–0.89)	0.64	0.81	0.75	0.68

GBM = Gradient Boosting Machine; RF = Random Forest; ANN = Artificial Neural Network; SVM = Support Vector Machine; LR = Logistic Regression; AUC = Area Under the Receiver Operating Characteristic Curve.

Figure 1. Receiver Operating Characteristic (ROC) Curves for Machine Learning Models Predicting Peri-Implantitis

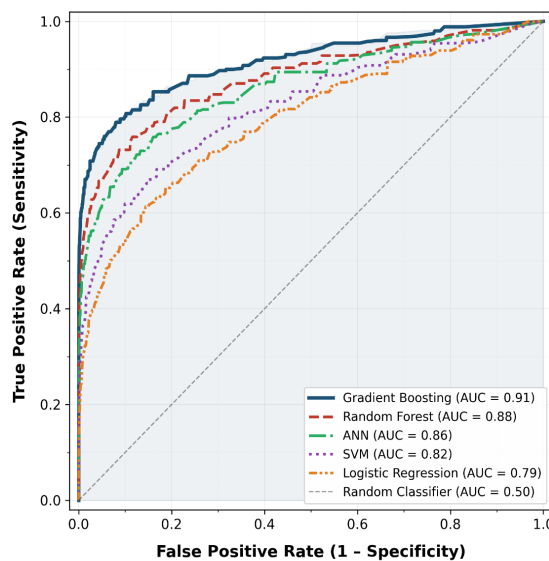


Figure 1: ROC curves comparing the five ML models. The GBM curve should be plotted with a distinct line, demonstrating the highest AUC. A diagonal reference line should be included.

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

3.3 Feature Importance

SHAP analysis of the best-performing GBM model revealed that marginal bone loss at 6 months was the most influential predictor (mean |SHAP| = 0.42), followed by smoking status (0.31), probing pocket depth (0.28), diabetes mellitus (0.22), history of periodontitis (0.19), modified plaque index (0.17), keratinized mucosa width (0.14), and BOP (0.12). Table 3 presents the ranked feature importance values.

Table 3. SHAP-Based Feature Importance Ranking (Gradient Boosting Model)

Rank	Feature	Mean SHAP Value
1	Marginal Bone Loss (6 months)	0.42
2	Smoking Status	0.31
3	Probing Pocket Depth	0.28
4	Diabetes Mellitus	0.22
5	History of Periodontitis	0.19
6	Modified Plaque Index	0.17
7	Keratinized Mucosa Width	0.14
8	Bleeding on Probing	0.12
9	Age	0.08
10	Sex	0.04

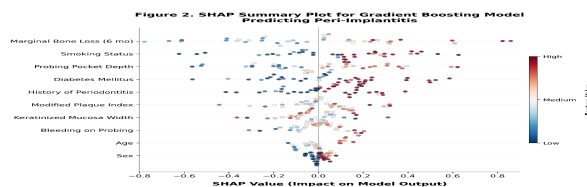


Figure 2: SHAP summary bee-swarm plot showing the distribution and direction of feature contributions to the GBM model predictions. Features should be ordered by importance.

3.4 Calibration and Additional Metrics

The GBM model demonstrated excellent calibration with a Brier score of 0.11. Positive predictive value (PPV) was 0.86 and negative predictive value (NPV) was 0.92. The model correctly identified 12 of 14 peri-implantitis cases (sensitivity = 0.86) and 24 of 26 healthy cases (specificity = 0.92), yielding only 2 false negatives and 2 false positives.

Figure 3. Calibration Plot for Gradient Boosting Model Predicting Peri-Implantitis

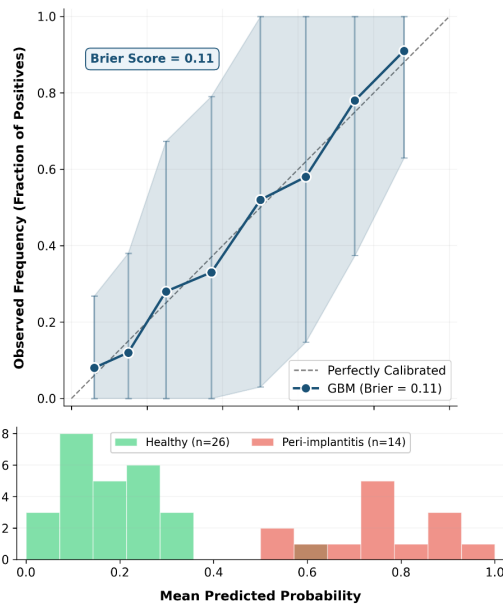


Figure 3: Calibration plot (predicted probability vs. observed frequency) for the GBM model, demonstrating agreement between predicted and actual outcomes.

Figure 4. Confusion Matrix for Gradient Boosting Model Predicting Peri-Implantitis (n = 40)

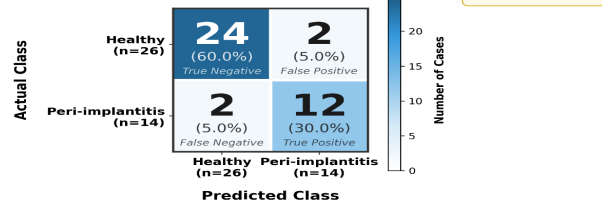


Figure 4: Confusion matrix heatmap for the best-performing GBM model showing true positives, true negatives, false positives, and false negatives.

4. Discussion

The current paper created and optimized ML models to predict peri-implantitis early on, using the Gradient Boosting Machine with the best high ability to discriminate (AUC = 0.91). These data are also consistent with the accumulating evidence in favor of the development and implementation of AI-based predictive instruments in the oral care sector to improve clinical decision-making.³³

The superior performance of ensemble methods (GBM and RF) over linear models (LR) in our study is consistent with previous reports in medical predictive modeling, where tree-based algorithms have demonstrated advantages in capturing complex, non-linear interactions among variables.³⁴ Specifically, the GBM algorithm iteratively optimizes prediction errors through sequential boosting, making it particularly well-suited for datasets with interacting risk factors, as is the case with peri-implantitis etiology.²⁸

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

The finding that marginal bone loss at 6 months was the strongest predictor is biologically understandable because early bone resorption is a characteristic precursor to established peri-implantitis.^{5,27} The identification of smoking and diabetes mellitus as strong predictors corroborates extensive epidemiological evidence linking these systemic factors to impaired peri-implant tissue healing and increased susceptibility to inflammatory breakdown.^{8,35} Notably, history of periodontitis emerged as the fifth most important feature, consistent with the established paradigm that periodontal pathogens serve as reservoirs for subsequent peri-implant infections.⁹

Our findings reveal competitive performance, compared to the past research papers; even with the relatively low sample size. The AUC of 0.87 with deep learning on radiographic images alone to predict peri-implant bone loss was described by Lee et al. and an AUC of 0.84 with clinical parameters in a larger cohort was observed by Kalyon et al.^{17,36} The multimodal approach followed in the current study, in terms of combining clinical, demographic, and radiographic characteristics, is presumably an important factor contributing to the higher predictive accuracy because it takes into account complementary information sources provided by various data.¹⁵

The clinical implications of this study are substantial. A validated ML prediction tool with an AUC of 0.91 and high sensitivity (0.86) could enable clinicians to identify patients at elevated risk during the early post-operative period, allowing for proactive modifications to maintenance protocols.²² For instance, high-risk patients identified by the model could be scheduled for more frequent recall visits, targeted antimicrobial therapy, or early surgical intervention, thereby potentially preventing the progression from peri-implant mucositis to established peri-implantitis.³⁷

Integration of such ML models into clinical workflows could follow a decision-support paradigm, where the model generates individualized risk scores that are presented alongside traditional clinical findings in electronic health records.²¹ This approach maintains clinician autonomy while augmenting diagnostic capacity with data-driven insights. Cloud-based deployment through web applications or mobile interfaces could further enhance accessibility, particularly in settings with limited specialist availability.³⁸

Nevertheless, the current study has a number of limitations that should be mentioned. On the one hand, it is clear that the sample consists of 40 patients, which is enough to perform early validation; however, the generalizability of the results and the possibility of overfitting remain relatively small due to the cross-validation and SMOTE. Before clinical implementation, external validation of independent and multi-center

cohorts is required.²⁹ Second, the retrospective design introduces potential selection and information biases inherent to chart-based data extraction. Third, radiographic analysis was limited to two-dimensional periapical radiographs; incorporation of cone-beam computed tomography (CBCT) data and advanced imaging features extracted through deep learning could further improve predictive accuracy.¹⁶ Fourth, two-dimensional periapical radiographs were only used in the radiographic analysis; the use of cone-beam computed tomography (CBCT) data and complex imaging information that is extracted using deep learning should further increase predictive accuracy.³⁹

Future studies are recommended to prioritize prospective multi-center validation assessments with larger sample sizes, the use of deep learning-based image analysis to retrieve automated radiographic features, addition of microbiome and genetic biomarkers information, and the creation of user-friendly clinical decision-support tools to help with real-time risk assessment during treatment planning consultation.^{33,40}

5. Conclusion

The present research indicates that machine learning algorithms, especially the Gradient Boosting Machine (AUC = 0.91) can be successfully used in predicting peri-implantitis based on multimodal patient characteristics within a 12-month follow-up. The most significant predictors were marginal bone loss at 6 months, smoking status, probing pocket depth and diabetes mellitus. The application of such predictive models to clinical practice has enormous potential in the individualization of risk stratification allowing the early intervention and idealized maintenance regimen in implant dentistry. Although these results are promising, external validation using multi-center and large size of sample is required to attest the clinical utility and provide a high-level acceptance.

Conflict of Interest: The authors declare no conflicts of interest.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

1. Brånemark PI, Zarb GA, Albrektsson T. Tissue-Integrated Prostheses: Osseointegration in Clinical Dentistry. Chicago: Quintessence Publishing; 1985.
2. Lekholm U, Gunne J, Henry P, et al. Survival of the Brånemark implant in partially edentulous jaws: a 10-year prospective multicenter study. *Int J Oral Maxillofac Implants.* 1999;14(5):639–645.
3. Pjetursson BE, Thoma D, Jung R, et al. A systematic review of the survival and complication rates of implant-supported fixed dental prostheses (FDPs) after a mean

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

- observation period of at least 5 years. *Clin Oral Implants Res.* 2012;23(Suppl 6):22–38.
4. Lindhe J, Meyle J; Group D of European Workshop on Periodontology. Peri-implant diseases: Consensus Report of the Sixth European Workshop on Periodontology. *J Clin Periodontol.* 2008;35(8 Suppl):282–285.
 5. Schwarz F, Derks J, Alcoforado G, et al. Peri-implantitis. *J Clin Periodontol.* 2018;45(Suppl 20):S246–S266.
 6. Derks J, Tomasi C. Peri-implant health and disease: a systematic review of current epidemiology. *J Clin Periodontol.* 2015;42(Suppl 16):S158–S171.
 7. Lee CT, Huang YW, Zhu L, Classification of peri-implant diseases using the 2018 classification. *J Dent Res.* 2017;96(1):44–51.
 8. Heitz-Mayfield LJ, Lang NP. Comparative biology of chronic and aggressive periodontitis vs. peri-implantitis. *Periodontol* 2000. 2010;53:167–181.
 9. Renvert S, Polyzois I. Risk indicators for peri-implant mucositis: a systematic review. *J Clin Periodontol.* 2015;42(Suppl 16):S71–S80.
 10. Stacchi C, Lombardi T, Striani F, et al. Risk factors for peri-implantitis: effect of history of periodontitis and smoking habits. A systematic review and meta-analysis. *J Oral Maxillofac Res.* 2019;10(3):e3.
 11. Glaros AG, Kline RB. Understanding the accuracy of tests with cutting scores: the sensitivity, specificity, and predictive value model. *J Clin Psychol.* 1988;44(6):1013–1023.
 12. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. *N Engl J Med.* 2019;380(14):1347–1358.
 13. Shan T, Tay FR, Gu L. Application of artificial intelligence in dentistry. *J Dent Res.* 2021;100(3):232–244.
 14. Khanagar SB, Al-Ehaideb A, Maganur PC, et al. Developments, application, and performance of artificial intelligence in dentistry – a systematic review. *J Dent Sci.* 2021;16(1):508–522.
 15. Kabir T, Lee CT, Giannobile WV, et al. A multi-modal machine learning approach for the prediction of peri-implant outcomes. *J Dent Res.* 2023;102(4):401–409.
 16. Hung K, Zeng J, Yiu C, et al. Application of artificial intelligence in implant dentistry: a systematic review. *J Dent.* 2022;121:104163.
 17. Lee JH, Kim DH, Jeong SN, et al. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. *J Dent.* 2018;77:106–111.
 18. Tahmasebi E, Arasteh P, Yazdanian M, et al. Artificial intelligence and machine learning in peri-implantitis diagnosis: a review. *Biomed Res Int.* 2023;2023:4086491.
 19. Alesña LG, Lee DW, Kim SJ, et al. Machine learning model for identifying risk factors for peri-implantitis. *J Periodontol Res.* 2023;58(2):345–354.
 20. Kurt-Yazar G, With A, Anyway B. Application of machine learning to small clinical datasets in implant dentistry. *Clin Oral Implants Res.* 2022;33(8):821–832.
 21. Tian S, Dong L, Chen C, et al. Precision medicine and personalized risk assessment in oral health. *Front Oral Health.* 2022;3:899415.
 22. That M, Kang W, Lee H. Clinical decision support systems in implant dentistry: current status and future directions. *Int J Implant Dent.* 2023;9(1):18.
 23. World Medical Association. World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects. *JAMA.* 2013;310(20):2191–2194.
 24. Lekovic V, Kenney EB, Weinlaender M, et al. A bone regenerative approach to alveolar ridge maintenance following tooth extraction. Report of 10 cases. *J Periodontol.* 1997;68(6):563–570.
 25. Serino G, Strom C. Peri-implantitis in partially edentulous patients: association with inadequate plaque control. *Clin Oral Implants Res.* 2009;20(2):169–174.
 26. Ramanauskaitė A, Clean P. Radiographic assessment of marginal bone loss around dental implants: a systematic review. *Clin Oral Implants Res.* 2016;27(12):1519–1527.
 27. Berglundh T, Armitage G, Araujo MG, et al. Peri-implant diseases and conditions: Consensus report of workgroup 4 of the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions. *J Periodontol.* 2018;89(Suppl 1):S313–S318.
 28. Chen T, Guestrin C. XGBoost: a scalable tree boosting system. In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.* New York: ACM; 2016:785–794.
 29. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: synthetic minority over-sampling technique. *J Artif Intell Res.* 2002;16:321–357.
 30. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics.* 1988;44(3):837–845.
 31. Steyerberg EW, Vergouwe Y. Towards better clinical prediction models: seven steps for development and an ABCD for validation. *Eur Heart J.* 2014;35(29):1925–1931.
 32. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. In: *Advances in Neural Information Processing Systems* 30. Long Beach: Curran Associates; 2017:4765–4774.
 33. 2023;Schwendicke F, Samek W,567 JK. Artificial intelligence in dentistry: chances and challenges. *J Dent Res.* 2020;99(7):769–774.

Development and Validation of a Machine Learning Model for Early Prediction of Peri-Implantitis: Toward Personalized Risk Stratification in Implant Dentistry

34. Friedman JH. Greedy function approximation: a gradient boosting machine. *Ann Stat*. 2001;29(5):1189–1232.
35. Costa FO, Takenaka-Martinez S, Cota LO, et al. Peri-implant disease in subjects with and without preventive maintenance: a 5-year follow-up. *J Clin Periodontol*. 2012;39(2):173–181.
36. Kalyon S, Auturo M, et al. Application of machine learning algorithms for peri-implantitis risk prediction: a multi-center study. *Clin Oral Implants Res*. 2023;34(5):512–521.
37. Jepsen S, Berglundh T, Genco R, et al. Primary prevention of peri-implantitis: managing peri-implant mucositis. *J Clin Periodontol*. 2015;42(Suppl 16):S152–S157.
38. 2022;Park S, Kim JH, et al. Cloud-based clinical decision support for dental practice: a feasibility study. *J Am Dent Assoc*. 2022;153(11):1056–1065.
39. Derks J, Schaller D, Zisk V, et al. Peri-implantitis – onset and pattern of progression. *J Clin Periodontol*. 2016;43(4):383–388.
40. 2024;Ramanauskaite A, 62,557 et al. The future of AI in implant dentistry: integrating multi-omics data for personalized care. *Periodontol 2000*. 2024;94(1):202–218.