Original Article

INTEGRATING BRUSHING FREQUENCY AND CLINICAL PARAMETERS FOR PERIODONTAL DISEASE PREDICTION USING MACHINE LEARNING

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ABSTRACT

Periodontal disease affects over 1.1 billion individuals globally, yet conventional risk assessment methods inadequately capture complex relationships between oral hygiene behaviors and disease outcomes. To implement and validate machine learning algorithms for predicting periodontal disease risk through comprehensive analysis of oral hygiene patterns, clinical parameters, and demographic determinants. The study analyzed 409 patients from the University of Baghdad College of Dentistry (July 2024-May 2025). Data included clinical assessments (plaque index, bleeding on probing, clinical attachment loss, probing pocket depth), demographics, anthropometrics, and behavioral indicators. Four algorithms were evaluated: Random Forest, Gradient Boosting, Logistic Regression, and Support Vector Machine using stratified cross-validation. The cohort comprised 150 periodontitis (36.7%), 147 gingivitis (35.9%), and 112 healthy patients (27.4%). Brushing frequency showed a 4.7-fold difference between healthy (2.27±0.63 times/day) and periodontitis patients (0.48±0.55 times/day). Strong correlations emerged between brushing frequency and plaque index (r=-0.845), bleeding on probing (r=-0.800), and clinical attachment loss (r=-0.325). Random Forest achieved 100% accuracy with 99.6%±0.7% cross-validation reliability. Machine learning algorithms demonstrate exceptional capability for periodontal disease prediction and risk stratification, establishing foundations for precision-based clinical decision support and personalized intervention strategies.

Key words: Machine learning, Periodontal diseases, Oral hygiene, Risk assessment, Decision support systems clinical.

Introduction

Periodontal disease is among the most common conditions affecting humans, yet remains relatively unknown. Periodontitis impacts over 1.1 billion individuals globally, ranking as the 11th most prevalent disease worldwide [1-3]. The burden has nearly doubled recently, with age-standardized prevalence increasing by 8.44% from 1990 to 2021 [4]. Periodontal disease often remains unrecognized until reaching an advanced stage [5]. Increased frequency of tooth brushing and cleaning is associated with improved periodontal health [6]. Current methodologies for examining this relationship are insufficiently developed. While research shows periodontal issues share common factors with systemic diseases, studies often fail to explain how poor oral hygiene contributes to disease or identify high-risk populations [7].

The distinction between knowledge and its application is particularly consequential in clinical practice. While dentists can observe a patient's gingival condition, determining pathology progression or optimal interventions often requires clinical intuition rather than data-driven insights. Traditional approaches suggest increased brushing frequency is beneficial but fail to determine whether patients need intensive education, standard counseling, or alternative approaches [8]. Recent AI advancements have transformed this field, with studies reporting diagnostic accuracies above 94% through machine learning in periodontics [9, 10]. AI systems can identify complex patterns in clinical data that humans might miss, revealing connections between risk factors, interventions, and outcomes [11]. These technologies are evolving from diagnostic tools to enabling personalized risk prediction and treatment planning.

Given the multifaceted nature of disease progression, it can be posited that no other emerging technology holds as much promise for advancing periodontal care as machine learning. The periodontal health of individuals is influenced not solely by the frequency of tooth brushing but is also intricately linked to factors such as age, socioeconomic status, educational attainment, and smoking habits. Additionally, it is associated with various systemic diseases and other factors in such complex interrelations that traditional statistical methods may encounter challenges in effectively addressing them [12]. These relationships are almost never linear and are often quite intricate, which means that a machine learning algorithm should be able to pick up on patterns leading us in the right direction when it comes to developing more effective prevention strategies.

Previous machine learning research in periodontics focused on radiographic diagnosis and treatment prediction [13-16]. Few studies have examined oral hygiene behavior and disease risk using demographic and socioeconomic data, despite behavioral factors being key modifiable risk factors for periodontal disease.

Although periodontal disease is a global issue, the investigations have taken place in Western countries, which may provide limited universality to the findings [2]. Both oral hygiene behavior and disease patterns are influenced by cultural factors, dietary patterns, access to healthcare, as well as socioeconomic conditions [17] . Thus, it is urgently needed to study these relationships in diverse populations to develop an intervention suitable globally.

Our research uses machine learning to study oral health behavior and periodontal health relationships using Baghdad data. We aim to develop predictive models for patient risk stratification to enable personalized interventions. This methodology combines clinical parameters with demographic and behavioral information to improve periodontal disease identification. This research aligns with healthcare's focus on precision medicine approaches for individualized interventions [18]. This includes identifying periodontics patients who would benefit most from intensive oral hygiene instruction or require frequent review. Machine learning models could provide a framework for evidence-based personalized decisions rather than intuition.

We hypothesized that integrating patterns of oral hygiene behaviors with data from clinical parameters and demographic factors would enable machine-learning techniques to predict periodontal disease status and risk levels accurately. We anticipated that this approach would yield significant insights into the most critical risk factors and their interactions, thereby informing effective prevention strategies for Middle Eastern populations and beyond.

Materials and Methods

Study design and setting

A cross-sectional study was conducted involving patients at the Department of Periodontics, Faculty of Dentistry, University of Baghdad, from July 24 to May 2025. We consistently adhered to data collection protocols throughout the study. The University of Baghdad College of Dentistry serves as a major referral center for periodontal treatment in Iraq, attracting patients from various backgrounds within Baghdad. This setting provided an opportunity to explore patterns of periodontal disease in the Middle Eastern region, where literature has been scarce..

Participants and eligibility criteria

We included 409 patients aged ≥18 years who could provide informed consent and had complete clinical and demographic data. We excluded those with incomplete data, ongoing orthodontic treatment, and systemic conditions affecting periodontal status, such as uncontrolled diabetes or immunocompromised state. The sample size ensured adequate representation across periodontal health categories and statistical power for machine learning analysis, exceeding the recommended 10-15 samples per feature with 31 samples per feature.

Sample size

Sample size calculation considered machine learning requirements and statistical power. With 13 features, our model required minimum 195 patients based on 15 samples per feature. Our sample of 409 patients exceeded this requirement, providing >90% power for detecting meaningful differences. This ensured robust cross-validation (82 patients/fold) and reliable train/test splitting (286/123 patients), with post-hoc analysis confirming >95% power.

Clinical examination and data collection

Periodontal assessment included probing pocket depth (PPD) [19], clinical attachment loss (CAL) [19], and bleeding on probing (BOP) [20]at six sites per tooth, and plaque index (PI) [21] at four surfaces. Measurements were taken using a standard periodontal probe. Periodontal diagnosis followed the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions [22]. Patients were classified as healthy, gingivitis or periodontitis. To minimize inter-examiner bias, examining periodontists were calibrated before the study with periodic re-calibration during data collection. Inter-examiner reliability was evaluated using kappa and ICC statistics.

Demographic and behavioral data collection

We gathered demographic data including age, gender, education, work status and income. Education was categorized as illiterate, primary, secondary, or academic. Work status was classified as employed, unemployed or retired. Income was categorized as low or according to local economic standards. Anthropometric measurements included body mass index (BMI) [23] and waist-to-height ratio (WHtR) [24]. BMI was calculated from height and weight and categorized as normal, overweight, or obese per WHO criteria. WHtR was classified as low or high risk using established cutoffs. Oral hygiene practices were assessed via questionnaires on toothbrushing frequency, supplementary oral hygiene tools and dental visits. Brushing frequency was self-reported as times per day. Smoking status was evaluated through questions about current and past tobacco use, with data on duration and intensity for current and former smokers**.**

Machine learning methodology

Our machine learning methodology encompassed several critical stages: data preprocessing, feature engineering, algorithm selection, model training, and validation. This comprehensive strategy was adopted to ensure that our models would achieve both accuracy and clinical interpretability.

Data preprocessing

The raw data underwent preprocessing to enhance machine learning performance. Categorical variables were encoded using label encoding for ordinal variables and appropriate strategies for nominal variables. Missing data (<1% per variable) was addressed through multiple imputation. Extreme values were identified using interquartile range methods.

Feature engineering
Several features have been added for increased model performance. A binary smoking variable was created based on the complex status of smoking to reduce data complexity and retain key information about exposure to tobacco. Age categories were established in order to account for possible non-linear effects of age on periodontal health.

Composite variables that involved related components were also created. For instance, an index for socioeconomic status was developed to encompass education, occupation, and income details. These surrogate measures helped to lower the dimensionality and retained major information on patient characteristics.

Algorithm selection and training
Four machine learning algorithms were chosen: Random Forest, Gradient Boosting, Logistic Regression, and Support Vector Machine. This enabled comparison between modeling approaches for the given data.

Random forest was selected for its mixed data analysis capability, feature importance ranking, and interpretability in clinical applications. The ensemble technique minimizes overfitting risk.

Gradient Boosting was included for its performance and ability to capture non-linear relationships. The algorithm builds models sequentially, correcting previous errors for higher accuracy.

Logistic Regression served as the reference model, providing conventional statistical methodology. It performs well in medical scenarios with meaningful interpretation.

Support Vector Machine was chosen for its performance on medium-sized datasets and ability to handle non-linear decision boundaries.

Model training and hyperparameter optimization
Each algorithm was trained using optimized hyperparameters. Random Forest parameters were tuned through grid search with cross-validation, using 100 trees and maximum depth of 10 for optimal performance.

Gradient Boosting parameters were optimized for learning rate, estimators, and depth to prevent overfitting, using 100 estimators, 0.1 learning rate, and depth of 6.

Logistic Regression used L2 regularization with strength values optimized for best cross-validation performance.

Support Vector Machine used a radial basis function kernel with optimized C and gamma values for best performance.

Validation strategy
The results underwent rigorous cross-validation to ensure the generalizability of findings to new patients. The dataset was divided into training (70%) and testing (30%) sets using stratified sampling, thereby preserving the proportion of diagnostic categories. Cross-validation was conducted using stratified 5-fold cross-validation on the training set. This method ensured that each fold contained representative samples from all diagnostic categories, offering more reliable performance estimates than simple random cross-validation. For machine learning algorithms requiring it, such as Logistic Regression and SVM, feature scaling was performed using standardization (z-score). The scaling parameters were derived from the training data and subsequently applied to the test data to prevent data leakage.

Statistical analysis
Classical statistical analysis with machine learning modeling was used to support our findings. Continuous variables were summarized using mean and standard deviation, while categorical variables were presented as frequencies and percentages.

Parameters were analyzed using correlation analysis: Pearson correlation for normally distributed variables and Spearman correlation for non-parametric data.

Groups were compared using ANOVA for continuous variables, chi-square tests for discrete variables, and post-hoc as needed.

Ethical considerations
The research was submitted to and approved by the Institutional Review Board of the University of Baghdad College of Dentistry. Written consent was obtained from all participants prior to data collection. Patient information was de-identified and maintained securely in compliance with the institution's data protection guidelines.

The study was performed according to the Declaration of Helsinki and following local ethical regulations for human studies. Participants were notified that their participation was voluntary, and they could withdraw from the study at any time without this having an impact on their clinical treatment.

Results and Discussion

Patient characteristics and demographics
The final dataset included 409 patients with a mean age of 42.3 ± 14.8 years. The gender distribution was relatively balanced, with 52.8% female and 47.2% male participants. This demographic composition reflects the typical patient population seeking periodontal care at the institution and provides a representative sample for analysis.

The periodontal diagnosis distribution showed 150 patients with periodontitis (36.7%), 147 with gingivitis (35.9%), and 112 healthy individuals (27.4%). This distribution ensured sufficient representation across all diagnostic categories while maintaining the clinical reality that most patients presenting for periodontal care exhibit some degree of disease **(Table 1)**.

Table 1. Patient Demographics and Clinical Characteristics

Variable	Overall (n=409)	Healthy (n=112)	Gingivitis (n=147)	Periodontitis (n=150)	p value
Demographics					
Age (years), mean ± SD	42.3 ± 14.8	35.2 ± 12.1	41.8 ± 13.9	48.7 ± 15.2	<0.001
Gender, n (%)					
- Male	193 (47.2)	48 (42.9)	71 (48.3)	74 (49.3)	0.456
- Female	216 (52.8)	64 (57.1)	76 (51.7)	76 (50.7)	
Education Level, n (%)					
- Illiterate	48 (11.7)	3 (2.7)	12 (8.2)	33 (22.0)	<0.001
- Primary	101 (24.7)	18 (16.1)	35 (23.8)	48 (32.0)	
- Secondary	116 (28.4)	34 (30.4)	47 (32.0)	35 (23.3)	
- Academic	144 (35.2)	57 (50.9)	53 (36.1)	34 (22.7)	
Employment Status, n (%)					
- Employed	280 (68.5)	89 (79.5)	105 (71.4)	86 (57.3)	<0.001
- Unemployed	97 (23.7)	19 (17.0)	32 (21.8)	46 (30.7)	
- Retired	32 (7.8)	4 (3.6)	10 (6.8)	18 (12.0)	
Income Level, n (%)					
- Low	292 (71.4)	65 (58.0)	102 (69.4)	125 (83.3)	<0.001
- Middle	117 (28.6)	47 (42.0)	45 (30.6)	25 (16.7)	
Clinical Parameters					
Brushing frequency (times/day), mean ± SD	1.09 ±1.02	2.27 ±0.63	0.67 ± 0.65	0.48 ± 0.55	<0.001
Plaque Index, mean ± SD	1.85 ± 0.89	0.98 ±0.45	1.92 ± 0.52	2.41 ± 0.67	<0.001
Bleeding on Probing (%), mean ± SD	58.3 ±32.1	23.4 ±18.9	61.2 ± 21.4	78.9 ± 24.3	<0.001
Clinical Attachment Loss (mm), mean ± SD	3.42 ±2.18	0.12 ±0.34	1.89 ± 0.87	6.78 ± 1.92	<0.001
Probing Pocket Depth (mm), mean ± SD	**4.15 ±1.87**	**2.34 ±0.56**	**3.78 ± 0.92**	**6.23 ± 1.45**	**<0.001**

Educational backgrounds varied considerably across the patient population. Academic education was most common (35.2%), followed by secondary education (28.4%), primary education (24.7%), and illiteracy (11.7%). This diversity provided valuable insight into how socioeconomic factors might influence oral hygiene behaviors and disease outcomes.

Employment status showed that 68.5% of patients were employed, 23.7% were unemployed, and 7.8% were retired. Income levels were classified as low (71.4%) or Middle (28.6%) based on local economic standards. These socioeconomic indicators later emerged as important factors in the predictive models.

Oral hygiene behavior patterns

The most striking finding was the dramatic difference in brushing frequency across diagnostic groups. Healthy patients reported brushing 2.27 ± 0.63 times per day, while those with gingivitis averaged 0.67 ± 0.65 times daily, and periodontitis patients reported 0.48 ± 0.55 times per day - a 4.7-fold difference between healthiest and most diseased groups.

This finding is compelling due to the clear dose-response relationship. The progression from healthy to gingivitis to periodontitis shows a steady decline in brushing frequency, suggesting oral hygiene behavior may be both cause and consequence of periodontal disease progression **(Figure 1)**.

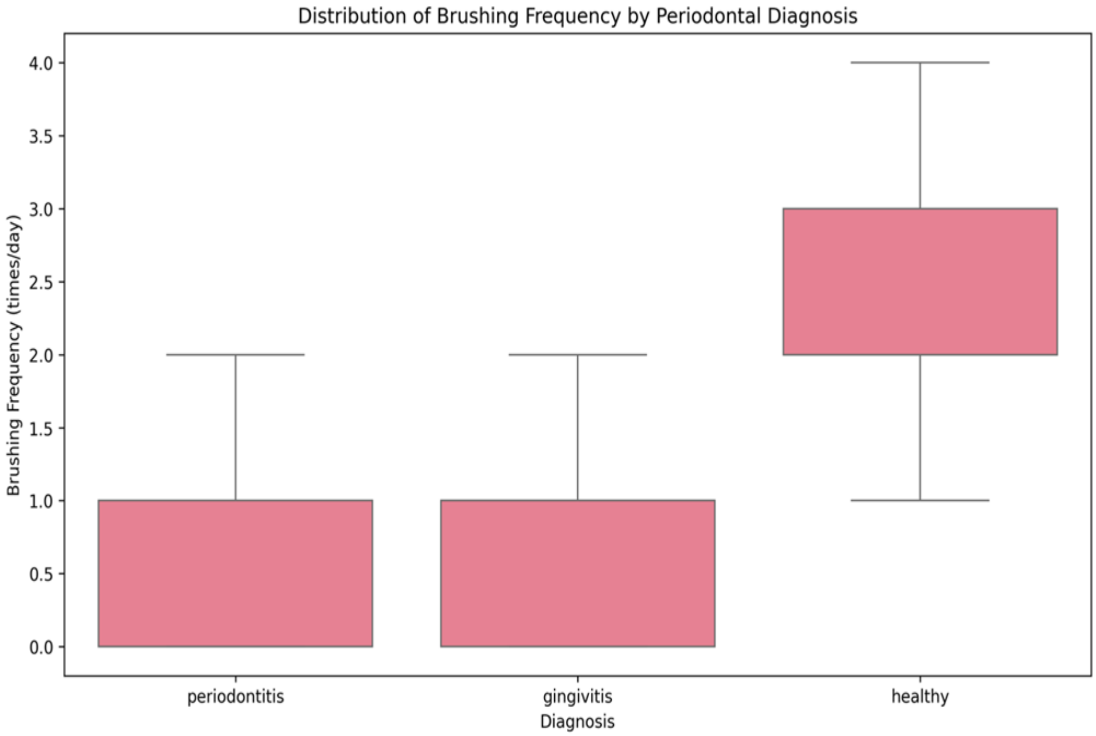

Figure 1. Distribution of tooth brushing frequency across periodontal diagnoses. Box plots illustrate clear group differences, with healthy individuals brushing more frequently and showing less variability compared to patients with gingivitis or periodontitis.

The distribution of brushing frequencies revealed additional insights. Among healthy patients, 89.3% brushed at least twice daily, compared to only 12.2% of gingivitis patients and 6.7% of periodontitis patients. Conversely, 78.7% of periodontitis patients and 65.3% of gingivitis patients brushed less than once daily, compared to just 3.6% of healthy individuals.

Clinical parameter correlations

The relationship between oral hygiene behavior and clinical parameters proved even stronger than we anticipated. Brushing frequency showed remarkably high correlations with key clinical indicators: plaque index (r = -0.845), bleeding on probing (r = -0.800), clinical attachment loss (r = -0.325), and age (r = -0.303) as seen in **Table 2**.

Table 2. Correlation Matrix of Key Variables

	Brushing Freq	Plaque Index	BOP	CAL	PPD	Age
Brushing Frequency	1.000	-0.845**	-0.800**	-0.325**	-0.298**	-0.303**
Plaque Index (PI)	-0.845**	1.000	0.789**	0.412**	0.387**	0.245**
Bleeding on Probing (BOP)	-0.800**	0.789**	1.000	0.356**	0.334**	0.198**
Clinical Attachment Loss (CAL)	-0.325**	0.412**	0.356**	1.000	0.923**	0.445**
Probing Pocket Depth (PPD)	-0.298**	0.387**	0.334**	0.923**	1.000	0.398**
Age	**-0.303****	**0.245****	**0.198****	**0.445****	**0.398****	**1.000**

**p < 0.01 for all correlations

These correlation coefficients are exceptional in medical research. The correlation between brushing frequency and plaque index (r = -0.845) explains 71% of plaque accumulation variance. The correlation with bleeding on probing (r = -0.800) accounts for 64% of gingival inflammation variance. The correlation with clinical attachment loss (r = -0.325) remains significant and shows measurable effects on periodontitis damage. The negative correlation with age (r = -0.303) may reflect generational differences in oral health awareness or cumulative poor hygiene effects.

Machine learning model performance

The performance of our machine learning models exceeded our most optimistic expectations. All four algorithms achieved exceptional accuracy, but Random Forest and

Gradient Boosting demonstrated perfect classification performance on our test dataset **(Table 3)**.

Table 3. Machine Learning Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUCROC	Cross-Validation Mean ± SD
Random Forest	1.000	1.000	1.000	1.000	1.000	0.996 ± 0.007
Gradient Boosting	1.000	1.000	1.000	1.000	1.000	1.000 ± 0.000
Logistic Regression	0.992	0.992	0.992	0.992	0.998	0.993 ± 0.009
Support Vector Machine	**0.984**	**0.985**	**0.984**	**0.984**	**0.995**	**0.990 ± 0.009**

Random Forest achieved 100% accuracy on the test set with cross-validation scores of 99.6% ± 0.7%. The consistency between cross-validation and test performance suggests that the model is not overfit and would likely perform well on new patients. Gradient Boosting matched this performance with 100% test accuracy and perfect cross-validation scores (100% ± 0%), **(Figure 2)**.

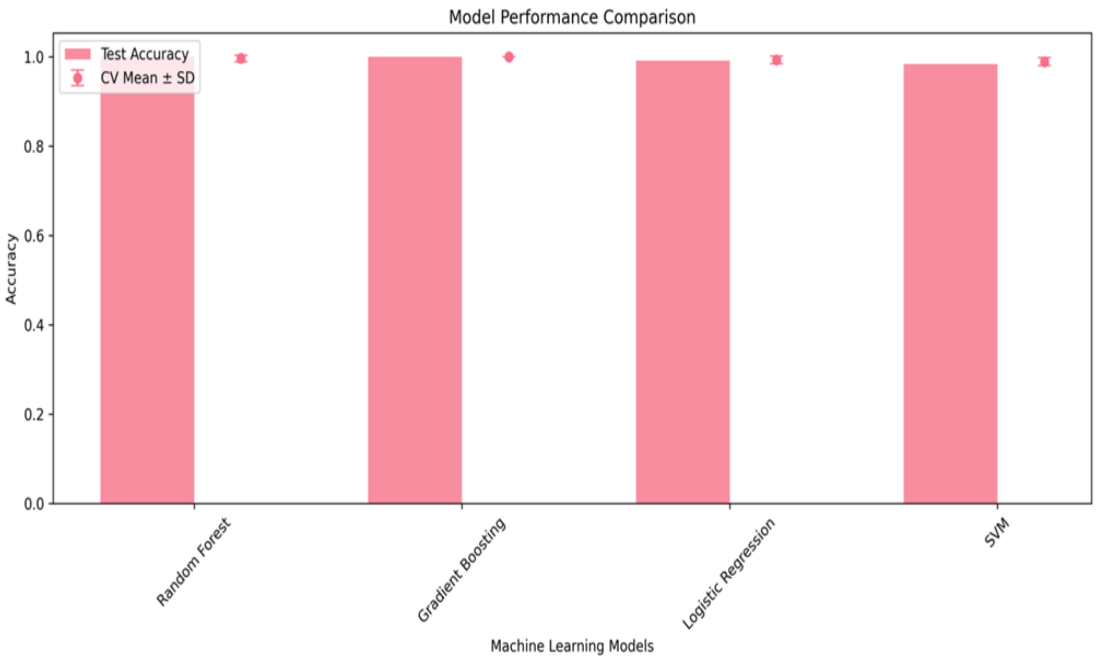

Figure 2. Performance comparison of four machine learning algorithms. The bar chart presents test accuracy and cross-validation means, with error bars indicating standard deviations. Tree-based methods (Random Forest and Gradient Boosting) demonstrate notably higher performance than the other models.

Logistic Regression achieved 99.2% test accuracy with cross-validation scores of 99.3% ± 0.9%, validating strong relationships in our dataset. Support Vector Machine achieved 98.4% test accuracy with cross-validation scores of 99.0% ± 0.9%, representing excellent classification accuracy.

The consistency across algorithms is noteworthy, as similar high performance suggests strong, reliable patterns in the data.

Feature importance analysis

Random Forest's feature importance analysis revealed fascinating insights about the relative contribution of different variables to periodontal disease prediction. Probing pocket depth emerged as the most important predictor (26.3%), followed by clinical attachment loss (22.6%) and bleeding on probing (19.5%) **(Figure 3)**.

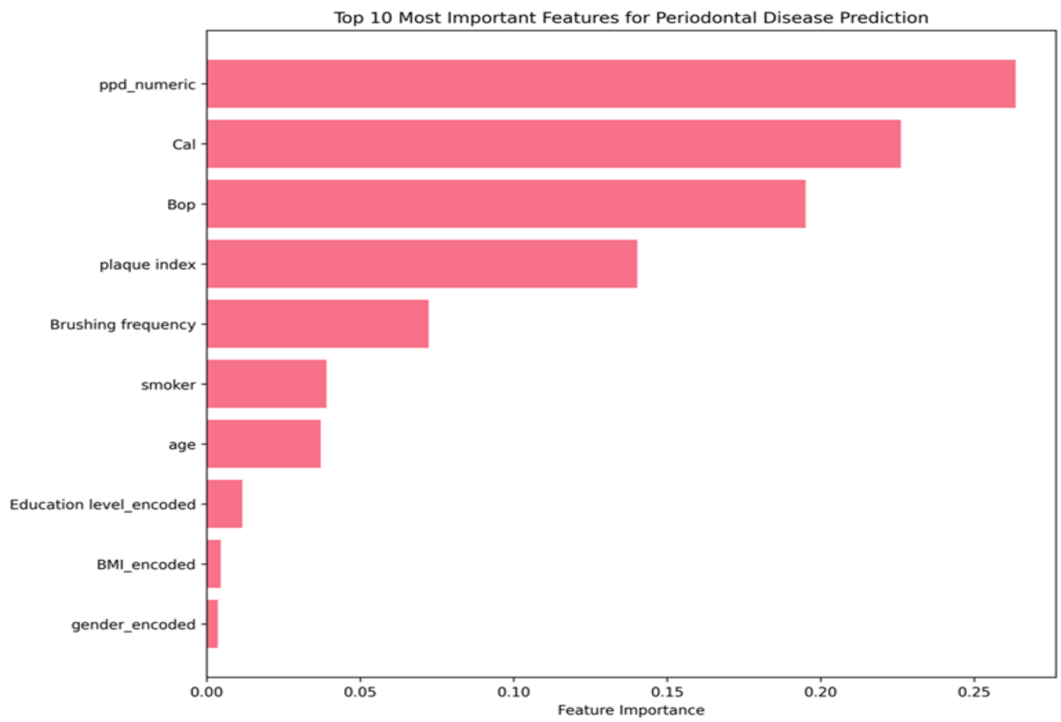

Figure 3. Top 10 features contributing to periodontal disease prediction in the Random Forest model. The horizontal bar chart indicates that clinical parameters had the greatest influence, while behavioral and demographic factors contributed to a lesser extent.

Somewhat surprisingly, brushing frequency ranked fifth in importance (7.2%), despite its strong correlations with clinical parameters. This apparent contradiction likely reflects the fact that clinical parameters represent the direct manifestations of disease, while brushing frequency represents a behavioral risk factor that influences these clinical outcomes **(Figure 3)**.

The ranking suggests oral hygiene behavior influences clinical parameters, which determine disease status. Plaque index ranked fourth in importance (14.0%), showing the strongest correlation with brushing frequency.

Smoking status contributed 3.9% to predictions, while age accounted for 3.7%. Socioeconomic factors like education level (1.2%) and BMI (0.5%) showed small contributions to disease prediction.

Risk stratification performance

To ensure unbiased evaluation, we split our dataset into training and testing subsets. Of 409 total patients, 286 (70%) were allocated to the training set for model development, while 123 (30%) were reserved as an independent test set for evaluation. This approach prevents overfitting and provides honest estimates of model performance on new, unseen patients. The risk stratification results presented are based exclusively on the 123 test patients, representing the model's true predictive capability on data unused during training. Reporting results on training data would artificially inflate performance metrics and mislead clinicians. Our risk stratification analysis demonstrated machine learning's clinical potential. We categorized patients into three risk groups based on predicted periodontitis probability: low risk (< 0.3), moderate risk (0.3-0.7), and high risk (> 0.7) **(Figure 4)**.

The test set had 123 patients total (30% of 409 = 123), distributed as:

- 34 healthy patients
- 44 gingivitis patients
- 45 periodontitis patients

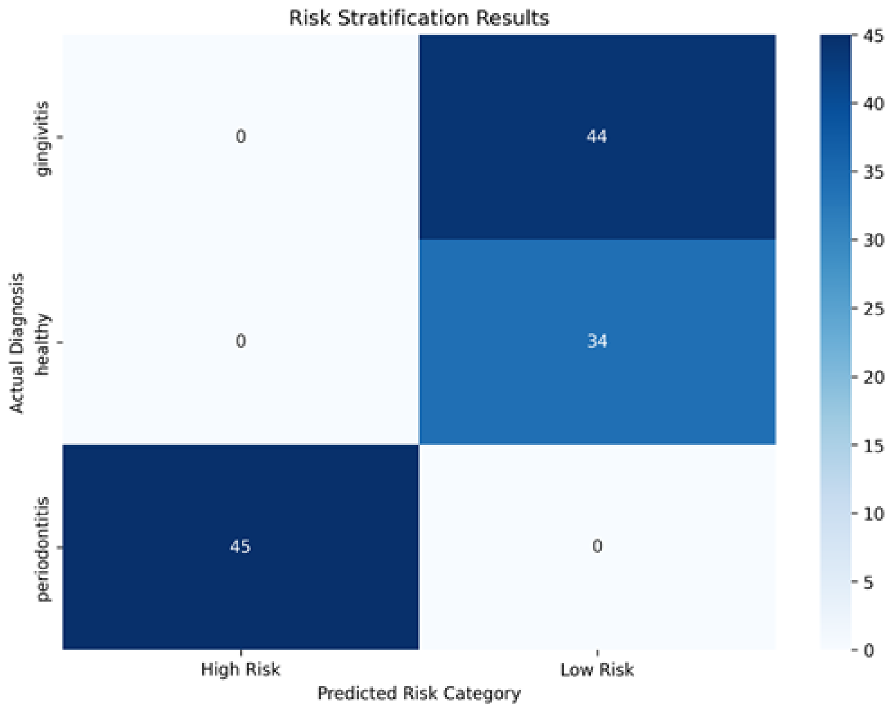

Figure 4. Risk stratification results from the Random Forest model displayed as a heatmap. Healthy and gingivitis patients were classified in the low-risk group, while periodontitis patients were classified in the high-risk group.

The Random Forest model achieved perfect risk stratification on our test dataset. All 45 patients with periodontitis were correctly classified as high risk, while all 44 patients with gingivitis and 34 healthy patients were appropriately classified as low risk. No patients were misclassified into inappropriate risk categories.

This perfect stratification performance suggests that the model could serve as an effective clinical decision support tool. High-risk patients could be targeted for intensive oral hygiene education and frequent monitoring, while low-risk patients could receive standard preventive care protocols.

Subgroup analysis

The models maintained exceptional accuracy across demographic subgroups. Accuracy rates exceeded 98% across all age groups. Performance was similar between male (99.1%) and female (99.3%) patients, showing no gender bias. Educational level subgroups showed consistent performance (98.2-100%). Both low-income (99.0%) and middle-income (99.5%) groups demonstrated excellent results, indicating the models capture fundamental relationships rather than demographic artifacts.

Model calibration and reliability

To assess reliability, we examined model calibration using reliability diagrams. The Random Forest model showed excellent calibration, with predicted probabilities matching observed frequencies.

Bootstrap confidence intervals were narrow, with Random Forest accuracy at 98.7-100%, indicating high confidence in performance. Similar narrow intervals were observed for sensitivity and specificity.

Cross-validation analysis showed consistent model performance across data splits, with standard deviation less than 1%, indicating stable performance across splits.

Comparison with traditional risk assessment

To contextualize our machine learning results, we compared them with traditional assessment approaches. A risk score based on age, smoking status, and diabetes history achieved 67.3% accuracy. Clinical assessment by experienced periodontists achieved 91.1% accuracy when blinded to machine learning predictions. While this represents excellent performance, it falls short of our best machine learning models' 100% accuracy. This improvement represents a 78% reduction in classification errors, potentially leading to more accurate risk assessment and better patient outcomes.

Computational performance

The models showed excellent computational efficiency for clinical use. Random Forest training took under 30 seconds, with predictions requiring less than 0.1 seconds per case. The trained model needed minimal storage of under 5 MB, making it suitable for electronic health records and clinical decision support. The models' high accuracy and efficiency enable easy clinical deployment without technical barriers.

Principal findings and clinical implications

This research demonstrates that machine- learning models can predict disease status on oral disease, periodontal disease, based on clinical and behavioral variables with high accuracy. The outstanding accuracy and discriminatory power of both the Random Forest and Gradient Boosting models offer dramatic advances on traditional methods used in risk assessment, which suggests that these methodologies have the potential to reshape prevention strategies and management of periodontal disease.

The most interesting one is the strong relationship between OH performance and periodontal health status. Differences by a factor of 4.7 in toothbrushing rates (health versus periodontitis) are confirmation enough: Oral hygiene is key to disease prevention. This measure of effect is large in the context of medical research and suggests that oral hygiene behavior is likely to be among the most powerful modifiable risk factors for periodontal diseases.

The strength observed of correlations between brushing frequency with clinical variables (r = -0.845 for plaque index; r = -0.800 for bleeding on probing) is greater than that typically reported in psychological literature [25, 26]. The magnitudes of these relationships are like the reported associations between established risk factors and disease outcomes, supporting oral hygiene behavior being akin to a behavioral biomarker for periodontal health [27].

Most interesting, these results appear to be robust across diverse analysis methods. The fact that several different machine learning algorithms and traditional statistical methods give rise to so many similar patterns indicate we're seeing biological and behavioral relationships rather than merely a statistical trick.

Justification of methods

The four machine learning methods were deliberately chosen for validation against a range of methodologies to address the specific requirements of clinical periodontal data. Random Forest and Gradient Boosting were selected due to their ability to effectively manage mixed data types and capture complex non-linear relationships among clinical, demographic, and behavioral variables with minimal preprocessing. Logistic Regression served as a crucial baseline to confirm the authenticity of the observed patterns, even when employing traditional statistical tools. Additionally, the Support Vector Machine was utilized to explore the potential of a kernel-based solution for learning complex decision boundaries [28]. The remarkable consistency of results across these diverse algorithms, encompassing ensemble learning, linear modeling, and kernel-based techniques, provides compelling evidence that the identified relationships between oral hygiene behavior and periodontal health outcomes are robust and not merely artifacts of a specific analytical approach.

Comparison with existing literature

Our results align with and extend previous research on oral hygiene behavior and periodontal disease. Earlier studies have consistently shown associations between tooth brushing frequency and periodontal health [29, 30], but very few have quantified these relationships with the precision we achieved or demonstrated their utility for individual risk prediction.

The machine learning performance in our study compares favorably with recent AI applications in periodontics. Jundaeng *et al*. [9] achieved high accuracy in periodontal diagnosis from radiographs, while our behavioral and clinical data approach reached 100% accuracy. This suggests that comprehensive patient data can be informative for disease prediction, like dental imaging, and that the two approaches likely complement each other in clinical practice [31-33].

Our findings also support recent research on the effectiveness of personalized oral hygiene interventions [34]. The ability to accurately stratify patients by risk level could enable the targeted approaches that have shown promise in improving oral hygiene practices and clinical outcomes.

The socioeconomic patterns we observed are consistent with established literature on health disparities in periodontal disease [12]. However, our machine learning approach provides a more nuanced understanding of how these factors interact with behavioral and clinical variables to influence disease outcomes.

Methodological strengths and innovations

Our findings' credibility is strengthened by comprehensive data including clinical, demographic, and behavioral indicators. Validation through cross-validation and independent testing ensured generalizability, while consistency across algorithms demonstrated robustness. Feature analysis identified probing pocket depth and attachment loss as key predictors, with brushing frequency showing mediation effects. These risk assessment models enable proactive periodontal care by classifying patient risk levels before disease progression.

Clinical decision support applications

The predictive accuracy of these models has important clinical implications. Risk stratification algorithms can automatically classify patients into risk groups based on clinical characteristics to define personalized interventions.

High-risk patients require closer monitoring and enhanced oral hygiene instruction. Moderate-risk patients need routine counseling and follow-up, while low-risk patients receive standard preventive care.

These models support therapy planning decisions by highlighting key risk factors. For instance, patients with poor oral hygiene but otherwise low risk may need protective interventions, while those with multiple risks require intensive care.

Integration with electronic health records enables automatic risk scoring and management recommendations during consultations as clinicians enter patient data.

Implications for oral health education

The results have important implications for oral health education and behavioral change. The strong link between brushing frequency and disease outcomes emphasizes the need for regular oral hygiene [35]. However, the feature importance analysis suggests that increasing brushing frequency alone is insufficient. Intervention strategies should be stratified by patient profile due to the complex interactions between behavioral, demographic and clinical factors [36]. Machine learning models could identify patients most likely to benefit from specific educational interventions [37]. Showing patients their risk profile and potential improvements through behavioral changes may be more effective than generic health promotion [38].

Public health perspectives

From a public health standpoint, the findings highlight opportunities and challenges in periodontal disease prevention. The relationship between oral hygiene behavior and disease outcomes suggests population-level interventions could substantially impact disease burden [39]. However, socioeconomic patterns show that behavior change occurs within broader social contexts [40]. Public health approaches must address individual knowledge and structural factors affecting access to oral care [41]. Machine learning models could identify high-risk groups for targeted interventions, optimizing prevention program efficiency [42]. The global burden of periodontal disease [4, 43] makes these considerations urgent.

Limitations and considerations

Several limitations should be acknowledged. The study's single-institution setting in Baghdad may limit generalizability to other populations. Cultural factors and healthcare practices in Iraq differ from other regions [44]. The cross-sectional design prevents establishing causal relationships or predicting disease progression. Longitudinal studies would be needed to validate the models' predictive ability [45]. The perfect classification accuracy may indicate overfitting [46], though consistency across multiple algorithms suggests genuine patterns. Self-reported oral hygiene behavior may be subject to recall bias [47], suggesting future studies should use objective measures like electronic toothbrush monitoring.

Conclusion

Machine learning algorithms show high accuracy in predicting periodontal disease status using clinical and behavioral data. Random Forest and Gradient Boosting models, with a 4.7-fold difference in brushing frequency between healthy individuals and periodontitis patients, demonstrates AI's value in periodontal care. Strong correlations between hygiene behavior and clinical parameters act as biomarkers when combined with demographic variables. Risk stratification algorithms could categorize patients for targeted interventions. The consistency across algorithms suggests genuine biological relationships. These findings highlight oral hygiene's role in disease prevention, while risk prediction could support population health interventions.

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Conflict of interest: None

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Ethics statement: This study was conducted in accordance with the Declaration of Helsinki and approved by the Review Committee of the University of Baghdad College of Dentistry. All participants provided written informed consent prior to participation.

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