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Research Progress on the Integration of Artificial Intelligence and Periodontitis Risk Prediction: A Review

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Abstract: Periodontitis is a chronic inflammatory disorder with multiple contributing factors, and conventional risk assessment remains limited in early prediction and personalized management. Artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), permits the integration of clinical, imaging, laboratory, microbiome, and genomic information for risk stratification. This review outlines the technical basis of AI-assisted periodontitis prediction, covering ML algorithms, deep-learning radiomics, multidimensional data integration, feature engineering, preprocessing, model training, validation, interpretability, and clinical translation. Available evidence shows encouraging predictive performance; however, data heterogeneity, inadequate external and prospective validation, privacy, fairness, and workflow integration continue to impede wider application.

Keywords: Artificial intelligence; Periodontitis; Risk prediction; Machine learning; Deep learning; Precision medicine

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1. Introduction

Periodontitis is a chronic inflammatory condition marked by progressive loss of periodontal supporting tissues and alveolar bone [1]. Conventional evaluation depends on probing pocket depth, clinical attachment loss, bleeding on probing, and radiographic bone loss. Although these measures are clinically indispensable, operator variability affects them, and they often describe damage only after it has developed [2,3]. Risk prediction is further complicated by the multifactorial origin of periodontitis, which involves microbial dysbiosis, host responses, genetic susceptibility, smoking, and systemic disease.

AI offers computational methods for detecting complex relationships in heterogeneous periodontal data. ML has been applied to clinical variables and salivary biomarkers, whereas DL has been used to assess periodontal structures on radiographs [4,5]. Transcriptomic information has likewise been incorporated into ML-based diagnostic models [6,7]. Together, these developments indicate that AI may support earlier and more individualized assessment of periodontal risk.

2. Technical foundation of AI in periodontitis risk prediction

2.1. Machine learning algorithms

Unsupervised and semi-supervised approaches may be valuable when labeled periodontal datasets are scarce. Unsupervised techniques can reveal patterns or phenotypes in high-dimensional clinical records, while semi-supervised strategies can use larger volumes of incompletely labeled data. Irrespective of the algorithm category, periodontal prediction is complicated by interactions among age, smoking, systemic conditions, clinical measurements, imaging findings, and biological markers. Hybrid approaches may therefore be advantageous, although added model complexity should be supported by better validation performance and clinically interpretable outputs rather than training accuracy alone [8].

Supervised ML techniques frequently used for periodontal prediction include logistic regression, support vector machines (SVM), random forests, and gradient-boosting algorithms. Logistic regression yields interpretable probabilities but may not adequately represent nonlinear interactions. Random forests combine decision trees, accommodate high-dimensional variables, and estimate feature importance. SVMs apply kernel functions to construct complex decision boundaries and may perform well on relatively small datasets, although kernel choice and parameter tuning affect overfitting and generalizability.

Gradient-boosting algorithms progressively correct prediction errors and can capture nonlinear associations between periodontal and systemic variables. One study combining thyroid-function parameters with clinical features achieved an AUC of 0.854 with XGBoost [9]. Algorithm choice should consequently reflect sample size, dimensionality, class imbalance, interpretability, and the intended clinical use rather than predictive accuracy alone.

2.2. Deep learning and radiomics

CNNs automatically derive imaging features from periapical radiographs, panoramic radiographs, and CBCT. They can detect alveolar bone loss, trabecular alterations, furcation defects, and other radiographic findings relevant to periodontal diagnosis and staging. U-Net-based methods have also been examined for segmenting periodontal bone loss [10].

Temporal information can be analyzed with recurrent neural networks and gated architectures. An Adaptive DenseNet coupled with a gated recurrent unit was designed to combine tooth segmentation and temporal modeling for periodontal bone-loss assessment [11]. CNN-based systems have likewise been used for radiographic bone-level evaluation, whereas newer detection and segmentation architectures have been investigated in panoramic imaging [12,13]. CBCT supplies three-dimensional information that segmentation networks can analyze for detailed evaluation of periodontal structures [14,15].

Explainability may be added to imaging models. For example, Eigen-CAM has been applied to display image regions that contribute to periodontal bone-loss classification [16]. These visualizations can support clinician review and error analysis, although they cannot fully account for model reasoning. Large annotated datasets and external validation are still required to confirm robustness across devices and populations.

3. Multidimensional data integration

3.1. Clinical and laboratory data

Periodontal risk models may combine probing depth, clinical attachment loss, plaque, bleeding, demographic characteristics, behavior, systemic conditions, and laboratory biomarkers. Inflammatory proteins and

metabolic indicators may add information beyond local periodontal measurements. Models combining clinical parameters, biomarkers, and periodontal pathogens have shown useful discrimination for disease progression [17]. Findings from large clinical datasets also suggest that integrating demographic, behavioral, systemic, and periodontal variables can improve prediction [18,19].

Multidimensional integration is technically important because variables differ in scale, distribution, biological significance, and missing-data patterns. Predictive models must therefore harmonize heterogeneous inputs while limiting redundant predictors and preventing data leakage.

3.2. Microbiome and genomic data

Microbiome composition adds another source of information for periodontal prediction. Periodontitis is linked to microbial dysbiosis and altered levels of organisms such as *Porphyromonas gingivalis*, *Tannerella forsythia*, and *Treponema denticola* [20]. ML classifiers based on salivary microbiome profiles have been developed to distinguish periodontal health and disease stages, while quantitative microbial measurements have been included in site-specific models of disease severity [21,22].

Host genomic information may further define susceptibility. Multimodal approaches can theoretically combine microbial abundance with genetic, clinical, and environmental variables to characterize nonlinear host-microbe interactions. However, high dimensionality together with relatively small cohorts creates a considerable risk of overfitting. Multi-omics models therefore need rigorous feature selection, independent validation, and assessment of whether added biological complexity yields meaningful gains over simpler clinical models.

4. Construction of AI-based risk prediction models

4.1. Feature engineering and preprocessing

Feature engineering determines the variables presented to predictive algorithms and has a major influence on performance and interpretability. Available selection strategies include filter methods, recursive feature elimination, and embedded techniques such as Lasso regression. By penalizing coefficients, Lasso can shrink less informative variables toward zero and thereby reduce model complexity [23].

Missing data must be handled carefully because complete-case analysis or unsuitable imputation may introduce bias. Mean imputation is computationally simple but can distort variance. Multiple imputation represents uncertainty across plausible values, whereas ML-based imputation can make use of relationships among variables [24].

Scaling becomes important when algorithms respond to differences in feature magnitude. Z-score standardization transforms variables to approximately zero mean and unit variance, whereas Min-Max normalization rescales values within a specified interval. Such procedures are particularly relevant when clinical indices, laboratory concentrations, imaging-derived variables, and questionnaire scores are analyzed together.

Preprocessing should be fitted exclusively on training data and then applied to validation or test data to avoid information leakage. Feature selection, imputation, normalization, and hyperparameter optimization should consequently occur within the model-development pipeline rather than being performed on the complete dataset [25].

4.2. Training, validation, and evaluation

Model development must also separate discrimination from calibration. A model may distinguish high-risk from low-risk patients effectively yet still generate inaccurate absolute probabilities. Calibration curves are therefore important when predicted risks are used to guide preventive or treatment decisions. Class imbalance requires explicit attention because seemingly high accuracy may result when the majority outcome dominates the dataset. External cohorts drawn from different geographic or healthcare settings test generalizability more rigorously than repeated internal splitting and are especially important before periodontal risk models enter routine care.

Cross-validation is commonly applied when available datasets are small. In k-fold cross-validation, the data are divided into subsets, and the model is repeatedly trained on all folds except one before evaluation on the remaining fold. When preprocessing or hyperparameter optimization is required, these steps should be conducted inside the training folds to prevent overly optimistic performance estimates.

Accuracy by itself is inadequate, particularly when outcomes are imbalanced. Evaluation should report sensitivity, specificity, precision, recall, F1-score, and AUC-ROC where appropriate. Calibration is equally relevant to risk prediction because a clinically useful model should generate probabilities consistent with observed risk rather than merely rank patients correctly.

Internal validation measures performance in the development population, whereas external validation examines transportability to independent populations, institutions, or healthcare systems. Transcriptomic ML models have been tested across several datasets, underscoring the value of independent evaluation [6]. Clinical models may also employ calibration plots, decision-curve analysis, and interpretable instruments such as nomograms [26].

5. Clinical validation and translation

5.1. Longitudinal and prospective validation

Longitudinal research is needed to establish whether AI predicts subsequent progression or tooth loss instead of merely classifying existing disease. In a retrospective longitudinal cohort of more than 3,000 teeth, a Random Forest model showed strong performance in predicting tooth loss [27]. Nomogram-based models have similarly combined smoking, mobility, and radiographic bone loss to predict tooth survival [28].

Nevertheless, retrospective performance alone cannot demonstrate prospective clinical utility. Prospective multicenter studies should adopt standardized data collection, predefined outcomes, suitable control of confounders, and representative patient populations. Evaluation should address calibration, reproducibility, clinical decisions, and outcomes relevant to patients.

5.2. Clinical decision support

Validated models could be embedded in electronic health records or dental clinical decision support systems (CDSS). These systems may automatically combine clinical measurements, radiographic findings, systemic factors, and biomarkers to produce individualized estimates of risk.

Interpretability methods such as SHAP can show how individual variables influence predictions. An effective CDSS should communicate this information in a clinically understandable manner rather than only displaying a numerical risk score. Successful integration also depends on interoperability, privacy protection, clinician training, and surveillance for model degradation as patient populations and data distributions

change.

6. Challenges and future directions

6.1. Data quality and privacy

Longitudinal and multicenter datasets create additional technical challenges because institutions may differ in missingness, measurement frequency, diagnostic criteria, and recording standards. Harmonization should retain clinically meaningful variation while limiting avoidable technical inconsistency. Federated learning may reduce the need to centralize raw records, but it does not automatically resolve differences in data distributions across participating centers. Likewise, synthetic data may enlarge training sets, yet generated observations must preserve plausible clinical relationships and cannot replace testing on real, independent patient cohorts.

Multicenter periodontal datasets vary in diagnostic criteria, measurement protocols, devices, populations, and recording practices. Missing values and inconsistent labels may further weaken model reliability. Standardized data acquisition and annotation are therefore essential for reproducible AI development.

Privacy requirements may limit centralized sharing of data. Federated learning provides a means of collaborative model training without transferring raw patient records. Synthetic-data methods, including generative adversarial networks, may augment limited datasets, but synthetic samples must be rigorously assessed to ensure that artifacts or biases are not introduced. Neither strategy removes the requirement for representative external validation [29,30].

6.2. Interpretability and fairness

Complex models can be difficult for clinicians to understand. SHAP and Local Interpretable Model-agnostic Explanations (LIME) can quantify or approximate feature contributions and have been applied to identify clinically relevant predictors. Even so, explainability outputs should be viewed as tools for model assessment rather than evidence of causal relationships.

Fairness is also critical because periodontal risk differs across demographic, socioeconomic, behavioral, and systemic factors. Model performance should therefore be evaluated in relevant subgroups. Diverse training populations, multicenter validation, bias analysis, and transparent reporting are required to reduce unequal performance [23,31].

For periodontal prediction, every stage of the modeling pipeline should be reported transparently. Feature selection, imputation, scaling, model fitting, and hyperparameter optimization are interdependent; conducting them before data separation may allow validation information to affect model development. Restricting preprocessing to training folds yields a more realistic performance estimate, especially for high-dimensional biomarker, microbiome, genomic, and imaging data. Clinical translation also depends on whether predicted risk can be communicated and translated into action. Risk estimates should therefore be assessed for calibration and presented with interpretable information about influential variables. Decision-support systems must remain compatible with existing records and consistent data capture. Prospective studies are still needed to determine whether these systems improve early identification and individualized periodontal management beyond conventional assessment.

7. Conclusion

AI provides a technical framework for combining heterogeneous clinical, imaging, laboratory, microbiome, and genomic data in periodontitis risk prediction. ML algorithms offer adaptable approaches for structured clinical variables, whereas DL supports automatic extraction of complex imaging features. Feature engineering, missing-data handling, normalization, cross-validation, calibration, external validation, and explainability remain central to dependable model development.

Current evidence indicates that AI may improve periodontal risk stratification, although clinical translation is still constrained by data heterogeneity, overfitting, inadequate prospective validation, privacy concerns, interpretability, and fairness. Future work should prioritize standardized multicenter datasets, leakage-resistant model-development pipelines, independent and prospective validation, clinically meaningful performance measures, and interpretable decision-support systems. Ultimately, the clinical value of increasingly complex multimodal models should be determined by reproducibility and improved patient care rather than algorithmic performance alone.

Disclosure statement

The author declares no conflict of interest.

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