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Machine learning for early detection and risk prediction in peri-implantitis: A review

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Abstract:
Peri-implantitis causes progressive bone loss around dental implants and arises from interacting microbial, host, behavioral and implant factors. Conventional clinical and radiographic criteria capture this complexity only partially, whereas machine learning can integrate heterogeneous data across early detection, risk stratification and outcome prediction. Convolutional neural networks detect peri-implant bone loss on radiographs with high reported accuracy. Supervised models, such as random forests, combine clinical and patient-level data to estimate individual risk, often outperforming conventional statistics. Thus, data shows that evidence rests largely on small, single-center, retrospective datasets, so machine learning should augment rather than replace clinical judgment until standardized, externally validated models are available.

Keywords: Peri-implantitis, machine learning (ML), deep learning (DL), risk prediction, dental implants

Background:
Peri-implantitis is a plaque-associated inflammatory disease with progressive loss of supporting bone; it is common and multifactorial, reflecting interactions among the microbiome, host responses, systemic conditions, behaviors and implant factors **[1]**. Diagnosis relies mainly on bleeding or suppuration on probing, probing depth and radiographic bone loss, which may not capture the underlying biological drivers **[2]**. Modern implant dentistry generates large, heterogeneous datasets that machine learning can integrate to detect patterns that conventional statistics miss **[4]**. Therefore, it is of interest to describe the current machine learning approaches for the early detection and risk prediction of peri-implantitis.

Evidence synthesis:
The studies were methodologically heterogeneous. Findings were therefore synthesized narratively. This followed current recommendations for reporting artificial intelligence research in dentistry **[5]**.

Search strategy:
Five databases were searched: PubMed/MEDLINE, Scopus, Web of Science, Embase and IEEE Xplore. The search covered records published between January 2021 and March 2026. Disease terms included peri-implantitis, dental implant and marginal bone loss. Computational terms included artificial intelligence, machine learning, deep learning, convolutional neural network, random forest and predictive modeling. Reference lists were hand-searched.

Machine learning approaches:
Machine learning spans supervised methods, including random forest, support vector machines, logistic regression and extreme gradient boosting and unsupervised clustering, with convolutional neural networks dominating image analysis; models are evaluated by accuracy, sensitivity, specificity, F1 score and the area under the receiver operating characteristic curve **[2]**.

Early radiographic detection:
Convolutional neural networks and segmentation models detect peri-implant marginal bone loss on periapical and panoramic radiographs without manual measurement and systematic review reports high pooled accuracy despite small, single-center studies **[6]**. A recent deep learning pipeline that segmented implants and classified peri-implant status across 7696 panoramic radiographs detected peri-implantitis with an F1 score of 0.835, demonstrating automated screening of routine images **[7]**.

Risk prediction from clinical records:
Models built on structured records also estimate patient-level risk; in 942 implants, a random forest achieved areas under the curve of 0.840 for peri-implantitis and 0.872 for implant failure **[8]**. Across clinical and prosthetic variables, random forest best predicted peri-implantitis onset, with functional time and oral hygiene the most influential predictors **[9]**. Representative studies are summarized in **Table 1**.

Molecular and immune risk stratification:
Beyond imaging, molecular data support risk stratification; integrative microbiome and metatranscriptome profiling of peri-implant biofilms identified taxonomic and functional biomarkers that distinguish health from disease, with machine learning reaching an area under the curve of 0.85 **[10]**. Machine-learning-assisted immune profiling further stratifies patients into risk

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groups with distinct immune and microbial signatures and treatment outcomes **[3]**. Risk models can also integrate clinical, behavioral and demographic variables, capturing nonlinear interactions among recognized risk factors such as smoking, diabetes, history of periodontitis and inadequate maintenance to improve individual risk estimation **[1]**.

Prognosis and early-stage prediction:

For prognosis, a convolutional neural network trained on radiographs predicted dental implant loss with good discrimination, illustrating image-based prognostic modeling **[11, 12]**. Consistent with this direction, a machine-learning model has been developed and validated to predict peri-implant mucositis one year after implant placement **[13]** and an artificial neural network has been applied to the early diagnosis of peri-implantitis onset **[14]**, extending data-driven prediction to the earliest and potentially reversible stage of peri-implant disease.

Table 1: Representative machine learning studies in peri-implant disease.

Data and sample	Reported performance	Primary task	References
942 implants; EHR clinical variables	AUC 0.840 (peri-implantitis); 0.872 (implant failure)	Risk prediction from clinical records	**[8]**
Clinical and prosthetic variables	Random forest best; AUC 0.71	Predicting peri-implantitis onset	**[9]**
7696 panoramic radiographs; CNN/U-Net	F1 0.835 for peri-implantitis detection	DL segmentation and detection	**[7]**
Dental radiographs (CNN)	Good discrimination for implant loss	Predicting implant-loss risk	**[11]**
Peri-implant biofilm microbiome and metatranscriptome	AUC 0.85 (integrated model)	Microbiome biomarker risk stratification	**[10]**
Radiographs across studies (review)	High reported accuracy; small single-center studies	Detecting peri-implant bone loss	**[6]**
Implant prediction models (review)	Limited external validity	Appraisal of prediction models	**[12]**

AUC: area under the receiver operating characteristic curve; CNN: convolutional neural network; DL: deep learning; EHR: electronic health record.

Validation, limitations and future directions:

A systematic appraisal found most implant prediction models limited by methodological quality, incomplete reporting, weak external validity and reliance on single-dataset internal resampling, with recurring predictors including implant position, length, age and history of periodontitis. External validation, calibration, transparent reporting and explainable models aligned with dental artificial intelligence reporting standards, together with prospective multicenter data, are therefore needed before clinical adoption.

Conclusion:

Machine learning can improve peri-implantitis detection, risk stratification and prognosis as a clinical support tool. Deep learning detects bone loss on radiographs and multimodal models sharpen individual risk assessment. Clinical translation still requires prospective multicenter studies and transparent, externally validated models.

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