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RESEARCH ARTICLE

Artificial Intelligence and Machine Learning Models in Diagnosis, Treatment Planning and Follow – Up of Periodontitis : A Systematic Review

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Abstract: ***Background***: Artificial intelligence (AI) and machine learning (ML) have shown high potential in periodontal diagnosis. However, their accuracy in diagnosis and consistency is not established adequately.***Objectives:*** To objectively evaluate the performance and accuracy of AI models in the diagnosis of periodontal diseases.***Methods:*** Thorough literature search was conducted in PubMed, ProQuest, Scopus, Cochrane Library and EBSCOhost. Studies that evaluated the diagnosis of periodontal diseases using AI were screened and the ones that used image processing alone were eliminated. Data was extracted from the selected studies and analyzed for diagnostic parameters like accuracy, sensitivity, specificity etc. The result was then tabulated and analyzed.***Results:*** It was observed that the selected studies showed variability in the parameters used to evaluate the accuracy. However, in most of the studies the accuracy of AI was found to be greater than 80%.***Conclusion:*** AI/ML demonstrated considerable promise in periodontal diagnosis. However, further refinement and validation are required for their adoption into periodontal practice. Ensemble learning and NLP models have shown the most consistent promise while large language models (LLM) are still developing as complementary tool.

Keywords: AI, ML, Periodontal, diagnosis, Accuracy.

INTRODUCTION

Periodontitis is a well known multifactorial pathologic process of paradental structures that is greatly affected by various factors such as microbial composition, systemic inflammatory processes and host immune response along with patient compliance [1]. This complex disease is diagnosed by the clinical signs and symptoms exhibited by the periodontal structures.

Currently, diagnosis is carried out manually, which is time consuming and a laborious process especially in a clinical setup visited by large number of patients. Monitoring involves recording soft tissue parameters, plaque and gingival bleeding scores, clinical attachment level (CAL) and the patterns of bone loss [2]. These conventional methods rely mainly on expert opinion, despite its laborious processes of documentation. Recent technological advancements like artificial intelligence and machine learning offers promising solution to these challenges [3].

Artificial intelligence refers to the computer systems that are able to perform tasks which normally requires human intelligence and perception to perform [4]. Machine Learning is the modality by which the computer system is trained to learn from data that is supplied without being explicitly programmed. Machine learning is therefore an application of AI that provides the system the ability to learn and improve by itself from experience [5].

Training the AI system utilizing the data from periodontal diseases like clinical parameters and images assist in disease diagnosis, monitoring and data management [6]. The system is fast, objective and accurate. The data stored in AI systems can be processed and then used for epidemiological analyses [7].

Although the role of AI and MI in periodontal diagnosis has been explored in various studies, knowledge on the nature of systems used in diagnosis and their performance remains limited [8]. Therefore, this systematic review aims to do such a task of consolidation.

Materials and Methods

Registration

The title was searched in PROSPERO database to ensure that similar title has not been registered before. Preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines were strictly adhered to in the review process.

Review Question

What are the types of AI and ML models that have been implemented in relation to diagnosis, treatment planning, and follow-up of patients with periodontitis and what are its effectiveness.

Search Strategy (PECO terms)

Search was conducted using keywords and MeSH terms related to the disease (periodontitis, periodontal disease), AI /MI (artificial intelligence, machine learning, deep learning, neural networks, support vector machines, decision trees, natural language processing) and clinical procedures (diagnosis, treatment planning, follow-up, recall, prognosis, risk assessment)

Inclusion Criteria

Studies conducted in subjects using AI/ML models for diagnosis, treatment planning, or follow-up for periodontitis, case reports, clinical study, clinical trial, clinical trial, phase I, clinical trial, phase II, clinical trial, phase III, clinical trial, phase IV, controlled clinical trial, randomized controlled trial and in English language were included in this study.

Exclusion Criteria

Animal studies or in vitro studies, reviews, editorials, letters, protocols, studies without clear AI/ML implementation and the studies that discuss image processing both photographs and radiographs with AI/ML implementation were excluded.

Search sources

Search was conducted in the following databases: PubMed/MEDLINE, ProQuest, Scopus, Cochrane Library and EBSCOhost.

Data Extraction

Data on study characteristics (author, year, country), AI/ML model type, clinical application (diagnosis, treatment, follow-up), evaluation metrics (accuracy, sensitivity, specificity), dataset size and type, the limitations and clinical implications were collected. QUADAS-2 (for diagnostic studies) and PROBAST (for prognostic/predictive models) were used for risk of bias assessment.

Data Synthesis

A qualitative synthesis was conducted and where possible, a meta-analysis was performed using pooled diagnostic accuracy metrics or predictive performance indicators.

RESULTS AND OBSERVATIONS:

Table 1 shows the characteristic of different studies analysed. The reviewed studies were from different geographic regions and followed varying methodologies, utilizing different models like random forest, BERT, deep neural networks and support vector machines. Parameters like precision, accuracy, recall, area under the curve (AUC) and F1 score were evaluated.

In table 2, the performance of AI and ML models of the selected studies in diagnosis and prediction were summarized. The accuracy was reported >80% for most of the models, with superior strength in prediction demonstrated by random forest and tree- based algorithms. Imaging the data was performed well by deep learning architectures like ResNet and DenseNet, while NLP models like BERT based on transformers reported promising results in diagnosis based on texts. In table 3, strong internal performance was highlighted in most of the studies but they also emphasized that before clinical transition larger externally validated data sets are required.

Table 4 reported the risk of bias across different studies using PROBAST and QUADAS-2. Though moderate to high accuracy was reported in majority of the studies, there were concerns regarding the selection of participants, transparency of analysis and predictor definition. The overall risk of bias was moderate to high, indicating the need for future research with improved methodology and validation.

Figure 1. PRISMA Flow Chart

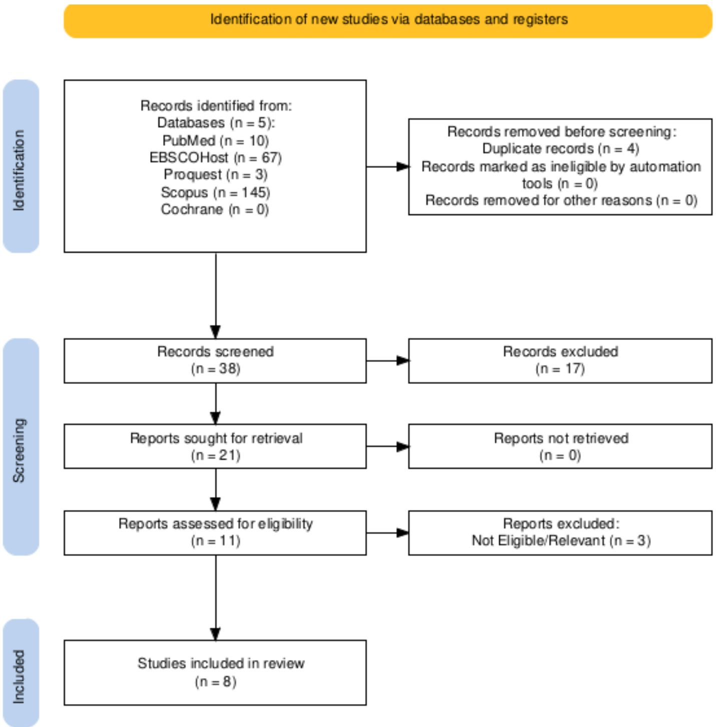

Table 1. Study Characteristics

Study	citation	country	design	Sample size	models	Metrics reported
Ameli et al., 2024(9)	Ameli N, Firoozi T, Gibson M, Lai H. PLOS Digital Health 2024;3(12):e0000692.	Canada/USA	Secondary data analysis (textual notes)	309 patient charts (text); unseen n=32	BERT, MLP (feature-engineered)	Accuracy, per-class precision/recall/F1 (selected classes), confusion matrices
Ertaş et al., 2022 (10)	Ertaş K, Pence I, Cesmeli MS, Ay ZY. J Periodontal Implant Sci. 2023;53(1):38-53.	Turkey	Retrospective; clinical + radiographic data + image processing	144 patients (clinical+images)	kNN, ANN, tree, SVM, RF, NB, LR; DenseNet, EfficientNet, ResNet, VGG + hybrids	CA (accuracy), AUC, precision, recall (per-model in Supplementary Table)
Özden et al., 2015 (11)	Özden FO, Özgönenel O, Özden B, Aydogdu A. Niger J Clin Pract.	Turkey	Preliminary study (training/testing split)	150 patients (training n=100, testing n=50)	SVM, DT, ANN (BPNN)	Accuracy (SVM/DT ~98%, ANN ~46%)

	2015;18(3):416-421.					
Papantonopoulos et al., 2014 (12)	Papantonopoulos G, Takahashi K, Bountis T, Loos BG. PLoS One. 2014;9(3):e89757.	Netherlands/Greece	Diagnostic study using immunologic/lab parameters	See full text (clinical + lab data)	ANNs with various input sets	Accuracy 90-98% (by input set)
Patel et al., 2022 (13)	Patel JS, Su C, Tellez M, Albandar JM, et al. Frontiers in Artificial Intelligence. 2022;5:	USA	EDR-based predictive modeling (retrospective)	27,138 patients (EDR)	XGBoost (and others explored)	AUC ~0.72, precision ~0.50, recall ~0.53 for some tasks
Rebeiz et al., 2025 (14)	Rebeiz T, Lawand G, Martin W, Gonzaga L, Revilla-León M, et al. Journal of Dentistry 2025;159:	Multinational	Retrospective longitudinal cohort (tooth-level)	3,347 teeth with ≥10 years follow-up	Various ML; Random Forest final model	AUC 0.91 (RF), Accuracy 0.93 (RF)
Satpathy et al., 2020 (15)	Satpathy A, Panda G, Gogula R, Sharma R. Int J Sensors Wireless Commun Control. 2020;10(4):508-521.	(not specified)	Low-complexity classifier development (algorithmic)	Dataset described in article	Low-complexity adaptive nonlinear models	Accuracy and algorithmic performance (details in article)
Tastan Eroglu et al., 2024 (16)	Tastan Eroglu Z, Babayigit O, Ozkan Sen D, Ucan Yarkac F. Clin Oral Investig. 2024;28(7):	Turkey	Evaluation of ChatGPT on standardized case texts (diagnostic classification)	200 patient cases (standardized textual descriptions)	ChatGPT (LLM)	Percent correct (Stage 59.5%, Grade 50.5%, Extent 84.0%), Cohen's kappa

Table 2. Study Outcomes

study	model	accuracy	n	AUC	precision	recall	f1
Ertaş 2023 (10)	kNN_staging_clinical	0.646	144	0.76	0.616	0.646	0.625
Ertaş 2023 (10)	ANN_staging_clinical	0.91	144	0.952	0.907	0.91	0.908
Ertaş 2023 (10)	Tree_staging_clinical	0.972	144	0.947	0.967	0.972	0.969
Ertaş 2023 (10)	SVM_staging_clinical	0.944	144	0.955	0.941	0.944	0.942
Ertaş 2023 (10)	RF_staging_clinical	0.965	144	0.975	0.959	0.965	0.962
Ertaş 2023 (10)	LR_staging_clinical	0.944	144	0.962	0.919	0.944	0.931
Ertaş 2023 (10)	ResNet50+SVM_image_preprocessed	0.882	144	0.799	0.864	0.882	0.872
Ertaş 2023	DenseNet121+SVM_image_preprocessed	0.854	144	0.761	0.83	0.854	0.841
Ameli 2024 (9)	BERT_stage_III		309		0.91	0.75	0.82
Ameli 2024 (9)	BERT_grade_B		309		0.65	0.47	0.54554
Patel 2022 (13)	XGBoost		27138	0.72	0.5	0.53	0.51456
Özden 2015 (11)	SVM	0.98	50				
Özden 2015 (11)	DT	0.98	50				
Özden 2015 (11)	ANN	0.46	50				
Rebeiz 2025 (14)	Random Forest	0.93	3347	0.91			
Tastan Eroglu 2024 (16)	ChatGPT_stage	0.595	200				
Tastan Eroglu 2024	ChatGPT_grade	0.505	200				

(16)							
Tastan Eroglu 2024 (16)	ChatGPT_extent	0.84	200				

Table 3. Data Extraction Table

Study characteristics (author, year, country)	Type of AI/ML model	Clinical application (diagnosis, treatment, follow-up)	Evaluation metrics (reported in paper)	Dataset size and type	Limitations and clinical implications	Sensitivity	Specificity	Accuracy	Recall	F1 Score	Conclusion
Ameli N., Firoozi T., Gibson M., Lai H. — PLOS Digital Health 2024 — Canada /USA	NLP: BERT (transformer) vs feature-engineered MLP	Diagnosis / classification (stage & grade) from clinical notes	Accuracy, confusion matrices; stage accuracy 77% (BERT overall); unseen sample stage 66%, grade 72%	309 patient periodontal charts/notes (text); unseen n=32	Small sample, class imbalance, retrospective notes; CDSS potential but needs larger prospective data	NR	NR	Stage overall 77%; unseen 66% (stage) / 72% (grade)	NR (confusion matrices provided in paper)	NR	BERT outperformed feature-engineered MLP; promising for extracting stage/grade from notes but limited generalizability.
Ertaş K., Pence I., Cesmeli M.S., Ay Z.Y. — JPIS 2022 — Turkey	Classical ML (k-NN, SVM, RF, NB, LR, tree) + CNNs (DenseNet, ResNet, EfficientNet, VGG) and hybrid models	Diagnosis / classification (stage & grade) using clinical data + panoramic radiographs	Classification accuracy (CA), AUC, precision, recall reported per-model in tables; top CA examples: clinical RF grading CA≈0.986; tree staging CA≈0.972;	144 patients; clinical attributes + panoramic radiographs (JPEG)	Small sample, class heterogeneity, need external validation; preprocessing affects performance	NR (per-model tables exist)	NR	Up to 0.986 (random forest, grading on clinical features); up to 0.972 (tree, staging)	NR (tables)	NR (tables)	High internal accuracy for clinical-feature-based models; image hybrids less accurate; external validation required before clinical use.

			image hybrid ResNet50+SVM CA≈0.882								
Özden F.O., Özgönenel O., Özden B., Aydogdu A. — Nigerian J Clin Pract. 2015 — Turkey	SVM, Decision Tree (DT), Artificial Neural Network (ANN)	Diagnosis / classification of periodontal disease category	Accuracy reported: SVM/DT ~94–98% (paper reports very high accuracy); ANN ~46%	150 patients total (training n=100, testing n=50); 11 clinical/demographic features	Preliminary small study; potential overfitting; needs larger validation	NR	NR	SVM/DT ≈94–98%; ANN ≈46%	NR	NR	SVM/DT performed best on this small dataset; findings are preliminary.
Papantonopoulos G., Takahashi K., Bountis T., Loos B.G. — PLoS ONE 2014 — Netherlands/Greece	Artificial Neural Networks (ANN) trained on immunologic/lab parameters	Diagnosis: classify aggressive periodontitis (AgP) vs chronic periodontitis (CP)	Accuracy range 90–98% depending on input variable sets; cross-validation used	Clinical + laboratory immunologic data (counts, cytokines); sample sizes reported in full text	Good discrimination using lab features; needs larger external cohorts for generalizability	NR	NR	90–98% (depending on input variable combinations)	NR	NR	ANNs can discriminate AgP vs CP with high accuracy on immunologic datasets; external validation required.
Patel J.S., Su C., Tellez M., Albandar J.M., Rao R., Iyer V., Shi E., Wu H. — Frontiers in AI 2022 — USA	XGBoost (gradient boosting)	Prediction / risk stratification for periodontal disease from EDR	Average AUC ≈0.72 (one-vs-all for healthy vs mild and mild vs severe); precision 0.50, recall 0.53 (reported for some tasks)	27,138 dental patients from EDR; 74 features (demographics, clinical findings, social determinants)	Moderate discrimination; EDR labeling/data-quality concerns; needs external validation and usability testing	NR (precision/recall reported: precision 0.50, recall 0.53 in comparison)	NR	NR (AUC reported ≈0.72)	Reported ~0.53 for some comparisons	NR (can be computed from precision/recall where available)	ML on large EDRs yields moderate discrimination (AUC~0.72); useful for risk stratification but not yet diagnostic-grade.
Rebeiz	Various	Treatm	AUC =	Data	Retrosp	NR	NR	0.93	NR	NR	Rando

T., Lawand G., Martin W., Gonzaga L., Revilla-León M., Khalaf S., Megarbané J.-M. — Journal of Dentistry 2025 — multinational	ML; Random Forest selected as final model	ent decision support / predicting tooth loss (treatment planning & prognosis)	0.91 (Random Forest); Accuracy = 0.93; precision/recall/F1 reported in full text	from 3,347 teeth with ≥10 years follow-up; clinical + radiographic features per tooth	ective cohort; needs prospective validation and external testing; promising for personalized therapy			(Random Forest)	(reported in full text)	(reported in full text)	m Forest showed high predictive performance for tooth-level tooth-loss risk (AUC 0.91, accuracy 0.93); needs prospective validation.
Satpathy A., Panda G., Gogula R., Sharma R. — Int J Sensors, Wireless Communications & Control 2020	Low-complexity adaptive nonlinear classifiers (lightweight models)	Diagnosis / classification of periodontal disease	Accuracy and algorithmic performance metrics reported in paper (not consistently in abstract)	Diagnostic data of periodontal findings at tooth/patient level (sample size in paper)	Designed for low-resource devices; limited dataset and external validation needed	NR	NR	NR (reported in paper)	NR	NR	Low-complexity adaptive models suitable for on-device diagnostics; require broader validation and benchmark comparisons.
Tastan Eroglu Z., Babayigit O., Ozkan Sen D., Ucan Yarkac F. — Clinical Oral Investigations 2024 — Turkey	Large language model (LLM): ChatGPT (GPT family)	Diagnosis / classification: stage, grade, extent using standardized textual case descriptions	Percent correct: Stage 59.5%; Grade 50.5%; Extent 84.0%. Cohen's kappa: stage 0.447, grade 0.284, extent 0.652	200 untreated periodontitis patient cases (standardized text descriptions); gold standard: 4 expert examiners	LLM not fine-tuned for clinical task; can hallucinate; moderate performance — not ready for autonomous	NR (study reports percent correct & kappa)	NR	Percent correct as above (stage 59.5%, grade 50.5%, extent 84.0%)	NR	NR	ChatGPT had moderate performance (better for extent); needs task-specific fine-tuning and oversight before clinical

					clinical use						use.

Table 4. Risk of BIAS

Study	**Year**	**Citation**	**PROBAST AI Participants**	**PROBAST AI Predictors**	**PROBAST AI Outcomes**	**PROBAST AI Analysis**	**Overall RoB**	**Applicability Participants**	**Applicability Predictors**	**Applicability Outcomes**
Ameli et al. **(9)**	2024	PLOS Digital Health 2024	Unclear	Unclear	Unclear	High	High	Unclear	Unclear	Unclear
Ertaş et al. **(10)**	2022	Journal of Periodontal and Implant Science 2022	Unclear	Low-Moderate	Unclear	High	High	Unclear	Low-Moderate	Unclear
Ozden et al. **(11)**	2015	Nigerian Journal of Clinical Practice 2015	High	High	High	High	High	High	High	High
Papantonopoulos et al. **(12)**	2016	Complexity methods in personalized Periodontology (2016)	High	High	High	High	High	High	High	High
Patel et al. **(13)**	2022	Frontiers in Artificial Intelligence 2022	Low-Moderate	Low-Moderate	Low-Moderate	Moderate	Moderate	Low-Moderate	Low-Moderate	Low-Moderate
Rebeiz et al. **(14)**	2025	Journal of Dentistry 2025	Unclear	Unclear	Unclear	High	High	Unclear	Unclear	Unclear
Satpathy et al. **(15)**	2020	International Journal of Sensors... 2020	High	High	High	High	High	High	High	High
Tastan Eroglu et al. (16)	2024	Clinical Oral Investigations 2024	High	High	High	High	High	High	High	High

DISCUSSION

This systematic review has synthesized evidence regarding the application of AI and ML models used in the diagnosis, treatment planning, and follow-up of periodontitis in patients. Specifically, it included studies that did not analyse images as this is a different dimension of AI based diagnosis. Eliminating these aspects, across the included studies, AI tools showed moderate-to-high performance as seen from pooled estimates for parameters like accuracy, precision, recall, F1, and AUC. These facts strongly imply their potential utility in adjunctive clinical decision-making.

From the stringent selection criteria, it can be seen that predominantly studies focused on diagnostic classification especially staging and grading of periodontitis as per the 2018 classification system. Accuracy was reported to be >85% consistently in machine learning models when supervised, where the highest pooled F1scores was attained by XGBoost. Likewise, natural language processing (NLP), which are based on deep learning methods also showed better accuracy (~0.84) when used for recording health electronically (Ameli et al., 2024) [9]. These indicate that periodontal diagnosis can be generalized by these models. Also, Eroglu et al., (2024) reported that tools like ChatGPT based on generative exhibited clinically relevant performance although it was less [16]. The accuracy was above 79%, emphasizing both the opportunities and the limitations of large language models (LLM) for disease classification. Technically, they may effectively capture diagnostic trends but their outputs are sensitive to prompt engineering and training data coverage.

The tree-based and ensemble learning methods like random forests and XGBoost demonstrated high accuracy in prediction and better performance consistently across different datasets. Study by Rebeiz et al. (2025) reported accuracy of 0.93 and AUC of 0.91 to predict tooth loss, underscoring the reliability of ensemble methods in clinical decision support [14]. Similarly, Ertaş et al. (2022) reported high accuracy (up to 0.986) for Random Forest and Decision Tree classifiers when utilized for disease staging and grading, demonstrating how organized clinical data combined with ML models improve the model performance [10].

AI systems which where text and transformer based also showed great potential. A transformer-based BERT model was utilized by Ameli et al. (2024) to classify stages and grades of the disease from electronic recorded dental records, with an accuracy of 77%, though the sample size was less in this study and showed class imbalance [9]. Thus, clinical data interpretation could be streamlined significantly by natural language processing (NLP) models when trained on diverse or larger datasets.

In contrast, variable results were reported by the deep learning models applied to imaging data. Models like ResNet and DenseNet achieved moderate accuracy (0.85–0.88), indicating that diagnosis based on image is challenging due to the difference in quality of the images, techniques used for preprocessing and limited datasets. While AI systems developed by Satpathy et al. (2020) showed promising results in environments with low resource, though validation is required among different population [15].

From the review, it can be observed that there is a scarcity in number of studies that addressed treatment planning and follow-up. For example, Rebeiz et al. (2025) have reported this by using retrospective longitudinal data to develop tools for decision-making [14]. This has shown satisfactory predictive accuracy. This aspect is still preliminary and require huge amounts of external validation, that too using diverse populations. Few studies did attempt modelling of long-term disease progression, but with limited accuracy. These aspects clearly point to the gap in current applications of AI within periodontology.

The systematic review has identified substantial heterogeneity across the studies on AI models in terms of dataset size, source, quality, outcome definitions, as well as evaluation metrics. In few studies, models were trained on small and single-centre datasets and in some studies, it was on multiple and large data sets. This is a concern that can affect generalizability. In similar lines, PROBAST-AI risk-of-bias assessment tool has highlighted inadequate participant description, unclear handling of missing data, and lack of external validation. Further, reporting of calibration metrics was also scanty. These aspects hinder clinical applicability of these AI models, in addition to eliminating the possibility of meta-analysis in the current review. Further, this clearly reflects broader reporting issues in AI/ML studies and emphasizes the need for adhering to emerging guidelines such as CONSORT-AI and TRIPOD-AI.

However, AI and ML do hold considerable promise for improving the periodontal care. However, it currently needs further training and address of limitation of these models. In future, large scale multicentre studies need to be done with standardised outcome reporting.
Limitations of current review include the reliance on reported metrics without assessing the raw data of the reports. Additionally, uniform reporting of evaluation was not provided by all the studies and potential publication bias that might favour positive findings.

Conclusion

Within the limitations of the study, AI and ML models have been seen to demonstrate good diagnostic accuracy and huge potential for supporting treatment planning in periodontitis. Ensemble learning and NLP models have the most consistent promise and LLMs are only emerging as adjuncts.

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