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Review

Modern Approaches to the Integration of Artificial Intelligence into the Diagnosis and Screening of Periodontal Diseases

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Abstract

Periodontal diseases represent a major global health burden and are closely associated with systemic conditions such as cardiovascular diseases and diabetes, making early detection and screening essential priorities in public health. The rapid development of digital dentistry has led to the accumulation of diverse clinical and non-clinical datasets, including intraoral images, radiographic data, salivary biomarkers, and electronic health records. These developments create opportunities for the application of AI technologies in improving diagnostic accuracy, standardization, and accessibility of periodontal care. This review aims to systematically analyze current approaches to the application of AI in periodontology and to propose a structured framework for integrating AI tools into clinical practice and population-based screening programs. A structured literature search was conducted in major databases including PubMed, Scopus, and Google Scholar, covering publications from 2005 to 2025. The review includes studies focusing on image-based analysis, radiographic interpretation, predictive modeling, natural language processing, and telemedicine applications.

The results demonstrate that AI models, particularly deep learning architectures such as convolutional neural networks, show high accuracy in detecting gingival inflammation, dental plaque, and alveolar bone loss. Machine learning methods are also effectively used for risk prediction and stratification based on clinical parameters and biomarkers. Additionally, natural language processing techniques enable automated extraction of diagnostic information from electronic dental records, enhancing data usability and clinical decision-making.

Despite promising results, the evidence remains heterogeneous, with common limitations including small sample sizes, lack of external validation, and variability in reference standards. Implementation challenges include data standardization, regulatory requirements, and integration into clinical workflows.

In conclusion, AI has significant potential to transform periodontal diagnostics and screening through improved accuracy, scalability, and accessibility. However, successful

implementation requires robust validation, standardized data protocols, and alignment with clinical and ethical guidelines.

Keywords: artificial intelligence, periodontitis, screening, panoramic radiography, Cone beam computed tomography, intraoral images, teledentistry.

1. Introduction

Periodontal diseases (gingivitis and periodontitis) are among the most common chronic oral pathologies and contribute significantly to the global burden of non-communicable diseases. According to World Health Organization (WHO) data, oral diseases affect approximately 3.5 billion people (≈45% of the world's population) [1], with more than 1 billion cases of severe periodontal disease [2]. To monitor and compare indicators at the country level, the WHO publishes an indicator of the prevalence of severe periodontitis among people aged 15+ years, calculated based on estimates from the Institute for Health Metrics and Evaluation Global Burden of Disease (GBD) 2019 [3].

The clinical significance of periodontitis goes beyond local inflammation: progressive loss of attachment and alveolar bone leads to tooth mobility, impaired chewing function, aesthetic problems and reduced quality of life, as well as socio-economic losses. International professional communities emphasize the need to strengthen prevention, early detection and access to periodontal care as priorities for health systems and dental services [4].

The modern diagnostic paradigm is based on the classification of the 2017 World Workshop American Academy of Periodontology/ European Federation of Periodontology (AAP/EFP), where periodontitis is described through staging and grading [5,6]. Staging reflects the severity and complexity of management (including the extent of attachment and bone loss), while grading reflects the likely rate of progression and the influence of modifying risk factors. The key features remain clinical attachment loss (CAL), periodontal pocket depth, bleeding on probing (BOP) and radiographically assessed alveolar bone loss [5,6]. This approach provides clinically interpretable criteria for severity and prognosis, but requires standardized data collection and high reproducibility of measurements.

The link between periodontal disease and systemic pathology adds further significance to the problem. The European Federation of Periodontology/World Heart Federation (EFP/WHF) and EFP/AAP consensus documents note the existence of independent associations between severe periodontitis and atherosclerotic cardiovascular disease and carbohydrate metabolism disorders, emphasizing the need for interdisciplinary collaboration and consideration of periodontal status in the management of high-risk patients [7,8]. Consequently, there is a growing need for reliable screening and risk stratification tools that are suitable for routine practice and public health programs.

Traditional diagnosis and screening for periodontitis rely on clinical probing and radiographic assessment, which in mass screening settings are limited by resources, time, and inter-expert variability. Radiographic assessment of bone loss using panoramic images and cone beam computed tomography (CBCT) is potentially amenable to standardization, but in practice depends on the experience of the clinician and the quality of the images. In recent years, the possibility of using deep learning for automated detection and quantitative assessment of alveolar bone loss and/or its staging based on radiographic data has been demonstrated [9,10].

At the same time, digital dentistry is rapidly accumulating arrays of heterogeneous data (intraoral photographs and scans, panoramic images and CBCT, clinical BOP/CAL indices, saliva biomarkers, electronic record texts, teledentistry data), which creates the basis for the introduction of artificial intelligence (AI) as a tool for clinical decision support, remote monitoring, and personalized prevention [11,12]. However, the transition from research prototypes to routine practice requires an evidence base, external validation, assessment of clinical utility, and transparent reporting; in this regard, international guidelines have been developed for reporting prediction models and AI intervention studies (TRIPOD+AI, CONSORT-AI, SPIRIT-AI) [13–16].

This review aims to systematically analyze current approaches to the application of artificial intelligence in periodontology and to propose a structured framework for integrating artificial intelligence tools into clinical practice and population-based screening programs.

2. Materials and methods

Study design

This review was conducted as a structured narrative (scoping) review with a targeted literature search and thematic synthesis. The reporting approach was aligned with PRISMA-ScR guidance for scoping reviews, and search reporting followed PRISMA-S principles where applicable [18,19].

Data sources

Electronic searches were performed in PubMed/MEDLINE, Scopus, and Google Scholar. To capture methodological and implementation guidance, we additionally considered consensus statements and reporting guidelines relevant to AI in healthcare and prediction modelling. Backward citation searching was conducted by screening reference lists of key papers and recent reviews.

Search strategy

The search covered publications from 1 January 2005 to 31 December 2025 (last update: 1 February 2026). Search terms combined four concept blocks: (1) periodontal diseases (periodontitis OR gingivitis OR periodontal disease), (2) AI methods (artificial intelligence OR machine learning OR deep learning OR convolutional neural network OR transformer OR natural language processing), (3) data modalities (intraoral photograph OR intraoral scan OR panoramic radiograph OR cone-beam computed tomography OR CBCT OR salivary biomarkers OR electronic dental records), and (4) clinical tasks (screening OR diagnosis OR staging OR grading OR bone loss OR risk prediction). Controlled vocabulary (e.g., MeSH in PubMed) and free-text terms were combined with Boolean operators; queries were adapted for each database and documented per PRISMA-S [19].

Representative PubMed strategy (simplified): (periodontitis OR gingivitis OR periodontal disease) AND (artificial intelligence OR machine learning OR deep learning OR CNN OR transformer OR NLP) AND (panoramic radiograph OR CBCT OR intraoral photo OR intraoral scan OR salivary biomarker OR electronic record).

Eligibility criteria

Inclusion criteria

- Original studies (development and/or validation) and systematic reviews where AI was applied to periodontal screening, diagnosis, staging/grading, bone-loss assessment, monitoring, or risk prediction.
- Human data with clearly described data modality (e.g., intraoral photographs/scans, panoramic radiographs, CBCT, salivary biomarkers, clinical indices such as BOP/CAL, or EHR/free-text notes).
- Reported model performance using at least one interpretable metric (e.g., AUC, sensitivity/specificity, F1, IoU/mIoU, and MAE) and described validation approach (internal split, cross-validation, and/or external validation).
- Publications in English or Russian.

Exclusion criteria

- Non-periodontal primary outcomes (e.g., caries-only detection without periodontal endpoints).
- Animal or in vitro studies, simulation-only papers, editorials, conference abstracts without sufficient methodological detail, and opinion pieces.
- Studies lacking sufficient information on dataset composition, reference standard/ground truth, or evaluation metrics.
- Duplicate reports of the same dataset/model without additional validation or clinically relevant outcomes (the most complete/updated version was retained).

Study selection process

Records were exported to a reference manager, and duplicates were removed prior to screening. Title/abstract screening was performed against the eligibility criteria, followed by full-text assessment for potentially relevant studies. When two independent reviewers were available, screening disagreements were resolved by discussion and, if necessary, arbitration by a third reviewer; otherwise, eligibility decisions were re-checked using a predefined checklist. The overall selection process can be summarized using a PRISMA flow diagram [20]. The selection process followed the PRISMA framework and is presented in the PRISMA flow diagram (Figure 1).

Data extraction

A standardized extraction form was used (based on CHARMS for prediction-model studies where applicable [21]). The following items were extracted: publication year/country; study setting; sample size and participant characteristics; data modality and acquisition protocol; definition of periodontal outcomes (e.g., BOP, CAL thresholds; radiographic bone-loss definition; staging/grading reference); annotation process and reference standard (number/type of annotators, inter-rater agreement when reported); preprocessing and augmentation; model family/architecture; training/validation/test split strategy and unit of splitting (patient-level vs image-level); performance metrics (including calibration if reported); external validation and domain shift assessment; explainability methods; and implementation considerations (workflow, time, usability).

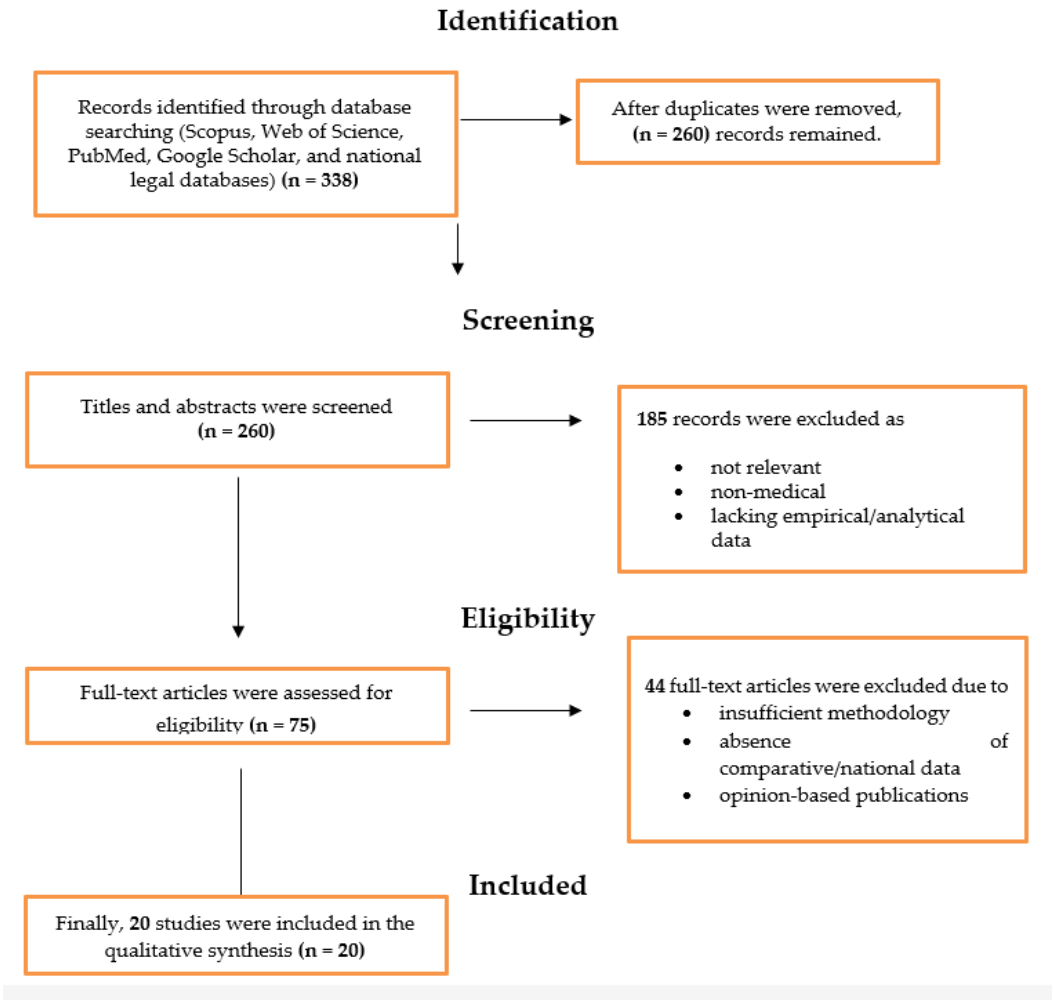


Figure 1 - PRISMA flow diagram of study selection for the systematic review of healthcare mediation

Risk of bias and limitations

Given the scoping nature and heterogeneity of included evidence, a full quantitative synthesis was not planned. Where feasible, methodological quality and applicability concerns were assessed qualitatively: diagnostic-accuracy studies were mapped to QUADAS-2 domains [22], and prediction/risk models were assessed against PROBAST signaling questions [23]. Common limitations anticipated in this field include selection bias (single-center datasets), spectrum bias, leakage due to non-patient-level splitting, incomplete reporting of reference standards/annotation, lack of external validation, and limited calibration/clinical utility evaluation.

Ethical considerations

As this study was based exclusively on publicly available data and published literature, ethical approval was not required.

3. Results

A systematic review of intraoral photograph analysis in periodontology (2024) showed that most studies use convolutional neural networks, with DeepLabv3+ and U-Net being the most common architectures. The included studies demonstrate high accuracy in the detection of gingivitis, plaque, keratinized gums and other signs, while the size of the datasets varies significantly, affecting the generalizability of the models [11].

For staging/assessing alveolar bone loss using panoramic images and CBCT, two-stage architectures are used, combining segmentation and detection of key points/teeth. Such systems are aimed at standardizing measurements and reducing inter-expert variability [10].

Machine learning is used to build multi-class models for screening periodontal status based on non-clinical parameters and saliva biomarkers, as well as for comparative evaluation of periodontitis prediction algorithms. These approaches are particularly relevant for population-based programs where rapid, non-invasive triage is required [24,25].

To extract diagnostic information from electronic dental records, NLP methods based on transformers

(e.g., BERT) are promising, allowing the stage and severity of periodontitis to be classified based on clinical notes and charts. This reduces dependence on manual data structuring and improves data readiness for analytics and model training [17].

Teledentistry and remote monitoring (including photo analysis, self-reports, and smart device data) expand access to prevention and allow AI to be integrated into care pathways, especially for groups with limited access to in-person dental care. Representative examples of studies and models used are presented in Table 5.

Table 5 - Examples of AI research in the diagnosis/screening of periodontal diseases

Source (year)	Task	Data	N	Model	Key result/metric
Aykol Şahin (2024) systematic review [11]	Gingivitis/plaque/gingival tissue	Intraoral photographs	110–7,220 images	DeepLabv3+, U-Net, YOLOv5, etc.	High accuracy; dataset size and augmentation influence performance
Alalharith et al. (2020) [16]	Early gingivitis detection	Intraoral photographs (orthodontic patients)	134	Faster R-CNN	Accuracy 77.12%
Andrade et al. (2023) [26]	Dental biofilm detection	Tooth photographs	480	U-Net	Accuracy 91.8%
Chau et al. (2023) [27]	Gingivitis detection	Intraoral photographs	567	DeepLabv3+	Accuracy >90%; comparable to a dentist
Krois et al. (2019) [9]	Assessment of periodontal bone loss (PBL)	Panoramic radiographs (segments)	2,001 segments	CNN	Discrimination comparable to or higher than dentists
Jiang et al. (2022) [10]	Bone loss staging	Panoramic radiographs	640	U-Net + YOLO-v4	Automated calculation of % bone loss and staging
Xue et al. (2024) [28]	PBL diagnosis and staging	Panoramic radiographs	320 patients	YOLOv8 + Mask R-CNN + TransUNet	mAP for tooth detection 94%; PBL deviation ~5.28%
Kim et al. (2022) [29]	Dental disease detection	Panoramic radiographs	—	DL system (proposed)	Platform for automated diagnosis (JMIR)
Deng et al. (2024) [25]	Periodontal status screening	Non-clinical parameters + salivary biomarkers	—	ML (multiclass)	Multiclass screening tool
Deng et al. (2022) [24]	Point-of-care (POC) test for active MMP-8	Saliva/rinse	—	Diagnostic test	Comparison of diagnostic accuracy across sample types
Bashir et al. (2022)	Comparison of ML prognostic algorithms	Tabular data	—	Multiple ML models	Systematic comparison and validation
Ameli et al. (2024) [17]	Stage/grade classification	Clinical note texts + charts	309 records; test set 32	BERT	Accuracy ~77% (stage) and 75% (grade)

Table 5 summarizes representative publications in key areas: intraoral photos and photographs (segmentation/detection of inflammation and plaque), radiological analysis of panoramic images and CBCT (assessment/staging of bone loss), risk stratification models based on tabular data and biomarkers, and NLP

analysis of electronic records. The table shows the data type, sample size (N), model class, and key metrics/results, which makes it easier to compare approaches and data requirements when planning your own dataset.

4. Discussion

Periodontitis is one of the most common chronic diseases of the oral cavity and contributes significantly to the global burden of disease; the WHO emphasizes the need to strengthen prevention, early detection and integration of dental care into universal health coverage [1-3]. The current classification (stage/grade) standardizes diagnosis and establishes requirements for data that must support digital and AI solutions (in particular, clinical indicators of bleeding on probing and loss of clinical attachment) [5-6].

Clinical significance of endpoints. For practical implementation of algorithms, it is critical to agree on a 'gold standard' for scoring: BOP reflects inflammatory activity, while CAL (together with pocket depth and recession level) characterizes cumulative loss of supporting tissues. These parameters form the basis for staging and assessing the severity of the disease, and clinical guidelines (including EFP S3-level guidelines) provide guidelines for treatment and subsequent supportive management [30]. Consequently, the data set should contain measurements that allow reproducible calculation of the stage/degree and formation of clinically interpretable model outputs (e.g., probability of periodontitis + stage/degree prognosis).

Interpretation of evidence and transferability. Most studies demonstrate high accuracy in segmentation/detection tasks using intraoral images and assessment of bone loss using X-rays, however, retrospective designs, limited samples, and lack of independent external validation are typical, which reduces the transferability of results between clinics and populations [11-12]. To reduce the risk of overestimating quality, it is necessary to: (i) prevent 'leakage' at the patient level when dividing samples; (ii) conduct external (inter-clinic and/or temporal) validation; (iii) analyse calibration and clinical utility (e.g., decision curve) along with AUC/accuracy [13].

Validation, risk of bias, and reporting. For diagnostic tasks, it is advisable to use critical appraisal tools for quality and applicability (e.g., QUADAS-2), and for prediction/classification models, tools for assessing risk of bias and applicability (e.g., PROBAST) [22,23]. Requirements for transparent reporting of results and protocols of AI interventions should be aligned with international guidelines: TRIPOD+AI for prediction models and CONSORT-AI/SPIRIT-AI for clinical trials and protocols [13-15]. This increases reproducibility, facilitates comparison of studies, and makes the results suitable for subsequent regulatory and clinical evaluation.

Data modalities: images, radiology, and CBCT. In periodontology, the largest evidence base has been accumulated for (a) intraoral photographs (inflammation/plaque/recession) and (b) panoramic radiographs (assessment of periodontal bone loss) [9-11]. When using CBCT, the principle of justification and optimization of radiation exposure must be taken into account: CBCT is not indicated as a routine screening method, but rather for clinical indications where 3D information influences treatment tactics; relevant recommendations are presented in the European Commission's evidence-based guidelines (Radiation Protection No 172) [31]. Due to differences in imaging angles, artefacts and reconstruction parameters, protocol standardization and noise/artefact resistance testing are particularly important for radiological models.

NLP and interoperability of electronic records. A promising direction is the extraction of features from text and semi-structured dental records using transformers (e.g., BERT) for automatic stage/degree determination and quality register formation [17]. However, the portability of NLP models depends on terminology, language environment, chart structure, and field completeness. Therefore, the data architecture should provide a unified dictionary (ontology) of clinical features and rules for mapping local codes/formulations to standardised variables (BOP, CAL, PPD, etc.).

Implementation framework: from development to clinical use. Taking into account regulatory and ethical requirements, it is advisable to view AI implementation as a total product life cycle process: development → validation → implementation → post-marketing monitoring. International documents on Good Machine Learning Practice (GMLP) emphasise data representativeness, model change management, evaluation of the effectiveness of the 'doctor-AI' team, and the availability of monitoring/improvement mechanisms [32,33]. In addition, the WHO emphasises the principles of AI ethics and governance (transparency, accountability, safety, fairness, data protection) and the need for risk assessment prior to implementation [34,35]. In practice, this means working on four levels simultaneously:

1) Data level: common feature dictionary (BOP, CAL), image acquisition and radiology protocols, anonymization, quality control and bias audit;

2) Model level: choice of task class (segmentation/detection/classification/prediction); interpretability, resistance to artefacts and dataset shift.

3) Validation level: internal split without leaks, external (inter-clinic/temporal) verification, calibration, and assessment of clinical utility;

4) Implementation level: integration into IS and workflows, staff training, drift monitoring, economic evaluation, and compliance with reporting (TRIPOD+AI, CONSORT-AI/SPIRIT-AI).

Confidentiality and legal compliance framework. Since the models are based on clinical records and images, requirements for personal data protection and access management must be built into the design of the dataset and IT architecture. In an international context, the GDPR (Regulation (EU) 2016/679) serves as a benchmark [36]. For the Republic of Kazakhstan, compliance with national legislation on personal data and its protection (including requirements for obtaining consent, processing purposes and security measures) is mandatory [37].

Overall, expanding the evidence base in periodontology requires a shift from 'accuracy on a local dataset' to prospective multicenter studies with clinical endpoints, as well as an assessment of the impact of AI on the quality of prevention and patient routing (screening coverage, reduction in missed severe cases, time savings for doctors). Following international guidelines on reporting and the life cycle of AI medical devices facilitates the translation of results into practice [13-15, 32-35].

5. Conclusion

AI tools in periodontology are moving from experimental image recognition tasks to multimodal screening and clinical decision support systems. Key conditions for successful implementation include data standardization, external validation, transparent reporting, and deep integration into clinical processes. The proposed framework can serve as a basis for developing data architecture and implementing AI solutions in dental services.

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Contribution of the authors. E.A. – conceptualization; A.I., K.D. – methodology; E.A., K.D., A.C. – forma analysis; A.C., A.A. – data curation; A.I., K.D. – validation; E.A. – writing – original draft; A.Z. - writing – review & editing; A.I. – project administration.

Declaration of Generative AI and AI-assisted technologies in the writing process. During the preparation of this work, the authors used ChatGPT in order to conduct a preliminary literature search and assist in organizing the conceptual framework of the review. The authors also used Grammarly to refine the language, improve grammatical accuracy, and enhance the overall readability of the manuscript. After using these tools, the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication. The authors confirm that all literature citations and data interpretations have been manually verified for accuracy and integrity.

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Пародонт аурулардың диагностикасы мен скринингіне жасанды интеллектті интеграциялаудың заманауи тәсілдері

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Түйіндеме

Пародонт аурулары жаһандық денсаулық сақтау саласында маңызды мәселе болып табылады. Бұл патология жүрек-қантамыр аурулары мен қант диабеті сияқты жүйелік аурулармен тығыз байланысты.

Сондықтан оларды ерте анықтау мен скрининг қоғамдық денсаулық сақтау жүйесінің басым бағыттарының бірі болып саналады. Сандық стоматологияның қарқынды дамуы әртүрлі клиникалық және клиникалық емес деректердің жиналуына әкелді. Оның ішінде ауызішілік суреттер, рентгенологиялық мәліметтер, сілекей биомаркерлері және электрондық медициналық жазбалар бар. Бұл жағдайлар пародонтологиялық көмектің диагностикалық дәлдігін, стандартталуын және қолжетімділігін арттыру үшін ЖИ технологияларын қолдануға мүмкіндік береді.

Бұл шолу жұмысының мақсаты: пародонтологияда ЖИ қолданудың заманауи тәсілдерін жүйелі түрде талдау, сондай-ақ, ЖИ құралдарын клиникалық тәжірибеге және халықтық скрининг бағдарламаларына енгізудің құрылымдық моделін ұсыну. Әдебиеттерге құрылымдалған іздеу PubMed, Scopus және Google Scholar сияқты негізгі дерекқорларда жүргізілді, 2005 жылдан 2025 жылға дейінгі жарияланымдар қамтылды. Шолу ауызішілік кескіндерді талдау, рентгенологиялық талдау, болжамдық модельдеу, табиғи тілді өңдеу және телестоматология салаларындағы зерттеулерді қамтиды.

Нәтижелер ЖИ модельдерінің, әсіресе конволюциялық нейрондық желілер сияқты терең оқыту архитектураларының қызыл иек қабынуын, тіс қағын және альвеолярлы сүйек жоғалуын анықтауда жоғары дәлдік көрсететінін көрсетті. Сонымен қатар, машиналық оқыту әдістері клиникалық көрсеткіштер мен биомаркерлер негізінде тәуекелді болжау және стратификациялау үшін тиімді қолданылады. Табиғи тілді өңдеу әдістері электрондық стоматологиялық жазбалардан диагностикалық ақпаратты автоматты түрде алуға мүмкіндік береді, бұл деректерді қолдануды және клиникалық шешім қабылдауды жақсартады. Перспективалық нәтижелерге қарамастан, дәлелдер әркелкі болып табылады. Зерттеу үлгілерінің шағын болуы, сыртқы валидацияның болмауы және эталондық стандарттардың әртүрлілігі негізгі шектеулер болып табылады. ЖИ енгізу барысында деректерді стандарттау, нормативтік талаптар және клиникалық жұмыс процестеріне біріктіру сияқты мәселелер туындайды.

Қорытындылай келе, ЖИ пародонтологиялық диагностика мен скринингті дәлдік, ауқымдылық және қолжетімділік тұрғысынан айтарлықтай жақсартуға үлкен мүмкіндік береді. Алайда оны тиімді енгізу үшін сенімді валидация, стандартталған деректер хаттамалары және клиникалық әрі этикалық талаптарға сәйкестік қажет.

Түйін сөздер: жасанды интеллект, пародонтит, скрининг, панорамалық рентгенография, конус сәулесінің компьютерлік томографиясы, ауызішілік суреттер, телестоматология.

Современные подходы к интеграции искусственного интеллекта в диагностику и скрининг пародонтальных заболеваний

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Резюме

Пародонтальные заболевания представляют собой значительную глобальную проблему здравоохранения. Эта патология тесно связана с системными состояниями, такими как сердечно-сосудистые заболевания и сахарный диабет, что делает ее раннюю диагностику и скрининг приоритетными задачами общественного здравоохранения. Быстрое развитие цифровой стоматологии привело к накоплению разнообразных клинических и неклинических данных, включая интраоральные изображения, рентгенологические данные, слюнные биомаркеры и электронные медицинские записи. Эти достижения

создают возможности для применения технологий ИИ с целью повышения точности диагностики, стандартизации и доступности пародонтологической помощи.

Цель данного обзора: систематиризованно проанализировать современные подходы к применению ИИ в пародонтологии, а также предложить структурированную модель интеграции ИИ-инструментов в клиническую практику и программы массового скрининга. Структурированный поиск литературы проводился в основных базах данных, включая PubMed, Scopus и Google Scholar, с охватом публикаций за период с 2005 по 2025 годы. В обзор включены исследования, посвященные анализу изображений, интерпретации рентгенологических данных, а также предиктивному моделированию, обработке естественного языка и телестоматологии.

Результаты показывали, что модели ИИ, особенно архитектуры глубокого обучения, такие как сверточные нейронные сети, демонстрируют высокую точность в выявлении воспаления десен, зубного налета и потери альвеолярной кости. Методы машинного обучения также эффективно применяются для прогнозирования риска и стратификации пациентов на основе клинических параметров и биомаркеров. Кроме того, методы обработки естественного языка позволяют автоматически извлекать диагностическую информацию из электронных стоматологических записей, что повышает удобство использования данных и улучшает принятие клинических решений. Несмотря на обнадеживающие результаты, доказательная база остается неоднородной. Основные ограничения включают небольшие размеры выборок, отсутствие внешней валидации и вариабельность эталонных стандартов. Ключевые проблемы внедрения ИИ связаны со стандартизацией данных, нормативными требованиями и интеграцией в клинические рабочие процессы.

ИИ обладает значительным потенциалом для трансформации диагностики и скрининга пародонтальных заболеваний за счет повышения точности, масштабируемости и доступности. Однако успешная реализация требует надежной валидации, стандартизированных протоколов данных и соответствия клиническим и этическим нормам.

Ключевые слова: искусственный интеллект, пародонтит, скрининг, панорамная рентгенография, конусно-лучевая компьютерная томография, интраоральные изображения, телестоматология.

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