UNIVERSITY OF BRASILIA
Faculty of Health Sciences
Department of Dentistry

FINAL COURSE WORK

MACHINE LEARNING IN PREDICTING DIAGNOSIS OF ORAL CAVITY DISEASES: A SCOPING REVIEW

ISABELA MACHADO LOPES

Brasilia
2025

ISABELA MACHADO LOPES

MACHINE LEARNING IN PREDICTING DIAGNOSIS OF ORAL CAVITY DISEASES: A SCOPING REVIEW

Research Project submitted to the Undergraduate Course in Dentistry, University of Brasília, as a partial requirement for completion of the Undergraduate Course in Dentistry

Advisor: Prof.ª. Drª. Eliete Neves da Silva Guerra

Brasilia

2025

ACKNOWLEDGMENTS

I thank God for making this dream of attending a public university possible, then my parents for keeping me strong so that I could overcome this long and tiring journey, my boyfriend who helped me through the most difficult moments of the semesters, my friends and my partner who made my day-to-day life in the clinics happier, my sister for all the advice and guidance about our profession, my little dog Jade, my grandparents, also Ste and Giovanna for their companionship and support during all these years, Professor Eliete and the entire research group for all the knowledge acquired and help during the development of this work

ABSTRACT

Introduction: Machine learning (ML) has proven to be a promising tool for predicting oral diseases from clinical and imaging data. Despite its potential, its application in dental practice is still limited.

Objective: This scoping review (ScR) aimed to perform a descriptive analysis of machine learning for predicting diagnoses of oral cavity diseases.

Methodology: An electronic search was performed using the following databases: MEDLINE/PubMed, EMBASE, and Web of Science. The grey literature search was performed on Google Scholar. Studies that used machine learning to predict the diagnosis of oral cavity diseases in humans were included. This ScR was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews checklist (PRISMA-ScR)

Results: Of a total of 3660 studies identified, 99 met the eligibility criteria. A total of 120 diseases were identified in the included studies, considering that each study could address more than one disease. The most commonly observed diseases were: dental caries and associated conditions (27.5%); oral cancer (20%); periodontal diseases (11.7%); salivary gland disorders and xerostomia (8.3%); mucosal lesions (6.7%) and others. Regarding the origin of the studies, China accounted for 13.1% of the publications, followed by India (12.1%), South Korea (11.1%) and the United States (10.1%). Regarding the predictor variables, clinical data were the most used (29.3%), followed by photographs (23.2%), radiographic examinations (17.2%) and histopathological examinations (7.1%). Stomatology was the most addressed specialty among the studies, covering 57.5% of the publications. The most frequent metrics for evaluating the models were sensitivity (18.9%), accuracy (17.0%), and specificity (13.6%). Finally, among the algorithms used, the Support Vector Machine (SVM) was the most applied (10.5%), followed by Random Forest (9.4%) and Logistic Regression (9.0%).

Conclusion: This scoping review identified that the application of Artificial Intelligence in the diagnostic prediction of oral cavity diseases focuses mainly on dental caries, oral cancer, and periodontal diseases. Despite the advances, gaps persist regarding methodological standardization and clinical validation of models. Thus, future studies are needed to strengthen the applicability of AI in dental practice, promoting greater safety and diagnostic efficacy.

Keywords: Artificial intelligence; Machine learning; Oral diseases; Prediction; Scoping review

RESUMO

Introdução: O aprendizado de máquina (ML) tem se mostrado uma ferramenta promissora para a predição de doenças orais a partir de dados clínicos e de imagem. Apesar do potencial, sua aplicação na prática odontológica ainda é limitada.

Objetivo: Esta revisão de escopo (RS) teve como objetivo realizar uma análise descritiva do aprendizado de máquina para predição de diagnósticos de doenças da cavidade oral.

Metodologia: Foi realizada uma busca eletrônica utilizando as seguintes bases de dados: MEDLINE/PubMed, EMBASE e Web of Science. A busca na literatura cinzenta foi realizada no Google Acadêmico. Foram incluídos estudos que utilizaram aprendizado de máquina para predição do diagnóstico de doenças da cavidade oral em humanos. Esta ScR foi relatada de acordo com a lista de verificação Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR).

Resultados: De um total de 3660 estudos identificados, 99 atenderam aos critérios de elegibilidade. Um total de 120 doenças foram identificadas nos estudos incluídos, considerando que cada estudo poderia abordar mais de uma doença. As doenças mais comumente observadas foram: cárie dentária e condições associadas (27,5%); câncer oral (20%); doenças periodontais (11,7%); distúrbios das glândulas salivares e xerostomia (8,3%); lesões da mucosa (6,7%) e outras. Em relação à origem dos estudos, a China foi responsável por 13,1% das publicações, seguida pela Índia (12,1%), Coreia do Sul (11,1%) e Estados Unidos (10,1%). Quanto às variáveis preditoras, os dados clínicos foram os mais utilizados (29,3%), seguidos por fotografias (23,2%), exames radiográficos (17,2%) e exames histopatológicos (7,1%).A estomatologia foi a especialidade mais abordada entre os estudos abrangendo 57,5% das publicações. As métricas mais frequentes para avaliação dos modelos foram sensibilidade (18,9%), acurácia (17,0%) e especificidade (13,6%). Por fim, entre os algoritmos utilizados, o Support Vector Machine (SVM) foi o mais aplicado (10,5%), seguido por Random Forest (9,4%) e Regressão Logística (9,0%).

Conclusão: Esta revisão de escopo identificou que a aplicação de Inteligência Artificial na predição diagnóstica de doenças da cavidade oral concentra-se principalmente em cárie dentária, câncer bucal e doenças periodontais. Apesar dos avanços, ainda existem lacunas quanto à padronização metodológica e à validação clínica dos modelos. Assim, estudos futuros são necessários para fortalecer a aplicabilidade da IA na prática odontológica, promovendo maior segurança e eficácia diagnóstica.

Palavras-chave: Inteligência artificial; Aprendizado de máquina; Doenças bucais; Predição; Revisão de escopo

SUMMARY

1 INTRODUCTION

According to the World Health Organization (WHO), oral diseases (OD) affect approximately 3.5 billion people worldwide, making them a significant public health problem[2]. The most common diseases include caries, periodontal disease, and cancer of the lip and oral cavity [2]. These conditions compromise quality of life, leading to problems such as pain, difficulties in chewing, speaking, eating, nutritional deficiencies or even mortality and morbidity. [2].This underscores the importance of their early detection and management.

In recent years, Artificial Intelligence (AI) has emerged as a promising tool in healthcare. AI refers to the ability of machines to perform tasks that typically require human intervention [1]. Within this field, Machine Learning (ML) — a subarea of AI — involves training algorithms to autonomously identify intrinsic patterns in unprogrammed data and make predictive decisions [1]. The integration of ML techniques with imaging modalities, such as X-rays and CT scans, and clinical data has the potential to improve diagnostic accuracy, predict recurrence, assess prognosis, and guide treatment strategies in dentistry and oral healthcare, ultimately reducing costs and improving patient outcomes [3]. Supporting this potential, recent evidence shows that ML algorithms perform well in predicting chronic diseases across various clinical contexts [4], reinforcing their value for enhancing diagnostic, prognostic, and risk assessment capabilities in healthcare [5].

In oral health, there has been considerable, albeit incipient, progress in the use of AI, offering new perspectives for the diagnosis, prediction and classification of its conditions[5]. One of the most promising areas for AI application is dentomaxillofacial radiology, where algorithms have been used for the detection of anatomical structures and the diagnosis of various oral conditions, including maxillary tumors, Sjögren's syndrome, calcified carotid atheroma, periodontal disease, dental caries, maxillary sinusitis, root fractures, and mandibular morphology [5].Given the growing body of evidence, it is essential to assess the ability of AI-based systems to predict oral diseases in order to optimize and enhance clinical care.

The growing number of studies in the literature evaluating the prediction of AI is notable. Deep learning algorithms have shown good performance in caries detection, supporting their use as auxiliary tools in clinical decision-making. AI models have also been applied to predict the risk of osteoradionecrosis, diagnose odontogenic lesions and maxillofacial tumors, and detect oral squamous cell carcinoma.

Despite these promising applications, the adoption of AI in clinical oral health practice remains limited. AI has gained prominence in dental radiography research, largely due to the frequent use of radiological images combined with clinical and patient data [1]. This wealth of data makes oral healthcare particularly suitable for ML approaches, which can integrate and analyze complex datasets to improve prediction, diagnosis, and clinical decision-making. However, effective implementation still faces challenges, including a shortage of qualified AI professionals, limited understanding of AI capabilities and appropriate algorithms, infrastructural limitations, and restricted access to confidential clinical data for algorithm training [3]. These limitations underscore the importance of mapping the existing literature to identify current trends, challenges, and research gaps in the application of AI to oral healthcare.

In this context, a scoping review is a type of study designed primarily to map the literature with the aim of examining the extent, scope and nature of evidence for a given research question, as well as helping to identify gaps in the literature, contributing to the planning of future research, being a method well suited to address the identified research needs [10]. Scoping reviews (ScR) are a useful methodological approach to gather available evidence on a topic, thus reporting the main concepts, theories, relevant sources of information and gaps in the body of knowledge [10]. Currently, it is possible to find derivative studies addressing the application of AI in dentistry that map the use of this technology in various specialties such as radiology, prosthetics, and orthodontics [11]. However, no study was found that focused specifically on predicting the diagnosis of oral cavity pathologies using ML, so the ScR study design was chosen to summarize the data on this topic.

Therefore, the main objective of this scoping review is to systematically map the use of ML techniques to predict the diagnosis of oral cavity diseases. This includes identifying the different types of ML algorithms used, as well as the oral diseases and specific predictor variables targeted for prediction. In addition, the review aims to analyze performance metrics and ML models used in predicting oral diseases in different populations and settings. The research question was defined as "How has machine learning been used to predict the diagnosis of oral cavity diseases?"

2 METHODS

This ScR was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews checklist (PRISMA-ScR) [10], and followed the JBI methodology for scoping reviews [12].

2.1 PROTOCOL AND REGISTRATION

The protocol was prepared using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA-P) protocols and registered in the Open Science Framework (OSF) under the identifier: DOI 10.17605/OSF.IO/TN7B3.

2.2 ELIGIBILITY CRITERIA

2.2.1 Participants, Concept and Context

The main objective was to identify what evidence is available in the literature on the use of ML to predict the diagnosis of oral diseases of the oral cavity. For this, the acronym PCC (Population, Concept and Context) was used, in which: (P) participants with oral diseases (C) prediction of diagnosis of oral cavity diseases, identifying which diseases, algorithms and metrics are most recurrent; (C) Oral Health.

2.2.2 Types of Sources

This scoping review covers primary studies: experimental and quasi-experimental study designs, randomized controlled trials, non-randomized controlled trials, before-and-after studies, and interrupted time series studies. Additionally, analytical observational studies were included, including prospective and retrospective cohort studies, case-control studies, and analytical cross-sectional studies. Descriptive observational study designs, such as case series, individual case reports, and descriptive cross-sectional studies, were also included. All types of reviews were excluded because they were not aligned with the specific objectives of this study.

The inclusion criteria were primary studies in humans that used MLto predict the diagnosis of oral diseases, without restrictions on language or publication time.The exclusion criteria consisted of (1) studies that did not predictdiagnosis of oral diseases byML; (2) studies that do not address oral diseases; (3) abstracts, protocols, reviews, brief communications, personal opinions, letters, posters, conference abstracts and laboratory research (in vitro and in vivo animal studies); and (4) studies that did not evaluate the predictive performance of the algorithm.

2.3 SOURCES OF INFORMATION AND RESEARCH

The electronic search was conducted on February 14, 2025, in the following databases: PubMed/MEDLINE, EMBASE, and Web of Science Core Collection. Additional searches were performed in gray literature using Google Scholar, limited to the 100 first results (Appendix 1).A manual search was also carried out in the reference list of included studies. An online reference management software (EndNote X7, Thomson Reuters, Philadelphia, PA) was used to collect references and remove duplicate articles.

2.4 SELECTION OF SOURCES OF EVIDENCE

The study selection process was conducted in two distinct stages. In the first phase, two reviewers independently assessed the titles and abstracts of all identified references using the online platform Rayyan (Qatar Computing Research Institute). In the second phase, the same two reviewers independently applied the eligibility criteria to the full texts of the previously selected studies. When discrepancies arose, a third reviewer was involved and all disagreements were resolved by consensus. Studies that did not meet the eligibility criteria were excluded, as detailed in (Appendix 2). The extracted data included: author, year of publication, country, disease investigated, study objective, sample size, algorithms and metrics used and reported predictive performance (Appendix 3). In addition, the 95% confidence interval was estimated using an online statistical calculator (OpenEpi; available at: www.OpenEpi.com).

2.5 DESCRIPTIVE SUMMARY

A descriptive analysis of the data was performed, with grouping and organization of the data described through frequency graphs. The main outcome consisted of identifying the oraldiseases most frequently used for diagnostic prediction through ML algorithms. Secondary outcomes included the identification of the types of variables most frequently applied in predictions, as well as the characterization of the most used algorithms and evaluation metrics, highlighting their respective predictive performances. To facilitate the analysis and presentation of the results, the oral diseases addressed in the included studies were categorized into 16 different groups, as detailed in Appendix 4.

3 RESULTS

3.1 SELECTION OF SOURCES OF EVIDENCE

A total of 4,714 studies were initially identified through database searches and grey literature. After removing duplicate references, 3,660 records remained. Of these, 3,459 studies were excluded during the initial screening of titles and abstracts, leaving 201 studies eligible for phase 2 After full-text reading, 102 studies were excluded (Appendix 2), resulting in the inclusion of 99 studies in the review. Figure 1 presents the flow diagram regarding the literature search and selection criteria, following the PRISMA framework.

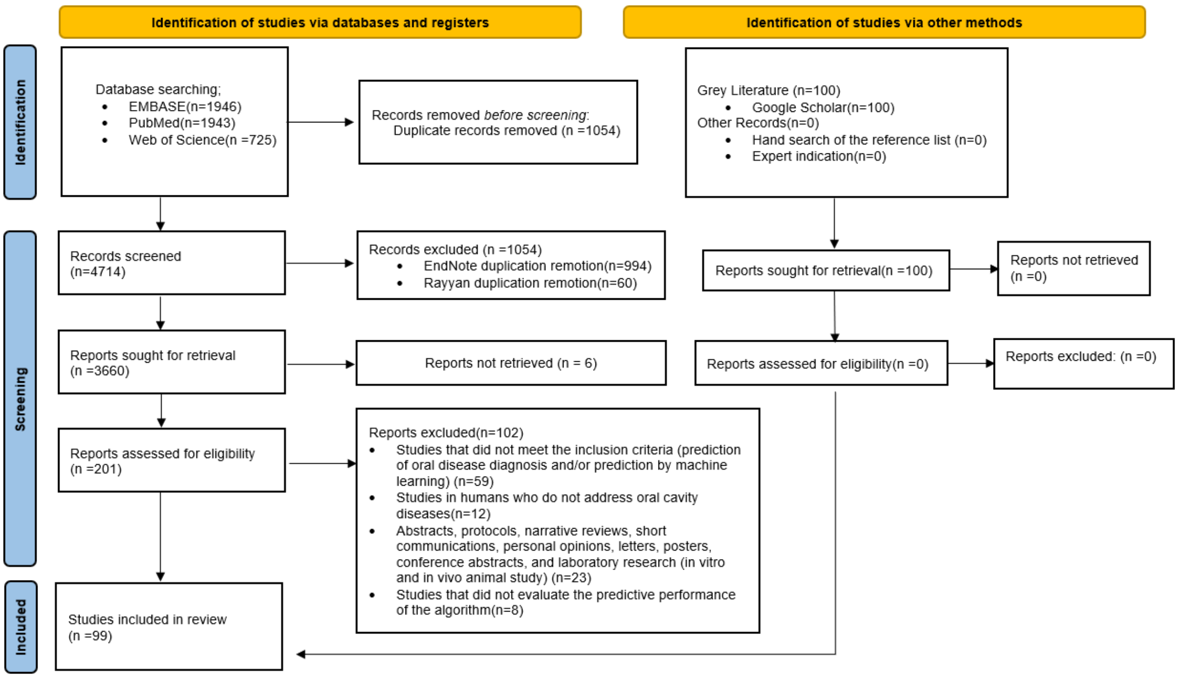

Figure 1 - Flow diagram of PRISMA literature search and selection criteria

3.2 CHARACTERISTICS OF INFORMATION SOURCES

Regarding the countries with the greatest representation in the production of studies that address ML and oral diseases, China stands out, responsible for 13.1%[13–25] of the publications included. Next are India (12.1%) [26–37], Korea (11.1%) [38–48], the United States (10.1%) [49–58], Japan and Saudi Arabia both with 6.1% [59–70], Turkey (5.1%) [71–75], Canada and Brazil with 4% each [76–83], Egypt, the United Kingdom and Iran 3% each [7,84–91], Germany, the Netherlands and Jordan (2% each)[92–97]. Other countries, such as Denmark, France, Indonesia, Italy, Malaysia, Morocco, Peru, Portugal, Sweden, Thailand and Ukraine, Uzbekistan, Vietnam presented individual participation of 1% each[98–110]. Thus, the continents with the highest frequency of studies are Asia, with 63.6% of the total[13–41,43–48,59–75,87–89,92,93,100,102,107,109–111], followed by North America, with 14.1%[49,51–58,80–83,112]. On the other hand, Africa had the lowest representation, covering only 4% of the studies [84–86,103]. Data on worldwide distribution of selected studies is presented byfigure 2.

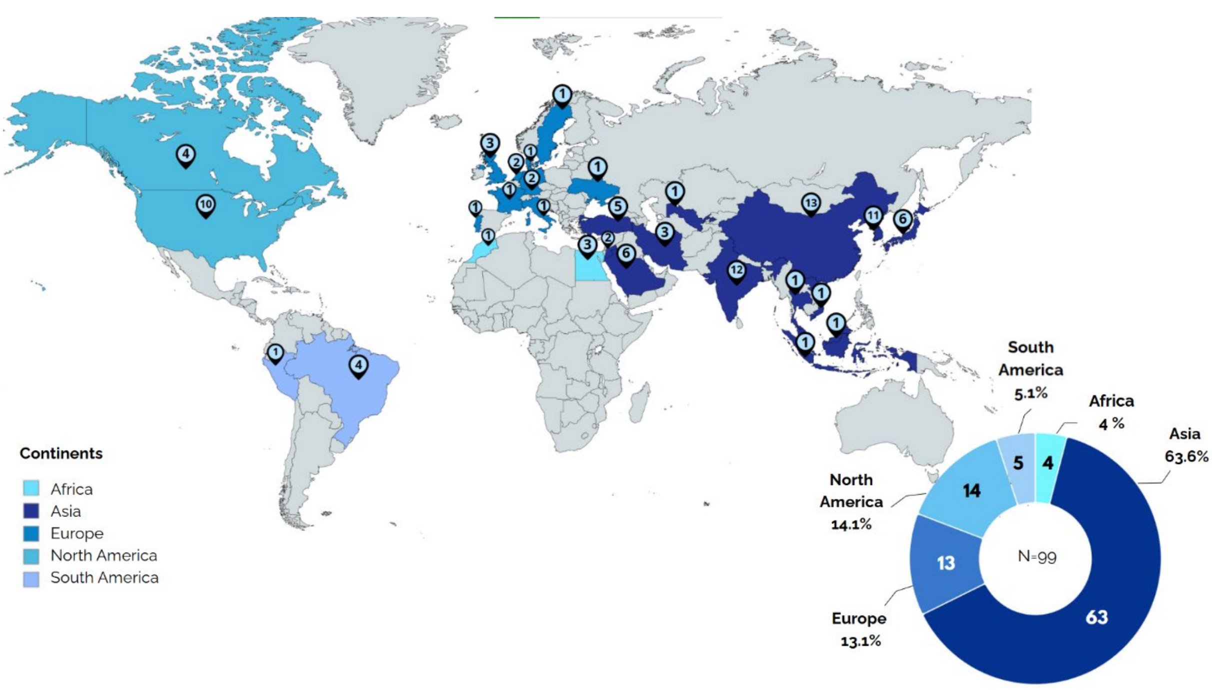

Figure 2 - Worldwide distribution of selected studies (n = 99) and their frequency by continent.

3.3 RESULTS FROM INDIVIDUAL SOURCES OF EVIDENCE AND DATA SYNTHESIS

The oral diseases addressed in the studies were quite heterogeneous. Among the disease categories, dental caries and associated conditions were the most frequently investigated by the ML algorithms, representing 27.5% (95% CI = 20.3–36.0) of the studies[15,17,25,28,31,33,39,40,43,47,50,53,56–59,61,67,73,74,76,78,79,83,94,95,100,102–104,108,109,111]. Following, oral cancer stood out with 20% (95% CI = 13.82–28.0)[16,23,24,32–36,54,55,65,66,68,69,77,80,82,84–86,91,93,99,106], periodontal diseases with 11.7% (95% CI = 7.0–18.6)[14,17,18,22,31,37,38,55,75,80,88,90,96,98], salivary gland disorders and xerostomia with 8.3% (95% CI = 4.5–14.6)[21,45,49,51,64,86,87,97,101,105], and mucosal lesions with 6.7% (95% CI = 3.4–12.6)[26,71,80,86,89,92,99,107]. Furthermore, odontogenic cysts and tumors accounted for 5.8% (95% CI = 2.8–11.5)[19,20,29,30,60,80,81]; bone necrosis and infections, 5% (95% CI = 2.3–10.4)[7,30,44,46,48,52]; and potentially malignant oral disorders, 3.3% (95% CI = 1.3–8.2)[70,80,86,99]. The categories of anatomical variations, periapical lesions, and tongue lesions each accounted for 2.5% (95% CI = 0.85–7.0) of the studies [13,27,30,41,70,72,80,110], whereas developmental anomalies, halitosis, peri-implant diseases, and syndromes each accounted for 1% (95% CI = 0.15–4.5) [20,31,62,63] (Figure 3). After analyzing the diseases, the studies were grouped into six major areas of expertise. Stomatology had the highest frequency, corresponding to 57.5% (95% CI = 48.5–65.9) of the studies[7,16,19–21,23,24,26,29–36,41,44,46,48,49,51,52,54,55,60,62,64–66,68–71,77,80–82,84–87,89,91–93,97,99,101,105–107,113], followed by cariology, with 24.2% (95% CI = 17.39–32.55)[15,17,28,39,40,43,47,50,53,56–59,61,67,73,74,76,78,79,83,94,100,102–104,108,109,111], periodontics, with 11.7% (95% CI = 7.0–18.6)[14,17,18,22,31,37,38,55,63,75,88,90,96,98], radiology, with 2.5% (95% CI = 0.85–7.0) [13,27,110], dentistry, also with 2.5% (95% CI = 0.85–7.0)[25,31,95], and anatomy, with 1.7% (95% CI = 0.45–5.87)[30,72] (Figure 4).

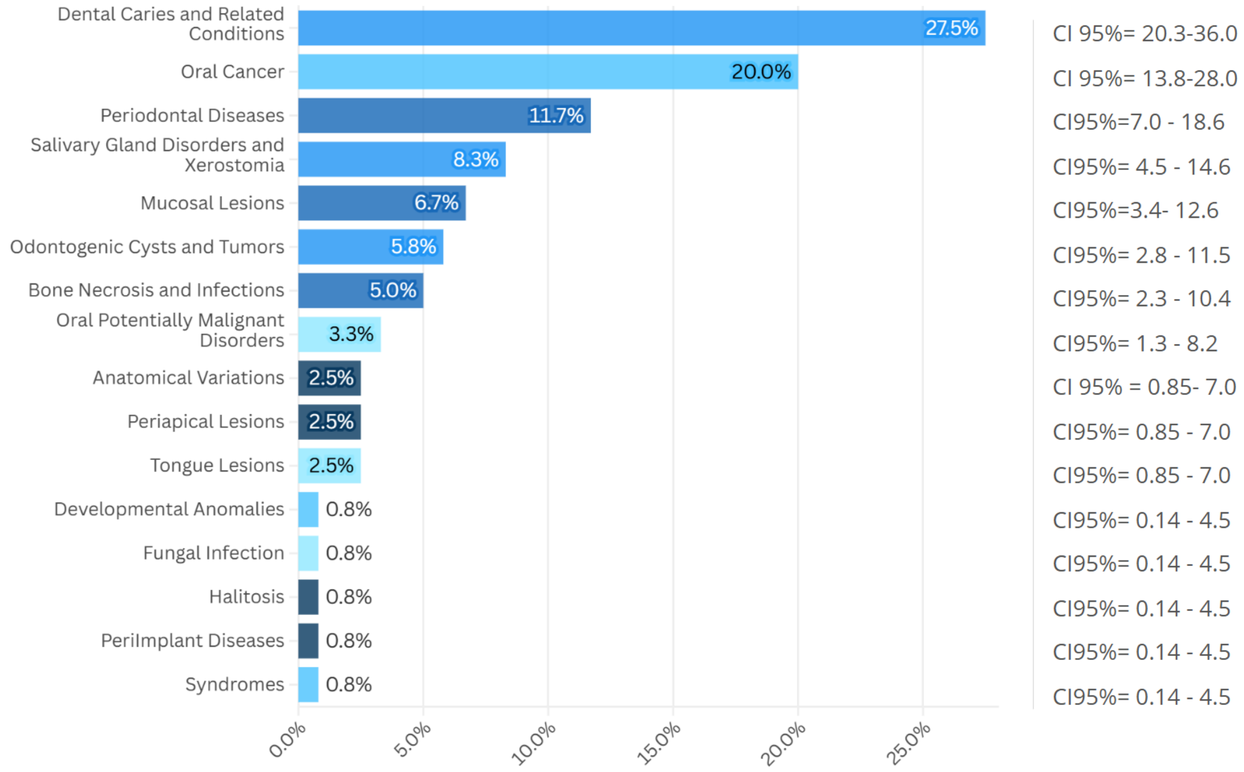

Figure 3 - Frequency of studies by group of oral diseases learning

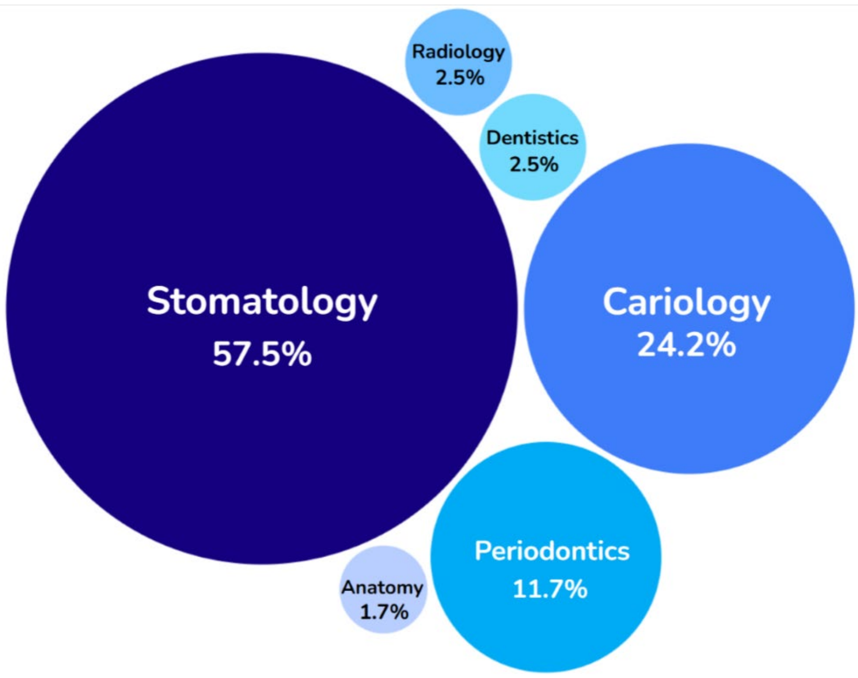

Figure 4 - Frequency of studies by specialty that predicted the diagnosis of OD

The annual distribution of studies, as shown in Figure 5, reveals significant variations in scientific production between 2008 and 2025. Significant growth was observed from 2020 onwards, with emphasis on the year 2024, which presented the highest frequency of publications, corresponding to 23.2% (95% CI = 16.0–32.4) of the total[13,16,20,23,38,45,53,54,57,69,74,78,80,86,89,91,95,97,100,102,104,106,110]. These data highlight the current and emerging nature of the topic, reflecting the growing interest of the scientific community in the application of AI for the diagnostic prediction of oral diseases.

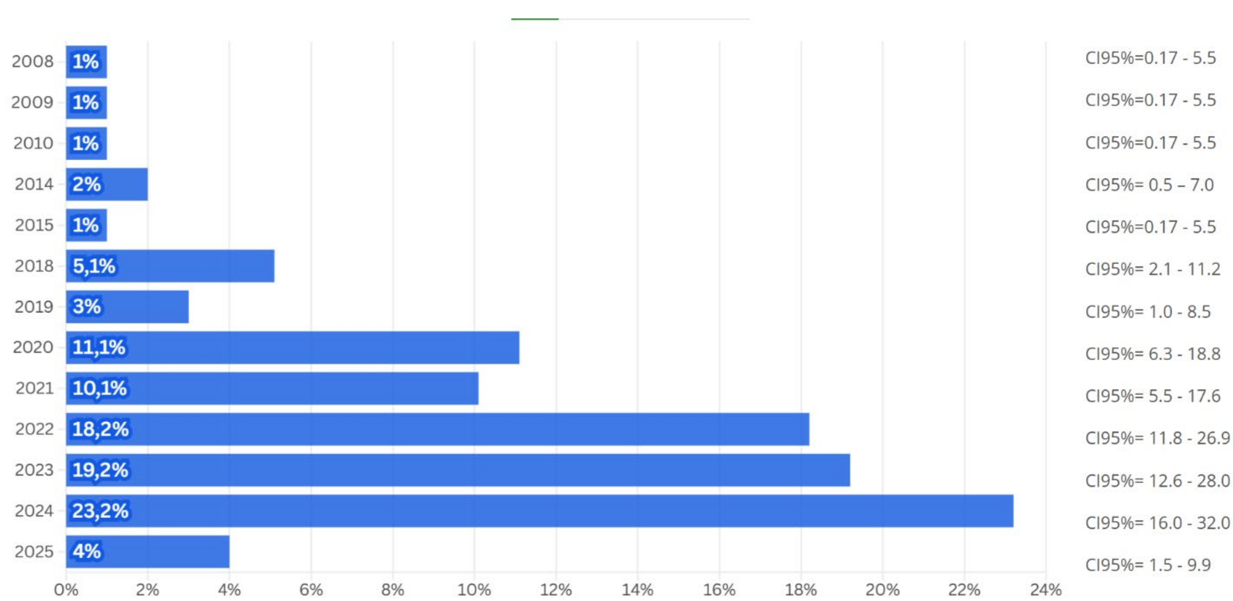

Figure 5 - Frequency of studies per year that ML predicted the diagnosis of OD

Regarding the types of predictor variables used by the studies to feed the algorithms, six distinct categories were found: clinical data, radiographic examinations, photographs, dosimetric data, histopathological examinations, radiomic characteristics and salivary tests. The most frequently used variable was the use of clinical data with 29.3%[21,24,25,37–39,43,44,46–48,53,57,58,63,67,75,76,78,82,88,91,92,95,96,98,104,108,112], photographs with 23.2%[14–16,22,23,26,29,32,33,36,41,54,56,60,65,70,71,80,90,93,94,103,107], radiographic examinations[13,17,19,27,28,31,40,59,66,72–74,79,100,109–111] and histopathological examinations[20,68,69,81,84,85,106] with 17.2% and 7.1% respectively. The combination of variables was also observed, with emphasis on the association between clinical data and salivary tests, used in 4% of the studies[18,34,45,61,102]. Other combinations, such as photographs associated with histopathological examinations, as well as radiographs with dosimetric data, were also reported, although with lower frequencies (Figure 6).

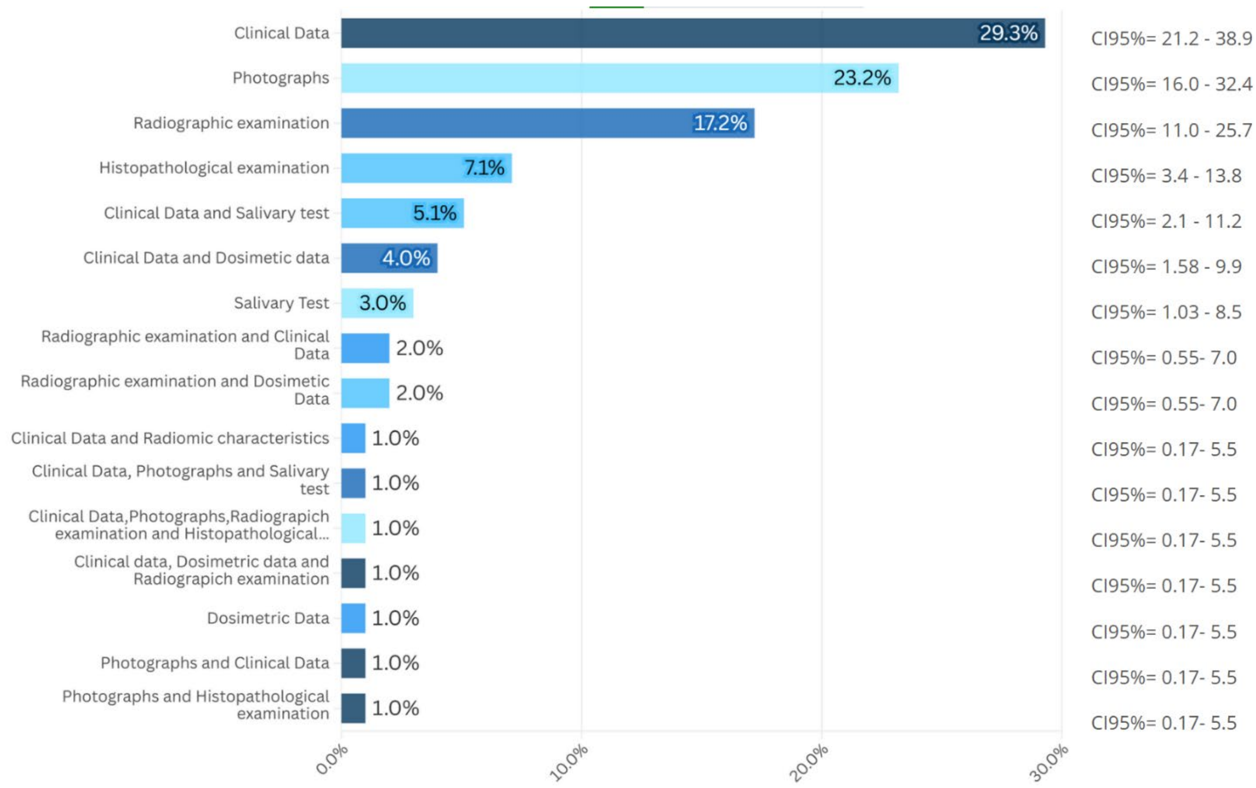

Figure 6 - Frequency of studies by type of variable used to perform diagnostic prediction

A total of 37 different types of metrics were used to evaluate prediction performance across the included studies. Among these, the ten most frequent stand out: sensitivity(SEN) 18.9% [7,13–19,21–24,26–34,36–44,46–49,51–54,56–70,72–74,77,78,82–87,89–91,93–96,98,101–104,106,110,112], accuracy (ACC) (17.0%[7,13,15,18,19,21–28,30,31,33–41,43,47–49,51–57,59,62–71,73,77–79,82–95,100–104,106,108–110,112], specificity(SPE) 13.6%[7,13–16,18,19,22,24–32,34,38,40,42–44,46,48,49,51,53,54,56,58,59,61,62,64,66,68,70,73,78,82,84–87,89–91,93–96,98,101,102,110,112], F1-score 9.8% [15,16,19,21–23,26–28,31,33,36,37,39,41,47,49,52,59,63–65,67–70,72–74,81,85,86,89,90,98,99,101,103,104,106,109], precision (PRC) 9.5% [7,13,17,21,23,26,28,29,31,33,34,36,38,39,41,47,52,54,57,63–65,67,69,70,72–75,81,83,85,89,90,102–104,106,110,114], area under the curve (AUC) 8.6% [16,17,20,21,25,38,41–46,48,49,52,57,63,76–80,82,87,89,91,93,94,96–98,101,104–106,112], negative predictive value (NPV) 3.6% [7,18,28,32,40,48,56,59,68,86,94,96,98,99,107], positive predictive value (PPV) 3.3% [18,30,32,40,48,56,59,68,86,94,96,98,99,107], Matthews correlation coefficient (MCC) 1.9% [27,28,30,43,70,73,90,104] and false positives (FP) 1.7% [26,29,60,72,81,98,107] (Figure 7).

Regarding the frequency of the algorithms applied, 277 models described in the literature were identified, classified into 115 different categories. The most frequently used were: Support Vector Machine (SVM), with 10.5% of applications[7,20,21,24,29,38,39,42,46,48,51–53,59,62–64,66,75,76,81,82,87,88,101,104,105,112,114]; Random Forest (RF), with 9.4%[7,18,21,38,39,42,43,46,48,51,52,59,63,64,67,77,82,84,87,89,91,98,104,105,112,114]; Logistic Regression (LR), with 9.0%[18,21,25,38,39,42,43,45,46,48,49,52,53,57,61,63,64,67,78,87,96,104,105,112,114]; Extreme Gradient Boosting (XGB), with 5.4%[31,38,42–44,48,53,57,67,78,82,84,87,98,112]; Artificial Neural Networks (ANN), with 4.3%[7,38,39,42,46,48,55,66,75,84,92,104]; Convolutional Neural Networks (CNN) [19,26,29,33,35,39,40,56,102,109] and K-Nearest Neighbors (KNN)[45,51,59,76,82,87,99,104,112,114], both with 3.6%; Decision Trees (DT)[46,67,75,76,78,82,87,99,114], with 3.2%; and, finally, Multilayer Perceptron (MLP) [45,66,76,82,87]and Naive Bayes (NB)[29,51,82,87,114], both with 1.8% of uses (Figures 7 and 8).

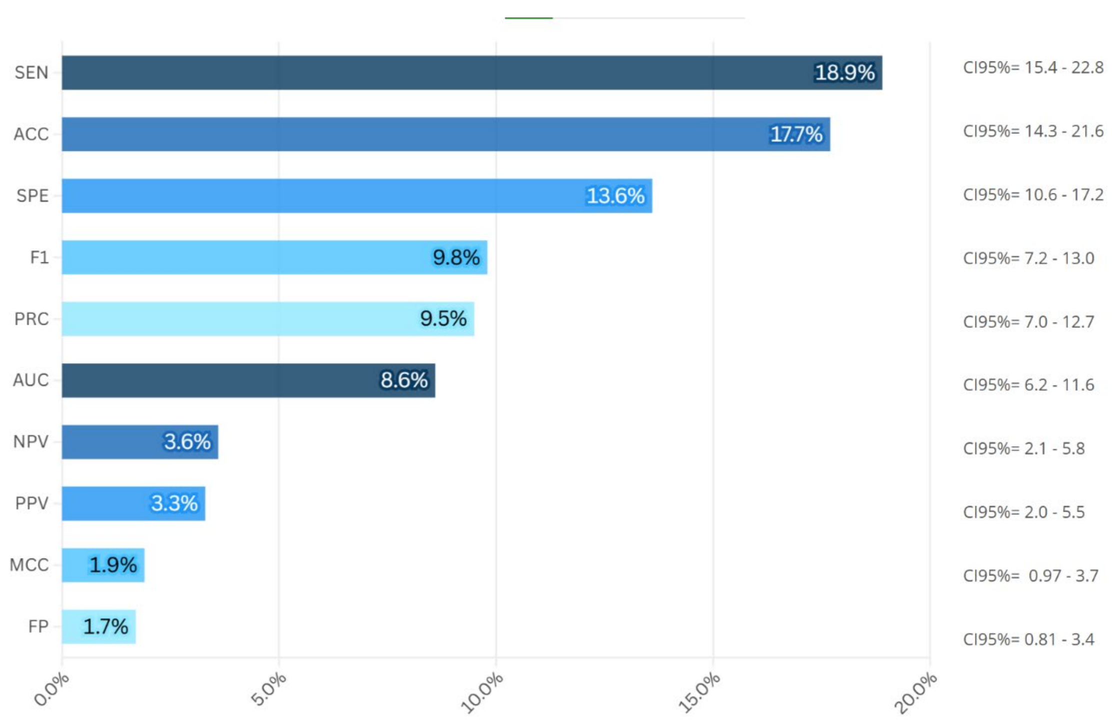

Figure 7 - Frequency of studies by type of ML metric used to assess the diagnostic prediction. Abbreviations ACC – Accuracy; AUC – Area Under the Curve; F1 – F1-score; FP – False Positive; MCC – Matthews Correlation Coefficient; NPV – Negative Predictive Value; PPV – Positive Predictive Value;

PRC – Precision; SEN – Sensitivity; SPE – Specificity

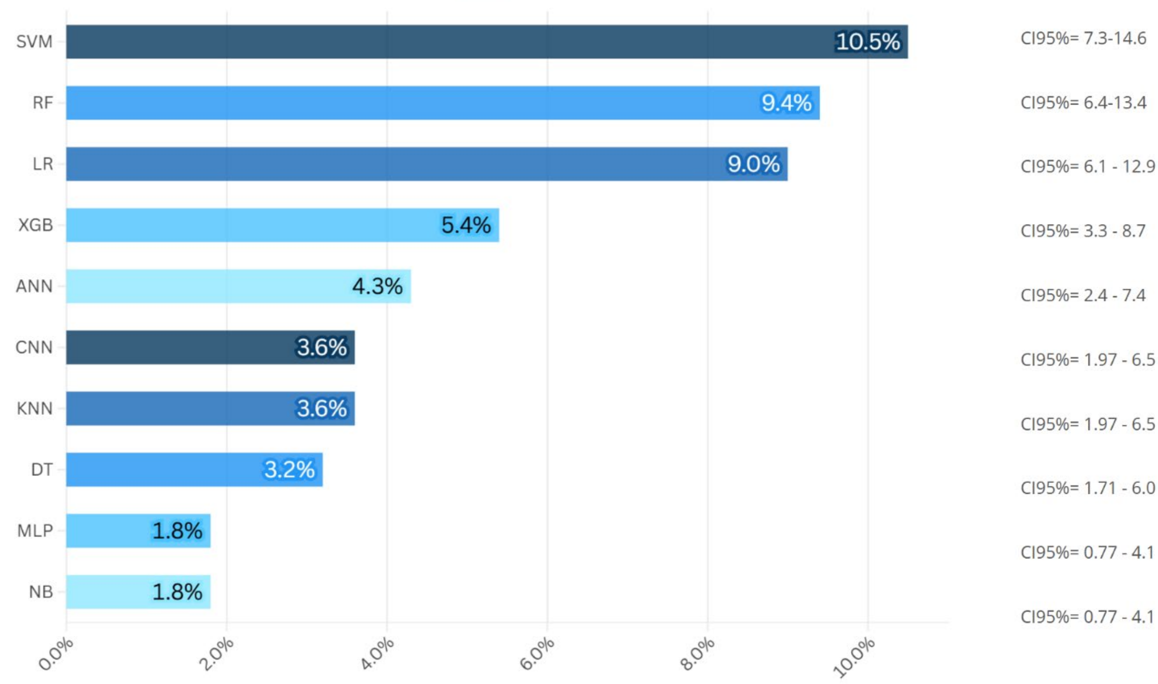

Figure 8 - Frequency of studies by type of ML algorithm used to perform diagnostic prediction of oral cavity diseases. Abbreviations: ANN – Artificial Neural Network; CNN – Convolutional Neural Network; DT – Decision Tree; KNN – K-Nearest Neighbors; LR – Logistic Regression; MLP – Multilayer Perceptron; NB – Naive Bayes; RF – Random Forest; SVM – Support Vector Machine; XGB – Extreme Gradient Boosting

4 DISCUSSION

The application of MLmodels to support diagnosis represents, in fact, a fundamental contribution to achieving greater agility and efficiency in the clinical practice of health professionals [115]. These technologies have the potential to optimize disease screening,monitoring processes, and the prediction of disease risks, consequently promoting an improvement in the population's quality of life [4]. However, the effective implementation of these solutions has not yet been consolidated in the dental clinical routine, reflecting both the necessary prudence adopted by professionals and authorities — since the health area involves considerable ethical and safety implications — and the limited dissemination of knowledge about the benefits that these algorithms can offer to patients [116].

In this context, the results of this scoping review contribute to systematizing and clarifying the main evidence produced to date, serving as a basis for the development of future research, as well as to guide health professionals interested in the safe and effective incorporation of these technologies.

The results demonstrate the growing application of ML algorithms in the diagnostic prediction of oral cavity diseases, highlighting, above all, the predominance of models such as Support Vector Machine (SVM), Random Forest (RF) and Logistic

Regression (LR), which demonstrates promising performance in several clinical applications. Recent evidence shows that SVM and RF generally outperform traditional LR in terms of accuracy and generalization capacity, especially in more complex and multivariate data sets [117].

Despite the superior performance of models such as RF and SVM, LR remains widely used, mainly due to its interpretability and ease of implementation [117]. In clinical contexts, the explain ability of models is essential for acceptance by health professionals and for ethical and legal support in decision-making. Therefore, the choice of algorithm should not be based exclusively on statistical performance, but also on the ability to provide comprehensive clinical insights [11].

Despite the potential of ML models inoral health, there are still significant barriers to their adoption in practice. These include the lack of standardization among studies, the scarcity of tests in diverse populations, and the difficulty of incorporating these technologies into professionals' clinical routine[1]. In addition, many studies are conducted in controlled environments that is, research contexts where variables are carefully selected and manipulated, data are clean and organized, and conditions are ideal for model performance (ref?). However, these environments do not reflect the complexity and variability of real clinical scenarios, which can limit the practical application of the results (ref?). To overcome these challenges, it is essential to invest in the construction of broad and representative databases, as well as in the development of models that combine precision and ease of interpretation, increasing confidence and freedom on the part of oral health professionals.

A relevant aspect highlighted in this review refers to the notable absence of studies aimed at underrepresented populations, especially in countries located in Africa and Latin America. It is observed that most of the investigations are concentrated in Asia, North America and Europe, which results in a gap in the scientific production related to the application of ML algorithms for diagnostic prediction in the context of these regions. This lack may compromise the generalizability and external validity of the developed models, since genetic, cultural and socioeconomic factors significantly impact the prevalence, clinical presentation and therapeutic response of oral diseases. Given this scenario, it is necessary for future research to prioritize the inclusion of data from these populations, to promote greater representation and ensure that the development and application of these health technologies are guided by equity and adequacy to the diverse epidemiological realities.

Furthermore, there was a significant concentration of studies focused on the diagnostic prediction of three major groups of oral diseases: dental caries, oral cancer and periodontal diseases. The emphasis on dental caries reflects its high global prevalence and significant impact on quality of life, especially in vulnerable populations [2]. Oral cancer, in turn, demands attention due to its clinical severity, frequently unfavorable prognosis and importance of early diagnosis, which makes predictive models promising tools for screening and detection in early stages [2]. Periodontal diseases, highly prevalent in adults, represent another important focus, as they are associated with systemic complications and tooth loss, reinforcing the relevance of predictive strategies in control and prevention[2].

Despite the clinical relevance of these approaches, the wide variety of metrics used to evaluate model performance, combined with the lack of methodological standardization among studies, makes direct comparison of results difficult. This scenario highlights the need for more consistent guidelines and uniform methodological protocols that allow greater reproducibility and clinical applicability of findings in dental practice [118].

Regarding the types of predictor variables used in the studies analyzed, a predominance of clinical data was observed, which occupied the first position in terms of frequency. This trend reflects the accessibility and wide availability of these data in dental practice, in addition to their direct relevance for the formulation of diagnostic hypotheses. In second place, clinical photographs stood out, used mainly for the analysis of lesions and visible changes in the oral cavity, demonstrating the growing role of computer vision in supporting diagnosis. Radiographic examinations occupied the third position, being widely used for the evaluation of bone structures and hard tissues, followed by histopathological examinations, which, although more specific and invasive, contributed significantly to the prediction of more complex pathological conditions, such as neoplasms. These results indicate a diversity of data sources used in prediction models, which suggests the need for greater multimodal integration of information to improve the accuracy of algorithms in the dental context.

4.1 LIMITATIONS

It is important to recognize some methodological limitations of this study when interpreting the results. The great heterogeneity between the studies, both in terms of methods used and in the types of variables and metrics evaluated, makes direct comparison and quantitative consolidation of the findings difficult. Another relevant point is the possible existence of publication bias, since studies with positive results tend to be more widely disseminated. Furthermore, many studies did not adequately detail the parameters and optimization of the algorithms, limiting the reproducibility of the results. Finally, due to the rapid evolution of the field of artificial intelligence, it is possible that recent research was not included in this review, highlighting the need for future updates and studies that perform quantitative analyses to comparatively evaluate the performance of the models.

Nevertheless, this scoping review offers a comprehensive overview of the current landscape, including a substantial number of studies (n = 99), which reinforces the relevance and reliability of the mapped evidence. The rigorous and systematic search strategy, combined with the application of PRISMA-ScR recommendations, helped to mitigate potential selection and reporting biases. Moreover, by identifying trends, gaps, and research priorities, this review provides valuable guidance for future investigations and contributes to the ongoing development of AI applications in oral healthcare.

5 CONCLUSION

This scoping review mapped the main applications of machine learning algorithms in predicting oral diseases, highlighting the predominance of studies focused on dental caries, oral cancer and periodontal diseases. A higher frequency of clinical and imaging variables was also identified, as well as the recurrent use of metrics such as sensitivity and accuracy. Despite the advances, the literature presents relevant limitations, such as the scarcity of studies in underrepresented populations and the lack of methodological standardization. The findings reinforce the importance of promoting more inclusive, robust research focused on external validation, to facilitate the safe and effective incorporation of these technologies into clinical dental practice.

REFERENCES

1. Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: Chances and Challenges. J Dent Res. 2020 Jul 21;99(7):769–74. DOI:10.1177/0022034520915714

2. World Health Organization 2022. Global oral health status report Towards universal health coverage for oral health by 2030. 2020.

3. Chen M, Decary M. Artificial intelligence in healthcare: An essential guide for health leaders. Healthc Manage Forum. 2020 Jan 24;33(1):10–8. DOI:10.1177/0840470419873123

4. Delpino FM, Costa ÂK, Farias SR, Chiavegatto Filho ADP, Arcêncio RA, Nunes BP. Machine learning for predicting chronic diseases: a systematic review. Public Health. 2022 Apr;205:14–25. DOI:10.1016/j.puhe.2022.01.007

5. Leite AF, Vasconcelos K de F, Willems H, Jacobs R. Radiomics and Machine Learning in Oral Healthcare. Proteomics Clin Appl. 2020 May 29;14(3). DOI:10.1002/prca.201900040

6. Mohammad-Rahimi H, Motamedian SR, Rohban MH, Krois J, Uribe SE, Mahmoudinia E, et al. Deep learning for caries detection: A systematic review. J Dent. 2022 Jul;122:104115. DOI:10.1016/j.jdent.2022.104115

7. Humbert-Vidan L, Patel V, Oksuz I, King AP, Guerrero Urbano T. Comparison of machine learning methods for prediction of osteoradionecrosis incidence in patients with head and neck cancer. Br J Radiol. 2021 Apr 1;94(1120):20200026. DOI:10.1259/bjr.20200026

8. Kang J, Le VNT, Lee DW, Kim S. Diagnosing oral and maxillofacial diseases using deep learning. Sci Rep. 2024 Jan 30;14(1):2497. DOI:10.1038/s41598-024-52929-0

9. Alanazi AA, Khayyat MM, Khayyat MM, Elamin Elnaim BM, Abdel-Khalek S. Intelligent Deep Learning Enabled Oral Squamous Cell Carcinoma Detection and Classification Using Biomedical Images. Comput Intell Neurosci. 2022 Jun 30;2022:1–11. DOI:10.1155/2022/7643967

10. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. Vol. 169, Annals of Internal Medicine. American College of Physicians; 2018. p. 467–73. DOI:10.7326/M18-0850

11. Arsiwala-Scheppach LT, Chaurasia A, Müller A, Krois J, Schwendicke F. Machine Learning in Dentistry: A Scoping Review. J Clin Med. 2023 Jan 25;12(3):937. DOI:10.3390/jcm12030937

12. Peters MDJ, Marnie C, Tricco AC, Pollock D, Munn Z, Alexander L, et al. Updated methodological guidance for the conduct of scoping reviews. JBI Evid Synth. 2020 Oct;18(10):2119–26. DOI:10.11124/JBIES-20-00167

13. Chau KK, Zhu M, AlHadidi A, Wang C, Hung K, Wohlgemuth P, et al. A novel AI model for detecting periapical lesion on CBCT: CBCT-SAM. J Dent. 2025 Feb 1;153. DOI:10.1016/j.jdent.2024.105526

14. Chau RCW, Li GH, Tew IM, Thu KM, McGrath C, Lo WL, et al. Accuracy of Artificial Intelligence-Based Photographic Detection of Gingivitis. Int Dent J. 2023 Oct 1;73(5):724–30. DOI:10.1016/j.identj.2023.03.007

15. Wang C, Zhang R, Wei X, Wang L, Wu P, Yao Q. Deep learning and sub-band fluorescence imaging-based method for caries and calculus diagnosis embeddable on different smartphones. Biomed Opt Express. 2023 Feb 1;14(2):866. DOI:10.1364/boe.479818

16. Lin H, Chen H, Lin J. Deep neural network uncertainty estimation for early oral cancer diagnosis. Journal of Oral Pathology and Medicine. 2024 May 1;53(5):294–302. DOI:10.1111/jop.13536

17. Chen H, Li H, Zhao Y, Zhao J, Wang Y. Dental disease detection on periapical radiographs based on deep convolutional neural networks. Int J Comput Assist Radiol Surg. 2021 Apr 1;16(4):649–61. DOI:10.1007/s11548-021-02319-y

18. Deng K, Zonta F, Yang H, Pelekos G, Tonetti MS. Development of a machine learning multiclass screening tool for periodontal health status based on non-clinical parameters and salivary biomarkers. J Clin Periodontol. 2023 Dec 1; DOI:10.1111/jcpe.13856

19. Liu Z, Liu J, Zhou Z, Zhang Q, Wu H, Zhai G, et al. Differential diagnosis of ameloblastoma and odontogenic keratocyst by machine learning of panoramic radiographs. Int J Comput Assist Radiol Surg. 2021 Mar 1;16(3):415–22. DOI:10.1007/s11548-021-02309-0

20. Cai X, Zhang H, Wang Y, Zhang J, Li T. Digital pathology-based artificial intelligence models for differential diagnosis and prognosis of sporadic odontogenic keratocysts. Int J Oral Sci. 2024 Dec 1;16(1). DOI:10.1038/s41368-024-00287-y

21. Zhang L, Zhang Z, Wang Y, Zhu Y, Wang Z, Wan H. Evaluation of machine learning models for predicting xerostomia in adults with head and neck cancer during proton and heavy ion radiotherapy. Radiotherapy and Oncology. 2025 Mar 1;204. DOI:10.1016/j.radonc.2025.110712

22. Li W, Jiang X, Sun W, Wang SH, Liu C, Zhang X, et al. Gingivitis identification via multichannel gray-level co-occurrence matrix and particle swarm optimization neural network. Int J Imaging Syst Technol. 2020 Jun 1;30(2):401–11. DOI:10.1002/ima.22385

23. Khan SUR, Asif S. Oral cancer detection using feature-level fusion and novel self-attention mechanisms. Biomed Signal Process Control. 2024 Sep 1;95. DOI:10.1016/j.bspc.2024.106437

24. Li X, Li L, Sun Q, Chen B, Zhao C, Dong Y, et al. Rapid multi-task diagnosis of oral cancer leveraging fiber-optic Raman spectroscopy and deep learning algorithms. Front Oncol. 2023;13. DOI:10.3389/fonc.2023.1272305

25. Zhang Y, Wang Y, Zhang Z, Wang Y, Jia J. Study on machine learning of molar incisor hypomineralization in an endemic fluorosis region in central China. Front Physiol. 2023;14. DOI:10.3389/fphys.2023.1088703

26. Thukral R, Aggarwal AK, Arora AS, Dora T, Sancheti S. Artificial intelligence-based prediction of oral mucositis in patients with head-and-neck cancer: A prospective observational study utilizing a thermographic approach. Cancer Research, Statistics, and Treatment. 2023;6(2):181–90. DOI:10.4103/crst.crst_332_22

27. Moidu NP, Sharma S, Chawla A, Kumar V, Logani A. Deep learning for categorization of endodontic lesion based on radiographic periapical index scoring system. Clin Oral Investig. 2022 Jan 1;26(1):651–8. DOI:10.1007/s00784-021-04043-y

28. Ramana Kumari A, Nagaraja Rao S, Ramana Reddy P. Design of hybrid dental caries segmentation and caries detection with meta-heuristic-based ResneXt-RNN. Biomed Signal Process Control. 2022 Sep 1;78. DOI:10.1016/j.bspc.2022.103961

29. Prabhakaran R, Mohana J. Article ID: IJEET_11_03_041 Cite this Article: R. Prabhakaran and Dr. J. Mohana, Detection of Oral Cancer Using Machine Learning Classification Methods. International Journal of Electrical Engineering and Technology. 2020;11(3):384–93.

30. Kumar VS, Kumar PR, Yadalam PK, Anegundi RV, Shrivastava D, Alfurhud AA, et al. Machine learning in the detection of dental cyst, tumor, and abscess lesions. BMC Oral Health. 2023 Dec 1;23(1). DOI:10.1186/s12903-023-03571-1

31. Jaiswal P, Katkar V, Bhirud SG. Multi Oral Disease Classification from Panoramic Radiograph using Transfer Learning and XGBoost Department of IT [Internet]. Vol. 13, IJACSA) International Journal of Advanced Computer Science and Applications.

32. James BL, Sunny SP, Heidari AE, Ramanjinappa RD, Lam T, Tran A V., et al. Validation of a point-of-care optical coherence tomography device with machine learning algorithm for detection of oral potentially malignant and malignant lesions. Cancers (Basel). 2021 Jul 2;13(14). DOI:10.3390/cancers13143583

33. Goswami M, Maheshwari M, Baruah PD, Singh A, Gupta R. Automated Detection of Oral Cancer and Dental Caries Using Convolutional Neural

Network. In: 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions), ICRITO 2021. Institute of Electrical and Electronics Engineers Inc.; 2021. DOI:10.1109/ICRITO51393.2021.9596537

34. Kavitha V, Hanumanthappa M. Predicting oral squamous cell carcinoma in tobacco users by utilising fuzzy-based decision tree algorithm. Vol. 12, Int. J. Medical Engineering and Informatics. 2020.

35. Trivedi A, Patra JP, Rathore YK. Identification and Classification of Oral Cancer Using Machine Learning Techniques. In: International Conference on Artificial Intelligence for Innovations in Healthcare Industries, ICAIIHI 2023. Institute of Electrical and Electronics Engineers Inc.; 2023. DOI:10.1109/ICAIIHI57871.2023.10489388

36. Muhammed Yaseer P, Arul Xavier VM, Shyni SS. Oral Cancer Using Deep Learning and Auto-Fluorescence Image Analysis. In: 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science, AMATHE 2024. Institute of Electrical and Electronics Engineers Inc.; 2024. DOI:10.1109/AMATHE61652.2024.10582207

37. TK L. Digital Decision Making In Dentistry: Analysis And Prediction of Periodontitis Using Machine Learning Approach. International Journal of Next-Generation Computing. 2022 Oct 31; DOI:10.47164/ijngc.v13i3.614

38. Beak W, Park J, Ji S. Data-driven prediction model for periodontal disease based on correlational feature analysis and clinical validation. Heliyon. 2024 Jun 15;10(11). DOI:10.1016/j.heliyon.2024.e32496

39. Kang IA, Njimbouom SN, Lee KO, Kim JD. DCP: Prediction of Dental Caries Using Machine Learning in Personalized Medicine. Applied Sciences (Switzerland). 2022 Mar 1;12(6). DOI:10.3390/app12063043

40. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. J Dent. 2018 Oct 1;77:106–11. DOI:10.1016/j.jdent.2018.07.015

41. Song HJ, Park YJ, Jeong HY, Kim BG, Kim JH, Im YG. Detection of Abnormal Changes on the Dorsal Tongue Surface Using Deep Learning. Medicina (Lithuania). 2023 Jul 1;59(7). DOI:10.3390/medicina59071293

42. Hur SH, Lee EY, Kim MK, Kim S, Kang JY, Lim JS. Machine learning to predict distal caries in mandibular second molars associated with impacted third molars. Sci Rep. 2021 Dec 1;11(1). DOI:10.1038/s41598-021-95024-4

43. Park YH, Kim SH, Choi YY. Prediction models of early childhood caries based on machine learning algorithms. Int J Environ Res Public Health. 2021 Aug 2;18(16). DOI:10.3390/ijerph18168613

44. Kwack DW, Park SM. Prediction of medication-related osteonecrosis of the jaw (MRONJ) using automated machine learning in patients with osteoporosis associated with dental extraction and implantation: a retrospective study. J Korean Assoc Oral Maxillofac Surg. 2023 Jun 1;49(3):135–41. DOI:10.5125/jkaoms.2023.49.3.135

45. Lee YH, Won JH, Auh QS, Noh YK, Lee SW. Prediction of xerostomia in elderly based on clinical characteristics and salivary flow rate with machine learning. Sci Rep. 2024 Dec 1;14(1). DOI:10.1038/s41598-024-54120-x

46. Kim DW, Kim H, Nam W, Kim HJ, Cha IH. Machine learning to predict the occurrence of bisphosphonate-related osteonecrosis of the jaw associated with dental extraction: A preliminary report. Bone. 2018 Nov 1;116:207–14. DOI:10.1016/j.bone.2018.04.020

47. Ngnamsie Njimbouom S, Lee K, Kim JD. MMDCP: Multi-Modal Dental Caries Prediction for Decision Support System Using Deep Learning. Int J Environ Res Public Health. 2022 Sep 1;19(17). DOI:10.3390/ijerph191710928

48. Choi SG, Lee EY, Lee OJ, Kim S, Kang JY, Lim JS. Prediction models for early diagnosis of actinomycotic osteomyelitis of the jaw using machine learning techniques: a preliminary study. BMC Oral Health. 2022 Dec 1;22(1). DOI:10.1186/s12903-022-02201-6

49. Men K, Geng H, Zhong H, Fan Y, Lin A, Xiao Y. A Deep Learning Model for Predicting Xerostomia Due to Radiation Therapy for Head and Neck Squamous Cell Carcinoma in the RTOG 0522 Clinical Trial. Int J Radiat Oncol Biol Phys. 2019 Oct 1;105(2):440–7. DOI:10.1016/j.ijrobp.2019.06.009

50. Hung M, Voss MW, Rosales MN, Li W, Su W, Xu J, et al. Application of machine learning for diagnostic prediction of root caries. Gerodontology. 2019 Dec 1;36(4):395–404. DOI:10.1111/ger.12432

51. Chao M, El Naqa I, Bakst RL, Lo YC, Peñagarícano JA. Cluster model incorporating heterogeneous dose distribution of partial parotid irradiation for radiotherapy induced xerostomia prediction with machine learning methods. Acta Oncol (Madr). 2022;61(7):842–8. DOI:10.1080/0284186X.2022.2073187

52. Reber B, Van Dijk L, Anderson B, Mohamed ASR, Fuller C, Lai S, et al. Comparison of Machine-Learning and Deep-Learning Methods for the Prediction of Osteoradionecrosis Resulting From Head and Neck Cancer Radiation Therapy. Adv Radiat Oncol. 2023 Jul 1;8(4). DOI:10.1016/j.adro.2022.101163

53. Dey P, Ogwo C, Tellez M. Comparison of traditional regression modeling vs. AI modeling for the prediction of dental caries: a secondary data analysis. Frontiers in Oral Health. 2024;5. DOI:10.3389/froh.2024.1322733

54. Solanki A. DETECTION OF ORAL CANCER FROM CLINICAL IMAGES USING DEEP LEARNING. 2024.

55. Kouznetsova VL, Li J, Romm E, Tsigelny IF. Finding distinctions between oral cancer and periodontitis using saliva metabolites and machine learning. Oral Dis. 2021 Apr 1;27(3):484–93. DOI:10.1111/odi.13591

56. Salehi HS, Barchini M, Mahdian M. Optimization methods for deep neural networks classifying OCT images to detect dental caries.

57. Ogwo C, Brown G, Warren J, Caplan D, Levy S. Predicting dental caries outcomes in young adults using machine learning approach. BMC Oral Health. 2024 Dec 1;24(1). DOI:10.1186/s12903-024-04294-7

58. Stewart PW, Stamm1 JW. Classification Tree Prediction Models for Dental Caries from Clinical, Microbiological, and Interview Data. Vol. 70, J Dent Res. 1991.

59. Bui TH, Hamamoto K, Paing MP. Automated Caries Screening Using Ensemble Deep Learning on Panoramic Radiographs. Entropy. 2022 Oct 1;24(10). DOI:10.3390/e24101358

60. Ariji Y, Yanashita Y, Kutsuna S, Muramatsu C, Fukuda M, Kise Y, et al. Automatic detection and classification of radiolucent lesions in the mandible on panoramic radiographs using a deep learning object detection technique. Oral Surg Oral Med Oral Pathol Oral Radiol. 2019 Oct 1;128(4):424–30. DOI:10.1016/j.oooo.2019.05.014

61. Tamaki Y, Nomura Y, Katsumura S, Okada A, Yamada H, Tsuge S, et al. Construction of a dental caries prediction model by data mining. J Oral Sci. 2009;51(1):61–8. DOI:10.2334/josnusd.51.61

62. Nakano Y, Suzuki N, Kuwata F. Predicting oral malodour based on the microbiota in saliva samples using a deep learning approach. BMC Oral Health. 2018 Jul 31;18(1). DOI:10.1186/s12903-018-0591-6

63. Mameno T, Wada M, Nozaki K, Takahashi T, Tsujioka Y, Akema S, et al. Predictive modeling for peri-implantitis by using machine learning techniques. Sci Rep. 2021 Dec 1;11(1). DOI:10.1038/s41598-021-90642-4

64. Noguchi K, Saito I, Namiki T, Yoshimura Y, Nakaguchi T. Reliability of non-contact tongue diagnosis for Sjögren's syndrome using machine learning method. Sci Rep. 2023 Dec 1;13(1). DOI:10.1038/s41598-023-27764-4

65. Marzouk R, Alabdulkreem E, Dhahbi S, Nour MK, Duhayyim M Al, Othman M, et al. Deep Transfer Learning Driven Oral Cancer Detection and Classification Model. Computers, Materials and Continua. 2022;73(2):3905–20. DOI:10.32604/cmc.2022.029326

66. Al-Ma'aitah M, AlZubi AA. Enhanced Computational Model for Gravitational Search Optimized Echo State Neural Networks Based Oral Cancer Detection. J Med Syst. 2018 Nov 1;42(11). DOI:10.1007/s10916-018-1052-0

67. Alsubai S. Enhancing prediction of tooth caries using significant features and multi-model classifier. PeerJ Comput Sci. 2023;9. DOI:10.7717/PEERJ-CS.1631

68. Rahman AU, Alqahtani A, Aldhafferi N, Nasir MU, Khan MF, Khan MA, et al. Histopathologic Oral Cancer Prediction Using Oral Squamous Cell Carcinoma Biopsy Empowered with Transfer Learning. Sensors. 2022 May 1;22(10). DOI:10.3390/s22103833

69. Albalawi E, Thakur A, Ramakrishna MT, Bhatia Khan S, SankaraNarayanan S, Almarri B, et al. Oral squamous cell carcinoma detection using EfficientNet on histopathological images. Front Med (Lausanne). 2023;10. DOI:10.3389/fmed.2023.1349336

70. Shamim MZM, Syed S, Shiblee M, Usman M, Ali SJ, Hussein HS, et al. Automated Detection of Oral Pre-Cancerous Tongue Lesions Using Deep Learning for Early Diagnosis of Oral Cavity Cancer. Computer Journal. 2022 Jan 1;65(1):91–104. DOI:10.1093/comjnl/bxaa136

71. Keser G, Bayrakdar İŞ, Pekiner FN, Çelik Ö, Orhan K. A deep learning algorithm for classification of oral lichen planus lesions from photographic images: A retrospective study. J Stomatol Oral Maxillofac Surg. 2023 Feb 1;124(1). DOI:10.1016/j.jormas.2022.08.007

72. Yesiltepe S, Bayrakdar IS, Orhan K, Çelik Ö, Bilgir E, Aslan AF, et al. A Deep Learning Model for Idiopathic Osteosclerosis Detection on Panoramic Radiographs. In: Medical Principles and Practice. S. Karger AG; 2022. p. 555–61. DOI:10.1159/000527145

73. Oztekin F, Katar O, Sadak F, Yildirim M, Cakar H, Aydogan M, et al. An Explainable Deep Learning Model to Prediction Dental Caries Using Panoramic Radiograph Images. Diagnostics. 2023 Jan 1;13(2). DOI:10.3390/diagnostics13020226

74. Mırzaeı O, Bilgehan B, Abduljalil M, Saleh M, Kayssoun A, İlhan A. Performance Evaluation of Deep Learning Models for Dental Caries Classification via Panoramic Radiograph Images. Clinical and Experimental Health Sciences. 2024 Dec 29;14(4):868–75. DOI:10.33808/clinexphealthsci.1466714

75. Ozden FO, Özgönenel O, Özden B, Aydogdu A. Diagnosis of periodontal diseases using different classification algorithms: A preliminary study. Niger J Clin Pract. 2015 May 1;18(3):416–21. DOI:10.4103/1119-3077.151785

76. Montenegro RD, Oliveira ALI, Cabral GG, Katz CRT, Rosenblatt A. A comparative study of machine learning techniques for caries prediction. In: Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI. 2008. p. 477–81. DOI:10.1109/ICTAI.2008.138

77. da Costa NL, de Sá Alves M, de Sá Rodrigues N, Bandeira CM, Oliveira Alves MG, Mendes MA, et al. Finding the combination of multiple biomarkers to diagnose oral squamous cell carcinoma – A data mining approach. Comput Biol Med. 2022 Apr 1;143. DOI:10.1016/j.compbiomed.2022.105296

78. Bomfim RA. Machine learning to predict untreated dental caries in adolescents. BMC Oral Health. 2024 Dec 1;24(1). DOI:10.1186/s12903-024-04073-4

79. De Araujo Faria V, Azimbagirad M, Viani Arruda G, Fernandes Pavoni J, Cezar Felipe J, dos Santos EMCMF, et al. Prediction of Radiation-Related Dental Caries Through PyRadiomics Features and Artificial Neural Network on Panoramic Radiography. J Digit Imaging. 2021 Oct 1;34(5):1237–48. DOI:10.1007/s10278-021-00487-6

80. Patel A, Besombes C, Dillibabu T, Sharma M, Tamimi F, Ducret M, et al. Attention-guided convolutional network for bias-mitigated and interpretable oral lesion classification. Sci Rep. 2024 Dec 1;14(1). DOI:10.1038/s41598-024-81724-0

81. Frydenlund A, Eramian M, Daley T. Automated classification of four types of developmental odontogenic cysts. Computerized Medical Imaging and Graphics. 2014 Apr;38(3):151–62. DOI:10.1016/j.compmedimag.2013.12.002

82. Patel K. Oral Cancer Prediction on Epigenomics Data using Machine Learning Methods.

83. Haghanifar A, Majdabadi MM, Haghanifar S, Choi Y, Ko SB. PaXNet: Tooth segmentation and dental caries detection in panoramic X-ray using ensemble transfer learning and capsule classifier. Multimed Tools Appl. 2023 Jul 1;82(18):27659–79. DOI:10.1007/s11042-023-14435-9

84. Deif MA, Attar H, Amer A, Elhaty IA, Khosravi MR, Solyman AAA. Diagnosis of Oral Squamous Cell Carcinoma Using Deep Neural Networks and Binary Particle Swarm Optimization on Histopathological Images: An AIoMT Approach. Comput Intell Neurosci. 2022;2022. DOI:10.1155/2022/6364102

85. Afify HM, Mohammed KK, Ella Hassanien A. Novel prediction model on OSCC histopathological images via deep transfer learning combined with Grad-CAM interpretation. Biomed Signal Process Control. 2023 May 1;83. DOI:10.1016/j.bspc.2023.104704

86. Zayed SO, Abd-Rabou RYM, Abdelhameed GM, Abdelhamid Y, Khairy K, Abulnoor BA, et al. The innovation of AI-based software in oral diseases: clinical-histopathological correlation diagnostic accuracy primary study. BMC Oral Health. 2024 Dec 1;24(1). DOI:10.1186/s12903-024-04347-x

87. Khajetash B, Hajianfar G, Talebi A, Ghavidel B, Mahdavi SR, Lei Y, et al. A comparison of different machine learning classifiers in predicting xerostomia and sticky saliva due to head and neck radiotherapy using a multi-objective, multimodal radiomics model. Biomed Phys Eng Express. 2025 Mar 31;11(2). DOI:10.1088/2057-1976/adafac

88. Farhadian M, Shokouhi P, Torkzaban P. A decision support system based on support vector machine for diagnosis of periodontal disease. BMC Res Notes. 2020 Jul 13;13(1). DOI:10.1186/s13104-020-05180-5

89. Agheli R, Siavashpour Z, Reiazi R, Azghandi S, Cheraghi S, Paydar R. Predicting severe radiation-induced oral mucositis in head and neck cancer patients using integrated baseline CT radiomic, dosimetry, and clinical features: A machine learning approach. Heliyon. 2024 Feb 15;10(3). DOI:10.1016/j.heliyon.2024.e24866

90. Yan Y. Knowledge Discovery and Machine Learning: Research in Gingivitis Detection. 2021.

91. Black H, Young D, Rogers A, Montgomery J. Machine Learning in Clinical Diagnosis of Head and Neck Cancer. Clinical Otolaryngology. 2025 Jan 14;50(1):31–8. DOI:10.1111/coa.14220

92. Najla S Dar-Odeh. Predicting recurrent aphthous ulceration using genetic algorithms-optimized neural networks. Advances and Applications in Bioinformatics and Chemistry. 2010 May;7. DOI:10.2147/AABC.S10177

93. Jubair F, Al-karadsheh O, Malamos D, Al Mahdi S, Saad Y, Hassona Y. A novel lightweight deep convolutional neural network for early detection of oral cancer. Oral Dis. 2022 May 1;28(4):1123–30. DOI:10.1111/odi.13825

94. Schwendicke F, Elhennawy K, Paris S, Friebertshäuser P, Krois J. Deep learning for caries lesion detection in near-infrared light transillumination images: A pilot study. J Dent. 2020 Jan 1;92. DOI:10.1016/j.jdent.2019.103260

95. Neumayr J, Frenkel E, Schwarzmaier J, Ammar N, Kessler A, Schwendicke F, et al. External validation of an artificial intelligence-based method for the detection and classification of molar incisor hypomineralisation in dental photographs. J Dent. 2024 Sep 1;148. DOI:10.1016/j.jdent.2024.105228

96. Nijland N, Overtoom F, Gerdes VEA, Verhulst MJL, Su N, Loos BG. External validation of a rapid, non-invasive tool for periodontitis screening in a medical care setting. Clin Oral Investig. 2021 Dec 1;25(12):6661–9. DOI:10.1007/s00784-021-03952-2

97. Chu H, de Vette SPM, Neh H, Sijtsema NM, Steenbakkers RJHM, Moreno A, et al. Three-Dimensional Deep Learning Normal Tissue Complication Probability Model to Predict Late Xerostomia in Patients With Head and Neck Cancer. Int J Radiat Oncol Biol Phys. 2024 Jan 1; DOI:10.1016/j.ijrobp.2024.07.2334

98. Enevold C, Nielsen CH, Christensen LB, Kongstad J, Fiehn NE, Hansen PR, et al. Suitability of machine learning models for prediction of clinically defined Stage III/IV periodontitis from questionnaires and demographic data in Danish cohorts. J Clin Periodontol. 2023 Dec 1; DOI:10.1111/jcpe.13874

99. Dubuc A, Zitouni A, Thomas C, Kémoun P, Cousty S, Monsarrat P, et al. Improvement of Mucosal Lesion Diagnosis with Machine Learning Based on Medical and Semiological Data: An Observational Study. J Clin Med. 2022 Nov 1;11(21). DOI:10.3390/jcm11216596

100. Tran Tuan Anh, Nguyen The Huy, Nguyen Thi Hoai Nhi, Tran Hoang Anh. Detecting Dental Caries Through Captured Images Using The Machine Learning Technology Teachable Machine. Asian Journal of Health Research. 2024 Apr 10;3(1):20–3. DOI:10.55561/ajhr.v3i1.148

101. Fanizzi A, Scognamillo G, Nestola A, Bambace S, Bove S, Comes MC, et al. Transfer learning approach based on computed tomography images for predicting late xerostomia after radiotherapy in patients with oropharyngeal cancer. Front Med (Lausanne). 2022 Sep 23;9. DOI:10.3389/fmed.2022.993395

102. Basri KN, Yazid F, Mohd Zain MN, Md Yusof Z, Abdul Rani R, Zoolfakar AS. Artificial neural network and convolutional neural network for prediction of dental caries. Spectrochim Acta A Mol Biomol Spectrosc. 2024 May 5;312. DOI:10.1016/j.saa.2024.124063

103. Lasri I, El-Marzouki N, Riadsolh A, Elbelkacemi M. Automated Detection of Dental Caries from Oral Images using Deep Convolutional Neural Networks. International journal of online and biomedical engineering. 2023;19(18):53–70. DOI:10.3991/ijoe.v19i18.45133

104. Blanco-Victorio DJ, López-Ramos RP, Blanco-Rodriguez JD, López-Luján NA, León-Untiveros GF, Siccha-Macassi AL. Early childhood caries (ECC) prediction models using Machine Learning. J Clin Exp Dent. 2024;16(12):e1523–9. DOI:10.4317/jced.61514

105. Soares I, Dias J, Rocha H, Khouri L, do Carmo Lopes M, Ferreira B. Predicting xerostomia after IMRT treatments: a data mining approach. Health Technol (Berl). 2018 May 1;8(1–2):159–68. DOI:10.1007/s12553-017-0204-4

106. Lian W, Lindblad J, Stark CR, Hirsch JM, Sladoje N. Let it shine: Autofluorescence of Papanicolaou-stain improves AI-based cytological oral cancer detection. 2024 Jul 1;

107. Achararit P, Manaspon C, Jongwannasiri C, Phattarataratip E, Osathanon T, Sappayatosok K. Artificial Intelligence-Based Diagnosis of Oral Lichen Planus Using Deep Convolutional Neural Networks. Eur J Dent. 2023 Dec 29;17(4):1275–82. DOI:10.1055/s-0042-1760300

108. Udod OA, Voronina HS, Ivchenkova OY. Application of neural network technologies in the dental caries forecast. Wiad Lek. 2020;73(7):1499–504. DOI:10.36740/wlek202007135

109. Chawla R, Hari Krishna K, Arvind Deshmukh A, Sagar Kvd, Saleh Al Ansari M, Taloba AI. A Hybrid Optimization Approach with Deep Learning Technique for the Classification of Dental Caries [Internet]. Vol. 13, IJACSA) International Journal of Advanced Computer Science and Applications.

110. Viet DH, Son LH, Tuyen DN, Tuan TM, Thang NP, Ngoc VTN. Comparing the accuracy of two machine learning models in detection and classification of periapical lesions using periapical radiographs. Oral Radiol. 2024 Oct 1;40(4):493–500. DOI:10.1007/s11282-024-00759-1

111. Hur SH, Lee EY, Kim MK, Kim S, Kang JY, Lim JS. Machine learning to predict distal caries in mandibular second molars associated with impacted third molars. Sci Rep. 2021 Jul 29;11(1):15447. DOI:10.1038/s41598-021-95024-4

112. Hung M, Park J, Hon ES, Bounsanga J, Moazzami S, Ruiz-Negrón B, et al. Artificial intelligence in dentistry: Harnessing big data to predict oral cancer survival. World J Clin Oncol. 2020 Nov 24;11(11):918–34. DOI:10.5306/wjco.v11.i11.918

113. Lee YH, Auh QS, Park HK. Determination of Xerostomia with Cutoff Value for Salivary Flow Rate using Machine Learning Algorithm [Internet]. 2023. DOI:10.21203/rs.3.rs-2404122/v1

114. Lakshmi TK. International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Predictive Analysis of Periodontal Disease Progression Using Machine Learning: Enhancing Oral Health Assessment and Treatment Planning [Internet]. Vol. 2023, Original Research Paper International Journal of Intelligent Systems and Applications in Engineering IJISAE.

115. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med. 2020 Feb 6;3(1):17. DOI:10.1038/s41746-020-0221-y

116. Patil S, Albogami S, Hosmani J, Mujoo S, Kamil MA, Mansour MA, et al. Artificial Intelligence in the Diagnosis of Oral Diseases: Applications and Pitfalls. Diagnostics (Basel). 2022 Apr 19;12(5). DOI:10.3390/diagnostics12051029

117. Gao X, Alam S, Shi P, Dexter F, Kong N. Interpretable machine learning models for hospital readmission prediction: a two-step extracted regression tree approach. BMC Med Inform Decis Mak. 2023 Jun 5;23(1):104. DOI:10.1186/s12911-023-02193-5

118. El Naqa I, Boone JM, Benedict SH, Goodsitt MM, Chan H, Drukker K, et al. AI in medical physics: guidelines for publication. Med Phys. 2021 Sep 21;48(9):4711–4. DOI:10.1002/mp.15170

119. Prasanna S, Govinda K. An Evaluation study of Oral Cancer Detection using Data Mining Classification Techniques. International Journal of Advanced Research in Computer Science. 3(1).

120. Maghsoudi R, Bagheri A, Maghsoudi MT. Diagnosis Prediction of Lichen Planus, Leukoplakia and Oral Squamous Cell Carcinoma by using an Intelligent System Based on Artificial Neural Networks. Journal of Dentomaxillofacial Radiology, Pathology and Surgery. 2013 Aug 1;2(2):1–8. DOI:10.18869/acadpub.3dj.2.2.1

121. Papantonopoulos G, Takahashi K, Bountis T, Loos BG. Artificial neural networks for the diagnosis of aggressive periodontitis trained by immunologic parameters. PLoS One. 2014 Mar 6;9(3). DOI:10.1371/journal.pone.0089757

122. Baik J, Ye Q, Zhang L, Poh C, Rosin M, MacAulay C, et al. Automated classification of oral premalignant lesions using image cytometry and Random Forests-based algorithms. Cellular Oncology. 2014;37(3):193–202. DOI:10.1007/s13402-014-0172-x

123. Liu Y, Li J, Liu X, Liu X, Khawar W, Zhang X, et al. Quantitative risk stratification of oral leukoplakia with exfoliative cytology. PLoS One. 2015 May 15;10(5). DOI:10.1371/journal.pone.0126760

124. Park S& QH& MT& PW& SR& LJunghoon. Predicting Radiation-Induced Xerostomia by Dosimetrically Accounting for Daily Setup Uncertainty During Head and Neck IMRT. Med Phys. 2016;43.

125. Imangaliyev S, van der Veen MH, Volgenant CMC, Loos BG, Keijser BJF, Crielaard W, et al. Classification of Quantitative Light-Induced Fluorescence Images Using Convolutional Neural Network. 2017 May 25;

126. Liu Y, Li Y, Fu Y, Liu T, Liu X, Zhang X, et al. Quantitative prediction of oral cancer risk in patients with oral leukoplakia [Internet]. 2017.

127. Lakshminarayanan P et al. A Shape-Based Dose Model for the Prediction of High Grade Radiation Induced Xerostomia for Head and Neck Cancer Patients. nternational Journal of Radiation Oncology, Biology, Physics. 2017;99(2).

128. Anantharaman R, Anantharaman V, Lee Y. Oro Vision: Deep Learning for Classifying Orofacial Diseases. In: Proceedings - 2017 IEEE International Conference on Healthcare Informatics, ICHI 2017. Institute of Electrical and Electronics Engineers Inc.; 2017. p. 39–45. DOI:10.1109/ICHI.2017.69

129. Gabryś HS, Buettner F, Sterzing F, Hauswald H, Bangert M. Design and selection of machine learning methods using radiomics and dosiomics for normal tissue complication probability modeling of xerostomia. Front Oncol. 2018 Mar 5;8(MAR). DOI:10.3389/fonc.2018.00035

130. Lee JH, Kim DH, Jeong SN, Choi SH. Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm. J Periodontal Implant Sci. 2018 Apr 1;48(2):114–23. DOI:10.5051/jpis.2018.48.2.114

131. Zanella-Calzada LA, Galván-Tejada CE, Chávez-Lamas NM, Rivas-Gutierrez J, Magallanes-Quintanar R, Celaya-Padilla JM, et al. Deep artificial neural networks for the diagnostic of caries using socioeconomic and nutritional features as determinants: Data from NHANES 2013–2014. Bioengineering. 2018 Jun 1;5(2). DOI:10.3390/bioengineering5020047

132. Tseng HH, RB, BK, EA, MM, CJT, THR, EN. A recurrent neural network for xerostomia prediction in head and neck cancer from daily CBCT images. Med Phys. 2018 Jun 11;45(6). DOI:10.1002/mp.12938

133. Feres M, Louzoun Y, Haber S, Faveri M, Figueiredo LC, Levin L. Support vector machine-based differentiation between aggressive and chronic periodontitis using microbial profiles. Int Dent J. 2018 Feb 1;68(1):39–46. DOI:10.1111/idj.12326

134. Jahantigh FF, Arbabi S. The use of artificial intelligence techniques for the Diagnosis of periodontal disease by clinical indices.

135. Alabi RO, Elmusrati M, Sawazaki-Calone I, Kowalski LP, Haglund C, Coletta RD, et al. Machine learning application for prediction of locoregional recurrences in early oral tongue cancer: a Web-based prognostic tool. Virchows Archiv. 2019 Oct 1;475(4):489–97. DOI:10.1007/s00428-019-02642-5

136. Agouropoulos A, Birpou E, Twetman S, Kavvadia K, Sc Md. Validation of Three Caries Risk Assessment Tools for Preschool Children From Areas with High Caries Prevalence [Internet].

137. Tseng H, RB, CJT, MM, THR, EN. A deep sequential learning architecture for xerostomia prediction in parotid glands using CBCT and rigid-registered dose images. Med Phys. 2019 Jun 11;46(6). DOI:10.1002/mp.13589

138. Humbert-Vidan L, Oksuz I, Patel V, King AP, Guerrero-Urbano T. Prediction of voxelwise mandibular osteoradionecrosis maps in HNC patients using deep learning. Radiotherapy and Oncology. 2019 Apr;133:S1050. DOI:10.1016/S0167-8140(19)32349-7

139. Kamezawa H. AH, YR, NK, HS. Deep learning-based malignancy grade prediction models of parotid gland cancer using preoperative mr images . Med Phys. 2019 Jun 11;46(6). DOI:10.1002/mp.13589

140. Machado V, Proença L, Morgado M, Mendes JJ, Botelho J. Accuracy of panoramic radiograph for diagnosing periodontitis comparing to clinical examination. J Clin Med. 2020 Jul 1;9(7):1–11. DOI:10.3390/JCM9072313

141. Wang X, Yang J, Wei C, Zhou G, Wu L, Gao Q, et al. A personalized computational model predicts cancer risk level of oral potentially malignant disorders and its web application for promotion of non-invasive screening. Journal of Oral Pathology and Medicine. 2020 May 1;49(5):417–26. DOI:10.1111/jop.12983

142. Na HS, Kim SY, Han H, Kim HJ, Lee JY, Lee JH, et al. Identification of potential oral microbial biomarkers for the diagnosis of periodontitis. J Clin Med. 2020 May 1;9(5). DOI:10.3390/jcm9051549

143. Alabi RO, Elmusrati M, Sawazaki-Calone I, Kowalski LP, Haglund C, Coletta RD, et al. Comparison of supervised machine learning classification techniques in prediction of locoregional recurrences in early oral tongue cancer. Int J Med Inform. 2020 Apr 1;136. DOI:10.1016/j.ijmedinf.2019.104068

144. Chu CS, Lee NP, Adeoye J, Thomson P, Choi SW. Machine learning and treatment outcome prediction for oral cancer. Journal of Oral Pathology and Medicine. 2020 Nov 1;49(10):977–85. DOI:10.1111/jop.13089

145. Yang YH, Kim JS, Jeong SH. Prediction of dental caries in 12-year-old children using machine-learning algorithms. Journal of Korean Academy of Oral Health. 2020;44(1):55. DOI:10.11149/jkaoh.2020.44.1.55

146. Nawandhar A, Kumar N, R V, Yamujala L. Stratified squamous epithelial biopsy image classifier using machine learning and neighborhood feature selection. Biomed Signal Process Control. 2020 Jan 1;55. DOI:10.1016/j.bspc.2019.101671

147. Dolic O, Obradovic M, Kojic Z, Trtic N, Sukara S, Knezevic N, et al. Validation of cariogram in caries prediction in women and their children 4 years after pregnancy – longitudinal study. Risk Manag Healthc Policy. 2020;13:549–57. DOI:10.2147/RMHP.S243907

148. Alvarez-Arenal A, Dellanos-Lanchares H, Martin-Fernandez E, Mauvezin M, Sanchez ML, de Cos Juez FJ. An artificial neural network model for the prediction of bruxism by means of occlusal variables. Neural Comput Appl. 2020 Mar 1;32(5):1259–67. DOI:10.1007/s00521-018-3715-7

149. Neves LVF, Danelichen AFB, Faustino A, Matsuura FK, Viani G, Azimbagirad M, et al. Feasibility Of Prediction Of Radiation-Related Caries In Head-Neck Cancer Patients Using Machine Learning And Radiomics Features. International

Journal of Radiation Oncology*Biology*Physics. 2020 Nov;108(3):e782. DOI:10.1016/j.ijrobp.2020.07.243

150. Nurimba M.C. PV, GJ, SM, KNC, CTN. Deep Learning for diagnosis of oropharyngeal squamous cell carcinoma using computed tomography imaging: A preliminary study. Otolaryngology–Head and Neck Surgery. 2020 Sep 8;163(S1). DOI:10.1177/0194599820934780

151. Karhade DS, Roach J, Shrestha P, Simancas-Pallares MA, Ginnis J, Burk ZJ, et al. Pediatr Dent. Vol. 43. 2021.

152. Li H, Zhou J, Zhou Y, Chen Q, She Y, Gao F, et al. An Interpretable Computer-Aided Diagnosis Method for Periodontitis From Panoramic Radiographs. Front Physiol. 2021 Jun 22;12. DOI:10.3389/fphys.2021.655556

153. Narayanan S, Anand S, Prasanna R, Managoli SP, Suvarnadas R, Shyamsundar V, et al. Bimodal multispectral imaging system with cloud-based machine learning algorithm for real-time screening and detection of oral potentially malignant lesions and biopsy guidance. J Biomed Opt. 2021 Aug 16;26(08). DOI:10.1117/1.jbo.26.8.086003

154. de Jesus VC, Khan MW, Mittermuller BA, Duan K, Hu P, Schroth RJ, et al. Characterization of Supragingival Plaque and Oral Swab Microbiomes in Children With Severe Early Childhood Caries. Front Microbiol. 2021 Jun 25;12. DOI:10.3389/fmicb.2021.683685

155. Adeoye J, Koohi-Moghadam M, Lo AWI, Tsang RKY, Chow VLY, Zheng LW, et al. Deep learning predicts the malignant-transformation-free survival of oral potentially malignant disorders. Cancers (Basel). 2021 Dec 1;13(23). DOI:10.3390/cancers13236054

156. Wang YC, Hsueh PC, Wu CC, Tseng YJ. Machine learning based risk prediction models for oral squamous cell carcinoma using salivary biomarkers. In: Public Health and Informatics: Proceedings of MIE 2021. IOS Press; 2021. p. 498–9. DOI:10.3233/SHTI210213

157. Camalan S, Mahmood H, Binol H, Araújo ALD, Santos-Silva AR, Vargas PA, et al. Convolutional neural network-based clinical predictors of oral dysplasia: Class activation map analysis of deep learning results. Cancers (Basel). 2021 Mar 2;13(6):1–18. DOI:10.3390/cancers13061291

158. Alhazmi A, Alhazmi Y, Makrami A, Masmali A, Salawi N, Masmali K, et al. Application of artificial intelligence and machine learning for prediction of oral cancer risk. Journal of Oral Pathology and Medicine. 2021 May 1;50(5):444–50. DOI:10.1111/jop.13157

159. Quivey RG, O'Connor TG, Gill SR, Kopycka-Kedzierawski DT. Prediction of early childhood caries onset and oral microbiota. Vol. 36, Molecular Oral Microbiology. John Wiley and Sons Inc; 2021. p. 255–7. DOI:10.1111/omi.12349

160. T Chinnery PLANSM. A Machine Learning Classifier for Predicting Recurrence in Oropharyngeal Cancer. 2021 Jul 25;

161. International BMR. Retracted: Artificial Neural Network Assisted Cancer Risk Prediction of Oral Precancerous Lesions. Vol. 2023, BioMed research international. 2023. p. 9862326. DOI:10.1155/2023/9862326

162. Basri KN, Yazid F, Megat Abdul Wahab R, Mohd Zain MN, Md Yusof Z, Zoolfakar AS. Chemometrics analysis for the detection of dental caries via UV absorption

spectroscopy. Spectrochim Acta A Mol Biomol Spectrosc. 2022 Feb 5;266. DOI:10.1016/j.saa.2021.120464

163. Mudrov VP. ARTIFICIAL INTELLIGENCE IN THE IMMUNODIAGNOSTICS OF CHRONIC PERIODONTITIS. Russian Journal of Infection and Immunity. 2022 Nov 1;12(6):1186–90. DOI:10.15789/2220-7619-AII-1999

164. Tseng YJ, Wang YC, Hsueh PC, Wu CC. Development and validation of machine learning-based risk prediction models of oral squamous cell carcinoma using salivary autoantibody biomarkers. BMC Oral Health. 2022 Dec 1;22(1). DOI:10.1186/s12903-022-02607-2

165. Rao RS, Shivanna DB, Lakshminarayana S, Mahadevpur KS, Alhazmi YA, Bakri MMH, et al. Ensemble Deep-Learning-Based Prognostic and Prediction for Recurrence of Sporadic Odontogenic Keratocysts on Hematoxylin and Eosin Stained Pathological Images of Incisional Biopsies. J Pers Med. 2022 Aug 1;12(8). DOI:10.3390/jpm12081220

166. Rimi IF, Arif MdAI, Akter S, Rahman MdR, Islam AHMS, Habib MdT. Machine learning techniques for dental disease prediction. Iran Journal of Computer Science. 2022 Sep;5(3):187–95. DOI:10.1007/s42044-022-00101-0

167. Ferrer-Sánchez A, Bagan J, Vila-Francés J, Magdalena-Benedito R, Bagan-Debon L. Prediction of the risk of cancer and the grade of dysplasia in leukoplakia lesions using deep learning. Oral Oncol. 2022 Sep 1;132. DOI:10.1016/j.oraloncology.2022.105967

168. Adeoye J, Hui L, Koohi-Moghadam M, Tan JY, Choi SW, Thomson P. Comparison of time-to-event machine learning models in predicting oral cavity cancer prognosis. Int J Med Inform. 2022 Jan 1;157. DOI:10.1016/j.ijmedinf.2021.104635

169. Wang R, Li KY, Su YX. Prediction of ameloblastoma recurrence using random forest—a machine learning algorithm. Int J Oral Maxillofac Surg. 2022 Jul 1;51(7):886–91. DOI:10.1016/j.ijom.2021.11.017

170. Thulaseedharan A, Lal Priya PS. Deep Learning based Object Detection Algorithm for the Detection of Dental Diseases and Differential Treatments. In: INDICON 2022 - 2022 IEEE 19th India Council International Conference. Institute of Electrical and Electronics Engineers Inc.; 2022. DOI:10.1109/INDICON56171.2022.10040109

171. Qu X, Zhang C, Houser SH, Zhang J, Zou J, Zhang W, et al. Prediction model for early childhood caries risk based on behavioral determinants using a machine learning algorithm. Comput Methods Programs Biomed. 2022 Dec 1;227. DOI:10.1016/j.cmpb.2022.107221

172. Ellis BG, Whitley CA, Triantafyllou A, Gunning PJ, Smith CI, Barrett SD, et al. Prediction of malignant transformation in oral epithelial dysplasia using infrared absorbance spectra. PLoS One. 2022 Mar 1;17(3 March). DOI:10.1371/journal.pone.0266043

173. Başaran M, Çelik Ö, Bayrakdar IS, Bilgir E, Orhan K, Odabaş A, et al. Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system. Oral Radiol. 2022 Jul 1;38(3):363–9. DOI:10.1007/s11282-021-00572-0

174. Ataş M, Yeşilnacar Mİ, Demir Yetiş A. Novel machine learning techniques based hybrid models (LR-KNN-ANN and SVM) in prediction of dental fluorosis in

groundwater. Environ Geochem Health. 2022 Nov 1;44(11):3891–905. DOI:10.1007/s10653-021-01148-x

175. Baek J, Kim S, Shin D. ANOMALY DETECTION FOR AN ORAL HEALTH CARE APPLICATION USING ONE CLASS YOLOV3. J Korean Soc Ind Appl Math. 2022;26(4):310–22. DOI:10.12941/jksiam.2022.26.310

176. Feng M, Du X, Yin Y, Yan L, Wang H, Yin Q, et al. Early Prediction Model of Radiation-Induced Xerostomia Based on Radiomics during Radiotherapy for Nasopharyngeal Carcinoma. International Journal of Radiation Oncology*Biology*Physics. 2022 Nov;114(3):S48. DOI:10.1016/j.ijrobp.2022.07.420

177. Kolokythas A, Zhu W, Luo J. Use of Artificial Intelligence in the Characterization of Oral Mucosal Lesions. Journal of Oral and Maxillofacial Surgery. 2022 Sep;80(9):S3–4. DOI:10.1016/j.joms.2022.07.009

178. Cai X, Li L, Yu F, Guo R, Zhou X, Zhang F, et al. Development of a Pathomics-Based Model for the Prediction of Malignant Transformation in Oral Leukoplakia. Laboratory Investigation. 2023 Aug 1;103(8). DOI:10.1016/j.labinv.2023.100173

179. Rachi T, Ariji T, Takahashi S. Development of programs to predict the occurrence of mucositis from digital imaging and communications in medicine data by machine learning in head and neck volumetric modulated radiotherapy. J Appl Clin Med Phys. 2023 Dec 1;24(12). DOI:10.1002/acm2.14125

180. Teza H, Pattanateepapon A, Lertpimonchai A, Vathesatogkit P, McKay GJ, Attia J, et al. Development of Risk Prediction Models for Severe Periodontitis in a Thai Population: Statistical and Machine Learning Approaches. JMIR Form Res. 2023 Jan 1;7(1). DOI:10.2196/48351

181. Busato F, Fiorentin D, Bettinelli A, Anile G, Ghi MG, Scaggion A, et al. Dosiomic-based prediction of dysgeusia in head & neck cancer patients treated with radiotherapy. Radiotherapy and Oncology. 2023 Nov 1;188. DOI:10.1016/j.radonc.2023.109896

182. Toledo Reyes L, Knorst JK, Ortiz FR, Brondani B, Emmanuelli B, Saraiva Guedes R, et al. Early Childhood Predictors for Dental Caries: A Machine Learning Approach. J Dent Res. 2023 Aug 1;102(9):999–1006. DOI:10.1177/00220345231170535

183. Gu X, Salehi A, Wang L, Coates PJ, Sgaramella N, Nylander K. Early detection of squamous cell carcinoma of the oral tongue using multidimensional plasma protein analysis and interpretable machine learning. Journal of Oral Pathology and Medicine. 2023 Aug 1;52(7):637–43. DOI:10.1111/jop.13461

184. Amasya H, Alkhader M, Serindere G, Futyma-Gąbka K, Aktuna Belgin C, Gusarev M, et al. Evaluation of a Decision Support System Developed with Deep Learning Approach for Detecting Dental Caries with Cone-Beam Computed Tomography Imaging. Diagnostics. 2023 Nov 1;13(22). DOI:10.3390/diagnostics13223471

185. Dörrich M, Hecht M, Fietkau R, Hartmann A, Iro H, Gostian AO, et al. Explainable convolutional neural networks for assessing head and neck cancer histopathology. Diagn Pathol. 2023 Dec 1;18(1). DOI:10.1186/s13000-023-01407-8

186. Adeoye J, Koohi-Moghadam M, Choi SW, Zheng LW, Lo AWI, Tsang RKY, et al. Predicting oral cancer risk in patients with oral leukoplakia and oral lichenoid

mucositis using machine learning. J Big Data. 2023 Dec 1;10(1). DOI:10.1186/s40537-023-00714-7

187. Wu MP, Hsu G, Varvares MA, Crowson MG. Predicting Progression of Oral Lesions to Malignancy Using Machine Learning. Laryngoscope. 2023 May 1;133(5):1156–62. DOI:10.1002/lary.30285

188. Yan X, Sun T, Lu Y, Tan X, Wang Z, Li M. Prediction model of dental caries in 12-year-old children in Sichuan Province based on machine learning. Hua Xi Kou Qiang Yi Xue Za Zhi / West China Journal of Stomatology. 2023 Dec 1;41(6):686–93. DOI:10.7518/hxkq.2023.2023124

189. Cai Y, Xie Y, Zhang S, Wang Y, Wang Y, Chen J, et al. Prediction of postoperative recurrence of oral cancer by artificial intelligence model: Multilayer perceptron. Head Neck. 2023 Dec 1;45(12):3053–66. DOI:10.1002/hed.27533

190. Tareq A, Faisal MI, Islam MS, Rafa NS, Chowdhury T, Ahmed S, et al. Visual Diagnostics of Dental Caries through Deep Learning of Non-Standardised Photographs Using a Hybrid YOLO Ensemble and Transfer Learning Model. Int J Environ Res Public Health. 2023 Apr 1;20(7). DOI:10.3390/ijerph20075351

191. Gomes RFT, Schmith J, Figueiredo RM de, Freitas SA, Machado GN, Romanini J, et al. Use of Artificial Intelligence in the Classification of Elementary Oral Lesions from Clinical Images. Int J Environ Res Public Health. 2023 Mar 1;20(5). DOI:10.3390/ijerph20053894

192. Bashir RMS, Shephard AJ, Mahmood H, Azarmehr N, Raza SEA, Khurram SA, et al. A digital score of peri-epithelial lymphocytic activity predicts malignant transformation in oral epithelial dysplasia. Journal of Pathology. 2023 Aug 1;260(4):431–42. DOI:10.1002/path.6094

193. Liu W, Wang Y, Yang X, Shen X, Shi L. The implications of nanodiagnostics and artificial intelligence for detecting oral potentially malignant disorders and oral squamous cell carcinoma. Int J Surg. 2023 Oct 1;109(10):3248–50. DOI:10.1097/JS9.0000000000000575

194. Humbert-Vidan L, Patel V, King AP, Guerrero Urbano T. Interpretability of a Deep Learning-Based Prediction Model for Mandibular Osteoradionecrosis. International Journal of Radiation Oncology*Biology*Physics. 2023 Oct;117(2):e468–9. DOI:10.1016/j.ijrobp.2023.06.1673

195. Ramesh S, Dolezal JM, Kochanny S, Lanzel E, Chang YL, Wu CT, et al. Artificial intelligence-based cancer progression prediction of oral premalignant lesions via self-supervised deep learning on histopathology. JCO Glob Oncol. 2023 Aug;9(Supplement_1):90–90. DOI:10.1200/GO.2023.9.Supplement_1.90

196. Hung KF, Ai QYH, Wong LM, Yeung AWK, Li DTS, Leung YY. Current Applications of Deep Learning and Radiomics on CT and CBCT for Maxillofacial Diseases. Vol. 13, Diagnostics. Multidisciplinary Digital Publishing Institute (MDPI); 2023. DOI:10.3390/diagnostics13010110

197. Khajetash B, Nikoofar A, Mahdavi SR, Tavakoli M. Investigation of Ensemble Learning Method in Predicting Early Xerostomia Using Radiomics Features from CT and MRI. International Journal of Radiation Oncology*Biology*Physics. 2023 Oct;117(2):e630. DOI:10.1016/j.ijrobp.2023.06.2024

198. Khajetash B, Nikoofar A, Mahdavi SR, Tavakoli M. The Role of Radiomics Model to Predict Early Xerostomia in Head and Neck Cancer after Radiotherapy.

International Journal of Radiation Oncology*Biology*Physics. 2023 Oct;117(2):e629. DOI:10.1016/j.ijrobp.2023.06.2023

199. Kantharimuthu M, Malathi M, Sinthia P, Mary GAA, Sunil NKB, Deen KJ. Oral Cancer Prediction Using a Probability Neural Network (PNN). Asian Pacific Journal of Cancer Prevention. 2023;24(9):2991–5. DOI:10.31557/APJCP.2023.24.9.2991

200. Moztarzadeh O, Liska J, Liskova V, Skalova A, Topolcan O, Jamshidi A, et al. Predicting Chronic Hyperplastic Candidiasis Retro-Angular Mucosa Using Machine Learning. Clin Pract. 2023 Dec 1;13(6):1335–51. DOI:10.3390/clinpract13060120

201. Florina Bogdan-Andreescu C, Liliana Defta C, Albu ŞD, Manea A, Botoacă O, Russu EA, et al. APPLICATION OF ARTIFICIAL INTELLIGENCE IN DENTAL CARIES PREDICTION RELATED TO DIET AND ORAL HYGIENE. Romanian Journal of Oral Rehabilitation. 16(2). DOI:10.6261/RJOR.2024.2.16.5

202. Pruthi N, Yap T, Moore C, Cirillo N, McCullough MJ. Applying Machine Learning for Enhanced MicroRNA Analysis: A Companion Risk Tool for Oral Squamous Cell Carcinoma in Standard Care Incisional Biopsy. Biomolecules. 2024 Apr 1;14(4). DOI:10.3390/biom14040458

203. Kahalian S, Rajabzadeh M, Öçbe M, Medisoglu MS. ChatGPT-4.0 in Oral and Maxillofacial Radiology: Prediction of Anatomical and Pathological Conditions from Radiographic Images. Folia Med (Plovdiv). 2024;66(6):863–8. DOI:10.3897/folmed.66.e135584

204. Öztürk EMA, Ünsal G, Erişir F, Orhan K. Prediction of bone invasion of oral squamous cell carcinoma using a magnetic resonance imaging-based machine learning model. European Archives of Oto-Rhino-Laryngology. 2024 Dec 1; DOI:10.1007/s00405-024-08862-z

205. Qing M, Yang D, Shang Q, Li W, Zhou Y, Xu H, et al. Humoral immune disorders affect clinical outcomes of oral lichen planus. Oral Dis. 2024 May 1;30(4):2337–46. DOI:10.1111/odi.14667

206. Çiftçi BT, Aşantoğrol F. Utilization of machine learning models in predicting caries risk groups and oral health-related risk factors in adults. BMC Oral Health. 2024 Dec 1;24(1). DOI:10.1186/s12903-024-04210-z

207. Gonca M, Gul BB, Sert MF. How successful is the CatBoost classifier in diagnosing different dental anomalies in patients via sella turcica and vertebral morphologic alteration? BMC Med Inform Decis Mak. 2024 Dec 1;24(1). DOI:10.1186/s12911-024-02643-8

208. Shephard AJ, Bashir RMS, Mahmood H, Jahanifar M, Minhas F, Raza SEA, et al. A fully automated and explainable algorithm for predicting malignant transformation in oral epithelial dysplasia. NPJ Precis Oncol. 2024 Dec 1;8(1). DOI:10.1038/s41698-024-00624-8

209. Peng J, Xu Z, Dan H, Li J, Wang J, Luo X, et al. Oral epithelial dysplasia detection and grading in oral leukoplakia using deep learning. BMC Oral Health. 2024 Dec 1;24(1). DOI:10.1186/s12903-024-04191-z

210. Adeoye J, Thomson P, Su Y. ARTIFICIAL INTELLIGENCE-BASED PREDICTION OF MALIGNANT TRANSFORMATION IN ORAL LEUKOPLAKIA AND ORAL LICHENOID MUCOSITIS. Int J Oral Maxillofac Surg. 2024 Jan;52:47–8. DOI:10.1016/j.ijom.2023.10.142

211. Chao M, Wei J, Liu T, Penagaricano JA. Parotid Voxel Dose Analysis with Machine Learning Toward Xerostomia Prediction in Head and Neck Cancer Irradiation. International Journal of Radiation Oncology*Biology*Physics. 2024 Oct;120(2):e738–9. DOI:10.1016/j.ijrobp.2024.07.1624

212. Lim JH, Heo J, Noh OK. Enhancing Oral Cancer Diagnosis: A Deep Learning-Based Approach for Malignant Tongue Tumors. International Journal of Radiation Oncology*Biology*Physics. 2024 Apr;118(5):e64–5. DOI:10.1016/j.ijrobp.2024.01.144

213. Mudrov VP, Kazakov SP, Baranov AA, Muraev AA, Myandiev MS, Fomenkov IS. Machine learning for laboratory diagnosis of chronic periodontitis. Clinica Chimica Acta. 2024 May;558:118806. DOI:10.1016/j.cca.2024.118806

214. Adeoye J, Chaurasia A, Akinshipo A, Suleiman IK, Zheng LW, Lo AWI, et al. A Deep Learning System to Predict Epithelial Dysplasia in Oral Leukoplakia. J Dent Res. 2024 Nov 1; DOI:10.1177/00220345241272048

215. Chu H, de Vette SP, Neh H, Sijtsema NM, Steenbakkers RJ, Fuller CD, et al. OC-0449 Deep learning based NTCP-modelling using 3D-information for predicting late xerostomia. Radiotherapy and Oncology. 2023 May;182:S352–4. DOI:10.1016/S0167-8140(23)08621-8

216. Liskova V, Liska J, Moztarzadeh O, Posta P, Topolcan O, Jamshidi A, et al. Predicting Chronic Hyperplastic Candidiasis in the Tongue using Machine Learning: A Study of 186 Cases. Open Dent J. 2024 May 27;18(1). DOI:10.2174/0118742106302342240502094935

217. Ahn SH, Lee SJ, Lee MJ, Chung PS, Kim HS. Prediction of Dry Mouth Condition Using Radiomics Features from Tongue Diagnosis Image. Applied Sciences (Switzerland). 2024 Nov 1;14(22). DOI:10.3390/app142210118

APPENDICES

APPENDIX 1 - Search strategies with appropriated key words and MeSH terms.

Database	Search strategy (Up to Feb 14th, 2025)
Medline/PubMed	("AI"[All Fields] OR "Artificial Intelligence"[MeSH Terms] OR "Machine Learning"[MeSH Terms] OR "Deep Learning"[All Fields] OR "Supervised Learning"[All Fields] OR "Unsupervised Learning"[All Fields] OR "Computational Intelligence"[All Fields] OR "Machine Intelligence"[All Fields] OR "Computer Reasoning"[All Fields] OR "Computer Vision Systems"[All Fields] OR "Computer Vision System"[All Fields] OR "Knowledge Acquisition"[All Fields] OR "Knowledge Representation"[All Fields] OR "Knowledge Representations"[All Fields] OR "algorithms"[All Fields] OR "ML"[All Fields] OR "neural networks"[All Fields])AND("predicting"[All Fields] OR "prediction"[All Fields] OR "prediction model"[All Fields] OR "Forecast"[All Fields] OR "disease-prediction"[All Fields] OR "predict"[All Fields])AND("mouth diseases"[MeSH Terms] OR "diagnosis oral"[All Fields] OR "mouth abnormalities"[All Fields] OR "mouth pathology"[All Fields] OR "oral diagnosis"[All Fields] OR "oral disease"[All Fields] OR "oral diseases"[All Fields] OR "oral manifestations"[All Fields] OR "oral pathology"[All Fields] OR "stomatognathic diseases"[All Fields] OR "oral health"[MeSH

	Terms] OR "Dentistry"[All Fields] OR "Endodontics"[All Fields] OR "dental cavity"[All Fields] OR "periodontics"[All Fields] OR "Xerostomia"[All Fields] OR "Head and Neck Cancer"[All Fields] OR "maxillofacial diseases"[All Fields] OR "osteoradionecrosis"[All Fields] OR "osteonecrosis"[All Fields] OR "caries"[All Fields])
Embase	('mouth disease'/exp OR 'mouth disease' OR 'oral health') AND ('prediction' OR 'predicting') AND ('machine learning'/exp OR 'machine learning' OR 'artificial intelligence'/exp OR 'artificial intelligence' OR 'supervised machine learning' OR 'algorithm' OR 'artificial neural network')
Web of Science Core Collection	TS=(“AI” OR “Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Supervised Learning” OR “Unsupervised Learning“ OR “Computational Intelligence” OR “Machine Intelligence” OR “Computer Reasoning” OR “Computer Vision Systems” OR “Computer Vision System” OR “Knowledge Acquisition” OR “Knowledge Representation” OR “Knowledge Representations” OR “ML” OR “neural networks” OR “algorithms”) AND TS=("predicting" OR "prediction" OR "prediction model" OR "Forecast" OR "disease-prediction") AND TS=("mouth diseases" OR "mouth abnormalities" OR "mouth pathology" OR "oral diagnosis" OR "oral disease" OR “oral diseases” OR "oral manifestations" OR “oral manifestation” OR "oral pathology" OR "stomatognathic diseases" OR "oral health" OR "Dentistry" OR "Endodontics" OR "dental cavity" OR "periodontics" OR "Xerostomia" OR "Head and Neck Cancer" OR "maxillofacial diseases" OR “maxillofacial disease” OR "osteoradionecrosis" OR “osteonecrosis” OR "caries")
Google Scholar	("oral diseases" OR "mouth diseases") AND ("predicting" OR "prediction") AND ("machine learning" OR "artificial intelligence") Sort by relevance the first 100. Without citations and patents

APPENDIX 2 - Excluded articles and reasons for exclusion (n=102)

Reference	**Author/Year**	**Reasons for Exclusion**
[119]	Prasanna S et al.,2012	2
[120]	Maghsoudi, R et al.,2013	4
[121]	Papantonopoulos G et al.,2014	1
[122]	Baik J et al.,2014	1

[123]	Liu Y et al.,2015	1
[124]	Park, S et al., 2016	3
[125]	Imangaliyev, S et al.,2017	1
[126]	Liu Y et al.,2017	1
[127]	Lakshminarayanan, P. et al 2017	3
[128]	R. Anantharaman et al.,2017	4
[129]	Gabryś HS et al.,2018	1
[130]	Lee JH et al.,2018	1
[131]	Zanella-Calzada LA et al., 2018	1
[132]	H.H. Tseng.,2018	3
[133]	Feres M et al.,2018	4
[134]	Jahantigh F et al.,2018	4
[135]	Alabi RO et al.,2019	1
[136]	Agouropoulos A et al.,2019	1
[137]	Tseng.,2019	3
[138]	Humbert-Vidan et al 2019	3
[139]	Kamezawa H et al 2019	3
[140]	Machado et al.,2020	1
[141]	Wang et al., 2019	1
[112]	Hung et al. 2020	1
[142]	Na et al.,2020	1
[143]	Alabi et al.,2020	1
[144]	Chu et al.,2020	1
[145]	Yang et al.,2020	1
[146]	Nawandhar et al.,2020	1
[147]	Dolic et al.,2020	1
[148]	Alvarez-Arenal et al.,2020	2
[149]	Neves, 2L.V.F. et al.2020	3
[150]	Nurimba M.C et al .,2020	3
[151]	Karhade et al., 2021	1
[152]	Li et al.,2021	1
[153]	Narayanan et al.,2021	1
[154]	Jesus et al.,2021	1
[155]	Adeoye et al.,2021	1

[156]	Wang et al.,2021	1
[157]	Camalan et al.,2021	1
[158]	Alhazmi et al., 2021	1
[159]	Quivey et al.,2021	3
[160]	T Chinnery et al.,2021	3
[161]	Chen.,et al 2022	1
[162]	Basri et al.,2021	1
[163]	Mudrov et al 2022	1
[164]	Tseng et al.,2022	1
[165]	Rao et al.,2022	1
[166]	Rimi et al.,2022	1
[167]	Ferrer-Sánchez et al.,2022	1
[168]	Adeoye et al.,2022	1
[169]	Wang et al.,2022	1
[170]	Thulaseedharan .,2022	1
[171]	Qu et al.,2022	1
[172]	Ellis et al., 2022	1
[173]	Başaran et al.2022	2
[174]	Ataş et al.,2022	2
[175]	Baek et al.,2022	2
[176]	Feng et al 2022	3
[177]	Kolokythas et al 2022	3
[113]	Lee et al.2023	1
[178]	Cai et al. 2023	1
[179]	Rachi et al. 2023	1
[180]	Teza et al., 2023	1
[181]	Busato et al.,2023	1
[182]	Toledo Reyess et al.,2023	1
[183]	Gu et al.,2023	1
[184]	Amasya et al.,2023	1
[185]	Dörrich et al.,2023	1
[186]	Adeoye et al.,2023	1
[187]	Wu MP et al.,2023	1
[188]	Yan et al.,2023	1

[189]	Cai et al.,2023	1
[114]	Lakshmi, T. K et al., 2023	1
[190]	Tareq et al., 2023	2
[191]	Gomes et al., 2023	2
[192]	Bashir et al.,2023	2
[193]	Liu et al.,2023	3
[194]	Humbert-Vidan et al 2023	3
[195]	Ramesh et al. 2023	3
[196]	Hung et al.,2023	3
[197]	Khajetash Bet al. 2023	3
[198]	Khajetash B et al. 2023	3
[199]	Kantharimuthu et al.,2023	4
[200]	Moztarzadeh et al.,2023	4
[201]	Bogdan-Andreescu C et al.,2024	1
[202]	Pruthi et al., 2024	1
[203]	Kahalian et al.,2024	1
[204]	Öztürk et al .,2024	1
[205]	Qing et al.,2024	1
[206]	Çiftç et al., 2024	1
[207]	Gonca et al.,2024	2
[208]	Shephard et al.,2024	2
[209]	Peng et al.,2024	2
[210]	Adeoye et al. 2024	2
[211]	Chao et al. 2024	3
[212]	Lim et al 2024	3
[213]	Mudrov et al 2024	3
[214]	Adeoye et al.,2024	3
[215]	Chu, Huishin et al.,2024	3
[216]	Liskova et al., 2024	4
[217]	Ahn S-H et al.,2024	4

(1) Studies that did not meet the inclusion criteria (prediction of oral disease diagnosis and/or prediction by machine learning) (n=59);

(2) Studies in humans who do not address oral cavity diseases (n=12);

(3) Abstracts, protocols, narrative reviews, short communications, personal opinions, letters, posters, conference abstracts, and laboratory research (in vitro and in vivo animal study)(n=23);

(4) Studies that did not evaluate the predictive performance of the algorithm (n=8).

APPENDIX 3 - Summary of descriptive characteristics of included studies (n=99)

Reference	Author	Year	Country	Objective	Diseases	Categorized Disease	Specialty	Sample Size	Variable Type	Algorithms	Metrics	Performance
[87]	Benyamin Khajetash et al.	2025	Iran	Compare different models in predicting radiation-induced xerostomia and sticky saliva in both early and late stages HNC patients using CT and MRI image features along with demographics and dosimetric information	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	85	Radiographic examination and Dosimetric data	(8) XGB,MLP, SVM,RF, KNN,NB,LR,DT	(4) AUC,ACC, SEN,SPE	Model:D-Dosimetric-T1-MLP AUC:0.64 ± 0.16 ; ACC:0.61 ± 0.11 ; SEN:0.59 ± 0.12 ; SPE: 0.67 ± 0.14 ; Model:D-Dosimetric-T2-XGB AUC:0.64 ± 0.16 ; ACC:0.66 ± 0.12 ; SEN:0.75 ± 0.13 ; SPE:0.5 ± 0.13 ; Model:D-Dosimetric-T2-DT AUC:0.55 ± 0.15 ; ACC:0.67 ± 0.12 ; SEN:0.67 ± 0.11 ; SPE:0.66 ± 0.14 ; Model:D-Dosimetric-T2-KNN AUC:0.53 ± 0.15 ;ACC:0.61 ± 0.11 ; SEN:0.67 ± 0.10 ; SPE:0.57 ± 0.15
[49]	Kuo Men et al.	2019	United States	Developing a xerostomia prediction model with radiation treatment data using a 3D rCNN	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	784	Radiographic examination and Dosimetric data	(2) 3D rCNN,LR	(5) ACC,SEN, SPE,F1,AUC	Model 3D rCNN ACC : 0.76 ; SEN:0.76; SPE 0.76; F1 0.70 . AUC 0.84 Model LR ACC:0.64; SEN: 0.72; SPE: 0.59; F-SCORE: 0.60; AUC: 0.74 (0.64–0.84);
[88]	Maryam Farhadian et al.	2020	Iran	To design a SVM based decision-making support system to diagnosis various periodontal diseases	Periodontal Disease	Periodontal Diseases	Periodontics	300	Clinical data	(1) SVM	(2) ACC,HUM	ACC: 88.7% e HUM :0912
[71]	Gaye Keser et al.	2022	Turkey	To develop a deep learning approach for identifying oral lichen planus lesions using	Lichen Planus	Mucosal Lesions	Stomatology	137	Photographs	(1) CranioCatch	(1) ACC	ACC:100%

				photographic images								
[72]	Selin Yesiltepe et al.	2022	Turkey	To create an AI system for detecting idiopathic osteosclerosis on panoramic radiographs for automatic, routine, and simple evaluation.	Idiopathic Osteosclerosis	Anatomical Variations	Radiology	493	Radiographic examination	(1) CranioCatch	(6) TP,FP,FN, SEN,PRC, F1	TP: 50; FP:10; SEN:0.88; ACC: 0.88; F1: 0.86
[109]	Riddhi Chawla et al.	2022	Uzbekistan	Provide a comprehensive examination of the application of deep learning to object detection, segmentation, and classification	Dental Caries	Dental Caries and Related Conditions	Cariology	10000	Radiographic examination	(4) U-CNN,CNN-LSTM,CNN,BWO-CNN	(2) ACC,F1	Model BWO-CNN ACC 99.12 F1score (%)91 Model CNN: ACC: 98.95 Model CNN-LSTM ACC: 96 Model U-CNN ACC:63.29; F1 64.14
[13]	Ka-Kei Chau et al.	2024	China	To propose a novel AI model for periapical lesion detection in CBTC, named CBCT-SAM. It combines the medical-based segmentation model, SAM-Med2D, with a lightweight U-Net model and an innovative Progressive Prediction Refinement (PPR) module.	Periapical Lesion	Periapical Lesions	Radiology	185	Radiographic examination	(4) CBCT-SAM,CBCT-SAM without PPR,Modified U-Net,PAL-Net	(4) ACC;SEN; PRC;SPE	Model CBCT-SAM PRCD-98.92% ± 010.37% , PRCMe 99.65% ± 0.66%. SEN 72.36 ± 21.61%, SPE 99.87% ± 0.11%, PRC 0.73 ± 0.21 e DSC 0.70 ± 0.19 Model:CBCT-SAM without PPR ACC:98.92; ACC-S 99.62 SEN:68.31 SPE:99.88 PRC:0.72 DSC:0.67 Model:Modified U-Net ACC-D:97.30 ACC-S:99.58 SEN:62.21 SPE:99.86 PRC:0.70 DSC:0.62 Model PAL-Net ACC-D:98.38 ACC-Se:99.64 SEN:70.98 SPE99.87 PRC0.73 DSC:0.69

[93]	Fahed Jubair et al.	2020	Jordan	To develop a lightweight deep CNN for discrimination between benign and malignant or potentially malignant oral lesions using a data set of verified clinical images, and the use of EfficientNet-B0 transfer model	Oral Cancer	Oral Cancer	Stomatology	716	Photographs	(3) EfficientNet-B0,VGG19 ,ResNet101	(4) ACC,SEN, SPE,AUC	Model EfficientNet-B0 ACC 85.0%;SPE 84.5% ,SEN 86.7% AUC0.928 Model:VGG19 ACC:83.0 ;SEN:86.4 SPE:81.5; AUC: 0.911 Model ResNet101 ACC:84.0; SEN:83.9 SPE:84.4; AUC: 0.915
[14]	Reinhard Chun et al.	2023	China	To develop and to validate a novel AI system that can be used to diagnose gingivitis on intraoral photographs with accuracy at or above 0.90	Periodontal Disease	Periodontal Diseases	Periodontics	567	Photographs	(1) DeepLabv3	(2) SEN,SPE	SEN: 0.92 SPE: 0.94
[73]	Faruk Oztekin et al.	2023	Turkey	Proposes an explainable deep learning-based method for computer-assisted automatic caries detection	Dental Caries	Dental Caries and Related Conditions	Cariology	562	Radiographic examination	(3) EfficientNet-B0, DenseNet-121,ResNet-50	(6) ACC,SEN, SPE,PRC, F1,MCC	Model ResNet-50 : ACC92.00%, SEN 87.33% SPE:96.67 F1-score de 91.61% PRC 96.67 MCC:84.37. Model EfficientNet-B0 ACC 90% SEN:83 SPE:97% PRC:96.51 F1 89.25 MCC80.80 Model DenseNet-121 ACC91.83 SEN:87.33 SPE:96.33 PRC:95.97 F1 91.45 MCC 84.01
[50]	Man Hung et al.	2020	United States	To identify the likelihood of a person to develop	Dental Caries	Dental Caries and	Cariology	5135	Clinical data	(5) SVM,XGB,	(5) ACC,SEN,	Model SVM: ACC 97.1%, PRC 95.1%, SEN 99.6%, SPE 94.3% AUC 0.997

				root caries by selecting the most relevant variables from demographic and lifestyle factors		Related Conditions				RF,KNN,L R	SPE,AUC, ROC	Model Model XGB ACC 0.947 PRC 0.908 SEN:1.000 SPE:0.889 AUC: 0.987 Model RF ACC 0.941; PRC:0.947 SEN:1.000 SPE:0.875 AUC:0.999 Model KNN ACC 0.832 PRC:0769 SEN: 0.971 SPE:0.679 AUC: 0.881 Model LR ACC:0.742 PRC: 0.742 SEN: 0.771 SPE:0.711 AUC: 0.818
[108]	Oleksandra et al.	2020	Ukraine	To develop and apply a software product to predict dental caries on the basis of neural network programming	Dental Caries	Dental Caries and Related Conditions	Cariology	73	Clinical data	(1) CariesPro	(1) ACC	ACC: 83.56%.
[107]	Paniti Acharari t et al.	2023	Thailand	To employ AI via CNN for the differentiation of OLP and nonOLP in biopsy-proven clinical cases of OLP and non-OLP	Lichen Planus	Mucosal Lesions	Stomatolo gy	1089	Photograph s	(3) Xception,R esNet152V 2,Efficient NetB3	(6) FN,FP,NP V,PPV,TN ,TP	Model Xception: ACC 88.18; PPV 85; NPV 92; SEN 92.73; SPE 83.64; F1 88.70; Model ResNet152V2 ACC84.55; PPV91.30; 79.69; SEN76.36; SPE92.73; F1 83.17; Model EfficientNetB3 ACC81.82; PPV74.65; NPV94.87; SEN96.36; SPE67.27; F1 84.13
[26]	Ruchika Thukral et al.	2023	India	To evaluate the accuracy of the automated computer-aided deep learning approach in predicting the occurrence of oral mucositis and to categorize	Mucositis	Mucosal Lesions	Stomatolo gy	386	Photograph s	CNN	(9) TP,TN,FP, FN,ACC,P RC,SEN,S PE,F1	TP :64(82.1%) ;TN64(82.1%); FP14 (17.9%); FN14 (17.9%); ACC82.1%; PRC 82.1%; SEN82.1%; SPE82.1%; F1:82.1%

				mucositis at the earliest occurrence into two grades, that is, Grade 0 (absence of mucositis) and Grade I (asymptomatic or mild symptoms of mucositis) using non-radiative, non-invasive, non-ionizing, non-destructive thermal imaging								
[102]	Basri et al.	2024	Malaysia	To identify the best algorithm for the prediction of dental caries	Dental Caries	Dental Caries and Related Conditions	Cariology	1	Photographs	CNN	(4) ACC, PRC, SEN, SPE	ACC: 0,85 PRC 1,00
[80]	Adeetya Patel et al.	2024	Canada	Proposes a deep learning model for oral lesion classification that emphasizes interpretability and robustness against dataset bias	Actinic solar cheilitis, Aphthous ulcers, Cheek lip tongue chewing, Denture stomatitis, Fordyce granules, Geographic tongue, Gingival hyperplasia, Gingival cyst, Gingivitis,	Oral Potentially Malignant Disorders; Mucosal; Odontogenic Cysts and Tumors Lesions; Periodontal Diseases; Anatomical Variations; Oral Cancer; Tongue Lesions	Stomatology	1888	Photographs	(3)Baseline, GAIN,GAIN+ASP	(3) BS,BA,AUC	Model Baseline BS.0.339; BA0.734; AUC0.902; Model GAIN BS0.327; BA0.787; AUC0.893; Model GAIN+ASP BS0.330; BA0.755; AUC0.914

					Hairy tongue, Leukoedema, Lymphoepithelial cyst, Lymphoid tissue, Mucocele, Palatal papillomatosis, Squamous cell carcinoma							
[59]	Toan Huy Bui et al.	2022	Japan	Proposes a method for segmentation and caries diagnosis for caries screening	Dental Caries	Dental Caries and Related Conditions	Cariology	95	Radiographic examination	(3) RF,KNN,SVM	(6) ACC,SEN, SPEC,PPV,NPV,F1	Model RF PRC 0.471; SEN 0.95; SPE 0.10; PPV 0.44; NPV 0.75; F1 0.44; Model KNN PRC 0.79; SEN 0.69; SPE 0.86; PPV 0.80; NPV 0.78; F1 0.59; Model SVM PRC 0.79; SEN 0.73; SPE 0.833; PPV 0.77; NPV 0.80; F1 0.60
[81]	A. Frydenlund et al.	2014	Canada	Proposes a set of image features that can be computed from epithelial regions to form region descriptions and shows that the proposed region descriptions can be used to accurately distinguish and classify samples of the four types of	Odontogenic Cysts	Odontogenic Cysts and Tumors	Stomatology	73	Histopathological examination	(2) SVM,BLR	(5) TP,FP,PRC,F1,ROC	Model BLR TP:0.954; FP 0.013; PRC0.959; F1 0.954; ROC0.998 Model SVM TP0.923; FP0.026; PRC 0.923; F1 0.922; ROC0.970

				developmental odontogenic cysts using standard classification algorithms.								
[103]	Imane Lasr et al.	2023	Morocco	Proposes an explainable deep learning-based approach for automatic caries detection in dental images, motivated by the urgent need to provide accurate and efficient diagnostic methods for dental care.	Dental Caries	Dental Caries and Related Conditions	Cariology	884	Photographs	(4) VGG-16,VGG19, DenseNet121,Inception V3	(4) ACC,PRC, SEN,F1	Model VGG-16 ACC98.3; PRC 98.3; SEN 98.3; F1 98.3; Model VGG-19ACC95; PRC 95; SEN 94; F1 94; Model DenseNet-121 ACC83; PRC 83; SEN 83; F1 83; Model Xception89; PRC 88;SEN 87; F1 88
[70]	Mohammed Zubair et ak	2020	Arabia	Proposes an AI-based computational method that can automatically detect potentially malignant oral lesions on the tongue directly from clinically annotated photographic images, to assist physicians/dentists in early diagnosis before they manifest into cancerous malignancies.	Candidiasis, Fissured Tongue, Geographic Tongue, Black Hairy Tongue and Pigmented Fungiform Papillae Malignant Hairy Leukoplakia and Erythroplakia	Tongue Lesions; Fungal Infection; Oral Leukoplakia	Stomatology	300	Photographs	(6) AlexNet,GoogLeNet, VGG19,Inceptionv3,ResNet50,SqueezeNet	(7) ACC,SEN, SPE,PRC, F1,MCC,KS	Model ResNet50 ACC = 0.967, F1 = 0.9664, Mcc = 0.9602 KS = 0.8958; SEN0.966; SPE 0.991; PRC 0.971; MCC 0.960) Model Vgg19 ACC 0.95; SEN 0.95; SPE 0.987; PRC 0.956; F149; MCC 0.939; KS.43; Model Inceptionv3 ACC 0.917; SEN0.916; SPEE0.979; PRC 0.931; F10.915; MCC0.901; KS 0.739; Model Squeezenet ACC0.900; SEN0.9; SPE 0.975; Prec0.908; F10.901; MCC0.901; MCC0.878; KS.687; Model GoogleNet ACC0.883; SEN0.883; SPE0.970; PRC 0.908; F10.886; MCC0.864; KS.635; Model

												AlexNetACC0.833; SEN0.833; SPE0.958; PRC 0.865; F10.831; MCC0.803; KS 0.479
[60]	Yoshiko Ariji et al.	2019	Japan	To evaluate the performance of a deep learning object detection technique for the automatic detection and classification of mandibular radiolucent lesions on panoramic radiographs	Ameloblasts, odontogenic ,keratocysts, dentigerous cysts, radicular cysts and simple bone cysts	Odontogenic Cysts and Tumors	Stomatology	210	Photographs	(1) DetectNet	(2) SEN,FP	SEN 0.88; FP 0.00; Testing 2 data set SEN0.88 FP 0.04
[51]	Ming Chao et al.	2022	United States	To develop and validate a cluster model incorporating heterogeneous dose distribution within the parotid gland for prediction of radiotherapy (RT)-induced xerostomia with machine learning (ML) techniques.	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	155	Dosimetric data	(4) SVM,KNN, NB,RF	(3) ACC,SEN, SPE	Model KNN ACC0.68 Model NB 0.69 Model SVM ACC0.67
[110]	Do Hoang Viet et al.	2024	Vietnam	To apply the performance of 2 state-of-the-art deep learning models, Faster R-CNN and YOLOv4, in diagnosing and	Periapical Lesion	Periapical Lesion	Radiology	2658	Radiographic examination	(2) Faster R-CNN,YOLOv4	(4) SEN,SPE, ACC,PRC	Model Fster-R-CNN SEN96.2; SPE95.41; ACC95.74; PRC 93.37; Model YOLOv4 SEN79.47; SPE91.47; ACC87; PRC 86.75

				classifying periapical lesions using the PAI score from PR with three diferent regions of the dental arch: anterior teeth, premolars, and molars							
[7]	Laia Humbert -Vidan	2021	United Kingdom	To compare the performance of different ML methods, including LR, SVM, RF, AdaBoost and ANN, in predicting the incidence of mandibular ORN	Osteoradi onecrosis	Bone Necrosis and Infections	Stomatolo gy	96	Clinical data and Dosimetric data	(4) SVM,RF,A DB,ANN	(5) ACC,SEN, SPE,PRC, NPV	Model ANN ACC0.77;SEN0.90; SPE0.64; PRC0.72; NPV0.90 ; Model SVM ACC0.76; SEN0.96; SPE0.56; PRC 0.68; NPV0.94 Model AdaBoost ACC0.75; SEN0.93; SPE0.56 PRC 0.68; NPV0.91 Model LR ACC0.75; SEN0.90; SPE0.60; PRC 0.71; NPV0.88; Model RFACC0.71; SEN0.77; SPE0.66; PRC 0.70; NPV0.76
[52]	Brandon Reber et al.	2023	United States	Compare the performance of traditional ML algorithms with DL algorithms for predicting the binary outcome of ORN using the radiation dose distribution of the HNC patient	Osteoradi onecrosis	Bone Necrosis and Infections	Stomatolo gy	2495	Clinical data and Dosimetric data	(8) LR,RF,SV M,RC,Res Net,Dense Net,Autoen coder,Ran dom	(7) ACC,B-ACC,SEN, PRC,F1,A UROC,AU PRC	Model LR ACC 0.69; Balanced accuracy0.70; SEN 0.72; PRC 0.27; F1 0.39; AUROC0.74; AUPRC0.28 Model SVM ACC0.69; B-ACC 0.70; SEN 0.71; PRC 0.27; F1 0.39; AUROC0.70; AUPRC0.24; 3
[53]	Priya Dey et al.	2024	United States	To compare the accuracy, precision, and differences	Dental Caries	Dental Caries and	Cariology	3586	Clinical data	(4) LR,XGB,L SS,SVM	(5) AUROC,A	Model XGB AUC-ROC0.86; ACC0.81; SEN0.84; SPE0.79; Kappa0.61 Model

				between the caries predictive capability of AI vs. traditional multivariable regression techniques		Related Conditions					CC,SEN,SPE,KS	SVM AUC-ROC0.86; ACC0.79; SEN 0.70; SPE0.84; KS0.56 Model Lasso AUC-ROC0.86;ACC0.79; SEN0.72;SPE0.84; Kappa0.57Modelo LR AUC-ROC 0.86; ACC0.78; SEN0.71; SPE0.83; KS.055.
[61]	Yoh Tamaki et al.	2009	Japan	Describe a new method for deriving a caries prediction model using data mining	Dental Caries	Dental Caries and Related Conditions	Cariology	560	Clinical data and Salivary test	(3) LR,NN,DA	(2) SEN,SPE	Model DA SEN0.73; SPE0.77 Model NN SEN0.83; SPE0.45 Model LR SEN0.61 ; SPE0.69
[38]	Woosun Beak et al.	2024	Korea	To develop data-driven prediction models for assessing PD risk and to evaluate their performance and reliability with clinical patient data for external validation	Periodontal Disease	Periodontal Diseases	Periodontics	7427	Clinical data	(5) LR,SVM,RF,XGB,NN	(5) ACC,SEN, SPE,PRC, AUROC	Model XGB SEN0.354; SPE0.919; PRC 0.607; ACC0.773; ROCAUC0.823 Model SVM SEN0.394; SPE0.924; PRC 0.646; ACC0.786; ROC-AUC0.828 Model NN SEN 0.399; SPE0.910; PRC 0.609; ACC0.777; ROC-AUC0.823 Model RF SEN0.342 SPE0.932; PRC 0.637; ACC0.778; ROC-AUC0.824 Model LR SEN0.399; SPE0.907; PRC 0.600; ACC0.775; ROC-AUC0.822
[39]	In-Ae Kang et al.	2022	Korea	Proposes the prediction of dental caries model using machine learning in personalized medicine.	Dental Caries	Dental Caries and Related Conditions	Cariology	22288	Clinical data	(7) ANN,CNN, LSTM, GBDT,RF, SVM,LR	(4) ACC,F1,PRC,SEN	Model RF ACC0.92; F1 0.91; PRC 0.94; SEN 0.88; Model ANN ACC0.88; F1 0.87; Prec0.87;SEN 0.87; Model CNN ACC0.87; F1 0.87; PRC 0.87; SEN 0.87; Model GBDT ACC0.85; F1 0.81; PRC 0.83;SEN 0.78; Model SVM ACC0.83; F1 0.79;

												PRC 0.82; SEN 0.76; Model LR ACC0.82; F1 0.78; PRC 0.80; SEN 0.76; Model LSTM ACC 0.75; F1 0.74; PRC 0.74;SEN 0.74
[15]	Cheng Wang et al.	2023	China	Proposes a method for automatic diagnosis based on fluorescence spectral sub-band imaging combined with deep learning.	Dental Caries	Dental Caries and Related Conditions	Cariology	83	Photographs	(1) 2-D-3-D hybrid convolutional neural network	(4) ACC,SEN, SPE,F1	ACC 90.69; SEN 90.19; SPE 97.71; F1 90.06
[94]	Falk Schwendicke et al.	2020	Germany	Apply deep convolutional neural networks (CNNs) to detect caries lesions in near-infrared light transillumination (NILT) images.	Dental Caries	Dental Caries and Related Conditions	Cariology	226	Photographs	(2) Resnet18, Resnext50	(6) AUC,ACC, SEN,SPE, PPV,NPV	Model Resnext50 AUC0.74; ACC0.68; SEN0.59; SPE0.76; PPV0.63; NPV0.73 Model Resnet18 AUC 0.73; ACC0.69; SEN0.46; SPE0.85; PPV 0.71; NPV0.69
[27]	Navas P. Moidu et al.	2022	India	To use a CNN model to score the periapical lesion on an IOPAR using the PAI scoring system	Periapical Lesion	Periapical Lesions	Radiology	3540	Radiographic examination	(1) YOLOv3	(7) ACC,SEN, SPE,VPP, VPN,F1,MCC	ACC:0.89; SEN92.1; SPE76; VPP86.4; VPN86.1; F10.89; MCC0.71
[16]	Lin	2024	China	To explore the application of uncertainty methods in deep neural networks for the diagnosis of oral mucosa-associated lesions. Our goal is to increase the accuracy and reliability of diagnosis by introducing an	Oral Cancer	Oral Cancer	Stomatology	1011	Photographs	(1) Probabilistic HRNet	(5) SEN,SPE, F1,AUC,BS	SEN 0.946 SPE 0.992 F1 0.953 AUC 0.969 BS0.017

				uncertainty prediction algorithm.								
[65]	Radwa Marzouk et al.	2022	Saudi Arabia	Recognize oral cancer using AI and image processing techniques	Oral Cancer	Oral Cancer	Stomatology	131	Photographs	(1) AIDTL-OCCM	(4) ACC,PRC, SEN,F1	ACC 90.8; PRC 89.05; SEN 88.60; F1 88.81
[17]	Hu Chen et al.	2020	China	Using faster R-CNN to detect caries, periapical periodontitis and periodontitis in dental periapical radiographs	Dental Caries and Periodontal Disease	Dental Caries and Related Conditions; Periodontal Diseases	Periodontics;Cariology	2900	Radiographic examination	(1) Faster R-CNN	(5) IoU,SE,AP,AUC,PRC	SEN 0.6; PRC 0.5
[28]	Ramana Kumar et al.	2022	India	To use the deep learning method for dental caries segmentation in an effective way	Dental Caries	Dental Caries and Related Conditions	Cariology	120	Radiographic examination	(1) HSLnSSOM−ResneXt−RNN	(10) ACC,SEN, SPE,PRC, FPR,FNR, NPV,FDR, F1,MCC	ACC; 93.67; SEN 94.66; SPE 92.73; PRC 92.44; FPR7.27; FNR5.34; NPV94.88; FDR7.56; F1 93.54; MCC87.35
[100]	Tran Tuan Anh et al.	2024	Indonesia	To apply artificial intelligence to identify deep tooth decay using the open-source tool Teachable Machine.	Dental Caries	Dental Caries and Related Conditions	Cariology	2063	Radiographic examination	(1) Teachable Machine	(1) ACC	ACC: 73,3
[40]	Jae-Hong Lee et al.	2018	Korea	To evaluate the efficacy of deep CNN algorithms for the detection and diagnosis of dental caries in periapical radiographs	Dental Caries	Dental Caries and Related Conditions	Cariology	3000	Radiographic examination	(1) CNN	(5) ACC,SEN, SPE,PPV, NPV	ACC 82; SEN81; SPE83 ; PPV82.7; NPV81.4
[41]	Ho-Jun Song et al.	2023	Korea	To investigate the efficacy of DL in detecting abnormal areas on the dorsal	Tongue coating; Hairy tongue;	Tongue Lesions	Stomatology	7782	Photographs	(1) VGG16	(5) PRC,SEN, F1,ACC,AUC	F1 0.960 ; PRC 0.935, SEN 0.986

				tongue surface in both patients and healthy adults	Fissures; Papillary atrophy,Erosion,Ulcer. Lichenoid change; Hyperkeratotic change, Papillary hypertrophy; Artifacts							
[54]	Anusha Solanki et al.	2024	United States	To detect and distinguish oral malignant and non-malignant lesions from clinical photographs using YOLO v8 deep learning algorithm.	Oral Cancer	Oral Cancer	Stomatology	427	Photographs	(1) Yolov8	(4) ACC,PRC, SEN,SPE	SEN : 54% ; SPE : 72%; PRC : 35% ; ACC : 55%
[29]	R. Prabhakaran et al.	2020	India	Focuses on accuracy and uptime for segmentation and classification of benign or malignant tumors	Oral Cancer	Oral Cancer	Stomatology	100	Photographs	(3) CNN,SVM, NB	(7) TP,TN,FP, FN,PRC,SEN,SPE	Model CNN TP 83; TN43; FP3; FN2; PRC 96.15; SEN97.64;SPE93.47; PRC 96.51; SEN 97.64; F 97.07 Model SVM TP67; TN29; FP4; FN3; PRC 93.20;SEN95.71;SPE87.87; PRC 94.36; SEN 95.71 F195.03 Model NB TP56; TN24; FP7; FN6; PRC 86.02; SEN90.32; SPE77.41; PRC 88.88; SEN 90.32; F1 89.60
[18]	Ke Deng et al.	2023	China	To develop a multiclass non-clinical screening tool for periodontal disease and assess	Periodontal Disease	Periodontal Diseases	Periodontics	408	Clinical data and Salivary test	(2) LR,RF	(5) ACC,SEN, SPE,PPV, NPV	Model RF *Gengivite* SEN91; SPE92.6; ACC92.4; AUROC0.97 *Periodontite* SEN 91; SPE92,6;ACC92.4; AUROC0.97 Model LR

				its accuracy for differentiating periodontal health, gingivitis and diferente stages of periodontitis								Gengivite SEN86.5; SPE83.4; PPV45.1; VPN97.5; ACC83.9; AUROC0.893 Periodontite SEN80.1; SPE92.9; PPV96.6. NPV65.3; ACC84.1; AUROC0.898
[84]	Mohanad A. Deif	2022	Egypt	Improve categorization of oral histopathological images into normal and OSCC classes	Oral Cancer	Oral Cancer	Stomatology	230	Histopathological examination	(3) XGB,RF,ANN	(3) ACC,SEN, SPE	Model XGB ACC96.3; SEN98.9; PRC 96.3 Model RF ACC93.1; SEN97.8; PRC 93.3 Model ANN ACC94.1; SEN97.8; PRC 94.7
[75]	FO Özden et al.	2014	Turkey	To develop an identification unit for classifying periodontal diseases using support vector machine (SVM), decision tree (DT),and artificial neural networks (ANNs)	Periodontal Disease	Periodontal Diseases	Periodontics	150	Clinical data	(3) SVM,DT, ANN	(1) PCR	Model SVM e DT : PRC 98%; Model ANN PRC 46%
[19]	Zijia Liu et al.	2021	China	To propose an algorithm based on convolutional neural networks (CNN) structure to signifcantly improve the classifcation accuracy of amelobastoma and OK	Ameloblastoma and odontogenic keratocyst	Odontogenic Cysts and Tumors	Stomatology	420	Radiographic examination	(1) CNN	(4) ACC,SEN, SPE,F1	ACC90.36; SEN92.86; SPE87.80; F1 90.70
[20]	Xinjia Cai et al.	2024	China	To develop two AI systems for building diagnostic and prognostic models	Odontogenic keratocyst (OKC),	Odontogenic Cysts and Tumors; Syndromes	Stomatology	2157	Histopathological examination	(1) SVM	(1) AUC	AUC OKC 0.935; AUC OOC 0.989; AUC GS 0.811

				of OKC using deep learning algorithms	orthokeratinized odontogenic cyst (OOC) and Gorlin syndrome (GS)							
[104]	Blanco-Victorio et al.	2024	Peru	To compare the performance of different prediction models based on machine learning to predict the presence or absence of early childhood caries.	Dental Caries	Dental Caries and Related Conditions	Cariology	183	Clinical data	(6) RF,GBDT, SVM,LR,ANN,KNN	(6) AUC,ACC, F1,PRC,SEN,MCC	Model NN AUC 0.904; ACC 0.927; F1 E 0.950; PCR 0.927; SEN 0.974; MCC 0.820 Model SVM AUC 0.868; ACC 0.927; F1 0.950; PRC 0.927; SEN 0.974; MCC 0.820 Model RF AUC 0.854; ACC 0.891; F1 0.927; PRC 0.884; SEN 0.974; MCC 0.728; Model Gradiente Boosting AUC 0.858; ACC 0.891; F1 0.925; PRC 0.902; SEN 0.949; MCC 0.729; Model KNN AUC 0.692; ACC 0.836; F1 0.892; PRC 0.841; SEN 0.949; MCC 0.580 Model LR AUC 0.911; ACC 0.909; F1 0.938; PRC 0.905; SEN I0.974; MCC0.774
[66]	Mohammed et al.	2018	Saudi Arabia	Present the optimized echo state neural networks for gravitational search to effectively predict oral cancer	Oral Cancer	Oral Cancer	Stomatology	*	Radiographic examination	(4) SVM,NN,MLP,GSOESNN	(3) ACC,SEN, SPE	Model (GSOESNN) : ACC 99.2; Model SVM ACC 89.2; Model NN ACC 94.1; Model MLP ACC 95.2
[67]	Shtwai Alsubai et al.	2023	Saudi Arabia	Introduce an ML-based detection approach using classifiers for more	Dental Caries	Dental Caries and Related Conditions	Cariology	10375	Clinical data	(8) LR,DT,RF, SGD,ETC,	(4) ACC,PRC, SEN,F1	Model VC (XGB+RF+ETC) ACC 97.36; PRC 96.14; SEN 96.84; F1 96.65 Model ETC ACC95.34; PRC 95.67; SEN

				accurate prediction of dental caries.						XGB, SVC,GNB		95.19; F1 95.38 Model XGB ACC 94.08; Prec 94.52; SEN 94.34 F1 94.43; Model RF ACC94.28; PRC 95.29; SEN 95.34; F1 95.32 Model SVC93.86; PRC94.45; SEN 93.21; F1 93.87; Model DT ACC92..35; PRC 92.62; SEN 92.34; F1 92.47 Model GNB ACC90.81; PRC 91.32; SEN 90.36; F1 90.86; Model LR ACC90.24; PRC 92.82; SEN 92.71; F1 92.80
[21]	Lijuan Zhang et al.	2025	China	Examine the prevalence of acute xerostomia during radiotherapy and evaluate the performance of machine learning approaches in predicting acute xerostomia in adults with HNC treated with proton and carbon ion radiotherapy	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	1769	Clinical data	(4) SVM,LSR, LR,RF	(5) B-ACC,AUROC,PRC, SEN,F1	Model SVM ACC0.66; AUC-ROC0.11; SEN 0.74; F1 0.19 Model Lasso ACC0.55; AUC-ROC0.48; PRC 0.07; SEN 1.00; F1 0.19; Model LR ACC0.54; AUC-ROC0.61; PRC 0.07; SEN.00; F1-score 0.13
[96]	N. Nijland et al.	2021	Netherlands	Examine the prevalence of acute xerostomia during radiotherapy and evaluate the performance of machine learning approaches in predicting acute xerostomia in adults with HNC treated	Periodontal Disease	Periodontal Diseases	Periodontics	155	Clinical data	(1) LR	(5) AUROC,SEN,SPE,PPV,NPV	AUROC 0.59; SEN 49; SPE 68; PPV 57; NPV 55

				with proton and carbon ion radiotherapy								
[95]	Julia Neumayr et al.	2024	Germany	To validate the diagnostic performance of this model in the detection, classification, localisation and segmentation of EH/MIH on independent image samples.	Molar incisor hypomineralization	Dental Caries and Related Conditions	Dentistics	455	Clinical data	(1) Demo.dental-ai.de	(3) ACC,SEN, SPE	ACC 94,3; SEN 94,4; SPE 94,2
[55]	Valentina L. Kouznetsova et al.	2020	United States	To analyse metabolite sets of different oral diseases, show their distinguishing and common features, and create a machine-learning (ML) model that can distinguish between different forms of oral disease	Oral Cancer and Periodontal Disease	Oral Cancer; Periodontal Diseases	Stomatology and Periodontics	156	Salivary Test	(3) NN,Logistic,SGD	(1) ACC	Model NN ACC 79.54; Model Logistic ACC 78.21; Model ACC 78.21
[77]	Nattane Luíza et al.	2022	Brazil	Using Random Forest classification along with Random Forest Importance Feature Selector was used to diagnose OSSC based on metabolites	Oral Cancer	Oral Cancer	Stomatology	68	Salivary Test	(1) RF	(3) ACC,SEN, AUC	ACC 86.76; SEN 80; AUC 0.91
[22]	Wen Li et al.	2019	China	Present a novel Artificial Intelligence (AI)-based method	Periodontal Disease	Periodontal Diseases	Periodontics	800	Photographs	(1) MGLCM	(4) SPE,SEN, ACC,F1	SEN 78.17; SPE 78.23; PRC 77.88; ACC 78.38; F1 78.55

				for diagnosing chronic gingivitis, which is based on multichannel gray-level co-occurrence matrix (MGLCM) and particle swarm optimization neural network (PSONN).								
[68]	Atta-ur Rahman et al.	2022	Saudi Arabia	Propose a transfer learning model model using AlexNet in convolutional neural network to extract classification features from oral squamous cell carcinoma (OSCC) biopsy images to train the model.	Oral Cancer	Oral Cancer	Stomatology	4946	Histopathological examination	(1) Transfer learning model	(11) ACC,SEN,SPE,F1,PPV,NPV,FPR,FNR,LPR,LNR,FMI	ACC 90.06; SEN 92.74; SPE 87.38; F1 90.15; PPV 87.69; NPV 92.55; FPR 12.62; FNR 7.26; LPR 7.35; LNR 0.08; FMI 90.18
[99]	Antoine Dubuc et al.	2022	France	To develop and evaluate a machine learning algorithm that allows the prediction of oral mucosa lesions diagnosis	Oral Lesions and Oral Cancer	Mucosal Lesions; Oral Cancer; Oral Leukoplakia	Stomatology	299	Photographs and Clinical data	(4)LightGBM,Elastic Net Regression,KNN,DT	(5) TPR,TNR,PPV,NPV,F1	Model LightGBM General ACC 0.84 gingival enlargement TPR 0.92; TNR1.00; PPV 1.00; NPV1.00; F10.96; *CEC* TPR 0.90; TNR1.00; PPV0.90; NPV1.0; F10.90; *Leukoplakia* TPR0.78; TNR1.00; PPV0.75; NPV0.98; F10.77; *Lichen planus* TPR0.89; TNR 0.89; PPV0.85; NPV0.92F10.87; Blistering Diseases *TPR0.72; TNR0.96; PPV0.76; NPV0.95; F10.74; Aphthous ulcers* TPR0.75; TNR0.99; PPV0.84; NPV0.97; F10.79

												Modelo Elastic Net Regression ACC geral0.54 gingival enlargement TPR0.92 ; TNR0.99; PPV0.85 ; NPV1.00; F10.88; CEC TPR0.60 ; TNR0.92; PPV0.21; NPV0.99; F10.32; Lekoplakia TPR0.74.; TNR0.91; PPV0.40; NPV0.98; F10.52; Lichen planus TPR0.38; TNR0.92; PPV0.77; NPV0.68F10.51; Blistering Diseases TPR0.70; TNR0.81; PPV0.38; NPV0.94; F10.49; TPR0.54; *Aphthous ulcers* TNR0.96; PPV0.56; NPV0.95; F10.55
[90]	Yan Yan et al.	2021	England	Propose a feature extraction model based on Fourier fractional entropy and wavelet energy entropy for gingival image segmentation, and several classification and optimization techniques are combined.	Periodontal Disease	Periodontal Diseases	Periodontics	180	Photographs	(1) FRFE+PSO	(7) SEN,SPE, PRC,ACC, F1,MCC,FMI	SEN 79; SPE80.89; PRC 80.55; ACC79.94; F1 79.75; MCC59.92; FMI 79.76
[106]	Wenyi Lian et al.	2024	Sweden	Improve AI-based oral cancer detection by predicting through exfoliative cytology	Oral Cancer	Oral Cancer	Stomatology	766.565	Histopathological examination	(3) MMTM,HcCNN,CAFNet	(5) F1,ACC,AUROC,SEN,PRC	Model CAFNet F1 0.8334; ACC 0.9179; ROC AUC 0.9686; SEN 0.8994; Prec 0.7934; Model HcCNN F1 0.8243; ACC 0.9141; ROC AUC 0.9591; SEN 0.8797; PRC 0.7887; Model MMTM F1 0.8151; ACC 0.9124;

												ROC AUC 0.9556; SEN 0.8541; PRC 0.7978
[91]	Hollie Black et al.	2024	United Kingdom	To investigate this with regards to HNC and identify which algorithm works best to classify malignant patients.	Oral Cancer	Oral Cancer	Stomatology	885	Clinical data	(6) OR,RF,LSS,Ridge,Elastic net,LDA	(4) AUC,B-ACC,SPE,SEN	Model Ordinal regression AUC0.66; ACC0.64; SPE0.77; SEN0.50; Model RF AUC 0.58; ACC0.60; SPE0.73; SEN0.46; Model classification tree AUC0.62; ACC0.60; SPE0.74; SEN0.47; Model Lasso AUC 0.64; ACC0.59; SPE0.75; SEN0.44; Model Ridge AUC0.65; ACC0.60; SPE0.75; SEN0.44; Model Elastic net AUC0.64; ACC0.59; SPE0.75; SEN0.43; Model Linear discriminant analyses AUC0.64; ACC0.60; SPE0.75; SEN0.45
[30]	Vyshiali Sivaram et al.	2023	India	To examine and compare the accuracy of several texture analysis techniques, such as Grey Level Run Length Matrix (GLRLM), Grey Level Co-occurrence Matrix (GLCM), and wavelet analysis in recognizing dental cyst, tumor, and abscess lesions.	Cystic lesions, dental abscesses, tumoral lesions include ameloblastoma, odontoma, ameloblastic fibroma, adenomatoid odontogenic tumor, hemangioma,	Bone Necrosis and Infections; Anatomical Variations; Odontogenic Cysts and Tumors	Stomatology	172	Radiographic examination and Clicial data	(3) WA,GLCLM,GLRLM	(5) ACC,MCC,SEN,SPE,PPV	Model GLCLM ACC 98; MCC 0.97; SEN97; SPE100; PPV100; Model GLRLM ACC95; MCC0.89; SEN94; SPE95; PPV94; Model Wavelet analysis ACC91; MCC0.82; SEN90; SPE90; PPV93

					enostosis, exostosis, cementoblastoma, torus mandibularis, torus palatinus, myxoma, osteoma, and osteoid osteoma.							
[111]	Sung-Hwi Hur et al.	2021	Korea	To develop and validate fve ML models designed to predict DCM2Ms arising from the proximity to M3Ms to provide guidelines for clinical decision making.	Dental Caries	Dental Caries and Related Conditions	Cariology	2642	Radiographic examination	(5) LR,RF,ANN,SVM,XGB	(3)SEN,SPE,AUROC	Model LR ACC0.81; SEN0.81; 0.81AUROC0.881; Model RF ACC0.83; SEN0.79; SPE0.83 AUROC0.881; Model ANN ACC0.80; SEN0.82; SPE0.80 AUROC0.882; Model SVM ACC0.81; SEN0.80; SPE0.81 AUROC0.876 Model XGB ACC0.81; SEN0.79; SPE0.81 AUROC0.891
[46]	Dong Wook et al.	2018	Koreia	To build and validate five types of machine learning models designed to predict the occurrence of BRONJ associated with dental extraction in patients taking bisphosphonates for the management of osteoporosis	Osteonecrosis	Bone Necrosis and Infections	Stomatology	125	Clinical data	(5) RF,ANN,SVM,LR,DT	(3) AUC,SEN,SPE	Model RF AUC 0.973 SEN 100; SPE83.3; Model ANN AUC0.915; SEN100; SPE76.7; Model SVM AUC0.882; SEN81.8; SPE86.7; Model LR AUC0.844 SEN90.9; SPE70.0; Model DT AUC0.821; SEN90.0; SPE73.3

[78]	Bonfim et al.	2024	Brazil	To predict adolescents with untreated dental caries using Sisson's theoretical model.	Dental Caries	Dental Caries and Related Conditions	Cariology	615	Clinical data	(3) XGB,DT,LR	(4) SEN,SPE, ACC,AUC	Model XGB AUC0.84; ACC 0.75; SEN0.42; SPE0.92 Model DT AUC0.81; ACC0.79; SEN0.44; SPE0.88; Model LR AUC 0.73; ACC0.76; SEN0.40; SPE0.80
[47]	Soualihou Ngnamsi et al.	2022	Koreia	To propose an identification mechanism to prevent the population from being affected by diseases like dental caries, gum disease, oral cancer, etc	Dental Caries	Dental Caries and Related Conditions	Cariology	22.371	Clinical data	(1) MMDCP	(4) ACC,F1,SEN,PRC	ACC 90; F1 89; SEN 90; PRC 89
[31]	Jaiswal et al.	2022	India	The current article has descended into a new solution for maximizing disease classification by utilizing the diferente pretrained deep learning models. The proposed study has a stepdown in the multi-disease classification model, which is defined as multiple parameters in the proposed framework being upgraded to classify multi-disease features.	Tooth wear, periapical, periodontitis, tooth decay, missing tooth, and impacted tooth	Developmental Anomalies; Periodontal Diseases	Periodontia	500	Radiographic examination	(1) XGB	(5) ACC,PRC, SEN,SPE, F1	ACC 93%; PRC82; SPE 93; SEN 93; F1 87

[85]	Heba M. Afify et al.	2023	Egypt	Proposes a novel model using deep transfer learning to predict oral squamous cell carcinoma (OSCC) histopathological images with gradient-class activation mapping (Grad-CAM) to locate the lesion area in the images	Oral Cancer	Oral Cancer	Stomatology	1224	Histopathological examination	(10) ResNet-101, GoogleNet, SqueezeNet, ShuffleNet, AlexNet, DenseNet-201, InceptionResNet-V2, EfficientNet-b0, VGG-19 and NasNetMobile	(5) ACC,SEN, SPE,F1,PRC	Model ResNet101 ACC 100; SEN 100; SPE100; F1100; PRC100; Model GoogleNet ACC98.11; SEN100; SPE97.73; F1 94.74; PRC 90 Model SqueezeNet ACC96.23; SEN100; SPE95.45; F1 90; PRC 81.82; Model ShuffleNet ACC96.23; SEN88.89; SPE97.73; F188.89; PRC 88.89 Model AlexNet ACC96.23; SEN100; SPE95.45; F1 90; PRC 81.82; Model DenseNet201 ACC96.23; SEN77.78; SPE100; F1 87.50; PRC100; Model InceptionResNetv2 ACC 96.23; SPE88.89; SPE97.73; F188.89; Prec88.89 Model EfficientNet-b0 ACC94.34; SEN88.89; SPE95.45; F1-SCORE80; Prec84.21 Model VGG-19 ACC88.68; SEN100; SPE86.36; F1 60; Prec75 Model NasNetMobile ACC 94.33; SEN88.89; SPE94.45; F1 80; PRC 84.21
[56]	Salehi et al.	2020	United States	To use seven optimization methods, namely Adadelta, AdaGrad, Adam, AdaMax, Nadam, RMSProp and Stochastic Gradient Descent (SGD) to improve	Dental Caries	Dental Caries and Related Conditions	Cariology	2139	Photographs	(1)CNN	(5) ACC,SEN, SPE,PPV, NPV	*Nadam*ACC88.70; SEN81.25; SPE93.01; PPV87.03; NPV89.57; *Adam* ACC86.86; SEN75.79; SPE93.26;PPV86.66; NPV86.96. AdaGrad ACC81.60; SEN65.06; SPE91.15; PPV80.84; NPV81.88 *RMSProp*

				the accuracy of a CNN classifier for dental caries diagnosis.								ACC79.87; SEN63.17; SPE89.51; PPV77.67; NPV80.80; SDG ACC75.03; SEN51.42; SPE88.67; PPV72.82; NPV75.97; *AdaDelta* ACC66.54; SEN17.21; SPE95.02; PPV66.67; NPV66.53
[23]	Saif Ur Rehman et al.	2024	China	To present a novel approach that combines two TL models, namely EfficientNetB0 and EfficientNetB1	Oral Cancer	Oral Cancer	Stomatology	5143	Photographs	(1) Feature Fusion self-attention Approach	(4) ACC,PRC, SEN,F1	PRC98.73; SEN98.82; F198.82; ACC98.83
[69]	Eid Albalaw et al.	2024	Saudi Arabia	To explore the discriminative potential of histopathological images of oral epithelium and OSCC.	Oral Cancer	Oral Cancer	Stomatology	1224	Histopathological examination	(1) EfficientNetB3	(4) ACC,PRC, SEN,F1	ACC: 99.13; PRC 99; SEN 99; F199
[83]	Arman Haghanifar et al.	2023	Canada	To develop a specialized model architecture based on pretrained models and the capsule network to detect tooth decay on Panoramic x-rays efficiently	Dental Caries	Dental Caries and Related Conditions	Cariology	5948	Radiographic examination and Clicial data	(1) PaXNet	(4) ACC,PRC, SEN,F0.5	ACC 86.05; PRC 89.41; SEN 50.67; F0.5 0.78
[74]	Mirzaei et al.	2024	Turkey	To evaluate the ability of deep learning models to classify mandibular molar teeth according to the presence and	Dental Caries	Dental Caries and Related Conditions	Cariology	1200	Radiographic examination	(5) EfficientNet-b0,GoogLeNet,Inception-v3,ResNet-	(3) PRC,SEN, F1	Model VGG-19 PRC 0.9111; SEN 0.9127; F1 0.9115; Model ResNet-50 PRC 0.8980 SEN 0.8975; F1 0.8957; Model Inception-v3 PRC 0.8933; SEN 0.8943; F1 0.8925; Model GoogLeNet Prec0.8558;

				proximity of caries to the dental pulp						50,VGG-19		SEN 0.8573; F1 0.8543; Model EfficientNet-b0 PRC 0.8373; SEN 0.8384; F1 0.8350
[57]	Ogwo et al.	2024	United States	To predict the dental caries outcomes in young adults from a set of longitudinally-obtained predictor variables and identify the most important predictors using machine learning techniques.	Dental Caries	Dental Caries and Related Conditions	Cariology	258	Clinical data	(4) LR,GBM,GLM,XGB	(4) ACC,PRC, SEN,AUROC	Model LASSO ACC83.7; PRC 85.9; SEN 93.1; ROC AUC80.6
[62]	Nakano et al.	2018	Japan	Present an effective deep learning approach to predict bad breath from salivary microbiota	Halitosis	Halitosis	Stomatology	90	Salivary Test	(2) SVM,Deep learning model (não falou o nome só se referiu assim)	(3) ACC,SEN, SPE;	Model Deep learning SEN100; SOE93.3; ACC96.7; Model SVM SEN77.8; SPE80; ACC78.9
[92]	Najla S Dar-Odeh et al.	2010	Jordan	To construct and optimize a neural network that is capable of predicting the occurrence of recurrent aphthous ulceration (RAU) based on a set of appropriate input data	Recurrent Aphthous Ulceration	Mucosal Lesions	Stomatology	96	Clinical data	(1) Optimized neural network	(1) ACC	ACC : 90
[89]	Razieh Agheli et al.	2024	Iran	To establish the early prediction models of radiation-induced oral	Mucositis	Mucosal Lesions	Stomatology	49	Clinical data,dosimetric data	(1) RF	(6) AUC,SEN, SPE,ACC, PRC,F1	AUC 91.7; SEN83; SPE100; ACC90; Prec100; F191

				mucositis (RIOM) based on baseline CT-based radiomic features (RFs), dosimetric data, and clinical features by machine learning models for head and neck cancer (HNC) patients								
[105]	Soares et al.	2018	Portugal	Applying several different data mining models for the prediction of radiation-induced complications in the salivary glands of head and neck cancer patients irradiated with IMRT	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	138	Clinical data and Dosimetric data	(6) RF,SB,SVM,NN,MBC,LR	(1) AUC	Model RF AUC0.73 ACC 72%; SEN 83%; Model SVM 0.66 Modelo Stochastic Boosting AUC 0.65; Model NN AUC 0.61; Modelo LR AUC 0.47
[48]	Choi et al.	2022	South Korea	Develop and validate five machine learning models designed to predict actinomytotic osteomyelitis of the jaw	Actinomytotic Osteomyelitis	Bone Necrosis and Infections	Stomatology	222	Clinical data	(5) LR,RF,ANN,SVM, XGB,	(6) AUC,ACC, SEN,SPE, PPV,NPV	Model RF AUC 0.883; ACC 82; SEN0.86; SPE0.80; PPV0.67; NPV0.92; Model SVM AUC 0.879 ; ACC0.82; SEN0.76; SPE0.84; PPV0.70; NPV0.88; Model XGB AUC0.872 ; ACC0.79; SEN0.90; SPE0.73; PPV0.61; NPV0.94; Model LR AUC0.83; ACC0.80; SEN0.81; SPE0.80; PPV0.65; NPV0.90 ; Model ANN AUC0.81; ACC0.79; SEN0.76; SPE0.80; PPV0.64; NPV0.88
[43]	Park et al.	2021	Korea	Develop machine learning-based prediction models	Dental Caries	Dental Caries and	Cariology	4195	Clinical data	(4) LR,RF, XGB,Light GBM	(5) AUROC,A	Model XGBAUROC 0.785; ACC0.237; SEN0.769; SPE0.581; MCC0.148;

				for early childhood caries and compare their performance with the traditional regression model		Related Conditions					CC,SEN,SPE,MCC	Model LR AUROC 0.784; ACC0.235; SEN0.799; SPE0.531; MCC0.258; Model RF AUROC0.780; ACC0.245; SEN0.759; SPE0.400; MCC0.040; Model LightGBM AUROC 0.774; ACC 0.236; SEN 0.782; SPE 0.546; MCC 0.204
[44]	Kwack et al.	2023	Korea	Develop and validate machine learning (ML) models using H2O-AutoML, an automated ML program, to predict medication-related osteonecrosis of the jaw (MRONJ) in osteoporosis patients undergoing tooth extraction or implantation.	Osteonecrosis	Bone Necrosis and Infections	Stomatology	340	Clinical data	(5) GLM,DRF, GBM, stacked ensemble, extreme gradient boosting,XGB	(3) AUC,SEN, SPE	Model GBM AUC 0.752; SEN88.6; SPE52.8
[79]	Araujo Faria et al.	2021	Brazil	Present an artificial intelligence neural network-based method to predict and detect regular caries or CRR in HNC patients undergoing RT using features extracted from panoramic radiographs	Radiation Caries	Dental Caries and Related Conditions	Cariology	15	Radiographic examination	(1) ANN k and PyRadiomics features	(2) ACC,AUC	ACC 99.2; AUC 0.9886;

[45]	Lee et al.	2024	Korea	Predict xerostomia with salivary flow rate in elderly based on artificial intelligence	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	829	Clinical data and Salivary test	(4) LR,LDA,KNN,MLP	(1) AUC	Model MLP AUC 0.64; Model KNN AUC 0.63;Model LDA 0.62; Model LR 0.62
[63]	Mameno et al.	2021	Japan	Create a model to predict the onset of peri-implantitis using machine learning methods and intuitive interactions between risk indicators	Peri-Implantitis	PeriImplant Diseases	Periodontics	254	Clinical data	(3) LR,SVM,RF	(5) AUC,ACC, PRC,SEN, F1	Model RF AUC: 0.71, ACC0.70, PRC 0.72, SEN 0.66; F1 0.69; Model SVM AUC 0.64 ; Model LR AUC0.63
[24]	Li et al.	2023	China	To propose a multitask network (MTN) Raman spectroscopy classification model that utilizes a shared backbone network to simultaneously obtain different clinical staging and histological classification diagnoses	Oral Cancer	Oral Cancer	Stomatology	36	Clinicl data	(3) MTN-ResNet50, MTN-VGG16,SVM	(3) ACC,SEN, SPE;	Model ResNet50 ACC 94.30; SPE98.48; SEN95.25; Model VGG-16 ACC 90.85; SPE97.58; SEN92.14; Model SVM ACC86.15; SPE96.32; SEN88.11
[64]	Noguchi et al.	2023	Japan	Investigate the possibility of diagnosing SS through non-contact observation and imaging of the tongue surface	Sjögren’s Syndrome	Salivary Gland Disorders and Xerostomia	Stomatology	60	Clinical data,Photographs and Salivary test	(3) LR,SVM,RF	(7) ACC,SEN, SPE,PRC, F1,KS,AP	Model SVM ACC 0.713; SEN 0.575; SPE 0781; PRC 0.591; F score 0.546; Kappa 0.354; mAP 0.664 Model RF ACC 0.615; SEN 0.692; SPE 0.580; PRC 0.448; F1 0.529; Kappa 0.239; mAP 0.609; Model LR ACC 0.432; SEN 1000; SPE 0.169; PRC

												0.361; F1 0.529; Kappa 0.119; mAP0.560
[25]	Zhang et al.	2023	China	To develop a machine learning model to predict the risk of molar incisor hypomineralization (MIH) and identify factors associated with MIH in a fluorosis-endemic region in central China.	Molar incisor hypominer alization	Dental Caries and Related Conditions	Dentistics	1568	Clinical data	(1) LR	(3) AUC,ACC, SPE	AUC 0.72; ACC 70; SPE 72
[98]	Enevold et al.	2023	Denmark	To evaluate if, and to what extent, machine learning models can capture clinically defined Stage III/IV periodontitis from self-report questionnaires and demographic data	Periodonta l Disease	Periodontal Diseases	Periodonti cs	1476	Clinical data	(2) XGB,RF	(11) FN,FP,AU ROC,AUP RC,KS,SE N,SPE,PP V,NPV,F1, BS	FN 43;FP 67; AUROC 0.69; AUPRC0.45; Kappa0.35; SEN0.58; SPE0.80; PPV 0.47; NPV0.86; F1 0.52; BS 0.18
[86]	Zayed et al.	2024	Egypt	Develop software to act as an AI-based program to diagnose oral diseases based on clinical and histopathological data	Salivary gland neoplasms , premalign ant, immune-mediated lesions, oral cancer and oral reactive lesions	Salivary Gland Disorders and Xerostomia; Potentially Malignant Oral Lesions; Mucosal Lesions; Oral Cancer	Stomatolo gy	3000	Clinical data, Photograph s,Radiograp hic examination and Histopathol ogical examination	(1) DOD	(8) SEN,SPE, PPV,NPV, PLR,NLR, ACC,F1	SEN 84; SPE 80; PPV80.77; NPV 83.33; PLR 4.20 ; NLR 0.20; ACC 82.; F1 0.824

[97]	Chu et al.	2024	Netherlands	Improve the prediction of late xerostomia using three-dimensional information from radiation dose distributions, computed tomography images, segmentations of organs at risk and clinical variables with deep learning (DL)	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	120	Clinical data,Dosimetric data and Radiograpich examination	(3) DCNN,EfficientNetV2-S,ResNet	(3) AUC,BS,R2	DCNN AUC 0.79 BS 0.18; R2 0.27 Model EfficientNetV2-S 0.78; Brier score 0.18; R2 0.25; Model ResNet AUC 0.78; BS 0.18; R2 0.28
[101]	Fanizz et al.	2022	Italy	To develop a radiomics-based support tool,exploiting pre-treatment CT images to predict the risk of late xerostomia at 3 months after radiotherapy in patients with oropharyngeal cancer (OPC)	Xerostomia	Salivary Gland Disorders and Xerostomia	Stomatology	61	Clinical data and Radiomic characteristics	(1) SVM	(5) AUC,F1,ACC,SEN,SPE	AUC 81.17; F1 76.92; ACC 83.33; SEN 71.43; SPE 90.91
[32]	Lee James et al.	2021	India	Report the integration of OCT images with automated image processing and deep learning to reduce subjectivity in image interpretation, and is a large-scale in	Oral Cancer	Oral Cancer	Stomatology	232	Photographs	(3) Algorithm-Score,DensNet-201-SVM,Inception-ResNet-v2-SVM	(4) SEN,SPE, PPV,NPV	Model Algorithm-Score SEN 95;SPE 76;PPV 95;NPV 76; Model DensNet-201-SVM SEN 84; SPE 82; PPV 78; NPV 86; Model Inception-ResNet-v2-SVM SEN 83; SPE 69; PPV 58; NPV 89

				vivo validation in delineating OSCC and dysplastic lesions from normal/benign lesions in community and tertiary care settings.							
[33]	Goswami et al.	2021	India	Propose a CNN-based model to classify healthy and unhealthy teeth images for computer-aided diagnosis	Dental Caries and Oral Cancer	Oral Cancer; Dental Caries and Related Conditions	Stomatology	598	Photographs	(1) CNN	(4) ACC,PRC, SEN,F1	Dental caries PRC0.92; SEN 084; F1-score 0.88 ACC 83; Câncer PRC 0.97; SEN 0.97; F1 0.97; ACC 94
[34]	Vasantha Kavitha et al.	2020	India	To predict CEO from efficient decision-making methods to predict cancer from hybrid algorithm; fuzzy-based decision tree algorithm	Oral Cancer	Oral Cancer	Stomatology	161	Clinical data and Salivary test	(1) Fuzzy-based decision tree algorithm	(4) ACC,SEN, SPE,PRC	ACC 90; SEN 95; SPE 83; PRC 91
[82]	Patel et al.	2021	Canada	Proposes a methodology for predicting oral cancers using epigenomics and machine learning methods.	Oral Cancer	Oral Cancer	Stomatology	582	Clinical data	(8) NB,K-NN,SVM-Kl; SVM with Radial Kernel,DT, RF,XGB,MLP	(4) ACC,SEN, SPE,AUC	Model NB ACC 0.94; SEN 0.91; SPE 0.97; AUC 0.94; XGB ACC 0.92; SEN 0.88; SPE 0.96; AUC 0.92; Model RF ACC0.92; SEN0.87; SPE 0.96; AUC 0.92; Model KNN 0.87; SEN 0.79; SPE 0.94; AUC 0.87; Model DT ACC 0.69; SEN 0.49; SPE 0.88; AUC 0.69 Model MLP ACC 0.5; SEN 0.2; SPE 0.8; AUC 0.5
[58]	Stewar et al.	2015	United States	Describe preliminary risk	Dental Caries	Dental Caries and	Cariology	1938	Clinical data	(1) Classificati	(2) SEN,SPE	SEN 62%; SPE77%

				assessment models developed by the U		Related Condition				on And Regression Tree (CARTIe)		
[35]	Trivedi et al.	2025	India	Use the CNN model and VGG-16 for the identification and detection process	Oral Cancer	Oral Cancer	Stomatology	38	Histopatologic and Photographs	(2) CNN,VGG-16	(1) ACC	ACC: 87.8%
[36]	Muhammed Yaseer P	2025	India	Develop a rapid, accurate and non-invasive approach to oral cancer detection that can be easily incorporated into standard clinical practice	Oral Cancer	Oral Cancer	Stomatology	5199	Photographs	(1) ResNet50	(4) ACC,PRC, SEN,F1	ACC 0.89; PRC 0.79; SEN 0.88; F1 0.83
[76]	Montenegro et al.	2008	Brazil	This paper presents an experimental study of the application of machine learning methods to the problem of caries prediction	Dental Caries	Dental Caries and Related Conditions	Cariology	3864	Clinical data	(4) DT,MLP,KNN,SVM	(1) AUC	Model MLP AUC 0.845; Model KNN AUC 0.817; C4.5 AUC 0.798; Model SVM AUC 0.763;
[37]	Lakshmi T.K et al.	2022	India	The current research paper is a result of using such Machine Learning approaches for the prediction of Periodontitis, a most common gum disease which leads to severe complications like	Periodontal Disease	Periodontal Diseases	Periodontics	206	Clinical data	(6)NB,SVM,RF,KNN,LR,DT	(4)PRC,SEN,F1,ACC	Model KNN PRC 1.0; SEN 0.50; F1 0.67 ACC 98.3; Model SVM PRC 1; SEN 0.75; F1 0.86; ACC 96.7; Model RF PRC 0.83; SEN 1.0; F10.91; ACC 96.7 Model DT PRC 0.75; SEN 1; F1 0.86 ACC 96.7; Model NB PRC 1; SEN 1; F1 1; ACC 95.1; Model LR PRC 0.62; SEN 1; F1 0.77; ACC 93.5

		tooth supporting structure loss like bone loss around tooth, ligament loss and finally the tooth loss if left untreated	

Algorithms Abbreviations:: 23DNN = 2-D-3-D Hybrid Convolutional Neural Network. 3D rCNN = Three-Dimensional Residual Convolutional Neural Network. ADB = AdaBoost. ANN = Artificial Neural Network. ANNPy = ANN K and PyRadiomics Features. BLR = Base Logistic Regression. CARTle = Classification And Regression Tree. DA = Decision Analysis. DCNN = Deep Convolutional Neural Network. DOD = Diagnosis Oral Diseases Software. DT = Decision Tree. DTfzy = Fuzzy-Based Decision Tree Algorithm. ETC = Extra Trees Classifier. GBDT = Gradient Boosting Decision Tree. GNB = Gaussian Naive Bayes. GSOESNN = Echo State Neural Networks Optimized by Gravitational Search. KNN = K-Nearest Neighbors. LR = Logistic Regression. LSR = Lasso Regression. LSS = Lasso. LSTM = Long Short-Term Memory. MLP = Multilayer Perceptron. MMDCP = Multi-Modal Dental Caries Prediction. NB = Naive Bayes. OR = Ordinal Regression. SB = Stochastic Boosting. SGD = Stochastic Gradient Descent. SVC = Support Vector Classifier. SVM = Support Vector Machine. WA = Wavelet Analysis. XGB = Extreme Gradient Boosting.

Metrics Abbreviations:: AUC = Area Under the Curve. ACC = Accuracy. B-ACC = Balanced Accuracy. BS = Brier Score. D-ACC = Diagnostic Accuracy. DSC = Dice Similarity Coefficient. F1 = F1 Score. FMI = Fowlkes-Mallows Index. FN = False Negative. FP = False Positive. HUM = Hypervolume Under the Manifold. IoU = Intersection Over Union. KS = Kappa Score. LNR = Likelihood Negative Ratio. LPR = Likelihood Positive Ratio. NPV = Negative Predictive Value. PPV = Positive Predictive Value. PRC = Precision. S-ACC = Segmentation Accuracy. SEN = Sensitivity. SPE = Specificity. TN = True Negative. TP = True Positive.

*= not reported

APPENDIX 4 - Categorization of Diseases

Category	Included Diseases / Lesions
Dental Caries and Related Conditions	Dental caries; Radiation caries; Tooth decay; Tooth wear; Molar-incisor hypomineralization (MIH)
Periodontal Diseases	Periodontal disease; Periodontitis
Peri-Implant Diseases	Peri-implantitis
Periapical Lesions	Periapical lesion
Odontogenic Cysts and Tumors	Odontogenic cysts; Ameloblastoma; Odontogenic keratocyst (OKC); Dentigerous cyst; Radicular cyst; Simple bone cyst; Adenomatoid odontogenic tumor; Odontoma; Ameloblastic fibroma; Cementoblastoma; Myxoma; Osteoma; Osteoid osteoma
Oral Cancer	Oral cancer
Oral potentially malignant disorders	Oral leukoplakia; Proliferative verrucous leukoplakia; Hairy leukoplakia; Erythroplakia; Actinic cheilitis; Oral submucous fibrosis
Mucosal Lesions	Lichen planus; Mucositis; Recurrent aphthous ulceration; General oral lesions; Reactive oral lesions; Lichenoid change
Salivary Gland Disorders and Xerostomia	Xerostomia; Sjögren’s syndrome
Bone Necrosis and Infections	Osteoradionecrosis; Osteonecrosis; Actinomycotic osteomyelitis; Dental abscess
Fungal Infections	Candidiasis
Tongue Lesions	Fissured tongue; Geographic tongue; Black hairy tongue; Pigmented fungiform papillae; Tongue coating; Hairy tongue; Fissures; Papillary atrophy; Erosion; Ulcer; Hyperkeratotic change; Papillary hypertrophy; Artifacts
Halitosis	Halitosis
Syndromes	Gorlin syndrome
Developmental Anomalies	Missing tooth; Impacted tooth
Anatomical Variations	Torus mandibularis; Torus palatinus; Enostosis; Exostosis; Idiopathic osteosclerosis