Universidad Europea

GRADUATION PROJECT

Degree in Dentistry

ARTIFICIAL INTELLIGENCE IN THE DIAGNOSIS AND TREATMENT OF ORAL DISEASE

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ABSTRACT

Introduction: An estimated 3.5 billion people suffer from oral diseases globally, making it a perpetually increasing concern. Traditional dental diagnostic methods are time consuming and often subjective to the dentist. This emphasises the need to integrate artificial intelligence (AI) in order to provide an early, accurate diagnosis, consequently, improving treatment outcomes. **Objectives:** To carry out a literature review to analyse the effectiveness of a plethora of AI-based diagnosis for different oral diseases when compared to traditional diagnostic methods. **Methods:** A comprehensive search was conducted in PubMed and IEEE Xplore with key terms and Boolean operators. After a thorough screening process, a total of 25 studies were selected using the specified inclusion and exclusion criteria. **Results:** AI-based diagnosis is commonly carried out using deep learning algorithms and convolutional neural networks. Across a wide range of oral diseases such as dental caries, periodontitis, temporomandibular disorders and tooth loss the diagnostic accuracy using AI algorithms was found to be higher than traditional diagnostic methods. AI helped reduce the time needed for diagnosis, improved treatment planning and patient outcomes. **Conclusions:** AI-based diagnosis was found to be more effective than conventional diagnostic methods consequently resulting in better treatment outcomes. The use of AI can be integrated with a dental professional’s opinion in order to further improve the dental diagnosis. Although AI presents limitations it represents great potential in improving diagnosis and treatment in dentistry.

KEYWORDS

Dentistry, artificial intelligence, diagnosis, oral diseases, deep learning.

RESUMEN

Introducción: Se estima que 3.500 millones de personas padecen enfermedades orales, lo que representa una preocupación creciente. Los métodos diagnósticos tradicionales en odontología requieren mucho tiempo, y son subjetivos. Esto resalta la necesidad de integrar la inteligencia artificial (IA) para proporcionar un diagnóstico temprano y preciso que, como consecuencia, mejora los resultados del tratamiento; **Objetivos:** realizar una revisión sistemática para analizar la eficacia de diagnósticos basados en IA para diferentes enfermedades orales en comparación con los métodos diagnósticos tradicionales; **Metodología:** Se realiza una búsqueda en las bases de datos PubMed e IEEE Xplore utilizando términos clave y operadores booleanos. Tras un proceso de selección, se eligieron 25 estudios basados en criterios de inclusión y exclusión; **Resultados:** Los estudios mostraron que el diagnóstico con IA se realiza con algoritmos de aprendizaje profundo y redes neuronales convolucionales. En enfermedades como la caries dental, periodontitis, enfermedades temporomandibulares y pérdida dental la precisión diagnostica con IA fue superior a la de métodos tradicionales. La IA ayuda a reducir el tiempo necesario para el diagnostico, mejora la planificación del tratamiento y los resultados para los pacientes; **Conclusiones:** El diagnóstico basado en IA es más eficaz que los métodos convencionales, lo que resulta en mejores resultados de tratamiento. El uso de IA puede integrarse con la opinión del profesional para mejorar aún más el diagnóstico. Aunque la IA presenta limitaciones, representa un gran potencial para mejorar el diagnóstico y tratamiento en odontología.

PALABRAS CLAVE

Odontología, inteligencia artificial, diagnóstico, enfermedades orales, aprendizaje profundo.

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1 INTRODUCTION

1.1 Definitions

The following section defines key terminology that is fundamental to the understanding of this documentary review.

1.1.1 Artificial Intelligence

Artificial intelligence (AI) is the emulation of human intelligence in machines (1–4). AI uses a plethora of algorithms and modelling designed to replicate human intelligence and cognitive abilities such as learning, making informed decisions, problem-solving and pattern recognition (1,2,4,5). AI can improve its accuracy constantly as it learns from new data, making it a pivotal development of technology. The use of AI is transforming diagnosis and treatment across a wide range of healthcare fields, including dentistry (6,7).

1.1.2 Oral diseases

Oral diseases include many diseases that affect the oral cavity, jaws and facial structures (8). Some common oral diseases include dental caries, periodontal disease, oral cancers, and temporomandibular disorders (9). Oral diseases are influenced by various risk factors including poor oral hygiene, dietary habits, genetic predisposition, and environmental influence (10). The diagnosis of oral diseases is commonly done through clinical examinations, imaging studies, and laboratory tests (11). Accurate diagnosis through these methods allows for early detection of the disease and better management and prevention (6).

1.1.3 Diagnosis

Diagnosis in dentistry includes identifying the cause of the disease based on patient history, clinical exploration and complementary diagnostic testing. Traditional methods rely on subjective interpretation (2,5). However, the integration of AI in diagnosis helps increase diagnostic accuracy by standardising interpretations (2,5). The current use of AI-based diagnostic tools can detect early signs of dental decay, abnormalities in soft tissues and structural deformities, therefore helping dentists with a comprehensive diagnosis (3,12).

1.1.4 Treatment

Treatment in dentistry includes devising an individualised plan to address the oral health needs of a patient, also including preventative recommendations tailored to a patient's individual needs. It could include choosing specific treatments, predicting the outcome and monitoring the future progress of the disease after treatment. AI has proven to be effective as it helps to optimise treatment plans by accurately analysing patient data and predicting the outcome. As a result, AI proves to offer minimally invasive treatment options whilst also being cost effective for the patient (3,13).

1.2 Subject background

Unlike traditional computer programs, created to follow specific information, AI, since its development in the 1950s, is a continually advancing area of computer science(2,4). Over time, as computational power has gone on to increase, AI systems have become capable of learning from extensive datasets, evolving to be able to conduct complex tasks such as predictive modelling, image and language processing. All of which are tasks commonly used in the field of healthcare (1–3,5,9,12). This breakthrough is having transformative applications in the fields of medicine and dentistry, leading to its application in diagnosis, complex dental imaging, and personalised treatment planning in healthcare (1–5,12–14).

In an overpopulated world, "it is estimated that 3.5 billion people suffer from oral diseases" (15), the most common including: dental caries, periodontal disease, tooth loss and oral cancer. Therefore, there is an increasing need for efficient diagnosis, early detection and treatment (16). The integration of AI in modern dentistry could be proven to become a necessity in order to optimise and improve diagnostic precision and treatment efficacy (16). Advances in AI are resulting in the early identification of disease preventing its progression into complex conditions (6,7,16).

Traditional diagnostic methods for oral diseases include a systematic process starting with the patient's medical and dental history, to reveal lifestyle factors and systemic conditions that may contribute to oral pathologies (16). The anamnesis is followed by visual examination of the oral cavity, checking for abnormalities or signs of oral disease (11,16). Systematically, palpation is conducted, which includes the physical examination of the mouth and surrounding structures for changes in texture or tenderness, showing disease (16). After the primary examination has been conducted, complementary testing will take place, where dental x-rays are commonly used to identify underlying diseases, such as dental caries, that may not be shown upon standard visual examination (16). Other complementary tests could include biopsy, microbial culture, or smear testing (14,16). (Refer to Annex 9.1 Figure 6 and 7)Traditional diagnostic methods are time consuming, labour intensive and often depend on subjective interpretation, which can lead to variations in treatment planning (2,5). This diagnostic variability produced by traditional diagnostic methods, highlights the necessity for a standardised, precise approach. AI has shown effectiveness in replicating and enhancing traditional diagnostic methods. AI-powered image analysis tools are now being used to conduct a visual examination by analysing images to detect abnormalities, comparing patient images against large datasets with solutions (17). AI is more frequently being used to detect and interpret dental radiographs with increasing accuracy (4,8,12,13). Deep learning (DL) models have been used to assess tooth decay and bone loss, diagnosing subtle signs of periodontal disease and even early-stage oral cancers (14).

The use of AI in dentistry includes various diagnostic and treatment applications. AI can be used to process radiographic images to detect the presence of dental caries, tumours, cysts and periodontal disease with high accuracy (4,8,11–13). Some deep learning (DL) models are able to identify images that indicate pathology, providing dentists with valuable information. AI is also being used to predict the progression of oral diseases, for example oral cancer (11). This is improving the efficiency of implementing preventive factors sooner (2).

1.3 Theoretical framework

AI systems operate by processing data through a plethora of mechanisms; the primary methodologies are centred on machine learning (ML) and deep learning (DL) algorithms (1–3,5,9,13,18). These methodologies allow AI to analyse complex datasets, identify patterns and make predictions accordingly, all of which are essential in diagnostic and treatment applications (1,2,4,5).

For diagnostic purposes in dentistry, AI systems often use ML, which easily identifies patterns within diverse data sets through two types of learning: supervised learning and unsupervised learning (3). Supervised learning is where input data is associated directly with specific known outcomes (11). In oral disease diagnosis, supervised learning models analyse different radiographic images previously annotated by experts to highlight features associated with specific conditions, for example dental caries (1,5,13). Once trained, the algorithm learns to identify and recognise these patterns and can apply this knowledge to new unlabelled radiographs (13). This process results in AI improving diagnostic accuracy by enabling the system to detect subtle features that may be overlooked in a traditional diagnostic approach (8).

In contrast, another model used is unsupervised learning, where AI identifies patterns, relationships, or groups within the data autonomously without predefined categories (13).

Unsupervised learning is particularly valuable in creating clusters of the population depending on their common characteristics, for example age, oral hygiene habits or genetic predisposition to an oral disease (13). Unsupervised learning facilitates a deeper understanding of oral disease prevalence across different demographics, helping to develop specific preventative strategies and tailored treatment plans (2,13).

Amongst the most successful ML applications in dentistry, lies a subset known as deep learning (DL), which has significantly advanced applications in the analysis of medical and dental imaging (18). In particular, a type of DL model known as convolutional neural networks (CNNs) (4,5,18). CNNs are specialised neural networks which are highly effective in image analysis due to their exceptional ability to process and interpret visual data (19). Unlike traditional ML methods that modify data regarding where specific patterns occur within an image, CNNs can maintain their relative position known as spatial hierarchy of features of an image as they process it (19). CNNs process any radiographic image by dividing the image into small overlapping regions called convolutions (19). Here, both what the feature is and where it is located will be recorded (19). In a CNN the early layers will detect simple features, middle layers will recognise different patterns or shapes that are more complex, and deeper layers will combine these patterns to identify highly specific characteristics of the dental image (2,19). The ability of spatial awareness is essential for detecting cavities, identifying bone loss and even for recognising abnormal growths (3).

More AI methodologies include Artificial neural networks (ANNs) and clinical decision support systems (CDSS) (3,4) ANNs are frequently used due to their ability to process complex imaging data and predict outcomes based on historical trends (3). ANNs are modelled following the function of the human brain, consisting of a wide range of well interconnected nodes that help process information together (3). In dentistry, ANNs are used to analyse Cone Beam Computed Tomography (CBCT) scans that help predict disease progression or assess treatment outcomes (3). The use of CDSS helps integrate AI into real time decision making, as it provides dentists with evidence-based recommendations derived from datasets, therefore helping to optimise and improve the treatment plan and ensuring personalised patient care (3).

AI methodologies such as ML, DL, CNNs, ANNs and CDSS are improving the diagnosis and treatment of oral diseases. They currently work by analysing complex datasets, recognising intricate patterns, and providing specific treatment plans. All these methodologies are driving the advancements in diagnostic precision, treatment effectiveness and providing personalised dental care.

1.4 Current state of the subject

AI is being implemented in the identification and management of dental caries and periodontal disease particularly through radiographic diagnosis (5,9). Currently, AI is transforming the diagnosis and treatment through a plethora of clinical applications. AI algorithms analyse radiographic and CBCT images to detect various lesions, and other dental pathologies with a higher accuracy than manual diagnostic methods (14). Furthermore, it excels in predicting the progression of disease aiding in the early management of chronic diseases. Moreover, AI plays a pivotal role in optimising patient treatment plans (3).

Currently, the application of AI in dentistry has a wide range of advantages including increased precision and consistency, as the model by which AI functions uses the same diagnostic criteria across all cases reducing the variability that may arise from subjective interpretation (2,5). AI has enhanced efficiency, as the process is automated and allows the patient to be treated faster. Additionally, AI systems are capable of personalising the treatment plan accordingly to each patient (2).

Despite its advantages, the integration of AI in dentistry presents various challenges. The use of AI in dentistry presents concern over data privacy issues, particularly regarding the ethical considerations associated with accessing and using extensive patient datasets (3). It is of the utmost importance that patient records and information is protected especially to be able to maintain patient trust. Additionally, dentists need to adapt to AI's emergent technologies, which requires training and time as well as requiring a significant financial investment, making them less accessible to smaller clinics (8). While many ongoing challenges exist within AI, advancements are addressing these challenges. There has been an increase in efforts to create cost effective AI solutions and provide accessible training programs for dentists to use the AI effectively. Additionally, enhanced cybersecurity measures are being developed to ensure ethical use and patient data protection (9). As AI continues to develop, its constant integration into dentistry is improving diagnostic accuracy, treatment efficacy and patient outcomes, whilst managing its current limitations by finding active solutions.

1.5 Justification

The use of AI in the diagnosis and treatment of oral diseases addresses critical gaps in traditional dental practices, making this research necessary. The use of traditional diagnostic methods, whilst effective, are subjective to limitations such as dental expertise, time limitations and the potential for human error. All these limitations can lead to a delay in diagnosing and slowing down the treatment outcome especially for complex cases. AI's ability to analyse large volumes of data rapidly whilst maintaining precision and consistency, directly helps respond to these challenges (2,9).

AI methodologies such as ML and DL algorithms have shown advantages in identifying oral diseases such as dental caries, periodontal disease and oral cancers (2,5,9,12,13). AI's ability to predict the progression of oral diseases helps manage the treatment plan effectively, reducing the risk of complications of the disease. Furthermore, radiographic analysis through AI helps reduce diagnostic variability and enhances clinical efficiency, allowing dentists to give more focus to patient care. The adaptation of AI in dentistry enhances patient satisfaction as AI is able to personalise the patient's treatment plan accordingly to each patient, making a shift towards patient centred care. The development of AI is expanding exponentially leaving smaller clinics struggling to adapt to this rapid evolution of AI. It will be important to identify strategies that can help AI's benefits to be distributed equally across all dental practices.

The application of AI in dentistry is revolutionising diagnostic approaches and treatment planning. Addressing the current gaps and limitations in the use of AI in dentistry will lead to more innovation in diagnosis, efficiency in treatment, and personalised care for the patient.

2 OBJECTIVE

2.1 Primary Objective

The primary objective of this documentary research is:

1. To analyse how artificial intelligence helps dentists in the diagnosis and treatment of oral diseases compared to conventional methods.

To systematically disclose and achieve the primary objective in this study, the following subsidiary objectives have been established:

1.1. To analyse what oral diseases are currently being diagnosed and treated with the aid of AI.
1.2. To assess the different types of AI being used to diagnose and treat oral diseases.
1.3. To measure to what extent AI is effective in diagnosing and treating oral diseases.
(Effectiveness is measured by accuracy, sensitivity, specificity, F1-score, area under curve (AUC), receiver-operating characteristics curve (ROC) and intersection over union (IoU)).
1.4. To analyse if AI-based diagnosis alters treatment outcomes.

2.2 Secondary Objective

Additionally, the secondary objective of this study is:

2. To analyse the different applications of artificial intelligence in order to help dentists specifically in the diagnosis and treatment of oral pre-malignant lesions and oral cancer compared to conventional methods.

The primary objective of this study will be achieved by using the methodology of a systematic review following the PRISMA guidelines (20) with the intention to publish the work in an academic indexed scientific journal.

The secondary objective of this research will generate a literature review that will be presented in the Sociedad Española de Medicina Oral (SEMO) Congress in Madrid (May 8-10, 2025). As of this moment (April 22, 2025), this literature review has been accepted by the scientific committee of the SEMO Congress to be presented.

2.3 Research question

In patients with oral disease, how does artificial intelligence-based diagnosis and treatment compare to conventional methods in terms of diagnostic effectiveness and treatment outcomes?

2.4 Hypothesis

The integration of artificial intelligence-based methodologies is more effective in diagnosing and treating oral diseases in the population, than traditional diagnostic and treatment methods.

2.5 Data measures

In accordance with the PICO (P = population, I = Intervention, C = comparison, O = outcome) (21)) the measures are outlined as follows:

2.5.1 Population

The population of interest includes patients with oral disease, in particular dental caries, periodontal disease, tooth loss, temporomandibular disorders (TMD) and oral cancer as they are the most prevalent oral diseases worldwide (15). Additionally, there will be a secondary focus on dental surgery, implants and orthodontics, as they are commonly associated treatment solutions to oral diseases.

2.5.2 Intervention

The intervention is artificial intelligence-assisted diagnosis and treatment, including all types of artificial intelligence, such as ML or DL methodologies and their subsets (e.g. CCN) to diagnose and manage oral diseases.

2.5.3 Comparison

Studies that reported results for a comparison with conventional diagnostic and treatment methods. A control group consisting of patients with oral disease being diagnosed through visual examinations or radiographs interpreted by professionals.

2.5.4 Outcome

The outcomes of the study will measure the accuracy of the AI-assisted methods compared to conventional methodologies in correctly diagnosing and treating oral disease.

3 MATERIAL AND METHODS

3.1 Eligibility Criteria

In order to correctly choose studies to answer the research question an inclusion and exclusion criteria was discussed and written as a guideline to be used as the basis for study selection. The criteria can be seen below.

3.1.1 Inclusion Criteria

1. Only publications using AI or subfields of AI in the context of a dentistry were eligible.
2. Studies that had a traditional diagnostic method as a comparative factor to AI were selected. Studies that compared AI models against other AI models were also selected to help diversify the search in understanding the effectiveness of different types of AI.
3. Studies considering all patients as previously defined by the PICO question were included.
4. Randomised controlled trials were the study type of choice. However, due to the limited number of studies available investigating AI-based diagnosis in oral diseases, high quality observational studies e.g. cohort and case-control studies were also selected to better reflect real clinical situations.
5. Studies in both English and Spanish were selected
6. Studies published in all years were considered, as it will be important to be able to compare diagnostic effectiveness of AI over time as it has evolved exponentially.
7. In the IEEE Xplore database, only journals were considered.
8. In PubMed, only randomised controlled trials or clinical trials were eligible.
9. In the IEEE Xplore database only journals were considered.

3.1.2 Exclusion Criteria

1. All studies that were not associated to dentistry or dental specialties were excluded.
2. All studies not related to AI were also excluded.
3. Any study that did not meet the requirements of the previously defined PICO research question were excluded.
4. Any studies that did not have at least one of the following quantitative measurements; accuracy, sensitivity, specificity, F1-score, AUC, ROC or IoU to measure effectiveness quantitively were removed.

5. Any literature reviews, scoping reviews and meta-analysis were excluded from this literature review as the focus needs to be on primary data to allow an accurate analysis and to avoid the duplication of studies.
6. Editorials or preprints were excluded to avoid the risk of bias.
7. Any studies not in English or Spanish were removed

3.2 Information sources

The following two electronic databases were queried on March 8, 2025:

1. PubMed (Last accessed March 8, 2025)
2. IEEE Xplore (Last accessed March 8, 2025)

These two databases were selected. PubMed is a large biomedical database essential to the practice of evidence-based dentistry and IEEE Xplore is the world's largest organisation dedicated to advancing technology.

In this literature review, non-academic were not used to maintian the reproducibility of the systematic review.

3.3 Search strategy

To build the search equation, key terms and appropriate Boolean operators were selected aligned with the PICO question.

The search equation in PubMed was as follows: ("artificial intelligence" OR "deep learning" OR "neural networks" OR "machine learning" OR "image recognition" OR "supervised learning" OR "unsupervised learning") AND (buccal OR oral OR dental OR dentistry OR tooth OR teeth OR dentofacial OR maxillofacial OR orofacial OR orthodontics OR endodontics OR periodontics OR prosthodontics). A total of 9358 results were obtained. The filters applied were randomised controlled trial and clinical trial, obtaining 138 results.

In IEEE Explore the search equation used was as follows: ("artificial intelligence" OR "deep learning" OR "neural networks" OR "machine learning" OR "image recognition" OR "supervised learning" OR "unsupervised learning") AND (buccal OR oral OR dental OR dentistry OR tooth OR teeth OR dentofacial OR maxillofacial OR orofacial OR orthodontics OR endodontics OR periodontics OR prosthodontics) AND (patients). A total of 665 results were obtained. A filter for journals was applied obtaining 112 results.

On March 8, 2025, two authors, independently, searched in PubMed and IEEE Xplore.

3.4 Study Selection process

All results from the search strategy were examined by each reviewer (n=2) independently. The title and abstracts of the results obtained were reviewed to filter the relevant studies.

To remove any duplicate studies found in both databases the Rayyan software specific to screening literature was used. After the initial screening process, full-text studies were retrieved and assessed using the eligibility criteria. For any discrepancies found between the two reviewers, the studies were discussed, to ensure a correct selection of articles of this literature review. This process is summarised in the PRISMA protocol (20) represented in Figure 1.

3.5 Data collection process

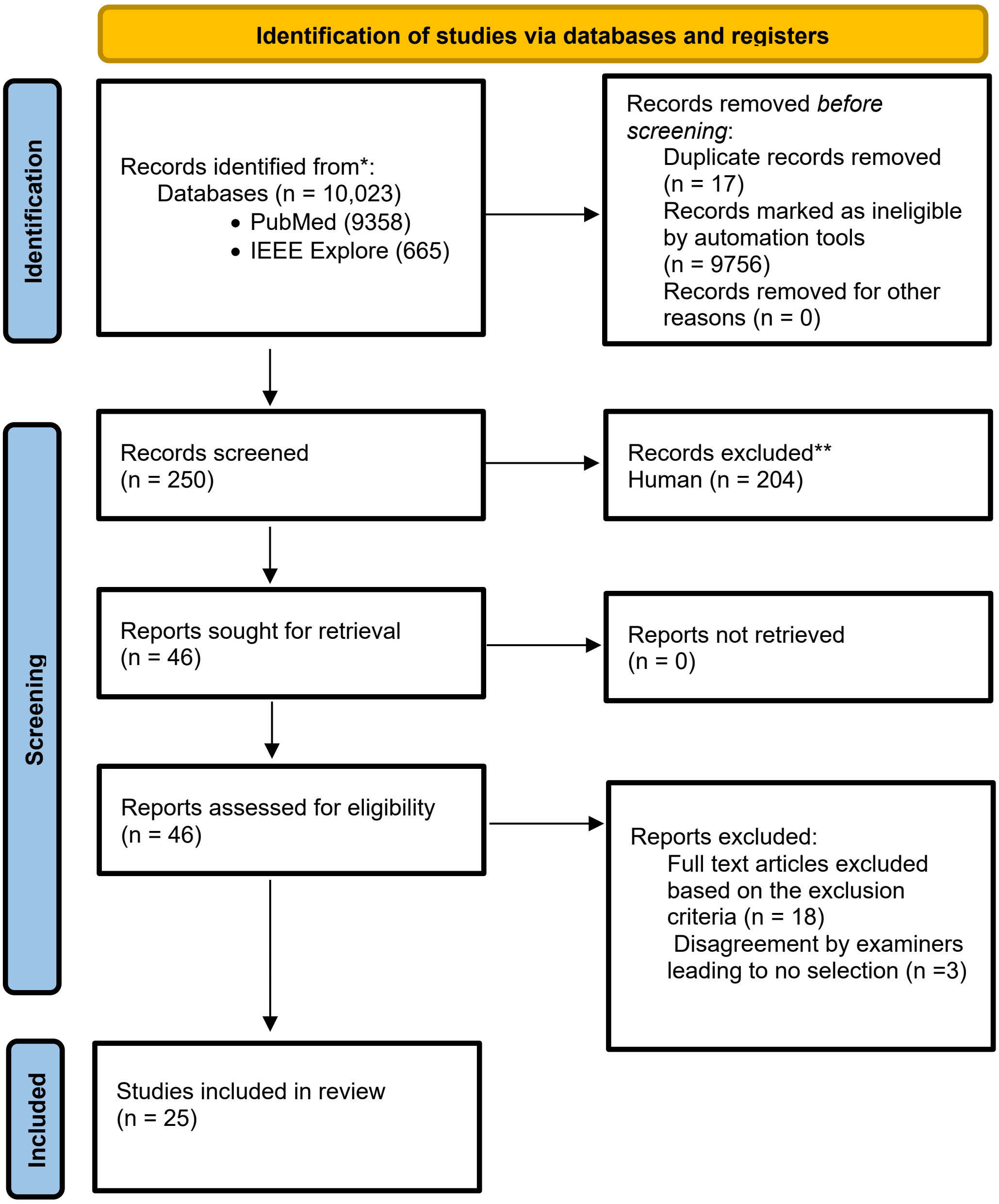

Figure 1. PRISMA flow chart diagram (20) showing the different stages of the systematic review

4 RESULTS

4.1 Tables showing results

Table 1. The table shows the author and year of publication of the study, the type of study and the different oral diseases considered in each case.

	Author and year of publication	Type of study	Oral disease
1	*Mertens et al. 2021* (22)	Randomised Controlled Trial	Proximal Caries
2	*Kokomoto et al. 2024 (23)*	Retrospective and observational study	Tooth development
3	*Lin et al. 2021 (24)*	Cross-sectional study	Teeth recognition and disease classification
4	*Chen et al. 2022* (25)	Cross-sectional study	Tooth recognition and disease classification
5	*Li et al. 2024* (26)	Cross-sectional study	Tooth position and dental pathology recognition
6	*Liu et al. 2020* (27)	Cross-sectional study	Dental disease detection
7	*Aljabar et al. 2024* (28)	Experimental study	Direct and hybrid approach to dental diagnosis
8	*Zannah et al. 2024* (29)	Experimental study	Segmentation of panoramic x-ray
9	*Shen et al. 2022* (30)	Randomised Controlled Trial	Periodontitis
10	*Li et al. 2024* (31)	Randomised Controlled Trial	Periodontitis
11	*Liang et al. 2020* (32)	Cross-sectional study	Oral Cancer
12	*Devindi et al. 2024* (33)	Experimental study	Benign and OPMD or Oral cancer diagnosis
13	*Shamim et al. 2020* (34)	Experimental study	Oral pre-cancerous tongue lesions diagnosis
14	*Yan et al. 2020* (35)	Observational study	Detect Tongue squamous cell carcinoma
15	*Tomita et al. 2021* (36)	Retrospective study	Cervical lymph node metastasis

	Author and year of publication	Type of study	Oral disease
16	*Men et al. 2019* (37)	Cross-sectional study	Xerostomia
17	*Al-Sarem et al. 2022* (38)	Cross-sectional study	Dental implant planning
18	*Picoli et al. 2023* (39)	Within-patient controlled study	Risk of IAN injury after wisdom teeth removal
19	*Jung et al. 2023* (40)	Cross-sectional study	Osteoarthritis in the TMJ
20	*Zou et al. 2022* (41)	Retrospective study	Temporomandibular joint disorders
21	*Ozsari et al. 2023* (42)	Experimental study	Temporomandibular joint disorders
22	*Fang et al. 2023* (43)	Retrospective study	Degenerative temporomandibular diseases
23	*Alqahtani et al 2023* (44)	Retrospective study	Orthodontic teeth segmentation
24	*Tao et al 2023* (45)	Cross-sectional study	Orthodontic Palatal mini-implant planning
25	*Weingart et al 2023* (46)	Cross-sectional study	Orthodontic Cephalometric analysis

Table 2: A summary of the literature review on AI application in dental diagnosis, in dental caries, periodontitis, TMD disorders, tooth loss and orthodontics.

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Mertens et al. 2021 (22)	Cloud-based ML	To detect and classify teeth and segment restorations and caries lesions	140 Bitewing radiographs	**With AI:** **Sensitivity:** 0.81 **ROC AUC:** 0.89	4 dentists **No AI:** **Sensitivity**: 0.72 **ROC AUC:** 0.85	Use of AI increases the sensitivity for enamel caries more than dentin caries. Specificity is not greatly altered. In advanced lesions the use of AI did not affect the accuracy. Non-invasive therapies increased by 36% and invasive therapies by 24% for enamel caries. Invasive therapy for early dentin caries increased from 55% to 66%.	The AI tool was used in a simulated clinical setting, not a dental environment. The sample size of images was limited as well as the number of dentists selected.
Kokomoto et al. 2024 (23)	Generative ML (StyleGAN-XL)	To generate images of the dental developmental stages in children	8092 Panoramic radiographs	**FID:** **Batch size 2048:** Resolution 16: 3.55 Resolution 32: 3.42 **FID Batch size 256:** Resolution 64: 4.39 Resolution 128: 6.92 Resolution 256: 6.83 **FID Batch size 128:** Resolution 512: 9.71	Panoramic x-ray of actual growth **FID:** **Batch size 32:** Resolution 16: 1.86 Resolution 32: 2.69 Resolution 64: 3.50 Resolution 128: 4.99 Resolution 256: 5.32 Resolution 512: 6.59	FID results were better at a constant batch size of 32. The lowest FID was shown at resolution 16 x 16, indicating the best ability of the model to generate images.	The best FID score may not produce the best quality images. There is a need for quantitive metrics to compare actual generative growth.
Lin et al. 2021 (24)	DL models (AlexNet, VGGNet, GoogLeNet, Xception, and ResNet)	To identify the teeth and classification of the dental conditions of the teeth	Panoramic radiographs	**Dental position tooth numbering:** **Accuracy:** 95.62% **Dental condition classification:** **Accuracy:** 98.33%	**Without image pre-processing and augmentation:** **Dental position tooth numbering:** **Accuracy:** 90.93% **Dental condition classification:** **Accuracy:** 93.33%	On average the different DL models were able to detect 6 out of 7 pathologies (98%) (including caries, periodontitis apical lesion, dental prosthesis, dental restoration, missing tooth, impaction, retained root, implant, endodontic therapy). The accuracy of identifying the teeth positions was 29 out of 32 (95%.)	The data only came from one institution and could be limiting.

ROC AUC*: Area under the Receiver-operating Characteristics curve. To demonstrate how well the classifier performs at all possible thresholds. A higher ROC AUC shows better performance (22).*

FID: *Fréchet inception distance. To measure the similarity between the real images and the generated images. A smaller FID shows the ability of the model to generate better images (23).*

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Chen et al. 2022 (25)	CNN models (AlexNet, GoogLeNet, VGG19, ResNet50, and ResNet101.)	To classify and segment retained roots, endodontic treated teeth and implants	1400 Panoramic radiographs	**Implant Accuracy:** AlexNet: 98.60% GoogLeNet: 99.70% VGG19: 97.70% ResNet50: 98.20% ResNet101: 98.60% **Endodontic teeth accuracy:** AlexNet: 96.70% GoogLeNet: 98.20% VGG19: 99.10% ResNet50: 98.40% ResNet101: 98.40% **Retained Root accuracy:** AlexNet: 98.80% GoogLeNet: 99.60% VGG19: 96.50% ResNet50: 97.10% ResNet101: 98.70%	Expert annotated three professional dentists	The different CNN models show accuracy rates above 96%. In the detection of implants GoogLeNet had the highest accuracy of 99.70% as well as for retained roots 99.60%. For endodontically treated teeth ResNet50 and 101 both showed the highest accuracies of 98.40%. The CNN models were efficiently able to detect these 3 diseases.	In this study the model detected 3 diseases.
Li et al. 2024 (26)	CNN model (AlexNet, ResNet, EfficientNet)	Tooth detection and diagnosis of dental caries, periodontal disease and dental restorations	Bitewing radiographs	**AlexNet recognition accuracy:** Caries: 92.85% Periodontitis: 92.10% Restoration: 96.51% **Original and enhanced image:** F1-score: 98% **Processing time:** Original image: 0.134s Enhanced image: 0.052s	**ResNet50 accuracy:** Caries: 90.47% Periodontitis: 86.84% Restoration: 96.90% **ResNet101 accuracy:** Caries: 76.19% Periodontitis: 84.21% Restoration: 98.06% **EfficientNetV2B0 accuracy:** Caries: 71.42% Periodontitis: 81.58% Restoration: 97.26%	CNN models could detect the tooth position with an accuracy of 98.01%. Enhanced images have a 60% reduced processing time compared to using the original image. AlexNet showed increasing accuracies by 2.5% to 7% in detecting caries, periodontitis, and restorations. Comparatively ResNet101 showed the highest accuracy for restoration recognition at 98.06%.	More training datasets are needed. It is difficult for a dentist to use, methods to make it easier to use should be developed. An automatic x-ray labelling system should be integrated into the workflow.

F1-Score: *To measure a ML model's accuracy combining the precision and recall scores **(26)***

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Liu et al. 2020 (27)	MASK R-CNN	To identify dental diseases	12600 clinical images	**Recognition rate:** Dental caries: 90.1% Fluorosis: 95% Periodontitis: 94.3% Cracked tooth: 94.1% Calculus: 98.1% Plaque: 100% Tooth loss: 98.4% **Sensitivity and specificity:** Dental fluorosis and plaque: 100%. Cracked tooth **sensitivity:** 75%, Decayed tooth **specificity:** 93%.	Expert dental professionals	MASK R-CNN showed a recognition rate over 90.1% for the 7 dental diseases as well as high sensitivity and specificity for all the dental diseases. Cracked tooth had a low sensitivity which could be due to smaller cracks were harder to detect by the model. The low specificity of tooth decay could be due to interproximal caries detection and level of staining the teeth had.	The patients will need to be taught how to use the app properly. Bigger data set will need to be tested.
Aljabar et al. 2024 (28)	DL models (AlexNet, DenseNet121, EfficientNet, MobileNetV2, MobileNetV3Large, ResNet50, VGG16, VGG19) ViT and YOLO and ML classifiers (DT, RF, SVM, SVM with RBF, KNN, NB and LR)	To carry out an automated oral diagnosis of teeth	Panoramic radiographs	**Direct and hybrid approaches:** **ViT** accuracy: 96% **AlexNet with SVM** accuracy: 94%.	Human annotated images	In all DL models using a hybrid approach improved the results compared to a direct approach. ViT produced the best accuracy in both direct and hybrid models, however using ALexNet with SVM and an RBF kernel was deemed better as it was able to work faster and without as many components.	The Data sample was small. The model misclassified the cavity class samples as fillings. There was only one image modality used.
Zannah et al. 2024 (29)	U-Net CNN based models	To segment dental x-rays	389 Panoramic x-rays	**2 layers Vanilla U-Net:** Accuracy: 95.56% IoU score: 88%. **3 layers Dense U-Net:** Accuracy: 95.94% IoU score: 89.07%.	Manual segmentations of the x-ray	All the U-Net models presented a similar segmentation of the dental x-rays, having 3 convolutional layers improved their accuracy instead of a 2-layer model. However, it takes longer to train the model. It is important to find a balance between efficiency and time.	Studies need to test this further using larger datasets.

***IoU score**: Intersection over union. To compares the predicted segmentation to the ground truth (29).*

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Shen et al. 2022 (30)	AI- assisted application (Dental Monitoring)	To use at home AI monitoring in periodontal patients	Smartphone based intraoral photograph	**Only AI and AI and home counselling:** Greatest improvement in periodontal measures, probing depth, clinical attachment level, plaque index at 3 months	**Control group with no AI:** Less improvement in periodontal measures, probing depth, clinical attachment level, plaque index at 3 months	AI monitoring improved at home oral hygiene and overall periodontal health compared to the control group. However, AI assistance as well as human counselling showed the best results as it helped improve patient motivation and compliance to treatment.	A small sample was used. The lingual side of teeth was not analysed by AI. AI could lack personalisation in treatment
Li et al. 2024 (31)	AI enabled multimodal-sensing power toothbrush, with an application	To guide patient oral hygiene practices and insure remote monitoring and guidance	N/A	**I-Brush** Baseline to 6 months: **7.9%** improvement in the proportion of inflamed periodontal pockets. There was a **5.6%** improvement in gingival inflammation. Mean periodontal pockets were the **same after 6 months in both groups**. Greater improvements in the oral health related quality of life.	Control group of patients with manual brushing, no I-brush use had reduced improvement in the proportion of inflamed periodontal pockets and gingival inflammation at 3 months. There was no statistical difference in the salivary biomarker a-MMP8	The use of AI powered technology improved healing rates by 8% demonstrating the improvement in sustained efficiency in oral health over time. AI in oral health shows potential in both stand alone practice as well as a complement to professional interventions.	Changes in clinical attachment level were not included as it was too considered too difficult in detecting the CJ with the presence of heavy calculus deposits.
Liang et al. 2020 (32)	Deep convolutional Generative adversarial network (DCGANs)	To generate3D images of the anatomical mandible	CT images	CTGAN was able to generate mandibles with different morphology, position and angle changes and local patterns.	Experienced doctors interpreted the results	The CTGAN was accurately able to generate 3D mandibles that have the correct anatomical morphology, that is often time consuming and difficult for doctors to do.	The calculation accuracy and efficiency in producing outcomes shows limitations.

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Devindi et al. 2024 (33)	Multimodal deep CNN with a SOTA DL models (DenseNet-121, Inception-v3, HRNet-W180-C, MixNet_s, ResNet50, MobileNetV3, MobileNetV3-Large).	To segment the oral cavity and detect and classify oral lesions	2271 Images from smartphone camera	**MobileNetV3-Large** MCC: 0.57, Accuracy: 0.81, F1-score: 0.78. F1- score for Benign lesions: 0.70 F1- score OPMD lesions: 0.86	Three experts labelled the images	The MobileNetV3-Large model had the best results with the highest accuracy. It showed higher F1-scores in OPMD compared to benign lesions. The use of early fusion of visual and metadata is better at paralleling the diagnostic method used by dentists, making it a better approach for classifying oral lesions.	A small dataset with limited ability to generalisations for all cases.
Shamim et al. 2020 (34)	Deep convolutional network	To identify and classify precancerous tongue lesions	Photographic images	**Binary Classification** **AlexNet, GoogLeNet, Inceptionv3, SqueezeNet:** Accuracy: 0.93% **ResNet50,0.90 and VGG19:** Accuracy: 0.98 **Multi-class classification accuracy:** AlexNet: 0.83 GoogLeNet: 0.88 ResNet50: 0.97 VGG19: 0.95 Inceptionv3: 0.92 SqueezeNet: 0.90	A certified physician with more than 15 years of experience	All models were effective in identifying pre-cancerous lesions and benign lesions. The VGG19 model had the highest accuracy in the binary classification. RestNet50 had the highest accuracy in the multi-class classification.	The DCNNs need to be further developed to classify lesions in other areas of the mouth.
Yan et al. 2020 (35)	CNN model	To classify TSCC	Raman Spectroscopy	**CNN model for TSCC diagnosis:** Accuracy: 97.25% Sensitivity: 97.76% Specificity 86.59% Precision 97.33%	Histopathology samples **Ensemble CNN model for TSCC diagnosis:** Accuracy: 98.75% Sensitivity: 99.10% Specificity 98.29% Precision 98.67%	Ensemble CNN compared to the new CNN model could accurately classify TSCC with very high accuracy, precision, sensitivity and specificity. The ensemble CNN is better at diagnosing TSCC compared to detecting normal tissue.	Only ex-Vivo samples were used, the dataset is small and it needs more clinical trials

***MCC**: Matthew's correlation coefficient. To compare the correlation between predicted values and actual outcomes in a binary classification (33).*

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Tomita et al. 2021 (36)	ML	To accurately identify benign and metastatic cervical Lymph Nodes in OSCC patients.	CT images	**ML model AUC:** Level I/II: 0.820 Level I: 0.820 Level II: 0.930	Two radiologists and a dentist AUC: Level I/II: 0.798–0.816 Level I: 0.773–0.798 Level II 0.825–0.865	The AUC and accuracy was higher at level I/II,I and II compared to the human observeers. The best model was more specific at level I/II and I.	A small number of patients were studied. Small sized cervical lymph nodes could have been missed on CT imaging and in surgery.
Men et al. 2019 (37)	3D residual convolutional network model (3D rCNN)	To predict Xerostomia in patients with head and neck squamous cell carcinoma	CT images	**Model with CT images, dose distribution and contours as variables:** AUC value: 0.84 **Model without contours:** AUC: 0.82 **Model without CT images** AUC: 0.78 **Model without dose distributions:** AUC: 0.70	**The LR model without clinical variables:** AUC of 0.68	The 3D rCNN model can accurately predict xerostomia with higher AUC values. The use of dosimetrics improves prediction of xerostomia. The fully automated framework helps reduce inter and intraobserver variability.	It needs to be tested on a larger dataset, clinical variables were not included but could change the toxicity profile and should be used in future models.
Al-Sarem et al. 2022 (38)	6 pretrained DL-CNN models: (AlexNet, VGG16, VGG19, ResNet50, DenseNet169, and MobileNetV3)	To detect and classify the missing teeth regions from segmented CBCT images	500 CBCT images	**F1-scores:** **AlexNet:** 0.64 **VGG16:** 0.90, **VGG19:** 0.85 **ResNet50:** 0.90 **DenseNet169:** 0.93 **MobileNetV3:** 0.82	1 professional expert	In classification with segmentation DenseNet169 presented the best precision, recall, F1-score and MCC against the U-Net segmentation compared to AlexNet which presented the worst scores. In classification without segmentation VGG16 showed the best overall results, with AlexNet showing the worst accuracy.	

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Picoli et al. 2023 (39)	Cloud based AI platform (Virtual Patient Creator) CNN	To generate a 3D model from the segmented mandibular teeth and canals	CBCT images	**3D-AI:** AUC: 0.63 Sensitivity: 0.87 Specificity: 0.39	Surgeon and radiologists **PANO:** AUC: 0.57 Sensitivity: 0.73 Specificity: 0.41 **CBCT:** AUC:0.58 Sensitivity:0.89 Specificity: 0.28	There was no statistical significance in diagnostic parameters amongst the 3 imaging types. But the use of CBCT and 3D-AI were favoured over PANO. Surgeons presented the highest confidence when using 3D-AI images, and radiologists when using CBCT.	The analysis was based only on image analysis, no other factors were considered.
Jung et al. 2023 (40)	DL model (CNNs)(ResNet-152 and EfficientNet-B7)	To classify TMJ into normal and osteoarthritis cases	858 Panoramic images	**ResNet-152 model** Accuracy: 0.87 Sensitivity: 0.94 Specificity: 0.79 AUC: 0.94 **EfficientNet-B7** Accuracy: 0.88 Sensitivity: 0.86 Specificity: 0.91 AUC: 0.95	Three TMD specialists and three general dentists	Both models present a similar accuracy in classify OA. Both accuracies significantly higher than the specialists and general dentists. Sensitivity of ResNet-152 was higher than EfficientNet-B7 and specialists and general dentists. The specificity of EfficientNetB7 was higher than ResNet-152 and specialists and general dentists. Large differences in accuracy were shown between the human observers compared to the trained models which showed more reliability as they had less differences.	Limited number of samples was used and the study was only done in one institution. As the region of interest was previously cropped, it could make it easier for the AI models.
Zou et al. 2022 (41)	Artificial neural network (ANN)	To predict temporomandibular disorders from a patients medical history	N/A	Sensitivity 92.31% Specificity 88.92% Accuracy 90.91%.	Doctor with more than 20 years experience and a doctor with only 2 years of experience	The high accuracy of the ANN model shows promising ability to diagnose a TMD, when compared to the experienced doctor, the model didn't perform as well but it was better than the young inexperienced doctor who had an accuracy of 75%. The high sensitivity and specificity show the ANN's ability to be able to correctly differentiate a TMD from a patient without TMD.	Limited dataset with data only from limited sites.

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Ozsari et al. 2023 (42)	CNN and pretrained CNN models (Xception, ResNet-101, MobileNetV2, InceptionV3, DenseNet-121 and ConvNeXt)	To diagnose TMD from Magnetic resonance images (MRI)	2567 MRI	**Closed mouth disc position:** MobileNetV2 accuracy: 0.97 **Open mouth disc position:** Xception accuracy: 0.8 **Joint cavity effusion:** ResNet-101 accuracy: 0.84. **Mandibular condyle degeneration:** MobileNetV2 accuracy: 0.97	Dentomaxillofacial specialist	The 6 CNNs showed great efficiency and accuracy in being able to diagnose TMD through MRIs. Different CNNs showed their strengths in different MRIs, MobileNet was found to have the highest result in 2 different categories and produce effective results in all the MRIs.	There is a need for more images for each group and incorporating patients with different diseases.
Fang et al. 2023 (43)	Predictive ML	To screen for degenerative temporomandibular joint diseases	CBCT images and Lateral cephalograms	**Combined model:** Training set ROC: 0.893 validation set ROC: 0.828 **Clinical model:** Training set ROC: 0.701 Validation set ROC: 0.60	2 TMJ specialist	The combined model performed better than the clinical model, it presented a better predictive ability and was able to identify DJD in different subgroups more accurately. The combined model was better at clinical decision making	The study was conducted in one hospital, as it is a predictive model some relevant cephalometric features may have been excluded.
Alqahtani et al. 2023 (44)	Cloud based AI Platform (Virtual Patient Creator) CNN	To carry out segmentation and classification of teeth with orthodontic brackets	215 CBCT images	CNN model IoU,DSC, precision, and recall score: 0.99 CNN classification time: 13.7s	Expert corrected AI driven segmentation (C-AI)	The CNN model was 3 times faster than the corrected AI. The CNN model showed close to perfect segmentation, presenting high efficiency and accuracy in the classification of teeth with brackets.	Training on the model was limited to CBCT images from one device.

Authors and years	AI	AI use	Image Modality	Results	Control comparison	Key findings	Limitations
Tao et al. 2023 (45)	Modified 3D-UnetSE model	To segment the palate to determine the optimum palatal mini-implant placement site	70 CBCT images	**Palatal bone mean**: DSC: 0.831 ASSD: 1.122 Sensitivity: 0.876 PPV: 0.815 **Palatal soft tissue** DSC: 0.741 ASSD: 1.091 Sensitivity: 0.861 PPV: 0.695	Well trained dentist and an orthodontic specialist	The 3D-UnetSE model presented higher DSC values in palatal bone segmentation compared to palatal soft tissue segmentation.There was significant difference between mean DSC in the premolar plane compared to the molar plane.	The segmentation of the bone from the soft tissue boundary was difficult to achieve. A small dataset was used.
Weingart et al. 2023 (46)	Deep neural patchworks	To identify different cephalometric landmarks for routine diagnosis and treatment planning	CT images	The DNP could accurately identify all 60 cephalometric landmarks. **Mean error:** 1.94mm	Two maxillofacial residents with equal experience **Manual mean error:** 1.32mm	The DNP model shows high accuracy as the mean error was less than 2mm. Better results were recorded for bone structures compared to dental landmarks which produced larger errors.	The errors produced could be due to intra-inter observer disagreement.

DSC*: Dice similarity coefficient. To compare the overlap between the predicted segmentation and ground truth (45).*

ASSD*: Average symmetric surface distance. To measure the average distance between the surface of the predicted segmentation and the ground truth (45).*

PPV*: Positive predictive value commonly known as precision in ML. It shows how many of the positive predictions were correct (45).*

4.2 Visual aids to summarise the results

Figure 2 shows most studies (n=8) focused on dental caries diagnosis and tooth recognition, indicative of the current emphasis on these prevalent diseases. A substantial number of studies were based on oral cancer and pre-cancerous lesions (n=6) which can be attributed to the necessity for early identification of lesions and hence early treatment to be able to manage oral cancer appropriately. Other studies were based on TMJ disorders, orthodontics, periodontal diseases and dental surgical planning. These different specialties presented an analysis of AI use for treatment planning, predicting the need for intervention or to monitor diseases e.g. periodontal disease which is a chronic inflammatory disease and needs lifelong monitoring (30).

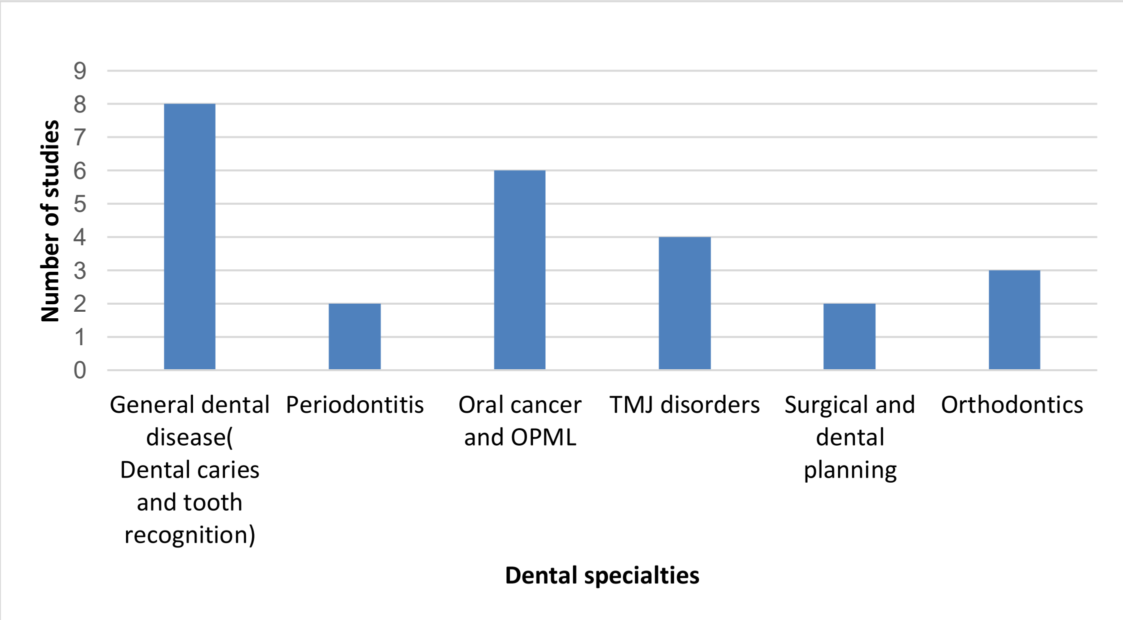

Figure 2. Graph showing the types of AI research according to dental specialties

The different applications of AI are seen in Figure 3. These applications help improve the efficiency in diagnosing oral diseases and treating them. The majority used AI to detect and classify oral diseases. Following this, a large number of studies used AI-based segmentation. Other uses of AI included disease prediction and diagnosis, image generation and modelling and remote monitoring and assistance.

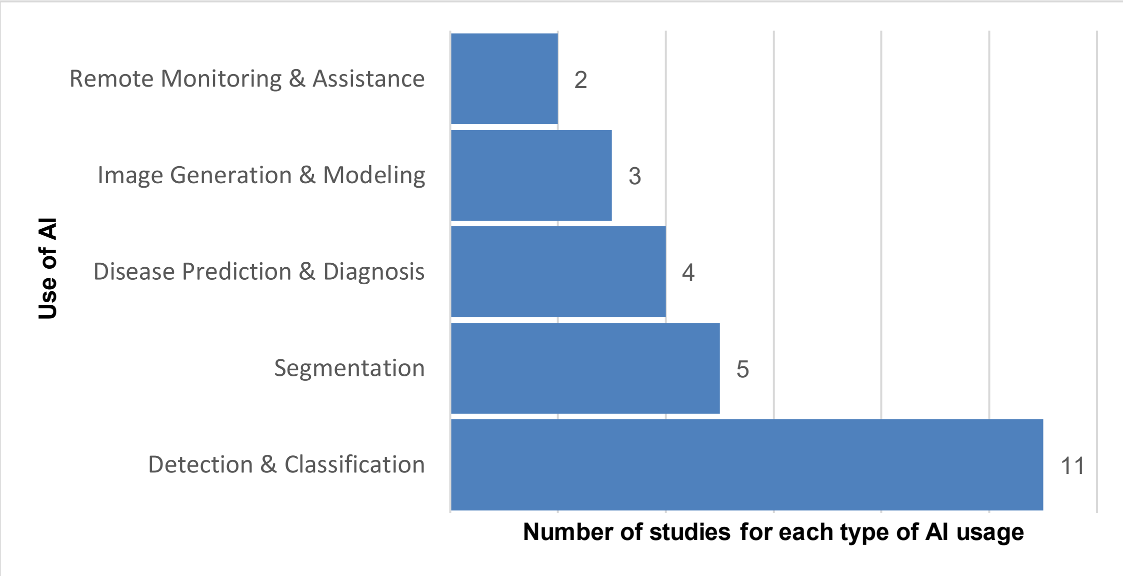

Figure 3. A Funnel chart showing the different uses of AI

Different image modalities were used in the studies included. In Figure 4, 27% of the studies, most frequently, used panoramic radiographs, followed by clinical images that made up 11% for the AI to analyse. Other imaging modalities such as, CT, and CBCT images collectively made up 36% of all the imaging types. Only two studies (9%) used bitewing radiographs as their imaging modality, this could be due to the extent of this literature review which only analysed two studies with their only focus on dental caries, other studies presented multiple objectives analysing multiple dental pathology in the same study, making it easier to use a panoramic radiograph for a global outlook.

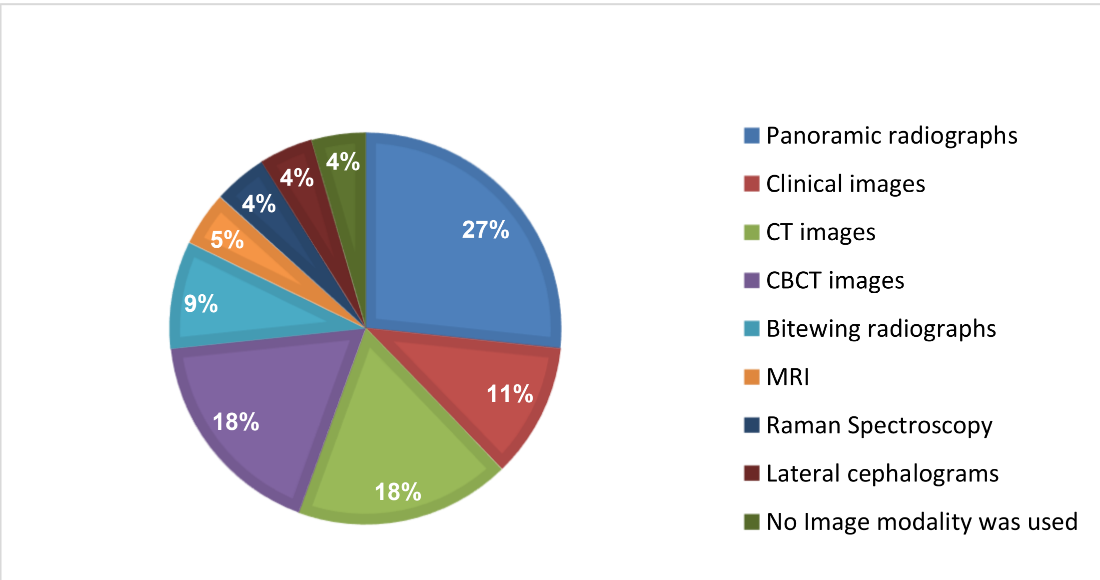

Figure 4. A pie chart showing the different imaging modalities used in this literature review

Figure 5 shows the different types of AI used to study oral diseases in this literature review. The most frequent types used are CNN models, which were used in 23% of the studies. DL and ML methods were also used in 20% to 15% of the studies. However, ANN models and detection/segmentation models were used in less than 5% of the studies. This could be due to the lack of research present.

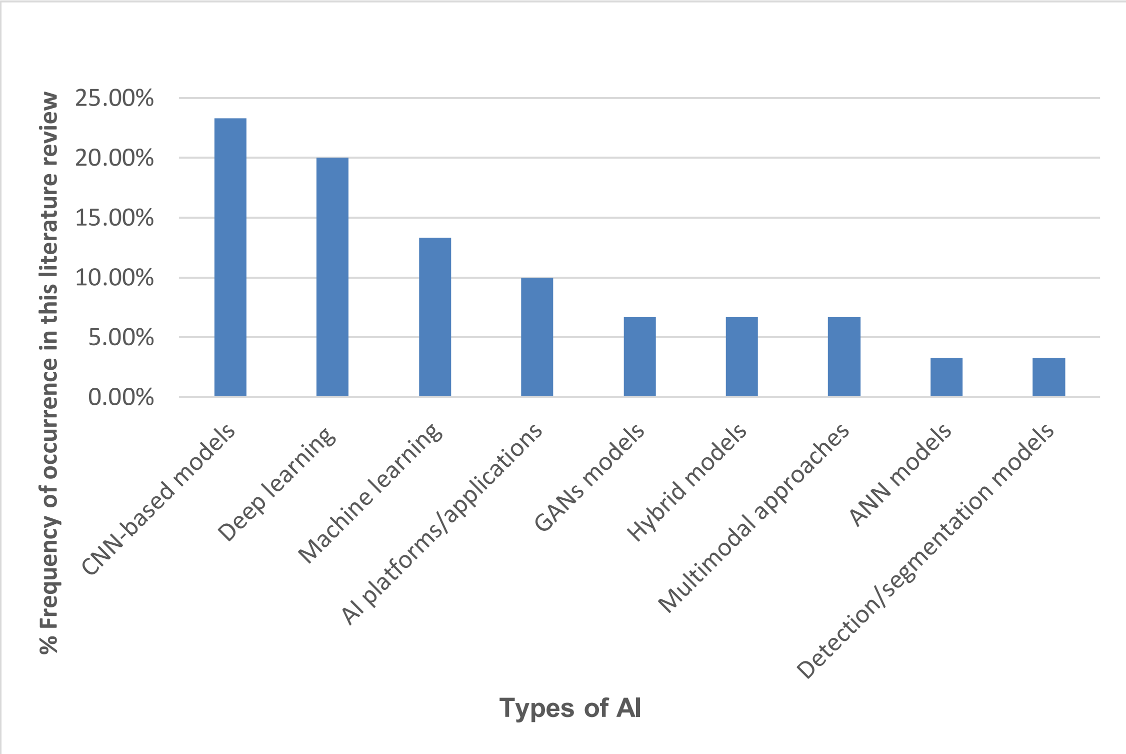

Figure 5. A graph showing the different types of AI present in this literature review

5 DISCUSSION

5.1 Summary of this literature review

This literature review identified a total of 25 different studies on the application of AI in the diagnosis and treatment of various oral diseases. The reviewed publications spanned from 2019 to 2024, with the majority being published in 2023 (n=8, data shown in Table 1), demonstrating AI's rapidly evolving nature.

5.2 General dental diagnosis and treatment

AI-based dental diagnosis and treatment relies on automated tooth segmentation and multiple dental pathology recognition, both strategies help the practitioner in achieving fast and accurate outcomes. The study by Kokomoto *et al.* (23) demonstrated the use of generative AI in modelling dental development. This may offer a predictive advantage in assessing the risk of developing oral diseases. Additionally, it allows the dentist to make more informed decisions including early interventions and personalised treatment plans. In an oral cavity it is increasingly common to find retained roots, endodontically treated teeth and dental implants which are often difficult to recognise (25) and time consuming as they require more diagnostic tests. In a study conducted by Chen *et al.* (25) detection accuracies exceeding 98.20% were shown. This emphasises the potential of CNN models in redistributing the dentist's clinical time to focus on effective communication with the patient and in treating the oral disease. In a study conducted by Zannah *et al.* (29) a U-Net model was used to segment teeth from a panoramic x-ray, similarly Chung *et al.* (47) and Duan *et al.* (48) used tooth segmentation from CT and CBCT images. Zannah *et al.* (29) shows the potential of tooth segmentation with an accuracy of 95.94% with efficient processing times, faster than the dentist. These findings align with meta-analytic evidence from Dudy *et al.* (49) which reported segmentation accuracies of 85% to 100% with significantly faster segmentation time compared to the ground truth.

5.3 Dental caries

Traditionally a dental caries diagnosis is attained with bitewing radiographs and a dentist who visually detects any changes on the anatomical tooth, this often leads to limiting the diagnosis and making it subjective to the practitioner themself (16). The automation of this diagnostic process is becoming more frequent with the use of AI. In particular, caries is detected using both ML and DL methods, more specifically, CNN models. In this literature review Lin *et al.* (24) , Li *et al.* (26) and Liu *et al.* (27) presented an accuracy of caries recognition above 90%, revealing a greater accuracy when compared with the dental practitioners using traditional methodologies. These results were consistent with previous meta-analysis data from Ammar *et al.* (50), where overall caries detection accuracies were more than or equal to 80%. Although the studies presented slight discrepancies in sensitivity and specificity for caries detection, they can be attributed to the varying use of different CNN models. Lin *et al.* (24) used 5 different CNN models where they concluded that using a model with more deep layers permitted more complexity to the model in order to extract more characteristics from the radiographic images, thus improving their learning abilities and performance outcomes. Aljabar *et al.* (28) suggests a hybrid approach to dental diagnosis, using a DL model with a ML algorithm. This hybrid approach showed efficiency in diagnosis, making the diagnosis faster and if errors were made, the AI was able to learn and correct itself along the way, making it a suitable solution for future caries diagnosis models compared to only using a CNN model.

Additionally, Mertens *et al.* (22) highlights AI's sensitivity to enamel caries lesions improving the dentist's accuracy in detecting proximal caries lesions by 12.5% when using AI. However, there was no alteration in the accuracy of AI when detecting advanced carious lesions. This difference could be due to the size of advanced lesions as they are easier to visualise intraorally, as well as radiographically, making them harder to misdiagnose by the dentist.

Although the prominent levels of sensitivity AI has for enamel caries is resulting in a better diagnosis, it is also causing an increase in invasive therapies by 24%, this could be a potential problem with using AI in enamel caries diagnosis. In order to counteract over-treatment, similar to research done by Ghosh *et al.* (51) on the management of over treatment of caries, where clinicians are given caries diagnosis recommendations, it would be necessary to train the dentists to be able to correctly treat enamel caries with non-invasive therapies, using further assessment methods before using invasive therapies unnecessarily.

The study of Schwendickie *et al.* (52) compares the sensitivities in dental caries detection by AI and by the dentists and consequently the cost effectiveness of AI. As AI presents a higher sensitivity in caries detection, early carious lesions can be treated non-restoratively making AI-based caries detection cost effective. This highlights another advantage of the implementation of AI in caries diagnosis.

5.4 Periodontitis

Periodontitis is a global burden with the incidence of cases increasing 83.4% from 1990 to 2019 (53). Periodontitis is a chronic, inflammatory disease and it is important that AI is able to detect cases accurately (53). It is becoming increasingly common for DL methods to be used in evaluating bone levels in periodontal patients(27). In a study conducted by Lui *et al.* (27) there was a recognition accuracy of 94.3% for periodontitis, this is higher than the accuracy found in Khubrani *et al.* (54) that had an average accuracy of 84%. This discrepancy could be associated with the number of studies included in this meta-analysis, compared to just one study.

Additionally, the management of periodontitis and its risk factors, e.g. smoking and oral hygiene are pivotal to ensuring periodontal management (30). AI monitoring at home is becoming increasing popular in controlling disease progression. Shen *et al.* (30) showed AI assisted oral hygiene management and counselling improved patient motivation and compliance to periodontal treatment. Similarly, Li *et al.* (31) showed the use of an AI-powered toothbrush that aided oral hygiene. The use of AI at home in periodontal patients improved oral health as the AI was effective in periodontal management.

On the contrary, the lingual side of teeth could not be analysed, which could be a disadvantage and could lead to an important proportion of surfaces without analysis. Additionally, the patients found a lack of personalisation in feedback, which could be considered a disadvantage of AI in periodontal management as seen in the review by Patel *et al.* (55) which also states that AI should be used a complementary tool and it should not replace dental specialists who will be able to provide a high-quality personalised treatment.

5.5 Oral cancer

Oral cancer is highly prevalent worldwide (56) Devindi *et al.* (33) had F1-scores between 0.78-0.86 demonstrating an excellent precision and recall for the diagnosis of benign lesions and OPML using a CNN model. Comparatively, Yan *et al.* (35) were able to diagnose tongue squamous cell carcinoma from histological samples with an accuracy of 98.75% using an ensemble CNN model. Shamim *et al.* (34) using different DCNN models complementary to a specialist was able to produce a 100% accuracy in diagnosing oral precancerous tongue lesions. All three studies not only have findings consistent with Vinay *et al.* (56) who have identified that AI-based oral cancer diagnosis outperforms traditional diagnostic methods with high accuracies and suggests the importance of AI integration in oral cancer diagnosis. A combined approach of DL methods and a dentist resulted in the highest accuracies; this could be due to the ability of the dentist to detect any errors that the AI may have presented and correct them at once.

Additionally, Tomita *et al.* (36) concluded that in patients with Oral Squamous Cell Carcinoma (OSCC), DL models in the analysis of CT scans could be an effective diagnostic measure in diagnosing cervical lymph nodes as it had high accuracies. Previous research by Vinay *et al.* (56) also states DL models were more successful in the classification of cervical lymph nodes compared to radiologists.

Patients with oral cancer commonly present the symptom xerostomia (37). Men *et al.* (37) suggests the use of the 3DrCNN model which can accurately predict xerostomia with higher AUC values, in this study the use of an automated framework helps reduce inter and intra observer variability. This is similar to a study conducted by Chu *et al.* (57) who also suggests DL based models are able to predict xerostomia in head and neck cancer patients with an AUC of between 0.78 and 0.79.

Patients who have to undergo rehabilitative surgery for oral cancer often suffer from bone defects (32). Liang *et al.* (32) suggests a generative adversial network to generate missing CBCT data from mandibles. When compared to traditional treatment methods such as mirror inversion the process with AI is suggested to be more efficient and time saving, this could be a great alternative and very advantageous for recovery after suffering from oral cancer.

5.6 Tooth loss

In the results obtained there was a lack of studies on tooth loss prediction, which are essential for analysing the diagnostic capabilities of AI. However, implant placement is becoming more frequent as a rehabilitative method for missing teeth as stated in the study by Al-Sarem *et al.* (38). This study presented a segmentation accuracy of 89% for missing teeth regions which will help reduce the planning time needed for implant placement. The conclusions were similar to the study Gerhardt *et al.* (58), where AI was found accurate and fast in segmenting teeth and edentulous areas, this is particularly important in planning for different treatments, especially those related to prosthodontics.

5.7 Temporomandibular disorders

TMD disorders are traditionally diagnosed using the diagnostic criteria for temporomandibular disorders (59). However, it presents limitations in its diagnostic accuracy. In studies conducted by Zou *et al.* (41), Ozsari *et al.* (42) and Fang *et al.* (43) the varying models of AI had an accuracy of up to 90.91%, being able to correctly differentiate between healthy and TMD patients from different imaging modalities including MRI, CBCT and lateral cephalograms. These findings are supported on studies by Jha *et al.* (59), which showed an average accuracy of

97%. This higher accuracy could be due to the high risk of bias in the included studies. In the study Jung *et al.* (40) different CNN models presented accuracies of up to 88% in diagnosing TMJ osteoarthritis, which was better than TMJ specialists and dentists who presented large discrepancies.

5.8 Orthodontics

Although orthodontics is a specialty that presents problems to do with malocclusion, it may not be considered an oral disease, but rather a dental specialty, due to its increasing use to treat malocclusions, the results have been included in this literature review.

Alqahtani *et al.* (44) presents a study with CNN models to accurately classify teeth with brackets, this is helping dentists speed up diagnosis by only taking 13.7 seconds in classification of orthodontic teeth. Similarly, Weingart *et al.* (46) also highlights the time saved when diagnosis uses AI in the identification of cephalometric landmarks, but in this instance, from CT images. Tao *et al.* (45) presents the use of AI in terms of segmentation. However, in this study it was used to segment the palate in order to improve diagnostic surgical guides for mini-implant placement. Although promising results were found, the segmentation of bone from soft tissue was challenging and led to some inaccuracies. Gracea *et al.* (60) similarly shows the use of AI in orthodontic diagnosis and treatment where it is most commonly used for landmark detection. However, this study also outlines the need for human supervision, which is common to other studies in the diagnosis of dental caries and periodontitis (55).

5.9 Limitations of this literature review

Firstly, for this literature review randomised controlled trials were the choice of primary evidence. However, less-evidence based studies such as case-control studies evaluating the comparison of AI and traditional methodologies had to be selected due to the evolving nature of AI and limitations present in ensuring ethical studies.

Secondly, there were a wide range of AI types, image modalities that were analysed making the data set very variable. Although, the studies measure the accuracy of their AI models quantitively, there was a lack of coherence in the types of quantitive measures e.g. accuracy, sensitivity, specificity, F1-score, making it challenging to directly compare the results.

Additionally, out of the results obtained, the majority of the studies had a small sample size and a limited number of images. Furthermore, in many studies the data was collected from one institution limiting the variability in the patient demographic and disease types.

Due to the nature of AI, a large number of studies that were obtained in the results require clinical trials to assess real world performance as well as further validation on larger and diverse datasets. A technical limitation could include pre-processing of the images by cropping them, making the results bias in favour of AI. As AI technology is continually developing, it could be deemed difficult to use for dentists, this could be a limiting factor when diagnosing with AI as it reduces the outcomes produced with AI.

5.10 Implications for future research

If this literature review was to be developed in the future, it would be important to analyse studies that use larger and variable datasets to be able to make generalised conclusions over large populations. The integration of non- imaging factors such as the medical history of the patient should be taken into consideration to improve the diagnostic accuracy. Also, the use of specific quantitative measures to be able to accurately compare diagnosis with different AI models. In addition to this, in order to understand the impact of AI on the dentist and patient, studies should be assessed over time. Finally, there must be further research concerning the ethical considerations of AI based diagnosis and treatment, to ensure no detriment is coming from its use.

6 CONCLUSIONS

In conclusion, this literature review aimed to analyse AI’s use in order to help facilitate the dentist in the diagnosis and treatment of oral diseases.

6.1 Conclusions regarding the primary objective

1. Many different oral diseases have been successfully studied with AI, the most common were dental caries, periodontitis, oral cancer and TMD.

2. This review confirms AI-based diagnosis is most commonly conducted, with a DL subset called CNN. CNN techniques demonstrate highly effective diagnosis in the detection of oral diseases especially by interpreting radiographic images.

3. AI is effective in aiding diagnosis, caring out automated diagnostic measure and in treatment. Studies showed up to 90% accuracy rates in detection and diagnosis.

4. AI- based diagnosis was seen to improve treatment outcomes as the dentist saved time that could be distributed more effectively for the patients, however there are concerns of over treatment that will need to be managed.

6.2 Conclusions regarding the secondary objective

1. DL methods are highly accurate in diagnosing oral cancer and pre-malignancy, often exceeding accuracy values produced by specialists. The CNN models were able to effectively analyse and classify photographs and radiographs to identify early malignant lesion, which is pivotal in the diagnosis of oral cancer.

6.3 Final conclusions

Overall, although AI effectively diagnoses oral diseases and oral cancer, a hybrid approach with both AI integration alongside a dental professional has shown the most potential in providing the best diagnostic outcomes.

7 SUSTAINABILITY

The integration of AI in the diagnosis and treatment of oral diseases aligns with the United Nations sustainable development goals (SDGs) (61). SGD 3 pertains to good health and well being.AI optimises diagnostic accuracy, enabling the early detection of oral diseases. AI directly contributes to improving health outcomes for the patient reducing the global burden of oral disease.

AI's automated diagnosis is reducing healthcare costs and minimising unnecessary interventions, promoting a minimally invasive approach. Consequently, supporting SDG 1, which is concerned with no poverty (61). AI should be accessible to a vast population as well as being embedded in health policies to ensure its equitable potential.

AI models should be trained on demographically diverse datasets in order to combat issues of bias, addressing SDGs 5 and 10 associated to gender equality and reduced inequalities (61). It is important to have AI algorithms provide equal assistance amongst both genders and in patients with oral disease globally.

Sustainable AI integration needs to be conscientiously approached. An interdisciplinary approach through global budgets for investment should be distributed towards AI education and training for dentists. This is not only essential for technological advancement but also to ensure that AI has an equitable lasting delivery globally.

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9 ANNEXES

9.1 Annex to show traditional and AI diagnostic schemes

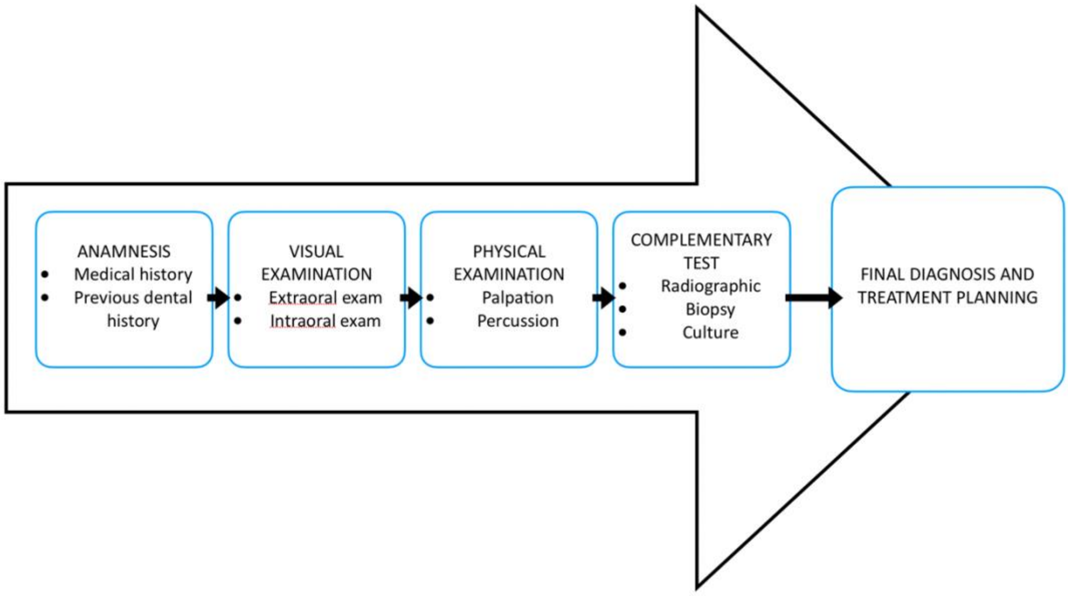

Figure 6. Diagram outlining traditional diagnostic method

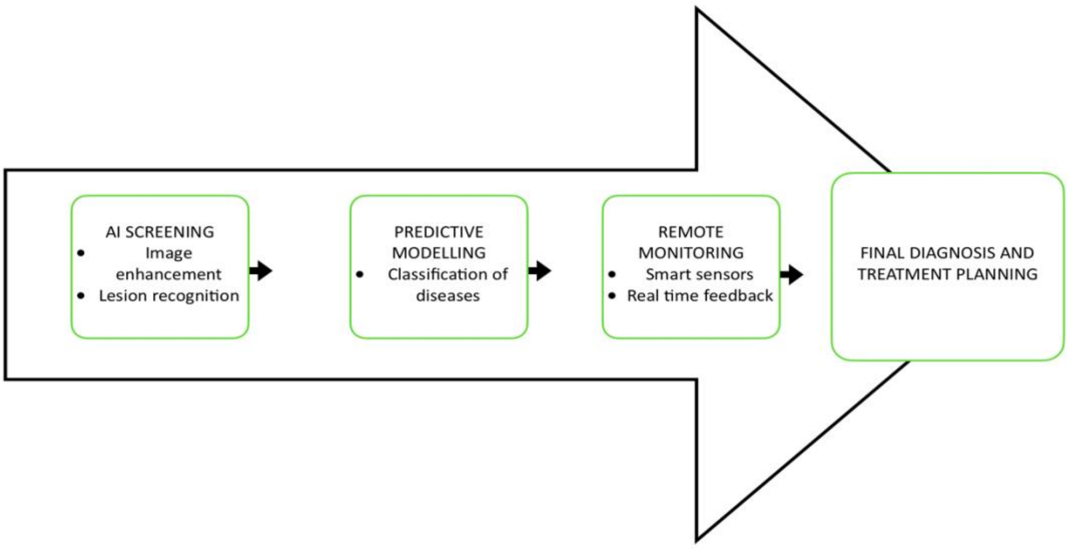

Figure 7. Diagram outlining the diagnostic process with AI