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INSTITUTO UNIVERSITÁRIO EGAS MONIZ

MESTRADO INTEGRADO EM MEDICINA DENTÁRIA

INTERDISCIPLINARY APPLICATIONS OF ARTIFICIAL INTELLIGENCE (AI) IN DENTISTRY: A FOCUS ON ENDODONTICS, ORAL PATHOLOGY, PROSTHODONTICS, ORTHODONTICS AND PERIODONTICS.

Trabalho submetido por
Hela Allani
para a obtenção do grau de Mestre em Medicina Dentária

julho de 2024

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Trabalho orientado por
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RESUMO

A tese explora o impacto revolucionário da Inteligência Artificial (IA) na Medicina Dentária refletindo sobre o seu potencial para remodelar práticas tradicionais e atender à crescente procura por cuidados dentários de alta qualidade.

O objetivo desta trabalho é compreender como evoluiu IA dentro da Medicina Dentária, guiada por duas questões cruciais: "Quais são as tendências e desenvolvimentos emergentes em IA na odontologia?" e "Quais implicações estas tendências têm para o futuro da IA no campo odontológico?".

Utilizando a base de dados *Scopus*, foi realizada uma análise bibliometrica abrangente da literatura de 2000 a 2023 para responder a estas perguntas. Os resultados revelam um aumento significativo nas publicações relacionadas com IA, especialmente entre 2018 e 2023, destacando uma rápida expansão nas aplicações de IA que melhoram a precisão diagnóstica e o planeamento de tratamento. Técnicas como a deep learning e as neural networks transformaram as práticas dentárias, melhorando a precisão do diagnóstico e reduzindo a carga de trabalho. As tecnologias de IA, em particular as CNN e as ANN, melhoraram a precisão da análise radiográfica, desde a deteção de patologias dentárias até à automatização das avaliações cefalométricas, otimizando assim os resultados do tratamento.

Esta advocacia é sustentada pela necessidade de que as aplicações de IA na medicina dentária sejam tanto eficazes quanto eticamente sólidas, garantindo que elas não só melhoram os resultados clínicos, mas também aderem aos mais altos padrões de cuidados ao doente.

Palavras-chave: Inteligência artificial, Medicina dentária, Planificação de tratamentos, Machine learning.

ABSTRACT

This thesis explores the revolutionary impact of Artificial Intelligence (AI) in dentistry, reflecting on its potential to reshape traditional practices and meet the increasing demands for high-quality dental care.

The aim of this research is to examine how AI has evolved in dentistry over the past two decades, driven by two pivotal questions: "What are the current emerging trends and developments in AI in dentistry?" and "What implications do these trends have for the future of AI in the dental field?".

Utilizing the Scopus database, a comprehensive bibliometric analysis of literature from 2000 to 2023 was conducted to address these inquiries. The findings reveal a significant increase in AI-related publications, especially between 2018 and 2023, underscoring a rapid expansion in AI applications that enhance diagnostic precision and treatment planning. Techniques such as deep learning and neural networks have transformed dental practices by enhancing diagnostic precision and reducing workload. AI technologies, particularly CNNs and ANNs, have improved the accuracy of radiographic analysis, from detecting dental pathologies to automating cephalometric evaluations, thereby optimizing treatment outcomes.

This advocacy is underpinned by the need for AI applications in dentistry to be both efficacious and ethically sound, ensuring that they not only improve clinical outcomes but also adhere to the highest standards of patient care.

Keywords : Artificial intelligence, Dentistry, Treatment planning, Machine learning.

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- **AI** - Artificial Intelligence
- **ANN** - Artificial Neural Network
- **AUC** - Area Under The Curve
- **BDT** - Boosted Decision Tree
- **BNN** - Bayesian Belief Network
- **BPNN** - Back-Propagation Neural Network
- **CAD/CAM** - Computer-aided design/computer-aided manufacturing
- **CAM** - Class Activation Maps
- **CBCT** - Cone Beam Computed Tomography
- **CBS** - Case-Based Reasoning
- **CNN** - Convolutional Neural Network
- **CP** - Chronic Periodontis
- **CT** - Computerized Tomography
- **DL** - Deep Learning
- **DT** - Decision Tree
- **FFNN** - Feed-Forward Neural Network
- **FPD** - Fixed Partial Dentures
- **KNN** - K-Nearest Neighbors
- **MFP** - Mandibular First Premolar
- **ML** - Machine Learning
- **MRI** - Magnetic Resonance Imaging
- **NB** - Naïve Bayes
- **NN** - Neural Network
- **OC** - Oral Cancer

- **PAL** - Periapical Lesion
- **PNN** - Propagation Neural Network
- **RCT** - Root Canal Treatment
- **RF** - Random Forest
- **SVM** - Support Vector Machines
- **TMD** - Temporomandibular Disorders
- **TMJ** - Temporomandibular Joint
- **TMJID** - Temporomandibular Joint Derangement
- **VRF** - Vertical root fracture
- **WL** - Working Length

I. INTRODUCTION

Artificial Intelligence (AI) has significantly reshaped modern healthcare, introducing ground-breaking enhancements in patient care and medical practice. Its integration into diverse medical fields has not only extended human capabilities but also improved efficiency and accuracy in clinical settings (Davenport & Kalakota, 2019). In this technological surge, the field of dentistry has not remained untouched by the AI wave, witnessing transformative changes in various aspects of dental practice (Shan et al., 2021). The integration of digital technologies in dentistry, as described by DaSilva et al. (2022), is advancing the frontiers of precision medicine at an unprecedented pace.

While the field of dentistry has made considerable strides with the adoption of AI, certain challenges persist. Variability in diagnostic precision and the subjectivity inherent in treatment planning are prominent concerns that require attention (Oh et al., 2022). AI stands as a robust solution to these issues, promising to strengthen decision-making processes, bring uniformity to clinical practices, and improve the quality of patient care outcomes.

The goal of this study is to thoroughly review and synthesize a broad spectrum of literature from 2000 to 2023, applying a bibliometric approach to provide a comprehensive overview of AI's applications and impact in dentistry. The focus extends to understanding emerging trends and pinpointing significant contributions and advancements in the field. Additionally, to showcase how AI technologies are effectively being utilized to enhance diagnostic accuracy, treatment planning, and prediction of treatment outcomes.

The expected outcome of our work was to provide a comprehensive overview of AI applications within dentistry, offer valuable contributions to the scientific discourse and inform further research and developments in this transformative field.

The thesis will be organized as follows: Chapter 1 establishes the theoretical framework by reviewing existing literature. Chapter 2 outlines the methodology, detailing search strategies, databases, and inclusion criteria. Subsequent chapters present findings and discuss key contributors and emerging trends in AI applications across dentistry, concluding with a summary of insights and recommendations for future research.

II. DEVELOPMENT

2.1. History of AI

The history of AI dates back to the mid-20th century, with its conceptual foundations laid during a period marked by rapid advancements in computational theory and technology. The term "Artificial Intelligence" was introduced by John McCarthy in the year 1956 during the Dartmouth Conference, a seminal event that catalysed AI as a distinct field of academic study (McCarthy et al., 2006). This era was marked by ground-breaking advancements, most notably the exploration of machines' ability to mimic human behaviour and thought. This concept was first introduced by Alan Turing, who developed the Turing Test as a measure of machine intelligence. Turing (1950)'s work laid the foundation for the field, challenging traditional perceptions of cognition and computational potential. Despite experiencing periods of reduced interest and funding, known as "AI winters", the field of AI underwent significant evolution, particularly with the advent of machine learning and neural networks in the late 20th century (Russell & Norvig, 2010). This historical journey set the stage for the integration of AI into various domains, including healthcare and dentistry, revolutionizing these fields with innovative applications and research.

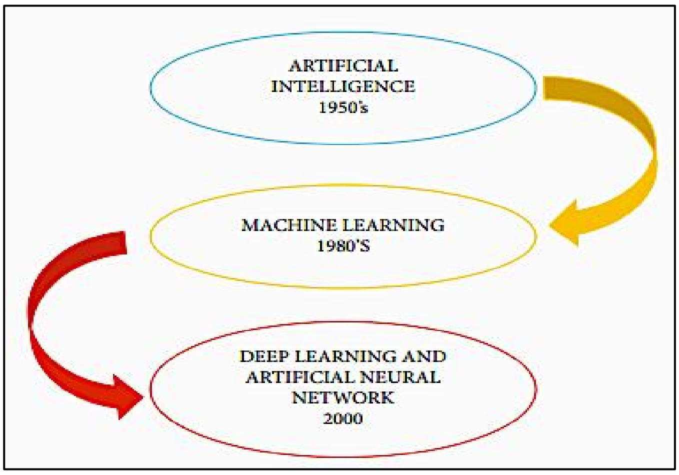

Figure 1 History of artificial intelligence. Adapted from Subramanian et al. (2022).

2.2. Introduction of AI in medical field

AI has made significant strides in the medical field, with its initial achievements marking a paradigm shift in healthcare. One of the earliest and most notable applications of AI in medicine was the development of expert systems in the 1970s, such as MYCIN, designed at Stanford University to diagnose blood-borne bacterial infections and recommend antibiotics. Another pioneering system, CADUCEUS, developed in the 1980s, was capable of diagnosing complex medical cases comparable to human experts (Miller, 1994). These early systems laid the groundwork for subsequent AI applications in medicine. The advent of machine learning and deep learning has further revolutionized medical diagnostics, notably in medical imaging (Shen et al., 2017). A landmark achievement in this area was the development of AI algorithms for analysing radiology images, significantly enhancing the accuracy and speed of diagnoses. These initial successes of AI in medicine have set the stage for ongoing innovation, transforming patient care and medical research.

2.3. Definitions of AI

In order to gain a more comprehensive understanding of the concept of AI, it is essential to clarify the distinction between AI, deep learning, machine learning, and data science as it can be observed in Figure 2. AI, deep learning, machine learning, and data science are interconnected yet distinct fields.

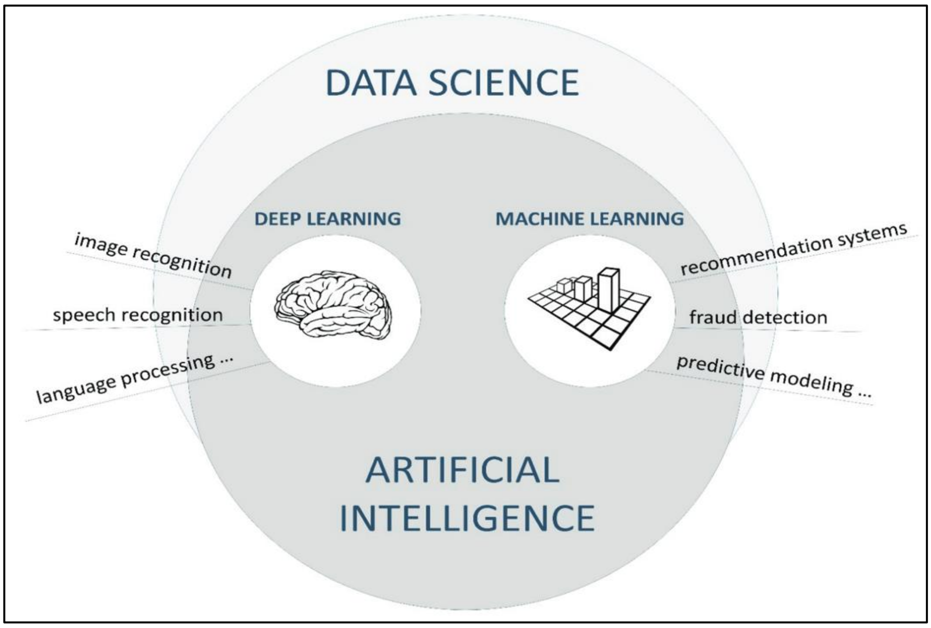

Figure 2 Representation of artificial intelligence, deep learning, machine learning and data science. Adapted from Vodanović et al. (2023).

❖ Machine Learning

Machine Learning is a subset of AI, that was initially described by one of the pioneers of ML, Samuel (1959), as “a field of study that gives computers the ability to learn without being explicitly programmed”, that involves the development of algorithms that can learn and make predictions or decisions based on data. This learning process is often categorized into supervised, unsupervised, and reinforcement learning, depending on the nature of the learning signal or "feedback" available to the system (Alpaydin, 2021).

❖ Deep learning

In the early 21st century, DL models, known for their multilayer neural networks, marked a significant development in the field of ML (Vodanović et al., 2023). It is a subset of ML, inspired by the structure of human brain, involving neural networks with many layers (hence "deep") that process data in complex ways. It considers various sets of data simultaneously, these sets of data are assessed and processed repeatedly until reaching an output. Every evaluation is processed in a different layer which is based on the previous output’s layer. These layers are called hidden layers, as their input and output are not visible (Mintz & Brodie, 2019). Deep learning algorithms are capable of autonomously detecting and extracting characteristics from unprocessed data, including images, sounds, and text. These algorithms then utilize these features for predictive analysis or decision-making.

❖ Artificial Neural Networks

ANNs are the foundation of many deep learning models. They were inspired by the biological neural networks in the human brain and consist of interconnected neurons, which process data in a layered structure (Vodanović et al., 2023). It has the capability to mimic human cognitive functions, encompassing abilities such as thinking, problem-solving, learning, and decision-making (Ossowska et al., 2022). ANN, in its basic structure, consists of three layers: the input layer where data is introduced, the hidden layer where the data undergoes processing, and the output layer where the system determines the appropriate action (Ossowska et al., 2022). Currently, a study shows that ANN could play the role of second opinion to locate the apical foramen on radiographs; it could also to enhance the accuracy of working length on radiographs (Ahmed et al., 2021).

❖ Convolutional Neural Networks

CNNs are a specialized kind of neural network used primarily for processing data that has a grid-like topology, such as images. CNNs employ a mathematical operation called convolution, which allows them to efficiently handle the high dimensionality of raw images. This makes them exceptionally well-suited for tasks like image recognition, object detection, and image classification (LeCun et al., 2015). Currently, CNNs have demonstrated strong performance, particularly in analysing periapical and bitewing images. They excel in tooth identification, segmentation, and classification; like determining the presence of a tooth on an image or pathologies like caries (Schwendicke et al., 2019). Additionally, they are used for diagnosing maxillary sinusitis through panoramic radiography, detecting cephalometric landmarks, and classifying root morphology (Rodrigues et al., 2021).

2.4. Application of AI in dentistry

2.4.1. Conservative Dentistry

Tooth decay, a common chronic infectious disease in childhood, is preventable and necessitates early diagnosis for effective treatment and to avoid advanced caries requiring invasive procedures. Research has focused on using CNNs, DL and ML for detecting dental caries in radiographs. Studies have utilized various imaging techniques, including extracted teeth images, bitewings, periapical radiographs and CBCT. For instance, Bayraktar and Ayan (2022) achieved an overall accuracy of 94.59% in diagnosing inter-proximal caries using 1,000 bitewing images with a YOLO-based CNN system. Figure 3 illustrates examples of successful and unsuccessful detections by an AI system.

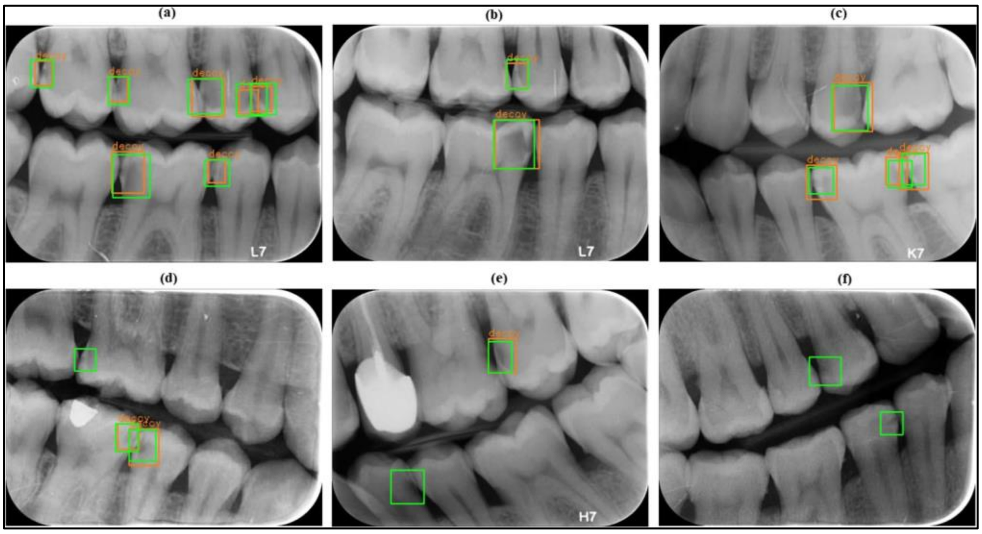

Figure 3 Comparison of Ground Truth (in green) and CNN Model Detections (in orange) - Successful detections (a, b, c) and Mixed Outcomes; successful detections and False Negatives (d, e, f). Adapted from Bayraktar & Ayan (2022).

However, the study faced a limitation in distinguishing whether the caries were limited to the enamel or had progressed to the dentine (Bayraktar & Ayan, 2022). Similarly, in the study by Ezhov et al. (2021), 24 dentists assessed 30 CBCT scans using the Diagnocat AI system, which led to a significant increase in diagnostic sensitivity (0.8537 for aided vs. 0.7672 for unaided) with comparable specificity. The results showed a statistically significant difference with a p-value of 0.032, demonstrating the AI system's efficacy in enhancing diagnostic accuracy. Lee et al. (2018) used a large dataset of 3,000 periapical radiographs, employing CNN, GoogleNet, and Inception-v3 architecture, achieving 82.0% accuracy in caries detection. Javed et al. (2020) reported a 99% accuracy in detecting Streptococcus mutans, a bacteria associated with dental caries, using feedforward backpropagation on 45 molar teeth images. Additionally, Devito et al. (2008) used backpropagation algorithms for caries prediction, and reported an 88.4% accuracy in detecting proximal caries from X-ray images. Moran et al. (2021) introduced an innovative approach for detecting and classifying the severity of proximal caries in bitewing images, utilizing two distinct CNNs with varied parameters. This method shows promise in aiding dentists, particularly in assessing bitewing images and determining the severity of approximal caries. The findings from these studies underscore the significant role AI can play in improving the accuracy of caries diagnosis, supporting dentists with varying levels of experience, and enhancing the quality of dental education.

2.4.2. Endodontics

AI applications in endodontics primarily include virtual tasks like identifying periapical lesions, detecting fractures in crowns and roots, determining the working length, and recognizing tooth morphology.

- **Detection of periapical lesions**

The integration of AI in endodontics has shown promising advances, particularly in the diagnosis of periapical lesions. Studies like Endres et al. (2020) highlight the proficiency of deep learning algorithms, notably CNNs, in diagnosing periapical radiolucency on radiographs, matching or even surpassing the diagnostic performance of experienced oral and maxillofacial surgeons and radiologists. These AI models demonstrate higher sensitivity, specificity, and accuracy in detecting lesions compared to traditional methods. Additionally, Setzer et al. (2020) determined that when trained within a restricted CBCT environment, a DL algorithm exhibited notable accuracy in lesion detection. Further advancements in AI technology could enhance voxel-matching precision, leading to the study achieving an impressive 93% accuracy rate. Therefore, in the study of Fu et al. (2024) a novel 3D deep learning model, PAL-Net, is proposed for automated detection and segmentation of periapical lesions (PALs) associated with apical periodontitis (AP) from CBCT images. PAL-Net not only showed high accuracy in its tasks but also outperformed dentists in diagnosing PALs, indicating its potential for clinical integration and training programs for inexperienced dentists. The study also highlights PAL-Net's capability to reduce diagnostic time and improve performance, especially among junior dentists.

- **Root and root canal morphology**

The knowledge of variations in root canal anatomy and morphology is crucial for the success of root canal treatments. AI technologies, particularly DL systems and CNN, have shown significant potential in enhancing these diagnostic processes. Hiraiwa et al. (2019) demonstrated the effectiveness of a DL system in classifying mandibular first molar root morphology on panoramic radiographs, particularly in determining the presence of single or additional roots in distal roots, with a diagnostic accuracy of 86.9%. Similarly, Lahoud et al. (2021) employed CNNs for automated 3-dimensional tooth segmentation, analysing 433 CBCT radiographic segmentations of teeth. This study found that AI performed on par with human operators, but much faster, setting a new benchmark in clinical efficiency. Another study using ResNet-101(CBAM) system achieved an 85% accuracy rate in identifying the presence of a single root canal in mandibular first premolars. Figure 4 illustrates positive and negative predictive values of 81.4% and 82.35%, respectively. Its performance matched that of experienced dentists and surpassed the average dentist's accuracy (Fu et al., 2023).

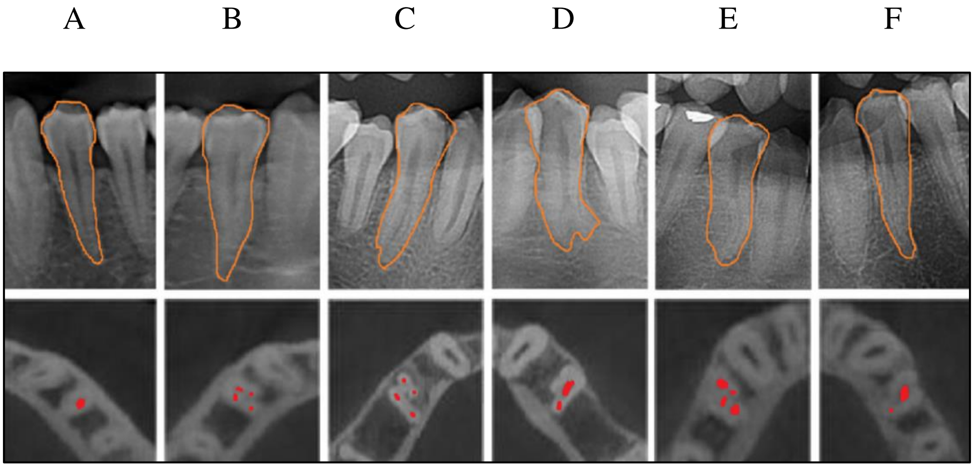

Figure 4 Panoramic and CBCT scans of MFP Root Canal Classifications; Single and Multiple Canals. Image A shows a MFP with a single root canal, classified as "single", while images B to F incorrectly categorize multiple root canals as “single”. Adapted from Fu et al. (2023).

❖ Detection of root fractures

Vertical root fractures (VRFs) can be elusive, often presenting with subtle symptoms or, frequently, no symptoms whatsoever (Tsesis et al., 2010). VRFs affect 3.7 to 30.8% of root canal-treated teeth, primarily in mandibular premolars and molars. They are difficult to treat, often requiring extraction or hemi section, but early intervention can lead to a high survival rate for remaining roots over five to ten years (Fukuda et al., 2020).

Johari et al. (2017) conducted a study to develop an AI model using a PNN framework, aimed at identifying VRFs in both intact and root canal-treated teeth through periapical and CBCT imaging. This model was particularly effective in detecting VRFs in CBCT scans, achieving an accuracy of 96.6%. Fukuda et al. (2020) suggested that CNNs could be effectively used for the detection and measurement of VRFs in panoramic radiographs (see Figure 5) with a successful detection case. Similarly, Kositbowornchai et al. (2013) utilized a probabilistic NN to ascertain the integrity of tooth roots, registering an accuracy of 95.7% in distinguishing between sound roots and those with vertical fractures.

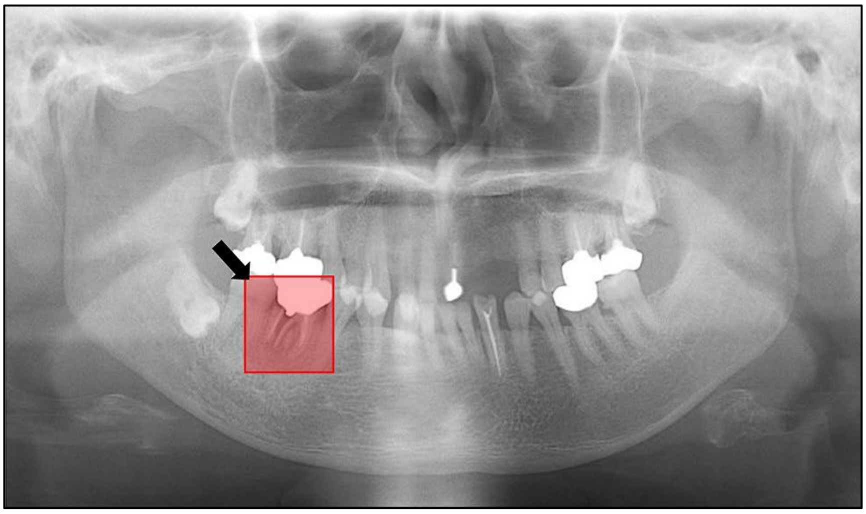

Figure 5 A case of successful detection. Black arrow represents a VRF tooth. Adapted from Fukuda et al. (2020).

❖ Determination of working length and identifying apical foramen

In Endodontics, measuring the correct working length (WL) is vital for the success of root canal treatments. This crucial process, which involves accurately identifying the apical foramen, benefits from the advancements in digital technology. However, these technological approaches also come with the challenge of potential errors. Addressing this, research has increasingly focused on applying ANN to achieve a more precise estimation of the correct WL of teeth. For instance, in a study utilizing a model of a cadaver human, Saghiri et al. (2012) employed an ANN to determine the optimal working length in endodontics, achieving an impressive accuracy rate of 96%. This level of accuracy exceeds that of experienced endodontists, who typically demonstrate a success rate of 76%. This research aligns with a separate investigation conducted by the same team, which involved extracting characteristics from radiographs and subsequently analysing them using an ANN. Their approach yielded a rate of accuracy of 93% in identifying the minor apical foramen (Saghiri et al., 2012). In addition, Qiao et al. (2020)'s study develops a NN-based multifrequency impedance method for root canal length measurement, achieving nearly 95% accuracy.

❖ Retreatment prediction

Endodontic treatments have a high success rate of 90% but still face a 10% failure rate. This makes the application of AI methods particularly valuable for dentists, as they can analyse and detect cases within this failure margin more accurately, incorporating vital information for better decision-making. Case-Based Reasoning (CBS), which involves solving problems based on past experiences with similar challenges, is one such method. Campo et al. (2016) utilized CBS to predict outcomes of nonsurgical root canal retreatments, providing insights into the procedure.

❖ **Prediction post-operative pain following root canal treatment**

Root canal therapy (RCT) is the prevalent treatment for diseases of the pulp and periapical region, often accompanied by post-operative pain. Several factors can affect this pain, including the number of treatment sessions, methods used, medication during RCT, whether it's initial or retreatment, and patient-related factors like age, oral hygiene, gender, and the severity of inflammation (Gao et al., 2021). NN have shown promise in medical outcome predictions, with ANN reportedly capable of predicting post-treatment pain with substantial accuracy. A particular study employing an ANN model achieved a 95.6% accuracy in estimating post-operative pain. The study's inclusion criteria were specific: no RCT contraindications, first-time RCT recipients, no psychoactive or analgesic drug use in the past month, absence of immune or diabetic conditions, non-pregnancy and non-lactation in female patients, with all treatments conducted by the same endodontist (Gao et al., 2021).

2.4.3. Periodontics

Periodontitis, a global disease affecting billions, leads to tooth loss if untreated, necessitating early detection and effective therapy. Dental probing, used for measuring pocket depth and clinical attachment loss, has limited accuracy due to examiner variability. Radiographs, another common diagnostic tool, also depend on the examiner's experience. To enhance diagnostic precision, NN have been employed; for instance, Krois et al. (2019) used CNN to evaluate panoramic radiographs (see figure 6) for detecting periodontal bone loss in percentage of the tooth root length. Results were compared with measurements done by six specialists. CNN achieved a higher accuracy (83%) than experienced dentists (80%) (Krois et al., 2019). Lee et al. (2022)'s research utilized deep CNN to analyse radiographs, measuring radiographic bone loss and comparing it with independent examiner measurements, which achieved an accuracy of 85%.

Other studies have developed automatic methods for staging periodontitis using NN, with Chang et al. (2020) utilizing panoramic images and CNNs to detect the cementoenamel junction level and periodontal bone levels thus, defining a diagnose of periodontitis stages. Although, Vadzyuk et al. (2021) considered psychological factors like anxiety and stress levels in predicting periodontal disease development, concluding these have a significant impact on periodontitis.

To sum up, the application of AI in periodontology includes using NN is now a great tool to predict periodontal disease risk in young people by evaluating psychological features, oral hygiene, and tissue conditions (Ossowska et al., 2022). Adding that, Models like Decision Tree (DT) and Support Vector Machines (SVM) have been effective in classifying periodontal conditions (healthy periodontium, gingivitis, aggressive or chronic periodontitis) by integrating patient information, radiographs, and clinical history (Shan et al., 2021). In their research, Papantanopoulos et al. (2014) found that ANN achieved an accuracy of 90-98% in patient classification, effectively differentiating between aggressive periodontitis (AgP) and chronic periodontitis (CP) by analysing immune response profiles.

Recent studies have also implemented automated techniques to measure radiographic bone loss and categorize periodontitis and peri-implant diseases following the criteria established by the 2017 World Workshop. Detecting peri-implant bone loss through dental periapical radiographs presents challenges, as bone margins around implants can be ambiguous or overlapping. CNNs offer a solution by accurately evaluating the marginal bone level, including the highest and lowest points of implants, in these radiographs. Another research utilized an automated system to quantify and categorize bone loss percentages, a process that proves beneficial in determining the severity of peri-implantitis (Cha et al., 2021).

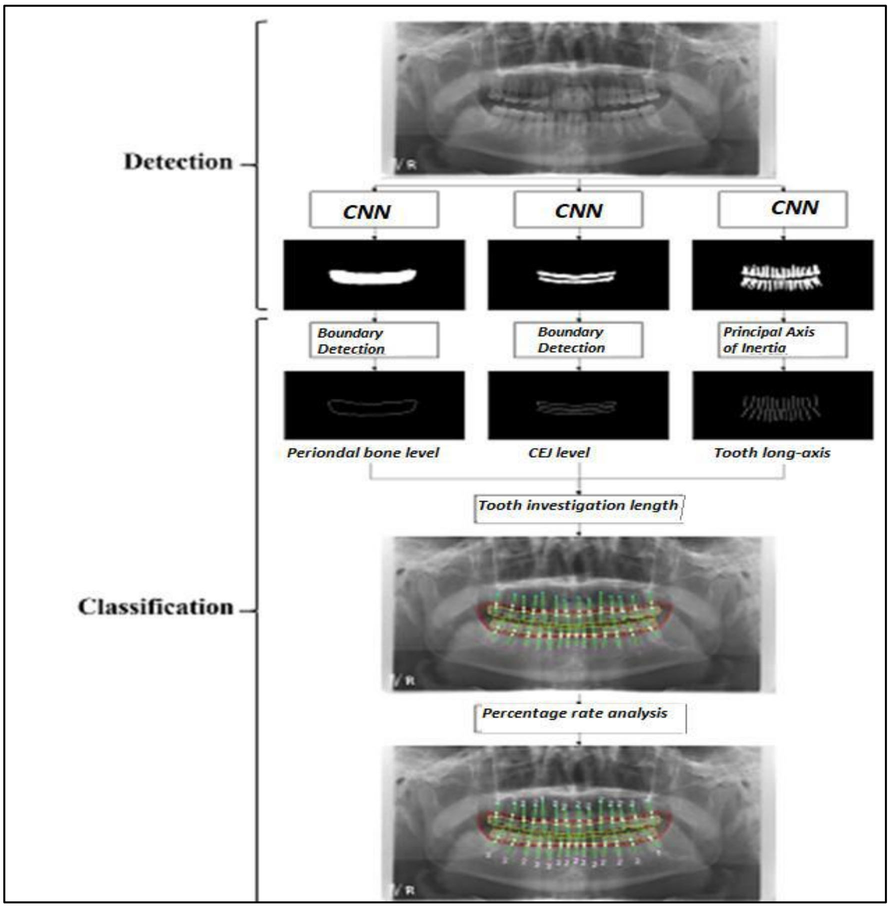

Figure 6 Overall procedure of deep learning architecture to detect and classify periodontal bone loss. Adapted from Chang et al. (2020).

2.4.4. Orthodontics

AI is revolutionizing diagnosis and treatment planning in the evolving field of orthodontics. It significantly improves consistency, speed, and accuracy by automating time-intensive tasks like patient examination, analysis of photographs, and radiographic recordings. The integration of AI, through algorithms such as ANN, CNN, SVM, and regression models, is transforming traditional orthodontic practices (Bichu et al., 2021). These technologies facilitate a range of tasks, including skeletal type diagnosis, bone age prediction, clinical decision-making, and automated anatomical analyses. AI's ability to simplify complex protocols, coupled with its predictive accuracy, is making orthodontic treatment more efficient and objective, thereby redefining patient care in this domain.

- **AI-driven diagnostic of Malocclusion**
  - **Automatic identification of landmarks**

The analysis of cephalometric radiographs is a process that includes the identification of key radiographic landmarks, followed by the measurement of various distances, angles, and ratios (Arik et al., 2017). This type of analysis serves three main objectives: firstly, it facilitates the sagittal evaluation of both hard and soft tissues in the head and face, according to established standards; secondly, it is used to monitor changes during treatment and reinforcement procedures; and lastly, it plays a role in assessing the impact of growth and development as contributing factors to changes observed (Alam & Alfawzan, 2020; Subramanian et al., 2022).

ANN are making a remarkable impact in orthodontics, especially in accurately placing cephalometric points on lateral cephalograms. The success of this method largely depends on how precisely and consistently landmarks are identified (Monill-González et al., 2021). Impressively, the accuracy of ANN in this task often equals or even surpasses that of highly skilled dentists (Ossowska et al., 2022), significantly reducing technical difficulties and improving the precision of detections.

ANN's usefulness now extends beyond just lateral cephalograms. It's being effectively used for the automated detection and analysis of anatomical landmarks in CBCT images and, more recently, in frontal cephalograms. Studies have highlighted that ANN not only streamlines the process but also eases the workload for dentists, traditionally involved in the meticulous task of identifying and analysing these landmarks (Bichu et al., 2021). This is a notable advancement from the conventional manual tracing method in cephalometric analysis, which is known for being laborious and prone to errors. Manual tracing can take upwards of 15 minutes, a duration influenced by factors like the orthodontist's expertise, the clarity of the cephalogram, and the number of parameters involved in the analysis (Dreyer & Geis, 2017).

Moreover, NN are also revolutionizing the way angles and lengths are measured in orthodontics. The advanced YOLO v3 model, a cutting-edge real-time object detection system, has shown exceptional results. In a comprehensive study with 1028 cephalograms, it outperformed human accuracy, maintaining a mean absolute error of less than 0.9 mm (Bichu et al., 2021; Monill-González et al., 2021). Additionally, the R-CNN model has been successful in detecting soft tissue landmarks, which is crucial for accurate facial profile assessments. This fusion of advanced technology with dentistry is not just about making processes more efficient, it's about transforming the precision with which orthodontic care is delivered (see Figure 7, 8).

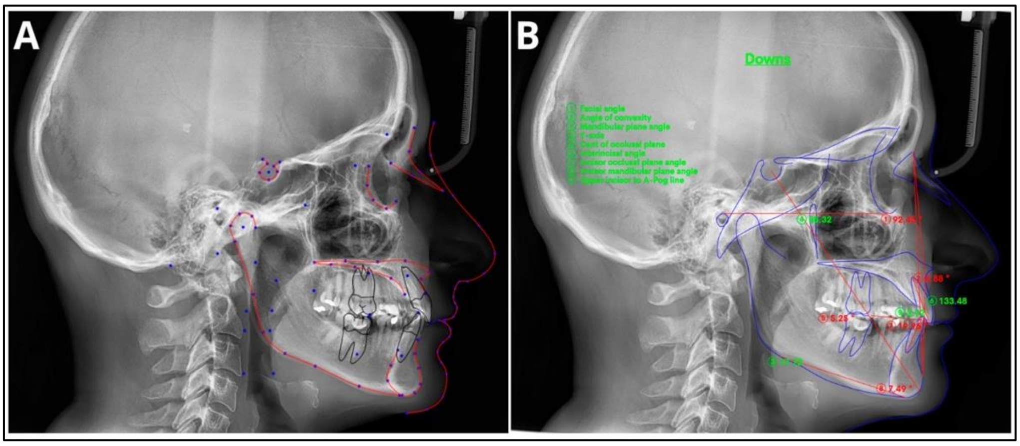

Figure 7 Automated Cephalometric Analysis with CephX (A) vs. WebCeph (B) on an 18-year-old male. (B) shows results with Downs cephalometric analysis. Measurements exceeding the normal parameters are indicated in red and an Asterix. Adapted from Kazimierczak et al. (2024)

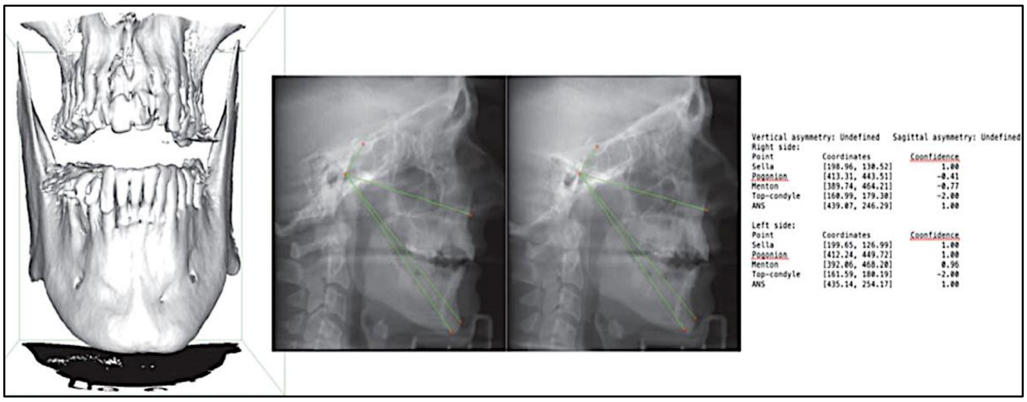

Figure 8 Automated tracing and cephalometric analysis using AI technology. Based on the CBCT scan, landmarks are identified for cephalometric analysis; Adapted from Chen et al. (2020).

❖ Skeletal classification

In pre-orthodontic examinations, assessing the jaw's position relative to the cranium is crucial, in addition to occlusion. Skeletal malposition is commonly classified using the Angle classification system, which categorizes anteroposterior jaw relationships into three types: class I (normal), class II (protrusion), and class III (retrusion). Traditional methods for skeletal classification rely on manually calculating linear and angular variables using landmarks on the maxillary and mandible. However, this is challenging due to the variability in mandible positions influenced by occlusion and the temporomandibular joint, whereas maxillary landmarks are more stable. SVM and ANN are used to predict mandible variables from maxillary variables, with ANN demonstrating higher correlation coefficients, particularly for the gnathion (Gn) and menton (Me) points (Bichu et al., 2021). Notably, the best predictors for ANN were derived from both literature and SVM-selected independent variables (Niño-Sandoval et al., 2017).

SVM is also employed for skeletal classification, using automatically extracted maxillary variables for regression tasks. While it shows high sensitivity and precision in predicting class II and III, its performance is less satisfactory for class I, often due to misclassification of cases with marginal values. CNN-based methods have outperformed traditional handcraft methods in skeletal classification, offering improved accuracy, sensitivity, and specificity (Yu et al., 2020). These methods use located regions of interest (ROI) instead of landmarks and can classify vertical skeletal classes as normal, hyperdivergent, or hypodivergent, in addition to sagittal relationships. However, the precision of classification could be enhanced with CBCT images due to issues with superimposition. Therefore, Kim et al. (2020) discovered that a CNN-based model with synchronized multi-channels produced optimal results. This approach, compared to single-channel models, achieved better classification performance through ensemble and synchronized multi-channel algorithms. However, it's essential to incorporate other significant factors, such as racial diversity and the extensive spectrum of normal cases, for a more thorough and accurate analysis.

- **AI-driven decision making**
  - **Bone age prediction**

The decision on the optimal timing for treatment is based on predicting bone age through cervical vertebral maturity, which shows how much growth deviates from the norm (Shan et al., 2021). This method can also forecast developmental periods. Using ANN software for this purpose has shown an accuracy rate of 94.27% (Ossowska et al., 2022), making it a preferred approach for identifying cervical vertebrae stages (CVS).

Besides cervical vertebral maturation, bone age assessment can also be conducted by examining the ossification centers in the proximal phalanx, distal radius, and metacarpal bone, especially in cases where the patient has cervical vertebrae deformity. This assessment is carried out using hand-wrist radiographs (Hiraiwa et al., 2019; Ossowska et al., 2022).

❖ **The decision on the need for advance extraction**

The ongoing debate in orthodontics regarding extraction versus non-extraction treatments remains unresolved. AI algorithms, particularly ANN, have been developed to assist in this decision-making process. These models, used for determining the necessity of tooth extraction in cases of dental protrusion, crowding, and jaw dysplasia, have shown promising results. For instance, one ANN-based decision-making model achieved a 100% success rate in training using backpropagation, although test outcomes were around 80% (Xie et al., 2010). However, Jung and Kim (2016) allocated one-third of their training dataset for validation purposes, a strategy aimed at preventing overfitting. This approach enhanced the performance of the ANN, resulting in a 94% concurrence rate with the assessments of an experienced orthodontist. Other ensemble methods like random forest (RF) also show lower error rates in predicting extraction needs and specific patterns. AI models have identified key factors such as incompetent lips and lower incisor inclination as crucial in deciding whether to extract teeth. These AI-based tools help simulate extraction decisions and optimize orthodontic treatment outcomes, with an accuracy of up to 93%, proving especially beneficial for less experienced clinicians.

❖ **The decision on the need for orthognathic surgery**

Due to the complexity of orthognathic surgery, more comprehensive factors must be taken into consideration, including facial asymmetry and a case's principal complaints; all of the below issues bring challenges to clinicians. A variety of measures need to be adopted in the training set to make applicable opinions. The generally agreed standard for orthognathic surgery is the skeletal class III and asymmetry. Additionally, Knoops et al. (2019) employed an SVM model to diagnose whether cases demanded orthognathic surgery using facial scanning images. Although the system achieved an accuracy of 95.4%, sample selection bias was used because of the fact that normal dentofacial individualities were chosen as non-surgery cases. To integrate further factors, Choi et al. (2019) incorporated further measures similar as E-line and occlusal plan into ML models, but the point values needed manual input rather of automatic image birth. The ANN model handed high accuracy during the test stage without overfitting. Besides deciding whether to undergo surgery or not, the system can also prognosticate the demand for tooth extraction for surgical cases using 4 classifiers. The decision-making system can be beneficial and give different clinical results for inexperienced orthodontists.

- **AI-driven prediction of outcomes treatments**

In the study by Volovic et al. (2023), ML models were tested for their ability to predict orthodontic treatment duration. The results showed that all models could predict treatment times within a clinically acceptable range, with linear models and RF emerging as the most predictive, whereas SVR and Gaussian process regression were less effective. Key predictive features included the decision to extract teeth, the intermaxillary relationship, lower incisor position, and the use of additional appliances. This study underscores the potential of ML models in aiding orthodontic treatment planning, highlighting the importance of specific treatment variables in determining treatment duration. Additionally, in the research of Tanikawa and Yamashiro (2021) where they developed AI systems to predict changes in facial morphology resulting from orthognathic surgery and orthodontic treatment, specifically focusing on a Japanese patient demographic. The study aimed to overcome the limitations of existing software, which often assumes a proportional relationship between hard-tissue and soft-tissue movements. Two AI systems were developed: System S for orthognathic surgery predictions and System E for orthodontic treatment predictions. Both systems utilized landmark-based geometric morphometric methods combined with deep learning. The study found that System S had an average error of 0.94 mm, with a total success rate of 54% for errors under 1 mm, and System E had an average error of 0.69 mm, with a 98% success rate for errors under 1 mm. Both systems achieved a 100% success rate for errors under 2 mm, indicating their clinical acceptability. These findings highlight the potential of using AI in clinical settings for predicting post-treatment facial morphology.

2.4.5. Oral pathology

- **Oral pathology diagnosis**
  - **Temporomandibular joint disorders**

Current AI technologies have been involved to help in Temporomandibular disorders (TMDs), which are common and often painful craniofacial conditions affecting the masticatory muscles and the temporomandibular joint (TMJ). Symptoms typically include deviations in mouth opening, jaw pain, and sounds from the preauricular area (Lee et al., 2021). TMD etiology is multifaceted, with both psychosocial and biological factors playing independent or interconnected roles. AI, particularly ML, has been utilized in studies to discern whether these factors are significant risk factors for TMDs. Such AI applications offer decision-support systems for predicting TMDs and analyzing their contributing elements, considering clinical factors like jaw function and psychosocial aspects such as stress and socioeconomic status (Lee et al., 2021). Orhan et al. (2021), utilized ML techniques, including KNN and Random Forest algorithms, to predict temporomandibular disorders with notable accuracy, using magnetic resonance imaging (MRI) data. This model demonstrated high accuracy rates for identifying condylar changes and disk displacement, suggesting its effectiveness in clinical settings. Choi et al. (2021), also utilized a CNN model, specifically ResNet, for diagnosing temporomandibular joint disorders from panoramic radiographs, outperforming human radiologists in diagnostic performance. In addition, Lövgren et al. (2017), published a solution that helps the domain of TMD. In their study, they used ANN to predict two subgroups of internal differences in TMJ and normal joints based on the clinical symptoms and signs. ANNs were trained using the diagnosis and symptoms of 161 patients having temporomandibular joint derangement (TMJID) as a golden standard. Then, after the training, diagnosis and symptoms of 58 new patients are introduced to test the ability and accuracy of ANNs in diagnosis. The results were compared to an experienced surgeon in TMD. The sensitivity and specificity of ANNs were respectively 80% and 95% in detection unilateral anterior disc displacement with reduction. While, in the detection of unilateral anterior disc displacement without reduction, the sensitivity and the specificity were respectively 69% and 91%. In the case of bilateral anterior disc displacement with reduction, sensitivity and specificity were 37% and 100%. For the detection of bilateral anterior disc displacement without reduction sensitivity and specificity were respectively 100% and 89%. Finally, in the case of detection of anterior disc displacement with reduction on one side and without reduction on the other side, sensitivity and specificity were 44% and 93% (Lövgren et al., 2017).

- **Maxillary sinusitis**

Extraoral radiographs frequently illustrate the maxillary sinuses, and AI's capability to automatically recognize these sinuses and pinpoint pathologies can significantly reduce diagnostic errors. Kuwana et al. (2020), leveraged a CNN to accurately detect maxillary sinus lesions from panoramic radiographs, achieving 90–91% accuracy, 81–85% sensitivity, and 91–96% specificity in detecting sinusitis, and even more robust results for cysts, which emphasizes the model's reliability. Moreover, Murata et al. (2019) employed a CNN to diagnose maxillary sinusitis from panoramic radiographs, with a sample size of 120 images. The AI model demonstrated strong diagnostic capabilities with an accuracy of 87.5%, a sensitivity of 86.7%, and a specificity of 88.3%. It was noted that the model could serve as an assistive tool for inexperienced dentists, potentially improving diagnostic processes by offering support to less experienced clinicians alongside the expertise of radiologists. Additionally, Hung et al. (2022), a three-step CNN based on V-Net and SVR applied to CBCT images, excelled in detecting maxillary sinusitis conditions from CBCT images, with Area Under the Curve (AUC) values up to 0.93. Applied to both low and high-dose scans, the model accurately identified mucosal thickening and mucous retention cysts, underscoring its potential for effective, non-invasive diagnostics. The use of low-dosed CBCT scans for these predictions underscores the technology's potential for non-invasive diagnostics.

AI models such as those developed by Kim et al. (2019), for analyzing Water's view radiographs, a CNN was used for diagnosing maxillary sinusitis from Water's view radiographs. The study involved analyzing 200 radiographs. The performance of the CNN model was notably high, showing better diagnostic accuracy than five radiologists, as evidenced by its AUC values for both temporal and geographic external performance.

❖ Oral cancer

Oral cancer (OC) is a globally prevalent and deadly disease with a complex origin and high mortality rate, often categorized under head and neck cancers. Its prognosis is heavily dependent on the stage at diagnosis, with a significant drop in survival rates from early (approximately 80%) to later stages (below 20%). Despite oral cancer being most commonly diagnosed by dentists during initial examinations, late detection is common and contributes to poor outcomes, highlighting the critical need for accurate early diagnosis (Khanagar et al., 2021). Clinical appearance alone is not always sufficient for determining the severity of the disease, necessitating invasive biopsies for confirmation (Khanagar et al., 2021). Recently, AI has emerged as a promising tool for the detection and management of OC, offering greater precision than traditional methods through the analysis of extensive digitized data (Ahmed et al., 2021). Employing neural network technologies like ANN and CNN, along with machine learning algorithms on large datasets, AI supports the early identification of OC and predicts risks, thereby refining the diagnostic process and patient care (Khanagar et al., 2021). AI's ability to integrate new information continuously improves its predictive capabilities, representing a significant advancement over existing diagnostic approaches (Khanagar et al., 2021). These advances highlight AI's role in augmenting diagnostic precision and efficiency in oral pathology, offering tools that complement the expertise of clinicians and potentially enhancing patient outcomes through earlier and more accurate diagnosis. AI learning tools utilize data from cytology and fluorescent images, computerized tomography (CT) scans, and measurements of tumor invasion depth to diagnose OC with increased speed and precision. Numerous studies have determined that AI-based learning models enhance the accuracy and effectiveness of oral cancer diagnosis. Namely, Jeyaraj and Samuel Nadar (2019), employed a partitioned CNN for hyperspectral images in OC detection, achieving high accuracy in distinguishing between benign 91,4% and malignant tissues 94,5%. Uthof et al. (2018) incorporated smartphone-captured images and AI technology for detection of precancerous and cancerous lesions, with the point-care concept. They added autofluorescence and white light imaging to the pictures, processed by AI algorithms to detect oral malignancies (Uthoff et al., 2018). This approach proved to be convenient and showed increased accuracy, though the authors noted that further studies with a larger population are necessary for robust validation (Khanagar et al., 2021). In another study, Kann et al. (2018) employed deep learning on a dataset from 106 OC patients, which included 2875 CT-segmented lymph node samples, to determine the presence of nodal metastasis and extra-nodal tumor spread. This investigation assessed the deep learning model's ability to aid in managing patients with head and neck cancer.

- **Oral pathology prognosis**
    - **Temporomandibular joint disorders prognosis**

AI models are increasingly demonstrating their ability to not only diagnose but also prognosticate conditions in oral pathology with high accuracy. Iwasaki et al. (2015) developed a Bayesian Belief Network (BNN) applied to MRI images to prognosticate Temporomandibular joint disorders (TMJ), achieving an impressive accuracy of 0.99. The BNN showed potential in predicting the progression of TMJ, evaluating bone changes, disc displacement, and the impact on bony space and disc with promising diagnostic performance. Furthermore, Bas et al. (2012), utilized a Back Propagation ANN analyzing electronic patient records to prognosticate clinical symptoms of TMJ. This model provided considerable sensitivity and specificity, aiding an experienced oral and maxillofacial surgeon in predicting the course of TMJ with and without reduction (Bas et al., 2012). These models signify a shift towards precision medicine in dentistry, offering the possibility of anticipating the progression of diseases and enabling clinicians to tailor more effective and timely treatments for patients.

- **Predicting occurrence of oral cancer**

Despite the advancement in treatment aids, OC remains challenging due to its high recurrence rates. Given the complexity of oral carcinoma data, AI-based predictive models offer promising avenues. Several studies using AI for oral cancer prediction have shown significant results. For instance, a study conducted in Brazil by Alabi et al. (2020) compared four ML algorithms and proved that all of them improved diagnostic accuracy, although boosted decision tree (BDT) was the one with the highest accuracy. The four machine-learning algorithm were SVM, Naïve Bayes (NB), BDT, and decision forest (DF). However, the study's limited sample size underscores the necessity for additional external data to enhance the robustness of the algorithms employed. Another study utilized AI with gene expression profiles to predict occurrence and the transformation of potentially malignant lesions (Khanagar et al., 2021). Their study, involving 86 subjects, demonstrated deep-learning machines achieving 96.5% accuracy, with multi-layer perception (MLP) reaching 94% accuracy. However, Rosma et al. (2010) AI's based her prediction on risk habits and demographic profiles and Tseng et al. (2015) explored symptom differences between deceased and surviving OC patients, comparing conventional logistic regression, DT, ANN models. DT model was also found to be easily interpretable, with accuracy comparable to conventional logistic regression. Their comparison of fuzzy regression models, fuzzy neural network prediction models, and clinician opinions concluded AI-based models outperform human judgment in OC prediction accuracy.

2.4.6. Prosthodontics

- **Prosthodontics**

The recent advancements in prosthodontics, are significantly influenced by the introduction of AI systems. These systems have revolutionized various aspects of dental care, prominently in areas like automated diagnostics, prediction, and classification. Foremost, the transition from traditional impression-making to digital impressions using intraoral scanners. These scanners, once predominantly used for single crowns or short-span fixed partial dentures (FPDs), have evolved to cater to comprehensive applications like complete denture fabrication and intricate maxillofacial intraoral scans. The reliability of intraoral scanners for everyday use is a testament to their accuracy and technological advancement. AI's impact extends to computer-aided design and manufacturing (CAD/CAM) systems, used extensively in both fixed and removable prosthodontic restorations. Machine learning, using data from numerous natural crowns, aids in crafting the ideal crown design for varied clinical scenarios. The integration of AI in prosthodontics has also broadened to include 3D face tracking and the utilization of virtual 3D data hybrids, combining elements like CBCT, intraoral scans, and facial scans. This integration is pivotal for treatments that alter a patient's smile, relying heavily on virtual representations of their anatomy. Initially, simple two-dimensional images served as the foundation for smile designs whereas now, AI and digital tools offer a more sophisticated and precise approach. It assists in generating occlusal morphology for crowns considering the opposing teeth's condition, even in cases of wear or fracture. It also enables programmed teeth setting for dentures and automatic framework designs for removable dental prostheses.

- **Margin Detection**

Margin detection in fixed prosthodontics has been notably enhanced by AI, following the acquisition of intraoral scans. This progression is critical for precise prosthesis fabrication, where margins play a significant role in the fit and longevity of the restorations. Zhang et al. (2019) conducted a study using a CNN on 380 dental preparation models. The models were distributed into groups for training, validation, and testing with 300, 40, and 40 preparations respectively. Their methodology included a cross-validation approach, which resulted in an accuracy of 97.43%, showcasing the efficacy of CNN in this critical area.

- **Prediction of debonding in CAD/CAM composite resin restorations**

On the functional front, a study conducted by Yamaguchi et al. (2019) in Japan utilized a retrospective cohort approach, analyzing a significant sample size of 8,640 images, with 6,480 for training and 2,160 for testing. The research aimed to evaluate the effectiveness of DL through a CNN model to predict the likelihood of debonding in CAD/CAM composite resin restorations. Remarkably, the AI demonstrated a high performance level, with the capacity to predict debonding in the test images of CAD/CAM crowns with a striking accuracy rate of 98.5%. This finding underscores the potential for AI to significantly enhance the reliability and predictiveness of dental restorative outcomes (Yamaguchi et al., 2019).

- **Color/shade matching**

In complex aesthetic cases, especially those involving front teeth like a single central incisor, AI stands out for its precision in shade matching, especially for anterior teeth such as a central incisor, where a perfect color match is essential for a natural look. The advancement of AI in prosthodontics, has been highlighted in several studies, mostly, the Back-Propagation Neural Network (BPNN) color-matching model, primarily consisting of a multilayer Feed-Forward Neural Network (FFNN) and back-propagation algorithms (Li et al., 2015). This model functions as an interactive gradient mechanism, effectively reducing the color variance between the anticipated shade and the actual target shade (Tabatabaian et al., 2023). It was used in one hand by Li et al. (2015) who studied 119 porcelain specimens. Their method, tested on 25% of the dataset in a single train-test split, achieved an accuracy of over 95%. In the other hand by Wei et al. (2018), to 43 metal-ceramic specimens. Their approach, compared to visual shade matching by three prosthodontists, yielded a color difference value of 1.12 ± 0.15, which is well below the acceptability threshold of 2.69. This study used 39 specimens for training and 4 for testing in a single split (Wei et al., 2018). However, Tam and Lee (2017) focused on tooth shade determination using SVM to analyze 1,300 images of 26 shade tabs, that were taken with a smartphone. Their methodology achieved 86% accuracy overall, with even higher accuracy rates for images taken randomly (98%) and fixed (100%) positions in the clinic. It was further evidenced by a study conducted by Kim et al. (2018) who employed also SVM to analyze color data from 26 shade tabs and 10 natural teeth. The color data for the shade tabs were gathered using five identical intraoral cameras, repeated seven times for reliability, while the natural teeth color data were collected with three different intraoral cameras. The results were impressive, showing accuracies of 91.9% and 95.0% in the first method and an even higher accuracy of 96.9% in the second.

- **Classification of dental arches**

In the field of removable prosthodontics, CNNs was employed to classify dental arches. This is particularly challenging in edentulous patients, where setting up denture teeth to meet functional and aesthetic requirements is crucial. CAD/CAM software, enhanced with ML, can effectively recreate suitable intermaxillary relations by correctly positioning teeth. The study conducted by Takahashi et al. (2021), where a deep CNN (ResNet152) was used to classify dental arches in oral photographs, specifically for designing removable partial dentures. The study analyzed 1,184 images and achieved an impressive accuracy of 99,5% for the maxilla and 99,7% for the mandible, demonstrating the effectiveness of the model in accurately classifying dental arches.

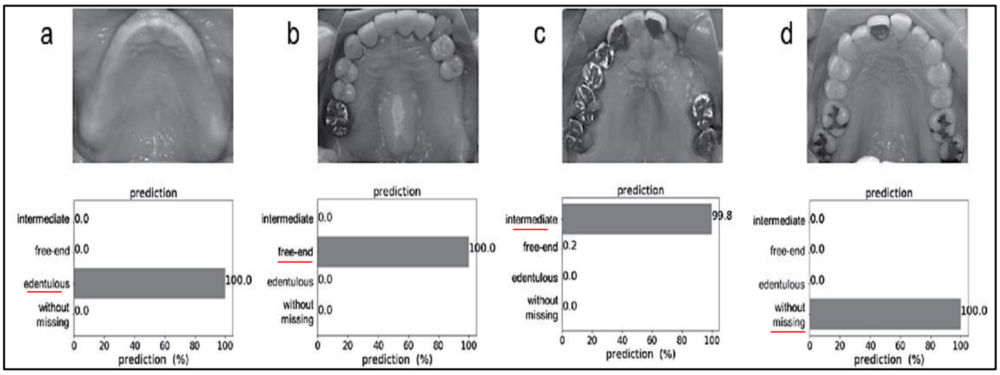

Figure 9 Photographs and graphs illustrating an example of the percentage of correct predictions (PCPs) in the maxilla. a: edentulous, b: arches with posterior tooth loss (distal extension missing), c: arches with embedded tooth loss (intermediate missing) and d: intact dentition (without missing). Adapted from Takahashi et al. (2021).

However, it was also found that AI's capabilities in RPD design are not without their challenges. One significant hurdle is the establishment of clear prosthodontic guidelines for AI models, which currently depend on textbook principles and subjective author insights (Revilla-León et al., 2022). The success of AI is also contingent upon the quality and completeness of data regarding teeth, ridges, and dental arches (Takahashi et al., 2021). Irregularities in these arches can decrease AI performance, emphasizing the need for meticulous data collection to ensure the accuracy of RPD designs.

➢ Implant prosthodontics

The accuracy of prostheses in implantology is crucial, as even minuscule deviations can lead to significant clinical complications. It's not only optimal function of the dental implant systems but also for ensuring long-term success and patient comfort. This demands meticulous attention to detail in every phase, from planning to the manufacturing and placement of the prosthetic components.

❖ Classifying implant

While experienced clinicians may find diagnosing different types of restorations straightforward, this task can be quite complex for less experienced dentists. The global market has approximatively 4000 implant brands and types, complicating the process of identifying the specific brand and type of an existing implant based on radiographic images alone. Often, this level of identification can be extremely challenging or even unfeasible, thereby posing significant hurdles in providing follow-up implant services (Takahashi et al., 2021).

The application of AI, as shown in the study by Lee et al. (2020), who utilized a range of 10,770 radiographic images, allocating 60% for training, 20% for validation, and the remaining 20% for testing purposes. The aim was to assess the effectiveness of a deep CNN model, specifically the GoogLeNet Inception v3 model, in accurately identifying and classifying three specific implant systems: Osstem TSIII, Dentium Superline, and Straumann BLT from panoramic and periapical radiographs. It attained its highest accuracy levels with the Straumann BLT, achieving 99.4% for panoramic and 99.5% for periapical radiographic images. The promising results indicate that the deep CNN architecture can provide a valuable tool for distinguishing and categorizing different dental implant systems. Additionally, as indicated by Kim et al. (2020), the figure shows a visual representation of Class Activation Maps (CAMs) generated by five different CNNS architectures analyzing dental X-rays to identify various dental implant types. It demonstrates the key regions each network utilizes, with warmer colors denoting more significant focus areas, and validates the accuracy of the networks The presentation of the CAMs clarifies how these networks process X-ray images to distinguish between different implant types.

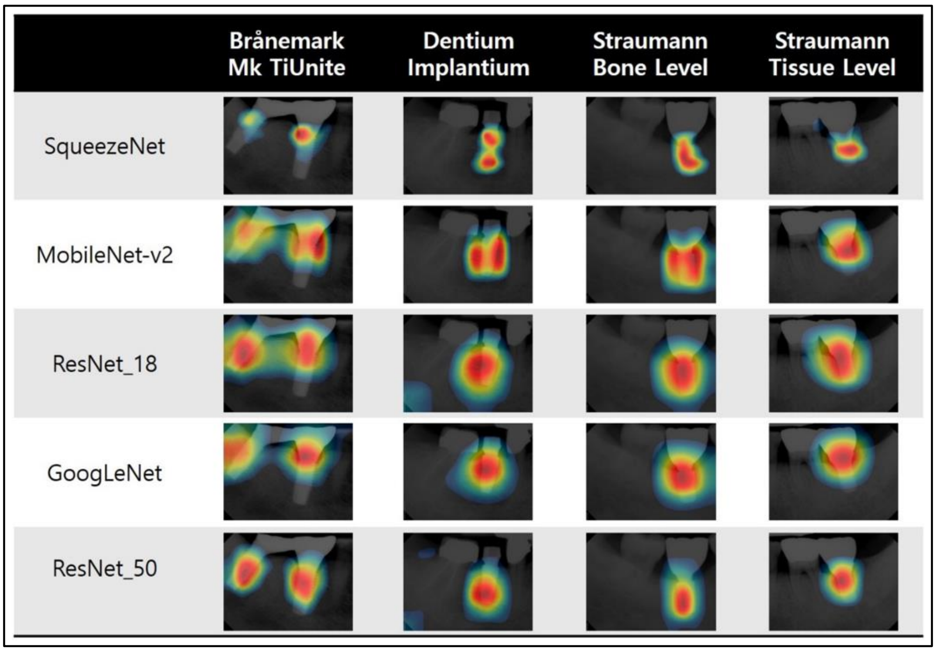

Figure 10 Illustration of CAM from Five Pretrained Networks for four selected Implant Fixture Types. Adapted from Kim et al. (2020).

In a different study, the use of a machine learning classifier for dental implants, employing techniques like SVM and logistic regression, was found to achieve an average accuracy of 67% (Benakatti et al., 2021). This creates limitation for using AI in real-world dentistry. Although AI shows promise in helping to differentiate between dental restorations and implants, further research is essential to broaden its utility and improve its precision in identifying a diverse category of dental treatments.

- **Tracing margin line of the implant abutment**

Lerner et al. (2020), conducted a retrospective cohort study detailed the production of implant-supported monolithic zirconia crowns, which were intricately positioned onto customized hybrid abutments. The heart of this innovation lies in the CAD software Valletta®, Exocad's intrinsic AI, which adeptly automated the tracing of the margin line for implant abutments, achieving this with notable accuracy even below the gum line. The results of the study were compelling, with marginal adaptation showing very high precision in more than 96% of the restorations. The precision of the margin line, a critical factor for the implant's functionality and its integration with the patient's natural gum line, was significantly enhanced by the AI's capabilities.

III. MATERIALS AND METHODS

3.1. Data Collection

To collect data for the article, a Boolean search strategy was deployed on Scopus in December 2023. Scopus has become a substantial collection of peer-reviewed literature consisting of books, scientific journals, and conference papers since it was established in 2004 (Thelwall & Sud, 2022). It spans a wide range of research topics, spanning from scientific and technical fields to medicine and community studies, and even arts and humanities (Borgohain, 2020). It operates as a prominently curated abstract and citation database, boasting an expansive reach at both the global and regional levels (Baas et al., 2020). Our strategy involves identifying articles with "dentistry" and "artificial intelligence" mentioned in their title, keywords, or abstract, and restricted to publications between 2000 and 2023. By closing our search window in 2023, we strategically aimed to capture the most updated collection of records, coinciding with the apex of interest in AI. Additionally, a rigorous filtering process was instituted to eliminate content forms such as books, book chapters, editorials, letters, retracted articles, non-English articles, those not directly pertinent to AI in dentistry, and any duplicates.

Subsequently, these articles were classified according to their primary focus areas, which may encompass diagnostics, treatment planning, or the utilization of AI within specific dental specialties like endodontics, conservative dentistry, prosthodontics, oral pathology, orthodontics, and periodontics.

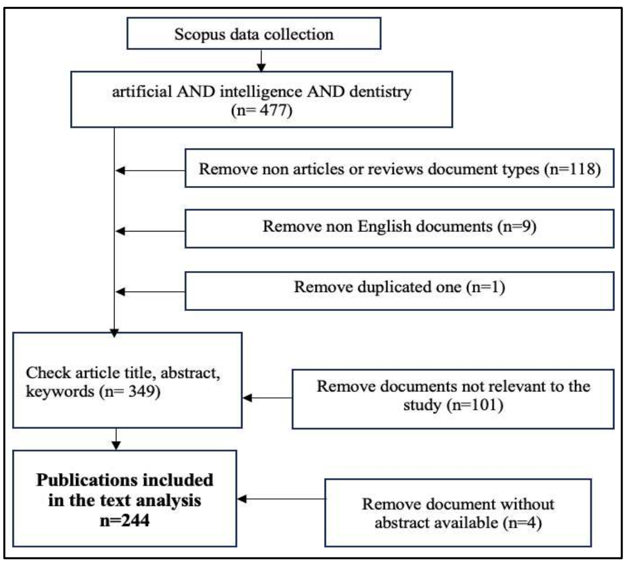

Figure 11 Flowchart of the literature identification and selection for this study

3.2. Methodology

Bibliometric is an invaluable method for both qualitative and quantitative analysis of scientific literature, offering an organized framework for assessing study outcomes and their implications and identifying emerging patterns of a specific topic (Ninkov et al., 2021). It enables the exploration of contributions from various countries, institutions, journals, and individual scholars within a particular field. These analyses typically involve the use of specialized software tools and visual assessments, designed to systematically scrutinize the knowledge base and trace the evolutionary trends of a given discipline. In the field of dentistry, bibliometric analyses have proven to be effective in assessing trends and guiding research as evidenced by the work of Chen et al. (2021). It has been widely used, such as in prosthodontics, endodontics, implantology, orthodontics, pediatric dentistry, and periodontology, which concisely delivered valuable information for future advancement (Chen et al., 2023). In this study, we applied bibliometric methodologies to conduct an in depth review of AI applications in dentistry, aiming to identify current trends in this field.

This bibliometric analysis follows the BIBLIO framework's guidelines for methodological transparency and quantitative approaches (Montazeri et al., 2023), as well as detailed guidance on scientific mapping (Donthu et al., 2021) and inclusive bibliometric indicator. This allowed us to present our data transparently, promoting replication and comprehension of the review's breadth, while also ensuring the analysis remained responsible and indicative of the diverse character of this study subjec

IV. RESULTS

4.1. The scientific discourse

4.1.1. The development of the field

The evolution of AI in dentistry from 2000 to 2023 has been marked by a gradual but accelerating interest, culminating in a significant surge in recent years. The early years, particularly from 2000 to 2017, saw a limited number of publications, indicating that AI's application in dentistry was a relatively unexplored area. However, this trend shifted notably in 2019, with an increase in research output. The period from 2020 to 2021 marked a substantial growth phase, reflecting advancements in AI technology and its applicability in dental research and practice (Thurzo et al., 2023). This growth trajectory peaked in 2022 and 2023, with an explosive increase in publications, underscoring a robust and widespread academic and practical interest in AI within the dental field.

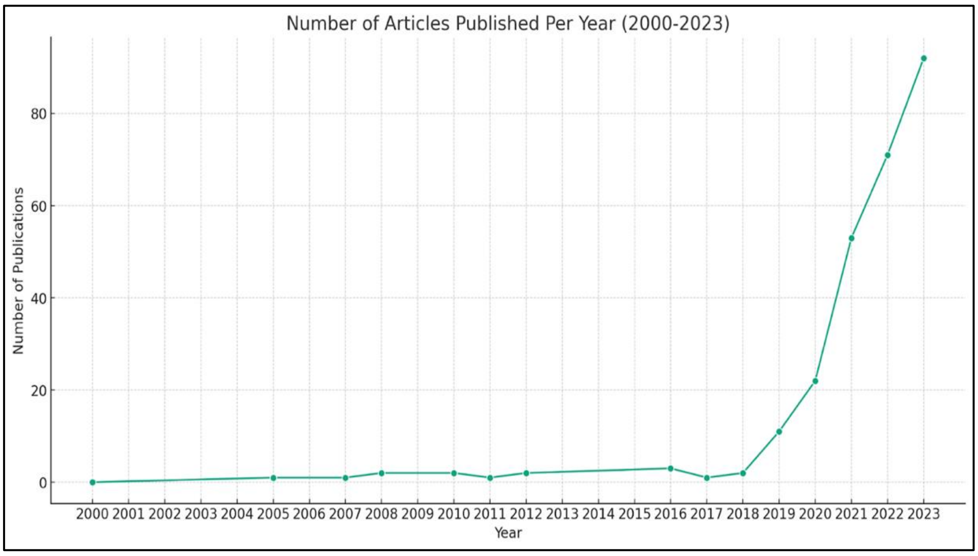

Figure 12 The number of papers published per year: 2000-2023

4.1.2. Publications outlets

From 2000 to 2023, our analysis uncovered 137 journals that have published 244 articles related to the use of AI in dental specialties; precisely a significant portion of these sources have published at least one article over the past 4 years. The top 20 journals in terms of the number of published articles are listed in the Figure 13. Throughout the years, the forefront of publishing AI in dentistry has been led by a select few journals.

Diagnostics emerges as the top publisher with a total of 14 manuscripts, followed closely by *Journal of Dental Research* with 12 articles. Equally impactful, *Applied Sciences (Switzerland)* and *Journal of Dentistry* have each contributed (n=8), illustrating their significant roles in advancing the field. Other notable contributors include *Dentomaxillofacial Radiology* and *Oral Radiology,* each adding a substantial number of articles to the growing body of knowledge. This varied landscape of publication venues showcases the multidisciplinary nature of AI research in dentistry, reflecting a widespread academic interest.

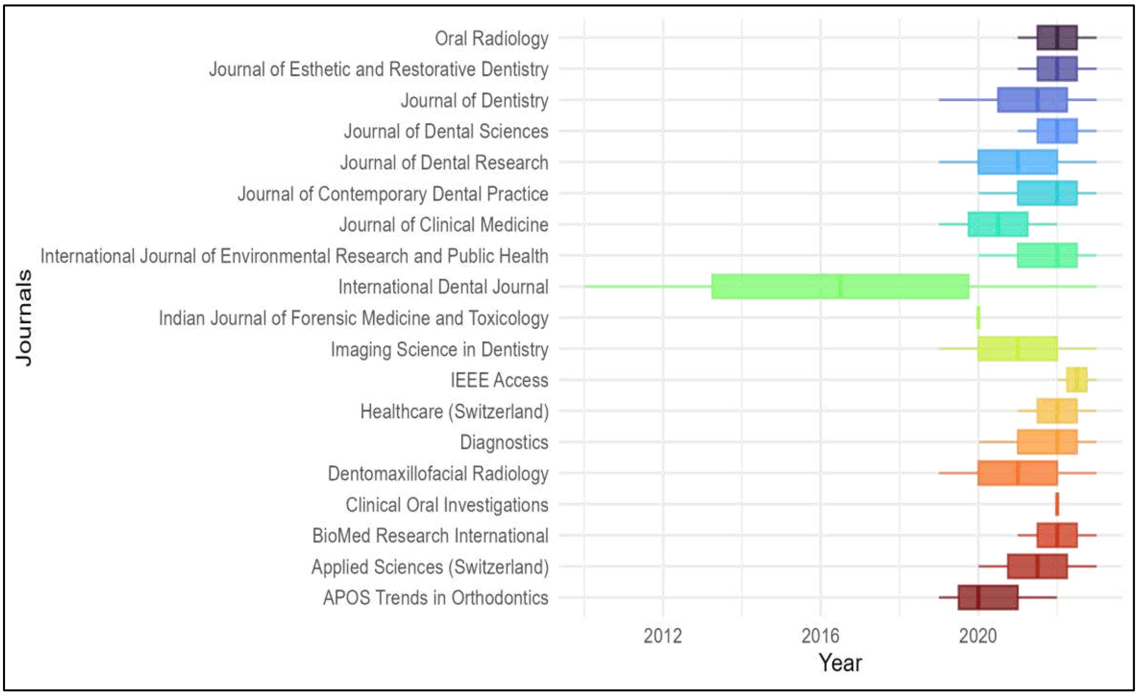

Figure 13 Publication Trends of Top 19 Journals: 2000-2023

4.1.3. Producers' locations

Regarding the number of countries represented in the authors list, we reviewed all affiliations provided and discovered writers in 40 countries/territories. The Figure 14 below shows the distribution of authorships by continent and nation. The darker the color, the larger the number of authors linked with national institutions. The gray color identifies the countries where no authors were found affiliated. Therefore, from 2000 to 2023, these countries published at least one paper on AI in dentistry. India had the highest number of publications (n = 30, 12.30 %), followed by the United States (n = 27, 11.07 %) and Turkey (n=24, 9.84 %). Germany had a fourth position (n=19, 7.79%) and Saudi Arabia immediately after (n=16, 6.56%). The University of Ankara had the highest number of publications (n = 16), followed by Eskisehir Osmangazi University (n = 11), Charité-Universitätsmedizin Berlin (n = 8), and Babol University of Medical Sciences (n = 6).

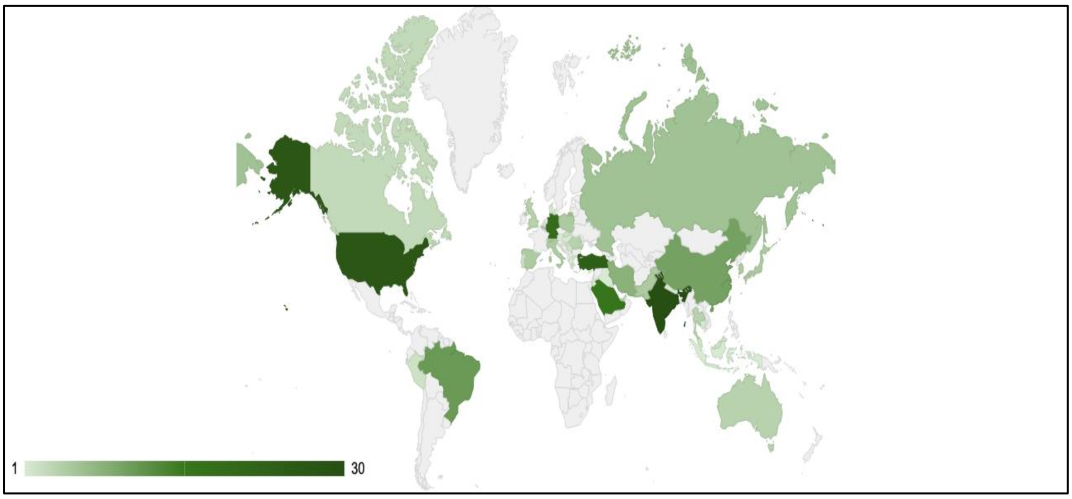

Figure 14 Global distribution of publications (2000-2023)

4.2.Thematic focus

4.2.1. Extraction from Keywords

We investigated research publications about the use of AI in dental specialties to identify prevailing themes within this domain. After pre-processing the data and setting a minimum occurrence of four times for each keyword, the words occurring the most were considered on their own. A total of 28 keywords were found with a frequency of 1147 times. These can be seen through a word cloud methodology (Figure 15). These keywords were categorized into clusters emphasizing types of AI, anomalies, dental specialties, types of radiography, the purpose of AI, and others. In each cluster, words share the same color, with darker and larger fonts highlighting the more frequent topics. Figure 15 suggests that the most frequently used words include “artificial intelligence”, “artificial/convolutional neural network”, “caries”, “CBCT”, “deep learning”, “diagnosis”, “machine learning”, and “panoramic radiography”.

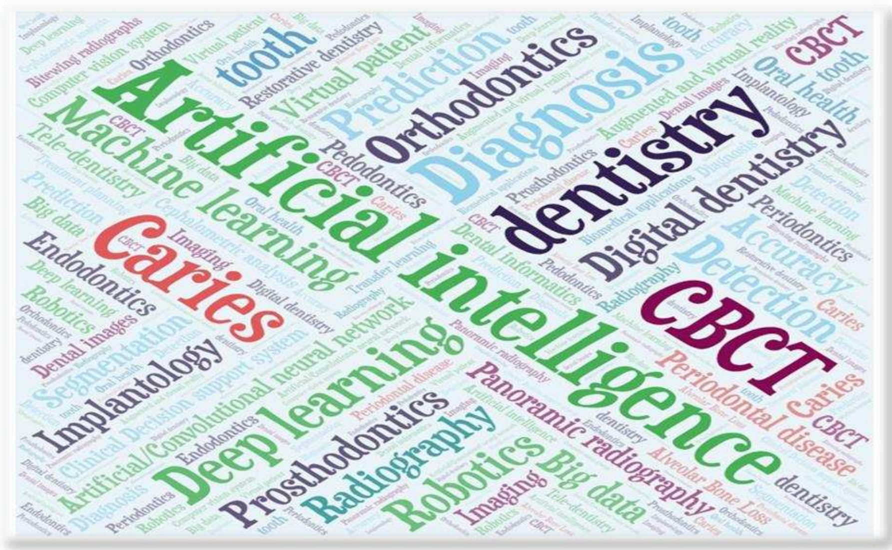

Figure 15 Word cloud visualization of frequently and repeatedly used words.

Around AI in dentistry, multiple themes emerge embracing digital technologies. Deep learning, and machine learning, with their notable occurrences in the literature, are revolutionizing diagnosis and treatment planning, significantly in areas like periodontal disease, orthodontics, and prosthodontics (Retrouvey & Conley, 2022). The frequent mention of panoramic radiography and CBCT (cone-beam computed tomography) highlights the importance of advanced imaging in the use of AI in dentistry (Leite et al., 2020). Furthermore, the recurrent themes of digital dentistry and tele-dentistry underscore a shift towards more accessible, efficient, and technologically integrated dental care. The integration of robotics, such as for computer-assisted surgery or crown preparation, into dental practices, although less frequent than other topics, still represents a significant trend toward automating and enhancing dental procedures (Monterubbianesi et al., 2022). The existing literature confirms the potential of robotics to improve dental procedure outcomes, but they are understudied due to their limited availability and the technical expertise required for their operation. Thus, progress in dental robotics hinges on collaborations between engineers and dentists (Grischke et al., 2020).

4.2.2. Extraction from Abstracts

From the abstract, we observed from 2000 to 2018, research on AI in dentistry was mainly focused on general “Artificial Intelligence” and “data”. Words like “Simulator” and “virtual” reflect the rise of digital training and augmented reality tools, enhancing dental education and practice. Terms like “treatment”, “expert”, and “decision support system" indicate AI's role in improving patient care and supporting dentists' decision-making. Other words such as "quality", "performance", and "accuracy" point to AI's impact on the precision and effectiveness of dental procedures (Tabatabaian et al., 2023). From 2019 to 2023, the landscape of AI in dentistry research has significantly evolved, as evidenced by the surge in related publications. Key themes such as "Artificial Intelligence", "Deep Learning", "Machine Learning" and "Neural Networks" indicate a robust integration of sophisticated AI methodologies in dentistry (Vodanović et al., 2023). Furthermore, the increasing mentions of "Dental Implants" and "AI-Assisted Procedures", alongside the "Analysis of Images", "Radiographs", and their "Segmentation" and "Classification", underscore AI's pivotal role in enhancing "diagnostic accuracy" and "detection" (Al-Sarem et al., 2022). This advancement is integral to the evolution of "Precision Medicine" in dentistry, revolutionizing both the planning and execution of dental treatments with unprecedented accuracy.

4.3. The evolving discussion

4.3.1. Longitudinal development

In order to analyze the longitudinal development of the field, a spaghetti plot was prepared to illustrate how some AI-related keywords in dentistry evolved in the scientific publications from 2000 to 2023. Figure 16 shows 20 words which can be identified by different colors.

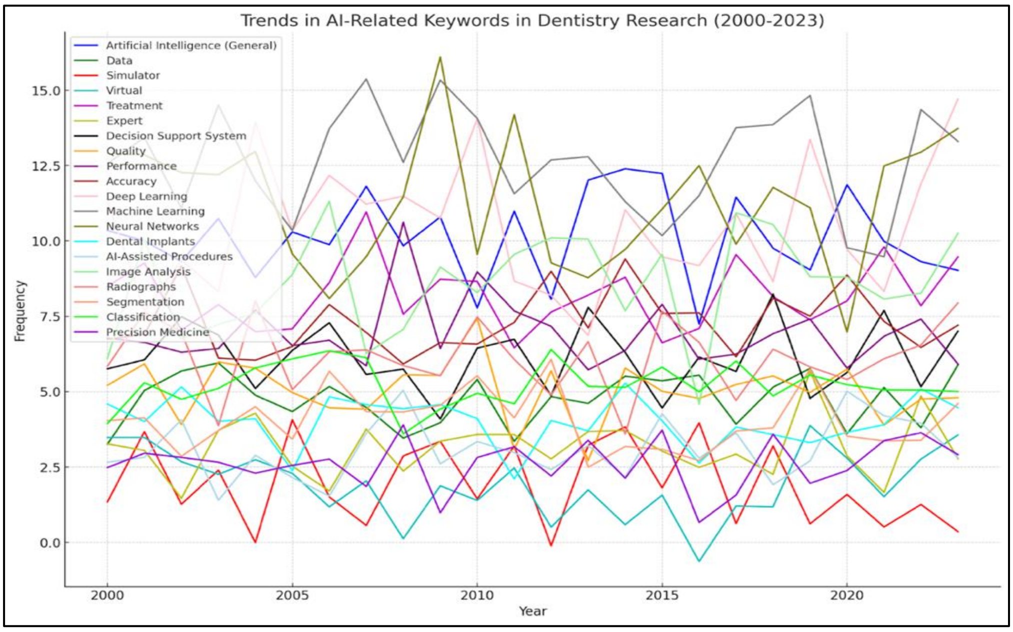

Figure 16 Tracing the Trajectory of AI Terminology in Dental Research: A Spaghetti Plot Analysis (2000-2023).

Early years (2000-2018), Terms like “artificial intelligence” and “data” show consistent presence, indicative of the foundational role of AI and data management in dentistry research. The rise of “simulator” and “virtual” around the mid-2000s reflects the advent of digital training tools and augmented reality in dentistry.

In an intermediate phase, a noticeable increase in terms like “Treatment”, “Expert”, and “Decision Support System” suggests a growing focus on AI's practical applications in patient care and decision-making support for dentists. The words “quality”, “performance”, and “accuracy” gain traction, highlighting AI's impact on enhancing the precision and quality of dental procedures.

More recently 2019-2023, there is a significant uptick in “Deep Learning”, “Machine Learning”, and “Neural Networks” indicating a shift toward more sophisticated AI methodologies. Concurrently, the rise in “Dental Implants” and “AI-assisted procedures” emphasizes AI's integration into practical dental procedures. Expressions like “Image Analysis” (see Singh & Raza, (2022)) “Radiographs”, "Segmentation”, and “Classification” peak, underscoring AI's pivotal role in diagnostic accuracy and detection. This aligns with the movement towards “Precision Medicine” revolutionizing the planning and execution of treatments (please see (Joda & Zitzmann, (2022)).

4.3.2. Trending topics

The trajectory of key terms in Figure 16 of AI-driven dentistry reveals a fascinating narrative of evolving focus and technology. The prominence of “Deep Learning” and “Neural Networks” in recent years underscores a shift toward advanced, complex data processing capabilities, particularly in image analysis. These terms surged as the dental field recognized the potential of AI for deep analysis of images and radiographs, using sophisticated techniques like image segmentation for enhanced detection and diagnosis (Leite et al., 2021). Simultaneously, “Machine Learning” steadily gained momentum, reflecting its integral role in predictive analytics and individualized treatment planning. The focused emergence of “Dental Implants” as a significant term marks AI's increasing practical application in dental treatments, with AI assisting in precision and accuracy, especially in implantology (Revilla-León et al., 2023). The discussion around “Image Analysis” and “Radiographs” evolved to not just encompass the enhancement of diagnostic procedures through AI but also extended to a deeper analysis using AI-driven techniques. This included leveraging AI for detailed segmentation and in-depth interpretation of radiographic data, enhancing the precision and reliability of diagnoses in dental care. Collectively, these keywords paint a picture of a field in transition, increasingly leaning on AI for more sophisticated, accurate, and patient-tailored dental solutions.

4.3.3. The most relevant discussion

The analysis has led to the formation of distinct clusters of application, each demonstrating the versatile and transformative impact of AI technologies. The Diagnostic Applications cluster, with its sub-clusters like caries detection and periodontal disease diagnosis, showcases AI's capability to enhance accuracy and efficiency in identifying dental conditions. Similarly, the Treatment Planning and Prediction cluster, encompassing areas such as implantology, orthodontics, and prosthodontics, where AI was mainly focused on refining treatment strategies, planning treatments, predicting outcomes, and monitoring cases. The Educational Applications cluster is revolutionizing the way dental education is delivered, utilizing AI for training simulations and skill development. Therefore, the Patient Management and Public Health cluster benefits significantly from AI, with tools designed for patient engagement, risk assessment, and large-scale epidemiological studies. Finally, the Technological Advancement and Innovation cluster is a testament to the ongoing evolution in AI, driving forward novel methodologies and tools that continually reshape dental practices. Each cluster, with its specific focus and advancements, collectively illustrates a comprehensive and multi-faceted integration of AI in dentistry, heralding a new era of precision, efficiency, and effectiveness in dental healthcare.

V. DISCUSSION

The analysis of our study indicated that between 2000 and 2023, a diverse group of 647 authors from 63 countries and 478 institutions contributed to 244 publications on the application of AI in dentistry field. These publications emphasize the extensive reach and diverse perspectives in this area of research. Notably, there was a marked escalation in the volume of publications between 2018 and 2023. We observed a significant rise in the number of publications, a trend that aligns with findings in broader literature (Xie et al., 2023). This surge can be linked to a variety of crucial factors. Thurzo et al. (2022) conducted a comprehensive review, revealing a remarkable and unparalleled increase in research activity in AI dental publications, with an average annual growth of 21.6% over the last decade and a 34.9% increase per year over the last 5 years, particularly in digital diagnostic methods like radiology. Ahmed et al. (2021) further supported this trend, highlighting the improvement in AI techniques and their outcomes in dentistry, emphasizing AI's role in accurate patient management, dental diagnosis, prediction, and decision-making. Moreover, the research by Mutlu-Sagesen & Sagesen. (2023) on dental esthetics indicates a growing interest in research trends and global productivity.

Notably, India and the United States have emerged as forefront leaders in this domain. Among these contributions, the University of Ankara, Eskisehir Osmangazi University, and Charité Universitätsmedizin Berlin stand out for their significant impact and leadership in the field. Additionally, the work of highly cited authors like Schwendicke F. and Krois J has been influential in shaping the current and future directions of AI applications in dentistry (Schwendicke et al., 2020). These findings align closely with those reported in a similar study by Xie et al. (2023), reinforcing the global relevance and consistency in AI dentistry research trends.

The transformative potential of AI in dentistry, as previously highlighted in our literature review, has been empirically validated by our bibliometric analysis. Between 2018 and 2023, there has been a pronounced surge in publications focusing on advanced AI techniques such as DL and NN. These methods have transitioned from experimental to core tools in dental AI applications, especially in the areas of diagnosis and treatment planning.

Our findings indicate a significant emphasis on the use of CNNs and ANNs for critical diagnostic tasks. CNNs, for example, have been increasingly applied to enhance the accuracy of diagnosing periapical lesions and identifying root anatomies from radiographic images, often producing results that surpass the diagnostic capabilities of experienced practitioners (Endres et al., 2020; Lahoud et al., 2021). Similarly, ANNs have shown quite high accuracy in predicting post-operative pain and accurately placing cephalometric points on lateral cephalograms and CBCT (Gao et al., 2021; Monill-González et al., 2021). Studies have highlighted that ANN not only simplifies the process but also eases the workload for dentists (Bichu et al., 2021). This correlates strongly with the trends identified in our bibliometric analysis, where these technologies have been employed to analyze a variety of radiographic data including bitewings, periapical and panoramic radiographs, and CBCT scans. Radiographic data is essential for AI use in dentistry, it serves as a critical resource for training AI models, enhancing accuracy in diagnostics, standardizing interpretations, and facilitating predictive analysis (Al-Sarem et al., 2022).

Notably, the literature underscores AI's capacity for improving image classification and segmentation. Segmentation allows AI systems to isolate specific areas within radiographs, such as distinguishing healthy tissue from pathological areas (Chen et al., 2020). Once segmented, these images are classified, enabling detailed diagnostics. For instance, in the literature in periodontics, CNNs are used for segmenting images to identify periodontal cysts and then classifying them as either having cysts or no cysts (Lakshmi & Dheeba, 2022). Similarly, CNNs are employed to detect approximal dental caries in bitewing radiographic images and classify them according to the severity of the lesion (Moran et al., 2021). This aligns with the observed bibliometric trends where AI's role in image segmentation and classification has markedly contributed to enhancing diagnostic precision and optimizing treatment outcomes.

Such advancements reflect a concerted effort within the dental research community to leverage AI not merely as a supplementary tool but as an integral component of modern dental practice, significantly influencing both current methodologies and future directions in dental care. By synthesizing the empirical data from our bibliometric analysis with the theoretical insights from the literature, it is evident that AI's capabilities in dental diagnostics are both evolving rapidly and proving indispensable. This dual approach not only supports but also enhances our understanding of AI's critical role in advancing dental diagnostics and treatment planning, paving the way for further innovation and application in the field.

VI. CONCLUSION

This bibliometric study highlights the progressive integration of digital technology in oral health from 2000 to 2023, showcasing a significant transformation in dental practices and patient care. The evolution of AI during this period reflects a shift from basic data management to advanced implementations like the use of DL and NN. This technological advancement has revolutionized diagnostic methods, treatment planning, and outcomes prediction in dentistry, significantly enhancing the efficiency, accuracy, and personalization of treatments across various specialties.

Moreover, this study presents an opportunity for policymakers to understand and leverage these technological trends, types, and applications to improve access, literacy, knowledge, and services in oral health. It emphasizes that technology types and classifications vary over time and across dental areas, underscoring the importance of context-specific applications.

However, it's important to recognize that while AI-developed algorithms have shown promising results, they are still in need of further development and refinement. Challenges like data security, ethical considerations, and maintaining the human element in patient care are crucial. These considerations call for a balanced and cautious approach to the integration of AI in dentistry. The study suggests that continuous evaluation, adaptation, and development are essential for AI to further integrate effectively into the dental field, guiding the future toward an informed, precise, and patient-centered approach in dental healthcare.

VII. REFERENCES

Ahmed, N., Abbasi, M. S., Zuberi, F., Qamar, W., Halim, M. S. B., Maqsood, A., & Alam, M. K. (2021). Artificial intelligence techniques: Analysis, application, and outcome in dentistry—A systematic review. BioMed Research International, 2021, 1–15. https://doi.org/10.1155/2021/9751564

Al-Sarem, M., Al-Asali, M., Alqutaibi, A. Y., & Saeed, F. (2022). Enhanced tooth region detection using pretrained deep learning models. *International Journal of Environmental Research and Public Health*, *19*(22), 15414. https://doi.org/10.3390/ijerph192215414

Alabi, R. O., Elmusrati, M., Sawazaki-Calone, I., Kowalski, L. P., Haglund, C., Coletta, R. D., Mäkitie, A. A., Salo, T., Almangush, A., & Leivo, I. (2020). Comparison of supervised machine learning classification techniques in prediction of locoregional recurrences in early oral tongue cancer. *International Journal of Medical Informatics, 136(*104068), 104068. https://doi.org/10.1016/j.ijmedinf.2019.104068

Alam, M. K., & Alfawzan, A. A. (2020). Evaluation of Sella turcica bridging and morphology in different types of cleft patients. *Frontiers in Cell and Developmental Biology*, *8*. https://doi.org/10.3389/fcell.2020.00656

Alpaydin, E.(2021). *Machine learning*. The MIT Press. https://doi.org/10.7551/mitpress/13811.001.0001

Arik, S. Ö., Ibragimov, B., & Xing, L. (2017). Fully automated quantitative cephalometry using convolutional neural networks. *Journal of Medical Imaging (Bellingham, Wash.)*, *4*(1), 014501. https://doi.org/10.1117/1.jmi.4.1.014501

Bas, B., Ozgonenel, O., Ozden, B., Bekcioglu, B., Bulut, E., & Kurt, M. (2012). Use of artificial neural network in differentiation of subgroups of temporomandibular internal derangements: A preliminary study. *Journal of Oral and Maxillofacial Surgery: Official Journal of the American Association of Oral and Maxillofacial Surgeons*, *70*(1), 51–59. https://doi.org/10.1016/j.joms.2011.03.069

Bayraktar, Y., & Ayan, E. (2022). Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. *Clinical Oral Investigations*, *26*(1), 623–632. https://doi.org/10.1007/s00784-021-04040-1

Benakatti, V., Nayakar, R., & Anandhalli, M. (2021). Machine learning for identification of dental implant systems based on shape – A descriptive study. *Journal of Indian Prosthodontic Society*, *21*(4), 405. https://doi.org/10.4103/jips.jips_324_21

Bichu, Y. M., Hansa, I., Bichu, A. Y., Premjani, P., Flores-Mir, C., & Vaid, N. R. (2021). Applications of artificial intelligence and machine learning in orthodontics: a scoping review. *Progress in Orthodontics*, *22*(1). https://doi.org/10.1186/s40510-021-00361-9

Borgohain, D. J. (2020). *Research output of Dibrugarh University: A scientometric analysis based on Scopus database*. https://digitalcommons.unl.edu/libphilprac/4827/

Campo, L., Aliaga, I. J., De Paz, J. F., García, A. E., Bajo, J., Villarubia, G., & Corchado, J. M. (2016). Retreatment Predictions in Odontology by means of CBR Systems. *Computational Intelligence and Neuroscience,* 2016, 1–11. https://doi.org/10.1155/2016/7485250

Cha, J.-Y., Yoon, H.-I., Yeo, I.-S., Huh, K.-H., & Han, J.-S. (2021). Peri-implant bone loss measurement using a region-based convolutional neural network on dental periapical radiographs. *Journal of Clinical Medicine, 10*(5), 1009. https://doi.org/10.3390/jcm10051009

Chang, H.-J., Lee, S.-J., Yong, T.-H., Shin, N.-Y., Jang, B.-G., Kim, J.-E., Huh, K.-H., Lee, S.-S., Heo, M.-S., Choi, S.-C., Kim, T.-I., & Yi, W.-J. (2020). Deep learning hybrid method to automatically diagnose periodontal bone loss and stage periodontitis. *Scientific Reports, 10*(1). https://doi.org/10.1038/s41598-020-64509-z

Chen, M.-C., Chen, S.-H., Cheng, C.-D., Chung, C.-H., Mau, L.-P., Sung, C.-E., Weng, P.-W., Cathy Tsai, Y.-W., Shieh, Y.-S., Huang, R.-Y., & Cheng, W.-C. (2023). Mapping out the bibliometric characteristics of classic articles published in a Taiwanese academic journal in dentistry: A scopus-based analysis. *Journal of Dental Sciences, 18(4),* 1493–1509. https://doi.org/10.1016/j.jds.2023.03.015

Chen, Y. W., Stanley, K., & Att, W. (2020). Artificial intelligence in dentistry: current applications and future perspectives. *Quintessence International, 51(3).* https://doi.org/10.3290/j.qi.a43952

Chen, Y., Yeung, A. W. K., Pow, E. H. N., & Tsoi, J. K. H. (2021). Current status and research trends of lithium disilicate in dentistry: A bibliometric analysis. *The Journal of Prosthetic Dentistry, 126*(4), 512–522. https://doi.org/10.1016/j.prosdent.2020.08.012

Choi, E., Kim, D., Lee, J.-Y., & Park, H.-K. (2021). Artificial intelligence in detecting temporomandibular joint osteoarthritis on orthopantomogram. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-89742-y

Choi, H.-I., Jung, S.-K., Baek, S.-H., Lim, W. H., Ahn, S.-J., Yang, I.-H., & Kim, T.-W. (2019). Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. *The Journal of Craniofacial Surgery*, *30*(7), 1986–1989. https://doi.org/10.1097/scs.0000000000005650

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–102. https://doi.org/10.7861/futurehosp.6-2-94

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Dreyer, K. J., & Geis, J. R. (2017). When machines think: Radiology's next frontier. *Radiology*, *285*(3), 713–718. https://doi.org/10.1148/radiol.2017171183

Ekert, T., Krois, J., Meinhold, L., Elhennawy, K., Emara, R., Golla, T., & Schwendicke, F. (2019). Deep learning for the radiographic detection of apical lesions. *Journal of Endodontics*, *45*(7), 917-922.e5. https://doi.org/10.1016/j.joen.2019.03.016

Endres, M. G., Hillen, F., Salloumis, M., Sedaghat, A. R., Niehues, S. M., Quatela, O., Hanken, H., Smeets, R., Beck-Broichsitter, B., Rendenbach, C., Lakhani, K., Heiland, M., & Gaudin, R. A. (2020). Development of a deep learning algorithm for periapical disease detection in dental radiographs. *Diagnostics (Basel, Switzerland)*, *10*(6), 430. https://doi.org/10.3390/diagnostics1006043

Ezhov, M., Gusarev, M., Golitsyna, M., Yates, J. M., Kushnerev, E., Tamimi, D., Aksoy, S., Shumilov, E., Sanders, A., & Orhan, K. (2021). Clinically applicable artificial intelligence system for dental diagnosis with CBCT. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-94093-9

Fu, D., Shi, K., Wu, F., Zhu, F., & Zhu, H. (2023). An artificial intelligence system for detecting the root canal morphology of the mandibular first premolar on panoramic radiographs. In *Research Square*. https://doi.org/10.21203/rs.3.rs-3201787/v1

Fu, W. T., Zhu, Q. K., Li, N., Wang, Y. Q., Deng, S. L., Chen, H. P., Shen, J., Meng, L. Y., & Bian, Z. (2024). Clinically oriented CBCT periapical lesion evaluation via 3D CNN algorithm. *Journal of Dental Research*, *103*(1), 5–12. https://doi.org/10.1177/00220345231201793

Fukuda, M., Inamoto, K., Shibata, N., Ariji, Y., Yanashita, Y., Kutsuna, S., Nakata, K., Katsumata, A., Fujita, H., & Ariji, E. (2020). Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiology, 36(4), 337–343. https://doi.org/10.1007/s11282-019-00409-x

Gao, X., Xin, X., Li, Z., & Zhang, W. (2021). Predicting postoperative pain following root canal treatment by using artificial neural network evaluation. *Scientific Reports,* 11(1). https://doi.org/10.1038/s41598-021-96777-8

Grischke, J., Johannsmeier, L., Eich, L., Griga, L., & Haddadin, S. (2020). Dentronics: Towards robotics and artificial intelligence in dentistry. *Dental Materials: Official Publication of the Academy of Dental Materials, 36(6),* 765–778. https://doi.org/10.1016/j.dental.2020.03.021

Hiraiwa, T., Ariji, Y., Fukuda, M., Kise, Y., Nakata, K., Katsumata, A., Fujita, H., & Ariji, E. (2019). A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography. *Dento Maxillo Facial Radiology, 48(3),* 20180218. https://doi.org/10.1259/dmfr.20180218

Iwasaki, H. (2015). Bayesian belief network analysis applied to determine the progression of temporomandibular disorders using MRI. *Dento Maxillo Facial Radiology*, *44*(4), 20140279. https://doi.org/10.1259/dmfr.2014027

Javed, S., Zakirulla, M., Baig, R. U., Asif, S. M., & Meer, A. B. (2020). Development of artificial neural network model for prediction of post-streptococcus mutans in dental caries. Computer Methods and Programs in Biomedicine, 186(105198), 105198. https://doi.org/10.1016/j.cmpb.2019.105198

Jeyaraj, P. R., & Samuel Nadar, E. R. (2019). Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm.

Journal of Cancer Research and Clinical Oncology, *145*(4), 829–837. https://doi.org/10.1007/s00432-018-02834-7

Joda, T., & Zitzmann, N. U. (2022). Personalized workflows in reconstructive dentistry—current possibilities and future opportunities. *Clinical Oral Investigations*, *26*(6), 4283–4290. https://doi.org/10.1007/s00784-022-04475-0

Johari, M., Esmaeili, F., Andalib, A., Garjani, S., & Saberkari, H. (2017). Detection of vertical root fractures in intact and endodontically treated premolar teeth by designing a probabilistic neural network: an *ex vivo* study. *Dento Maxillo Facial Radiology*, *46*(2), 20160107. https://doi.org/10.1259/dmfr.20160107

Jung, S.-K., & Kim, T.-W. (2016). New approach for the diagnosis of extractions with neural network machine learning. *American Journal of Orthodontics and Dentofacial Orthopedics: Official Publication of the American Association of Orthodontists, Its Constituent Societies, and the American Board of Orthodontics*, *149*(1), 127–133. https://doi.org/10.1016/j.ajodo.2015.07.030

Kann, B. H., Aneja, S., Loganadane, G. V., Kelly, J. R., Smith, S. M., Decker, R. H., Yu, J. B., Park, H. S., Yarbrough, W. G., Malhotra, A., Burtness, B. A., & Husain, Z. A. (2018). Pretreatment identification of head and neck cancer nodal metastasis and extranodal extension using deep learning neural networks. *Scientific Reports*, *8*(1), 1–11. https://doi.org/10.1038/s41598-018-32441-y

Kazimierczak, N., Kazimierczak, W., Serafin, Z., Nowicki, P., Nożewski, J., & Janiszewska-Olszowska, J. (2024). AI in orthodontics: Revolutionizing diagnostics and treatment planning—A comprehensive review. *Journal of Clinical Medicine*, *13*(2), 344. https://doi.org/10.3390/jcm13020344

Khanagar, S. B., Naik, S., Al Kheraif, A. A., Vishwanathaiah, S., Maganur, P. C., Alhazmi, Y., Mushtaq, S., Sarode, S. C., Sarode, G. S., Zanza, A., Testarelli, L., & Patil, S. (2021). Application and performance of artificial intelligence technology in oral cancer diagnosis and prediction of prognosis: A systematic review. *Diagnostics (Basel, Switzerland)*, *11*(6), 1004. https://doi.org/10.3390/diagnostics11061004

Kim, J.-E., Nam, N.-E., Shim, J.-S., Jung, Y.-H., Cho, B.-H., & Hwang, J. J. (2020). Transfer learning via deep neural networks for implant fixture system classification using periapical radiographs. *Journal of Clinical Medicine*, *9*(4), 1117. https://doi.org/10.3390/jcm9041117

Kim, M., Kim, B., Park, B., Lee, M., Won, Y., Kim, C.-Y., & Lee, S. (2018). A digital shade-matching device for dental color determination using the support vector machine algorithm. *Sensors (Basel, Switzerland)*, *18*(9), 3051. https://doi.org/10.3390/s18093051

Kim, Y., Lee, K. J., Sunwoo, L., Choi, D., Nam, C.-M., Cho, J., Kim, J., Bae, Y. J., Yoo, R.-E., Choi, B. S., Jung, C., & Kim, J. H. (2019). Deep learning in diagnosis of maxillary sinusitis using conventional radiography. *Investigative Radiology*, *54*(1), 7–15. https://doi.org/10.1097/rli.0000000000000503

Knoops, P. G. M., Papaioannou, A., Borghi, A., Breakey, R. W. F., Wilson, A. T., Jeelani, O., Zafeiriou, S., Steinbacher, D., Padwa, B. L., Dunaway, D. J., & Schievano, S. (2019). A machine learning framework for automated diagnosis and computer-assisted planning in plastic and reconstructive surgery. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598-019-49506-1

Kositbowornchai, S., Plermkamon, S., & Tangkosol, T. (2013). Performance of an artificial neural network for vertical root fracture detection: an *ex vivo* study. *Dental Traumatology: Official Publication of International Association for Dental Traumatology*, *29*(2), 151–155. https://doi.org/10.1111/j.1600-9657.2012.01148.x

Kuwana, R., Ariji, Y., Fukuda, M., Kise, Y., Nozawa, M., Kuwada, C., Muramatsu, C., Katsumata, A., Fujita, H., & Ariji, E. (2020). Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs. *Dento Maxillo Facial Radiology*, *50*(1), 20200171. https://doi.org/10.1259/dmfr.20200171

Lahoud, P., EzEldeen, M., Beznik, T., Willems, H., Leite, A., Van Gerven, A., & Jacobs, R. (2021). Artificial intelligence for fast and accurate 3-dimensional tooth segmentation on cone-beam computed tomography. *Journal of Endodontics, 47(5),* 827–835. https://doi.org/10.1016/j.joen.2020.12.020

Lakshmi, T. K., & Dheeba, J. (2022). Classification and Segmentation of Periodontal Cyst for Digital Dental Diagnosis Using Deep Learning. *Computer Assisted Methods in Engineering and Science*, *30*(2), 131–149. https://doi.org/10.24423/CAMES.505

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lee, C.-T., Kabir, T., Nelson, J., Sheng, S., Meng, H.-W., Van Dyke, T. E., Walji, M. F., Jiang, X., & Shams, S. (2022). Use of the deep learning approach to measure alveolar bone level. *Journal of Clinical Periodontology*, *49*(3), 260–269. https://doi.org/10.1111/jcpe.13574

Lee, J.-H., & Jeong, S.-N. (2020). Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs: A pilot study. *Medicine*, *99*(26), e20787. https://doi.org/10.1097/md.0000000000020787

Lee, J.-H., Kim, D.-H., Jeong, S.-N., & Choi, S.-H. (2018). Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. *Journal of Dentistry*, *77*, 106–111. https://doi.org/10.1016/j.jdent.2018.07.015

Lee, K.-S., Jha, N., & Kim, Y.-J. (2021). Risk factor assessments of temporomandibular disorders via machine learning. *Scientific Reports*, *11*(1), 1–11. https://doi.org/10.1038/s41598-021-98837-5

Leite, A. F., Van Gerven, A., Willems, H., Beznik, T., Lahoud, P., Gaêta-Araujo, H., Vranckx, M., & Jacobs, R. (2021). Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs. *Clinical Oral Investigations*, *25*(4), 2257–2267. https://doi.org/10.1007/s00784-020-03544-6

Leite, A. F., Vasconcelos, K. de F., Willems, H., & Jacobs, R. (2020). Radiomics and machine learning in oral healthcare. *Proteomics. Clinical Applications*, *14*(3). https://doi.org/10.1002/prca.201900040

Lerner, H., Mouhyi, J., Admakin, O., & Mangano, F. (2020). Artificial intelligence in fixed implant prosthodontics: a retrospective study of 106 implant-supported monolithic zirconia crowns inserted in the posterior jaws of 90 patients. *BMC Oral Health*, *20*(1). https://doi.org/10.1186/s12903-020-1062-4

Li, H., Lai, L., Chen, L., Lu, C., & Cai, Q. (2015). The prediction in computer color matching of dentistry based on GA+BP neural network. *Computational and Mathematical Methods in Medicine*, *2015*, 1–7. https://doi.org/10.1155/2015/816719

Lövgren, A., Marklund, S., Visscher, C. M., Lobbezoo, F., Häggman-Henrikson, B., & Wänman, A. (2017). Outcome of three screening questions for temporomandibular disorders (3Q/TMD) on clinical decision-making. *Journal of Oral Rehabilitation*, *44*(8), 573–579. https://doi.org/10.1111/joor.12518

McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12–14.

Miller, R. A. (1994). Medical diagnostic decision support systems--past, present, and future: A threaded bibliography and brief commentary. Journal of the American Medical Informatics Association: JAMIA, 1(1), 8–27. https://doi.org/10.1136/jamia.1994.95236141

Mintz, Y., & Brodie, R. (2019). Introduction to artificial intelligence in medicine. *Minimally Invasive Therapy & Allied Technologies: MITAT: Official Journal of the Society for Minimally Invasive Therapy*, *28*(2), 73–81. https://doi.org/10.1080/13645706.2019.1575882

Monill-González, A., Rovira-Calatayud, L., d'Oliveira, N. G., & Ustrell-Torrent, J. M. (2021). Artificial intelligence in orthodontics: Where are we now? A scoping review. *Orthodontics & Craniofacial Research*, *24*(S2), 6–15. https://doi.org/10.1111/ocr.12517

Montazeri, A., Mohammadi, S., M.Hesari, P., Ghaemi, M., Riazi, H., & Sheikhi-Mobarakeh, Z. (2023). Preliminary guideline for reporting bibliometric reviews of the biomedical literature (BIBLIO): a minimum requirements. *Systematic Reviews*, *12*(1). https://doi.org/10.1186/s13643-023-02410-2

Monterubbianesi, R., Tosco, V., Vitiello, F., Orilisi, G., Fraccastoro, F., Putignano, A., & Orsini, G. (2022). Augmented, virtual and Mixed Reality in dentistry: A narrative review on the existing platforms and future challenges. *Applied Sciences (Basel, Switzerland)*, *12*(2), 877. https://doi.org/10.3390/app12020877

Moran, M., Faria, M., Giraldi, G., Bastos, L., Oliveira, L., & Conci, A. (2021). Classification of approximal caries in bitewing radiographs using convolutional neural networks. *Sensors (Basel, Switzerland)*, *21*(15), 5192. https://doi.org/10.3390/s21155192

Murata, M., Ariji, Y., Ohashi, Y., Kawai, T., Fukuda, M., Funakoshi, T., Kise, Y., Nozawa, M., Katsumata, A., Fujita, H., & Ariji, E. (2019). Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. *Oral Radiology*, *35*(3), 301–307. https://doi.org/10.1007/s11282-018-0363-7

Mutlu-Sagesen, H., & Sagesen, A. (2023). The evolution of esthetic publications in dentistry, research trends and global productivity: a bibliometric analysis. *The International Journal of Prosthodontics*, 1–22. https://doi.org/10.11607/ijp.8159

Ninkov, A., Frank, J. R., & Maggio, L. A. (2021). Bibliometrics: Methods for studying academic publishing. *Perspectives on Medical Education*, *11*(3), 173–176. https://doi.org/10.1007/s40037-021-00695-4

Niño-Sandoval, T. C., Guevara Pérez, S. V., González, F. A., Jaque, R. A., & Infante-Contreras, C. (2017). Use of automated learning techniques for predicting mandibular morphology in skeletal class I, II and III. *Forensic Science International*, *281*, 187.e1-187.e7. https://doi.org/10.1016/j.forsciint.2017.10.004

Oh, S.-L., Jones, D., Kim, J. R., Choi, S. K., & Chung, M.-K. (2022). Comparison study of diagnosis and treatment planning for dental infections between dental students and practitioners. *Healthcare (Basel, Switzerland)*, *10*(8), 1393. https://doi.org/10.3390/healthcare10081393

Papantonopoulos, G., Takahashi, K., Bountis, T., & Loos, B. G. (2014). Artificial neural networks for the diagnosis of aggressive periodontitis trained by immunologic parameters. *PloS One*, *9*(3), e89757. https://doi.org/10.1371/journal.pone.0089757

Prasai Dixit, L., Shakya, A., Shrestha, M., & Shrestha, A. (2013). Dental caries prevalence, oral health knowledge and practice among indigenous Chepang school children of Nepal. *BMC Oral Health*, *13*(1). https://doi.org/10.1186/1472-6831-13-20

Qiao, X., Zhang, Z., & Chen, X. (2020). Multifrequency impedance method based on neural network for root canal length measurement. *Applied Sciences (Basel, Switzerland)*, *10*(21), 7430. https://doi.org/10.3390/app10217430

Retrouvey, J.-M., & Conley, R. S. (2022). Decoding Deep Learning applications for diagnosis and treatment planning. *Dental Press Journal of Orthodontics*, *27*(5). https://doi.org/10.1590/2177-6709.27.5.e22spe5

Revilla-León, M., Gómez-Polo, M., Vyas, S., Barmak, A. B., Özcan, M., Att, W., & Krishnamurthy, V. R. (2022). Artificial intelligence applications in restorative dentistry: A systematic review. *The Journal of Prosthetic Dentistry*, *128*(5), 867–875. https://doi.org/10.1016/j.prosdent.2021.02.010

Revilla-León, M., Gómez-Polo, M., Vyas, S., Barmak, B. A., Galluci, G. O., Att, W., & Krishnamurthy, V. R. (2023). Artificial intelligence applications in implant dentistry: A systematic review. *The Journal of Prosthetic Dentistry*, *129*(2), 293–300. https://doi.org/10.1016/j.prosdent.2021.05.0

Rodrigues, J. A., Krois, J., & Schwendicke, F. (2021). Demystifying artificial intelligence and deep learning in dentistry. *Brazilian Oral Research*, *35*. https://doi.org/10.1590/1807-3107bor-2021.vol35.0094

Rosma, M.D., Sameem, A.K., Basir, A., Siti Mazlipah, I., & Norzaidi, M.D. (2010). The use of artificial intelligence to identify people at risk of oral cancer: Empirical evidence in Malaysian university. *International Journal of Scientific Research in Education, 3*, 10–20.

Russell, S. J., Norvig, P., & Davis, E. (2010). Artificial intelligence: A modern approach (3rd ed). Upper Saddle River: Prentice Hall.

Saghiri, M. A., Asgar, K., Boukani, K. K., Lotfi, M., Aghili, H., Delvarani, A., Karamifar, K., Saghiri, A. M., Mehrvarzfar, P., & Garcia-Godoy, F. (2012). A new approach for locating the minor apical foramen using an artificial neural network. *International Endodontic Journal*, *45*(3), 257–265. https://doi.org/10.1111/j.1365-2591.2011.01970.x

Saghiri, M. A., Garcia-Godoy, F., Gutmann, J. L., Lotfi, M., & Asgar, K. (2012). The reliability of artificial neural network in locating minor apical foramen: a cadaver study. *Journal of endodontics*, *38*(8), 1130–1134. https://doi.org/10.1016/j.joen.2012.05.004

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, *3*(3), 210–229. https://doi.org/10.1147/rd.33.0210

Schwendicke, F., Golla, T., Dreher, M., & Krois, J. (2019). Convolutional neural networks for dental image diagnostics: A scoping review. *Journal of Dentistry*, *91*(103226), 103226. https://doi.org/10.1016/j.jdent.2019.103226

Schwendicke, F., Samek, W., & Krois, J. (2020). Artificial intelligence in dentistry: Chances and challenges. *Journal of Dental Research*, *99*(7), 769–774. https://doi.org/10.1177/0022034520915714

Setzer, F. C., Shi, K. J., Zhang, Z., Yan, H., Yoon, H., Mupparapu, M., & Li, J. (2020). Artificial intelligence for the computer-aided detection of periapical lesions in cone-beam computed tomographic images. *Journal of Endodontics*, *46*(7), 987–993. https://doi.org/10.1016/j.joen.2020.03.025

Shan, T., Tay, F. R., & Gu, L. (2021). Application of artificial intelligence in dentistry. *Journal of Dental Research, 100*(3), 232–244. https://doi.org/10.1177/0022034520969115

Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. *Annual Review of Biomedical Engineering, 19(1),* 221–248. https://doi.org/10.1146/annurev-bioeng-071516-044442

Singh, N. K., & Raza, K. (2022). Progress in deep learning-based dental and maxillofacial image analysis: A systematic review. *Expert Systems with Applications*, *199*(116968), 116968. https://doi.org/10.1016/j.eswa.2022.116968

Subramanian, A. K., Chen, Y., Almalki, A., Sivamurthy, G., & Kafle, D. (2022). Cephalometric analysis in orthodontics using artificial intelligence—A comprehensive review. *BioMed Research International*, *2022*, 1–9. https://doi.org/10.1155/2022/1880113

Tabatabaian, F., Vora, S. R., & Mirabbasi, S. (2023). Applications, functions, and accuracy of artificial intelligence in restorative dentistry: A literature review. *Et al [Journal of Esthetic and Restorative Dentistry]*, *35*(6), 842–859. https://doi.org/10.1111/jerd.13079

Takahashi, T., Nozaki, K., Gonda, T., & Ikebe, K. (2021). A system for designing removable partial dentures using artificial intelligence. Part 1. Classification of partially edentulous arches using a convolutional neural network. *Journal of Prosthodontic Research*, *65*(1), 115–118. https://doi.org/10.2186/jpr.jpor_2019_354

Tam, W.-K., & Lee, H.-J. (2017). Accurate shade image matching by using a smartphone camera. *Journal of Prosthodontic Research*, *61*(2), 168–176. https://doi.org/10.1016/j.jpor.2016.07.004

Tanikawa, C., & Yamashiro, T. (2021). Development of novel artificial intelligence systems to predict facial morphology after orthognathic surgery and orthodontic treatment in Japanese patients. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-95002-w

Thelwall, M., & Sud, P. (2022). Scopus 1900–2020: Growth in articles, abstracts, countries, fields, and journals. *Quantitative Science Studies*, *3*(1), 37–50. https://doi.org/10.1162/qss_a_00177

Thurzo, A., Strunga, M., Urban, R., Surovková, J., & Afrashtehfar, K. I. (2023). Impact of artificial intelligence on dental education: A review and guide for curriculum update. *Education Sciences*, *13*(2), 150. https://doi.org/10.3390/educsci13020150

Tsesis, I., Rosen, E., Tamse, A., Taschieri, S., & Kfir, A. (2010). Diagnosis of vertical root fractures in endodontically treated teeth based on clinical and radiographic indices: A systematic review. *Journal of Endodontics*, *36*(9), 1455–1458. https://doi.org/10.1016/j.joen.2010.05.003

Turing, A. M. (1950). I.—computing machinery and intelligence. *Mind; a Quarterly Review of Psychology and Philosophy*, *LIX*(236), 433–460. https://doi.org/10.1093/mind/lix.236.433

Uthoff, R. D., Song, B., Sunny, S., Patrick, S., Suresh, A., Kolur, T., Keerthi, G., Spires, O., Anbarani, A., Wilder-Smith, P., Kuriakose, M. A., Birur, P., & Liang, R. (2018). Point-of-care, smartphone-based, dual-modality, dual-view, oral cancer screening device with neural network classification for low-resource communities. *PloS One*, *13*(12), e0207493. https://doi.org/10.1371/journal.pone.0207493

Vadzyuk, S., Boliuk, Y., Luchynskyi, M., Papinko, I., & Vadzyuk, N. (2021). Prediction of the development of periodontal disease. *Proceeding of the Shevchenko Scientific Society. Medical Sciences, 65*(2). https://doi.org/10.25040/ntsh2021.02.10

Volovic, J., Badirli, S., Ahmad, S., Leavitt, L., Mason, T., Bhamidipalli, S. S., Eckert, G., Albright, D., & Turkkahraman, H. (2023). A novel machine learning model for predicting orthodontic treatment duration. *Diagnostics (Basel, Switzerland)*, *13*(17), 2740. https://doi.org/10.3390/diagnostics13172740

Wei, J., Peng, M., Li, Q., & Wang, Y. (2018). Evaluation of a novel computer color matching system based on the improved back-propagation neural network model. *Journal of Prosthodontics: Official Journal of the American College of Prosthodontists*, *27*(8), 775–783. https://doi.org/10.1111/jopr.12561

Xie, B., Xu, D., Zou, X. Q., Lu, M. J., Peng, X. L., & Wen, X. J. (2023). Artificial intelligence in dentistry: A bibliometric analysis from 2000 to 2023. *Journal of Dental Sciences*. https://doi.org/10.1016/j.jds.2023.10.025

Xie, X., Wang, L., & Wang, A. (2010). Artificial Neural Network Modeling for Deciding if Extractions Are Necessary Prior to Orthodontic Treatment. *The Angle Orthodontist*, *80*, 262–266. https://doi.org/10.2319/111608-588.1

Yamaguchi, S., Lee, C., Karaer, O., Ban, S., Mine, A., & Imazato, S. (2019). Predicting the debonding of CAD/CAM composite resin crowns with AI. *Journal of Dental Research*, *98*(11), 1234–1238. https://doi.org/10.1177/0022034519867641

Zhang, B., Dai, N., Tian, S., Yuan, F., & Yu, Q. (2019). The extraction method of tooth preparation margin line based on S-Octree CNN. *International Journal for Numerical Methods in Biomedical Engineering*, *35*(10). https://doi.org/10.1002/cnm.3241