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A REVIEW OF ADVANCEMENTS OF ARTIFICIAL INTELLIGENCE IN DENTISTRY

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Abstract

"For several decades, artificial intelligence (AI) has played an integral role in healthcare, progressively transforming clinical diagnostics and treatment methodologies. In the realm of dentistry, AI presents a groundbreaking opportunity to enhance diagnostic precision, optimize treatment strategies, and alleviate the burden on clinicians. Among the most pressing concerns in dental health, periodontal disease and cariology stand out as critical areas where AI-driven innovations can significantly contribute to early intervention and management. Periodontal disease, a progressive condition affecting the periodontium—including gingival tissues and alveolar bone—is a predominant factor in adult tooth loss. Simultaneously, cariology, which encompasses the etiology, diagnosis, and treatment of dental caries, represents another domain where AI algorithms exhibit substantial potential.

Leveraging sophisticated computational models, AI systems can process and interpret dental imaging data with remarkable accuracy, enabling the early identification of pathological changes that might otherwise evade detection in conventional examinations. This review traces the historical trajectory of AI integration in healthcare before delineating its transformative role in contemporary dentistry. Additionally, it examines the fundamental architectures of AI frameworks, including artificial neural networks (ANNs), convolutional neural networks (CNNs), and ensemble methods such as random forest algorithms, emphasizing their respective contributions to diagnostic advancements.

Furthermore, this article critically evaluates AI's expanding influence across various dental subspecialties, encompassing periodontology, cariology, endodontics, prosthodontics, and orthodontics. From automating disease classification and quantifying alveolar bone deterioration to refining image-based diagnostics, AI introduces unprecedented analytical capabilities into dental practice. However, despite its transformative potential, the widespread adoption of AI in dentistry remains constrained by a range of technical, ethical, and infrastructural challenges that necessitate comprehensive resolution for seamless clinical integration."

Keywords: Artificial intelligence Dentistry Advancements Clinical challenges.

INTRODUCTION

Artificial intelligence (AI), broadly defined as the emulation of cognitive functions exhibited by humans and animals through computational processes, has emerged as a transformative force across numerous disciplines. AI encompasses various domains, including machine learning (ML), natural language processing (NLP), computer vision, and robotics, each characterized by distinct algorithms and methodologies designed to optimize decision-making and automate complex tasks. When appropriately trained, AI systems can outperform human cognition in terms of speed, precision, and analytical depth, offering groundbreaking advancements in multiple sectors, including healthcare.

The integration of AI into medical practice is not a recent phenomenon; its roots trace back to the mid-20th century. One of the earliest applications was the "MIT Programmed Autoanalyzer," developed by researchers at Jack Whitehead's Technicon Corporation in the 1950s to automate biochemical analysis of blood and urine samples [1]. By the 1970s, expert systems such as MYCIN were introduced, employing rule-based AI models to facilitate the diagnosis and management of infectious diseases [2]. In subsequent decades, machine learning algorithms gained traction in medical imaging and pharmaceutical research, paving the way for AI-assisted diagnostics and precision medicine. The 1990s witnessed the emergence of specialized AI-driven platforms like "IntelliCare" for mental health assessment and "CardioCom" for cardiovascular disease management [3]. The rapid progress in ML and NLP during the early 2000s further cemented AI's role in disease detection, personalized treatment planning, and real-time patient monitoring [4].

AI applications in healthcare can be broadly classified into two major paradigms: virtual AI and robotic AI. The former primarily involves mathematical and computational models that assist in data analysis, clinical decision-making, and predictive modeling, whereas the latter integrates AI with robotic systems to enhance procedural accuracy and automate physical interventions. Table 1 provides an overview of various implementations of AI in virtual healthcare technologies.

Table 1
Examples of how AI is being used in virtual applications.

Application	Description
Diagnosis	AI algorithms can analyze medical images such as X-rays and 3D scans to detect abnormalities and make diagnoses
Predictive analytics	AI can analyze large amounts of data such as electronic medical records and genetic information to predict the prospect of certain diseases and patient outcomes.
Personalized medicine	By analyzing a patient's medical history and genetic makeup, AI can help create a personalized treatment plan
Drug discovery	AI can analyze compounds, predict their potential efficacy as drugs, and accelerate the drug discovery process
Clinical decision support	AI can provide doctors with real-time recommendations based on the latest medical evidence and guidelines

The field of dentistry has undergone profound technological transformations over the past few decades, departing from the conventional, often imprecise methodologies of the past. As journalist William Ecenbarger once noted in the 1990s, "Going to the dentist is nothing to smile about. Dentistry is a stunningly inexact science" [5]. However, modern advancements have significantly

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mitigated these limitations. Innovations such as intraoral scanners, three-dimensional (3D) printing for prosthodontics, robotic-assisted surgical procedures, regenerative therapies, and AI-enhanced imaging techniques have revolutionized contemporary dental practice. AI has gained increasing prominence in areas such as radiographic interpretation, pathology detection, caries identification, electronic health record management, and robotic-assisted interventions, demonstrating its potential to refine diagnostic accuracy and treatment efficacy.

This review seeks to provide an in-depth examination of AI's expanding role in the dental sciences, emphasizing its potential to redefine clinical workflows and improve patient outcomes. The discussion will encompass a range of AI methodologies, including supervised learning, unsupervised learning, and deep learning, along with their specific applications in different dental subfields. Additionally, the article will critically analyze the challenges associated with AI adoption in dentistry, addressing issues related to implementation feasibility, economic viability, and data security concerns.

Assessment of AI Performance Metrics in Healthcare

The effectiveness of artificial intelligence (AI) in healthcare applications is determined by a variety of performance metrics. The selection of an appropriate metric depends on the intended function of the AI system and the objectives it is designed to achieve. These evaluation criteria are not independent of one another but instead work in tandem to assess different aspects of AI-driven solutions. A detailed breakdown of the key performance indicators and their specific roles is presented in Table 2.

Table 2
List of key metrics that are used to monitor and measure the performance of a model.

Metric	Description	Formulation
Accuracy	Measures the overall correctness of the model's predictions	(TP + TN) / (TP + TN + FP + FN)
Precision	Proportion of true positives among positive predictions	TP / (TP + FP)
Recall (Sensitivity)	Proportion of true positives correctly identified	TP / (TP + FN)
Specificity	Proportion of true negatives correctly identified	TN / (TN + FP)
F1 Score	Harmonic mean of precision and recall	2 * (Precision * Recall) / (Precision + Recall)
Area Under ROC Curve (AUC-ROC)	Measures the model's ability to rank predicted probabilities	ROC curve represents the TPR plotted against the FPR
Mean Absolute Error (MAE)	Average absolute difference between predicted and actual	(1 / N) * Σ
Mean Squared Error (MSE)	Average squared difference between predicted and actual	$(1 / N) * \Sigma (y - \hat{y})^2$
Root Mean Squared Error (RMSE)	Square root of the MSE	$\sqrt{(1 / N) * \Sigma (y - \hat{y})^2}$
R-squared	Proportion of the variance in the dependent variable	1 - (SSE / SST)
Confusion Matrix	Summarizes the performance of a classification algorithm	–

TP: True Positives, TN: True Negatives, FP, FN: False Negatives, TPR: True positive rate, FPR: False positive rate, N: The total number of instances, y: The actual (true) values, ŷ: The predicted values, SSE: Sum of Squared Errors, SST: Total Sum of Squares.

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Core Principles of AI Model Functionality

Artificial intelligence encompasses a broad spectrum of computational strategies designed to facilitate problem-solving in diverse domains. These methodologies range from predictive analytics and image recognition to complex decision-making processes. As outlined by Nguyen [6], AI-based approaches can be categorized into four principal classifications: statistical learning techniques, artificial neural network (ANN)-driven systems, evolutionary algorithm-based frameworks, and hybrid AI methodologies.

Statistical Learning Approaches

Statistical learning is a subset of AI that relies on mathematical models to extract meaningful insights from datasets, enabling informed decision-making. These methods typically involve fitting predictive models to data and employing probabilistic reasoning to optimize accuracy. Commonly utilized statistical learning approaches include regression models (linear and logistic), decision tree algorithms, and ensemble learning techniques such as random forests (RF). Given their interpretability and efficiency, these models have found extensive applications in clinical diagnostics and disease risk assessment.

Neural Networks and Deep Learning Architectures

Artificial neural networks (ANNs) are machine learning models that mimic the functionality of biological neural structures, enabling them to identify intricate patterns in data. These models consist of multiple layers of interconnected nodes that process information hierarchically. Convolutional neural networks (CNNs), a specialized ANN variant, have demonstrated exceptional performance in medical image analysis, including dental anomaly classification and automated radiographic diagnostics. Additionally, recurrent neural networks (RNNs) are widely employed for sequential data analysis, such as monitoring the progression of orthodontic treatments and forecasting temporomandibular joint disorder (TMJ) development [10]. A comparative illustration of ANN and CNN operational structures is provided in Figure 1.

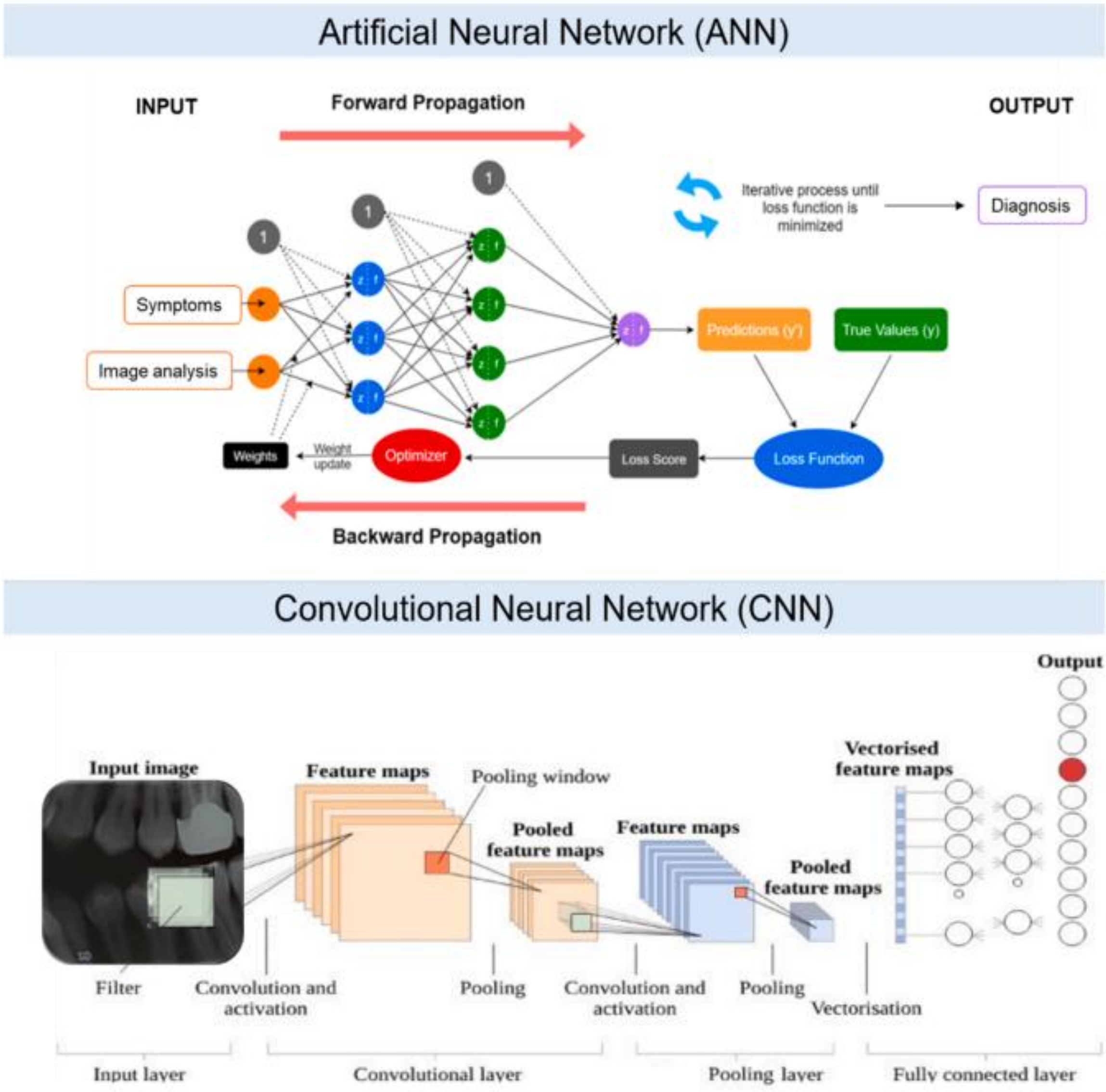

Fig. 3. The ANN and CNN algorithms play vital roles in clinical studies, particularly in image analysis. ANN comprises interconnected artificial neurons arranged in layers: input, hidden, and output. During training, weights representing neuron connections are adjusted to enhance performance, typically using backpropagation. CNN, specialized for image analysis, features layers extracting crucial image features. Convolutional layers capture edges and textures, followed by pooling layers reducing data dimensionality. Fully connected layers then analyze features to generate output probabilities for different classes. Both ANN and CNN employ backpropagation to refine model performance. Figures were adapted and modified from [11,12].

Evolutionary Algorithms and Optimization Techniques

Genetic algorithms (GAs) represent an advanced class of optimization techniques inspired by principles of natural selection and evolutionary adaptation. These algorithms iteratively refine potential solutions by employing mechanisms such as selection, crossover, and mutation. Their ability to navigate large solution spaces makes them particularly valuable in dentistry, where they are used to optimize treatment planning, prosthetic design, and orthodontic modeling. GAs also facilitate parameter tuning in dental implant procedures, structural optimization of prosthetic appliances, and development of patient-specific treatment strategies [13].

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Hybrid AI Frameworks

Hybrid AI methodologies combine multiple machine learning paradigms to enhance predictive accuracy and address the limitations of individual models. These approaches often integrate statistical learning with neural networks or employ evolutionary algorithms for feature selection and optimization. By leveraging the strengths of various AI models, hybrid systems contribute to improved risk assessment and personalized treatment planning in dentistry [14]. The integration of diverse AI methodologies fosters the development of more sophisticated diagnostic tools, ultimately advancing the precision and efficacy of modern dental care.

Artificial Intelligence Applications in Periodontal Disease

Chronic inflammatory disorders of the oral cavity encompass a spectrum of conditions that lead to prolonged inflammation of both soft and hard tissues. These diseases arise due to multifactorial etiologies, including microbial dysbiosis, host immune response abnormalities, and environmental influences. Among these, **gingivitis** and **periodontitis** represent two of the most prevalent and clinically significant conditions, with potential implications for systemic health. The early detection of periodontal diseases is paramount to improving therapeutic outcomes, preventing tissue destruction, and mitigating associated complications. However, periodontal disease diagnosis necessitates an advanced level of clinical expertise, given its dependence on a combination of morphological and biochemical markers.

Periodontal disease detection traditionally relies on **clinical examination, periodontal probing, radiographic imaging, quantitative light-induced fluorescence (QLF), and bacterial DNA sequencing.** Although clinical assessment remains fundamental, its accuracy is inherently subjective, influenced by the clinician's expertise and the constraints of clinical time. Radiographic interpretation, while providing structural insights, lacks sensitivity in detecting initial-stage disease manifestations. Additionally, QLF imaging is comparatively less precise, and bacterial DNA analysis, although highly specific, is not yet widely implemented due to cost and accessibility constraints [15].

Recent advances in **artificial intelligence (AI) and machine learning (ML)** have demonstrated significant potential in refining periodontal disease detection and classification. AI-driven models can enhance diagnostic accuracy, ensuring standardization in disease identification while augmenting clinician decision-making. In a systematic review by Revilla-León et al. [16], AI-based models were evaluated for their capacity to diagnose **gingivitis and periodontitis**, with reported accuracy rates ranging from **47% to 99%** in detecting **dental plaque, gingival inflammation, and alveolar bone loss quantification**. Although these findings underscore AI's potential in periodontal diagnostics, the review highlighted the necessity for continued algorithm refinement to achieve optimal clinical reliability. **Table 3** presents a summary of key AI-driven periodontal diagnostic methodologies.

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Table 3
Applications of AI in chronic oral inflammatory diseases.

Diagnostic	Diagnostic tool	Input data	Framework	Results	Ref
Gingivitis	Supragingival dental plaque	Oral endoscope images	CNNs	No significant differences between the AI model and the human specialist (P > .05)	[17–19]
	Supragingival dental plaque (Biofilm)	QLF images	GMRF	No significant differences between the AI model and the human specialist (P > .05)	[20]
Periodontitis	Pocket depth of teeth	oral images	CNNs	Accuracy: 0.76	[21]
	Clinical examination	Periapical radiographic	CNNs	Premolars diagnostic accuracy: 0.81 Molars diagnostic accuracy: 0.76	[22]
	Alveolar bone loss	Periapical radiographic	Bayesian classifier	True positive fraction: 92.5 % False positive fraction: 14.0 %	[23]
	Alveolar bone loss	Panoramic radiograph	CNNs	Mean (SD) accuracy: 0.81 Mean (SD) sensitivity: 0.81 Mean (SD) specificity: 0.81	[24]
	Alveolar bone loss	Panoramic radiograph	CNNs	The Pearson correlation coefficient of the automatic method with the diagnoses by radiologists was 0.73 overall for the whole jaw	[14]
	Alveolar bone loss	Panoramic radiograph & clinical examination	DeNTNet	F1 score of 0.75	[25]
	Abnormalities in the periapical region	CBCT	CNNs	Accuracy: 0.93 Specificity: 0.88	[26]
	Pathogenic microflora	Proinflammatory component	Random forest	The importance of proinflammatory cytokines, monocytes, T-lymphocytes, and memory B-cells in the development of osteodestructive inflammatory process	[27]
Lichen planus	Counting inflammatory cells	Digitized H&E-stained microscopic slides	ANNs	Accuracy: 0.95 Sensitivity: 1 Specificity: 0.91	[28]
	Cytology slides	Positively stained protein expression	Regression models	Accuracy: 0.95 Sensitivity: 1 Specificity: 0.9	[29]

Artificial Intelligence in the Diagnosis of Oral Mucosal Pathologies

Oral lichen planus (OLP) is a **chronic inflammatory mucocutaneous disorder** affecting keratinized and non-keratinized oral tissues. It is characterized by **reticular, atrophic, and erosive lesions** and is associated with an increased risk of malignant transformation. The diagnostic workflow for OLP is inherently complex, requiring a combination of **clinical assessment, histopathological analysis, immunofluorescence studies, and advanced imaging modalities.**

AI-driven diagnostic systems have been explored for their utility in facilitating **automated image classification and lesion characterization**. Keser et al. [30] employed **Inception v3, a convolutional neural network (CNN)-based deep learning model,** to classify OLP lesions from intraoral photographic datasets. The study reported an **accuracy of 100%**, indicating the feasibility of deep learning-based **computer-aided diagnostic (CAD) systems** in **differentiating pathological from non-pathological mucosal presentations.** These findings suggest a potential role for AI in augmenting **diagnostic precision and reproducibility** in **oral pathology.**

Artificial Intelligence in Cariology

Dental caries is a **multifactorial, biofilm-mediated chronic disease**, constituting a significant global public health burden [31]. Conventional caries detection methodologies include **visual-tactile examination, radiographic assessment, fluorescence-based detection (e.g., DIAGNOdent, Caries Detector, and Spectra), and salivary biomarkers.** However, early-stage caries lesions often exhibit **heterogeneous clinical presentations**, complicating their detection. Additionally, **radiographic interpretation is subject to observer variability,** leading to inconsistencies in diagnosis. Consequently, deep learning approaches have been proposed to **enhance diagnostic objectivity and sensitivity.**

Lee et al. [32] proposed an AI-based **convolutional neural network (CNN) model** for **early-stage caries detection** utilizing **bitewing radiographic datasets.** Their study implemented the **U-Net deep CNN architecture**, demonstrating a significant increase in clinician sensitivity for detecting **incipient and moderate caries lesions.** However, the model exhibited an elevated **false-positive rate**, particularly in **overlapping proximal surface lesions,** indicating the need for algorithmic refinement.
Chen et al. [33] employed a **Faster R-CNN deep learning model** for **proximal caries detection.** The algorithm, after extensive training, achieved **an accuracy of 0.87, closely approximating the performance of dental students (0.82).** Additionally, the AI model demonstrated a **sensitivity of 0.72 and specificity of 0.93**, whereas students exhibited **sensitivity levels below 0.40,** reinforcing the model's superior **diagnostic sensitivity.**
A comprehensive systematic review by Mohammad-Rahimi et al. [34] evaluated **42 studies** investigating **deep learning applications in caries detection** across multiple imaging modalities. The reported accuracy rates varied as follows:

- **Intraoral images:** 71%–96%
- **Periapical radiographs:** 82%–99.2%
- **Bitewing radiographs:** 87.6%–95.4%
- **Near-infrared transillumination images:** 68%–78%
- **Optical coherence tomography images:** 88.7%–95.2%
- **Panoramic radiographs:** 86.1%–96.1%

The heterogeneity in accuracy is likely attributable to **differences in image resolution, lesion morphology, dataset size, and model architecture.**
Beyond diagnostic applications, AI has also been leveraged for **predictive analytics in cariology.** Hung et al. [35] applied **support vector machine (SVM) learning algorithms** to **develop predictive models for caries risk assessment** using data derived from the **National Health and Nutrition Examination Survey (NHANES).** These models enable **early intervention strategies**, guiding clinical decision-making and improving **preventive care outcomes.**

Artificial Intelligence in Endodontic Diagnosis and Treatment

Endodontics is a specialized field of dentistry that focuses on understanding and treating conditions affecting the **dental pulp and periradicular tissues**. Diseases of the pulp and surrounding structures often arise due to factors such as **dental caries, trauma, and microbial infections**. Early and accurate diagnosis is essential for **preserving tooth vitality, preventing periapical infections, and optimizing treatment success**. Advancements in **artificial intelligence (AI) and machine learning (ML)** are now being explored to improve diagnostic precision and treatment planning in endodontics.

AI in Diagnosing Endodontic Disease

Radiographic imaging, particularly **periapical radiographs**, plays a fundamental role in assessing endodontic pathology. However, the interpretation of these images is **highly subjective and depends on the clinician's expertise**. AI-powered diagnostic systems have been developed to enhance accuracy and reduce variability in detection.

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Recent research has shifted from **single-disease classification models** to **multi-disease detection systems**, which better align with real-world clinical scenarios. Li et al. [46] introduced an **AI-driven deep learning framework** for detecting **dental caries and periapical lesions** using periapical radiographs. Their model demonstrated an **accuracy rate of 86% and an F1-score of 0.8288**, indicating performance comparable to that of experienced endodontists. This highlights the potential of **AI-assisted diagnostic tools** in streamlining clinical workflows and enhancing **decision-making precision**.

AI for Endodontic Treatment Planning

Accurate **working length determination and assessment of root canal morphology** are critical challenges in endodontic treatment. The working length is essential for ensuring **complete cleaning and shaping** while preventing over-instrumentation, which may lead to **treatment failure**.

Conventional working length determination methods include:

- **Radiographic imaging** (standard 2D X-rays)
- **Electronic apex locators (EALs)**
- **Manual estimation using reference markers on radiographs**

However, radiographic images often suffer from **overlapping anatomical structures**, making precise working length measurement difficult. Cone-beam computed tomography (CBCT) has been shown to **enhance root canal visualization**, but its widespread use is limited due to **radiation exposure concerns and accessibility constraints** [47].

AI-driven approaches are being developed to **increase accuracy and efficiency** in working length determination. Saghiri et al. [48] designed an **artificial neural network (ANN)-based model** that significantly improved **apical foramen detection accuracy (93%)** when compared to measurements performed by trained endodontists. These results suggest that AI can potentially **minimize human error** and enhance precision in **endodontic procedures**.

In addition to measuring working length, **predictive modeling with AI** can forecast **treatment success rates** based on large datasets of endodontic cases. Herbst et al. [49] compiled **555 root canal treatment cases** and utilized **six machine learning algorithms**, including:

- **Logistic regression (LogR)**
- **Support vector machines (SVMs)**
- **Random forests (RFs)**
- **Decision trees (DTs)**
- **Gradient boosting machines (GBMs)**
- **Extreme gradient boosting (XGB)**

Their study concluded that **root canal visibility was a key determinant of treatment success**. While their models provided valuable insights, **further refinement and larger datasets** are necessary to improve AI-driven **treatment outcome predictions**.

AI in Root Canal Morphology Analysis

Variations in **root canal anatomy** present significant challenges in **instrumentation, irrigation, and obturation**. Complex configurations such as **C-shaped canals** are particularly difficult to manage using conventional imaging methods.

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To address this issue, Jeon et al. [51] developed a **deep learning-based CNN model** to identify **C-shaped root canals in mandibular second molars** using **panoramic radiographs**. Their model significantly outperformed human specialists, achieving an **AUC score of 0.982 compared to 0.872 and 0.885 for radiologists and endodontists, respectively**. These findings highlight the potential of **AI in preoperative assessment**, enabling clinicians to tailor **treatment strategies to individual anatomical variations**.

AI-Enhanced Electronic Apex Locators

Electronic apex locators (EALs) are widely used for **working length determination**, yet their reliability can be compromised by **irrigants, resorption, or anatomical complexities**. To address these limitations, Qiao et al. [50] developed an **AI-enhanced EAL model** using **neural networks**. Their dataset incorporated **multifrequency signal data from 21 extracted teeth**, and the optimized model demonstrated **improved measurement precision**. By reducing **operator-dependent variability**, AI-powered EALs could enhance **consistency and accuracy** in root canal procedures.

Conclusion

The integration of **artificial intelligence in endodontics** holds significant potential for **improving diagnosis, treatment planning, and procedural precision**. AI-driven models are proving to be **valuable tools** in enhancing **radiographic interpretation, working length determination, and treatment outcome prediction**. However, continued advancements in **data quality, algorithm refinement, and clinical validation** are essential to fully realize AI's role in **modern endodontic practice**.

The Role of Artificial Intelligence in Prosthodontics

Introduction to Prosthodontics

Prosthodontics is a specialized field in dentistry that focuses on **restoring missing or damaged teeth** through various prosthetic solutions such as **dentures, crowns, and bridges**. This discipline also extends to the treatment of **facial and jaw abnormalities**, including **TMJ disorders, cleft lip and palate, and complex craniofacial conditions**.

With advancements in **artificial intelligence (AI)**, prosthodontic treatments have become more **precise, efficient, and tailored to individual patient needs**. AI is helping to **reduce errors, improve diagnostic accuracy, and enhance the fabrication of dental prosthetics**, making it an invaluable tool in modern dental care [64].

The Integration of AI in CAD/CAM Technology

One of the most significant advancements in prosthodontics has been the adoption of **Computer-Aided Design and Computer-Aided Manufacturing (CAD/CAM)**. This technology enables **the digital creation of dental restorations**, eliminating the need for traditional mold impressions. Instead, **intraoral scanners capture digital impressions**, which are then used to construct **3D models** of a patient's teeth. These digital models serve as a guide for designing and manufacturing **crowns, bridges, inlays, onlays, and implant-supported restorations**.

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With **AI-powered CAD/CAM systems**, dentists can now achieve:

- **Greater accuracy** in restoration design, reducing the need for manual adjustments.
- **Shorter chair-side time**, making procedures more efficient for both patients and practitioners.
- **Enhanced occlusal fit and function**, ensuring a seamless integration with the patient's natural bite.
- **Optimized aesthetic outcomes**, where AI assists in selecting the ideal **tooth shape, color, and alignment**.

By integrating **CBCT imaging and AI algorithms**, clinicians can now **plan implant placement with greater precision**, leading to **more predictable and successful outcomes** [65,66,67].

AI Applications in Tooth-Supported Prostheses

Restorative prosthetics include **fixed (e.g., crowns, bridges) and removable (e.g., dentures) dental appliances**. These prostheses must be carefully adapted to a patient's oral environment to restore **functionality and aesthetics**.

AI innovations in this area focus on:

- **Predicting facial changes post-prosthesis placement** to enhance treatment planning.
- **Automating tooth shade selection** using AI-driven color-matching systems.
- **Improving the precision of manufacturing processes**, leading to better adaptation and durability.

A notable development in AI-assisted prosthodontics is the use of **Generative Adversarial Networks (GANs)**. This deep-learning technique can **analyze and recreate natural tooth structures**, enabling the automated **design of highly customized restorations**. Studies have demonstrated that GAN-based models can generate **accurate digital molar prostheses**, streamlining the fabrication process and reducing human intervention [70,71].

AI's Influence on Implantology

Dental implants serve as a permanent solution for missing teeth, offering superior **functionality, stability, and longevity** compared to traditional prosthetics. The success of an implant largely depends on **accurate placement, integration with bone, and the design of the prosthetic restoration**.

With AI, **implant procedures have become more predictable and efficient**. AI contributes to:

- **Automated segmentation of dental structures** for better implant positioning.
- **CBCT-assisted surgical planning**, reducing errors during implantation.
- **Machine learning models predicting implant success and identifying potential complications**.

Furthermore, AI-driven 3D modeling allows clinicians to assess **bone density and occlusion**, ensuring **optimal implant placement and long-term stability**. AI also helps in tracking implant **performance over time**, alerting practitioners to possible **failure risks** before complications arise [72-77].

Advancements in Maxillofacial Prosthetics with AI

Maxillofacial prosthetics plays a crucial role in **restoring facial structures** that may be missing due to **birth defects, trauma, or surgical procedures**. These prostheses, which include **artificial ears, noses, and orbital prosthetics**, are customized to match the patient's natural appearance as closely as possible.

AI has transformed maxillofacial prosthetic fabrication by:

- **Utilizing facial recognition technology** to develop highly accurate **3D models** for prosthetic design.
- **Enhancing material selection** through machine learning, ensuring lightweight and durable prostheses.
- **Speeding up the design process** by predicting how different prosthetic materials will behave under various conditions.

A groundbreaking application in this field is the integration of **augmented reality (AR) with AI**. Wang et al. [80] introduced an **AR-based surgical workflow** where patient **CT scans and video imaging** were combined to generate **precise 3D visualizations**. This method improved **surgical accuracy** and enabled **real-time guidance** for maxillofacial reconstruction procedures.

By leveraging AI, maxillofacial prostheses are now **more functional, aesthetically refined, and tailored to individual patients** [81,82].

AI in Orthodontics and Dentofacial Orthopedics

Orthodontics involves the **correction of dental misalignments and jaw irregularities** to enhance both **function and aesthetics**. AI is playing an increasingly **important role in orthodontic treatment planning**, offering **more accurate predictions and improved patient outcomes**.

Notable AI-driven advancements include:

- **Deep learning for orthodontic image classification**, allowing automated monitoring of treatment progress.
- **AI-assisted cephalometric analysis**, reducing the time required for skeletal and dental measurements.
- **Predictive modeling of treatment duration and final tooth positioning**, enabling better patient communication.

Li et al. [84] developed a **deep convolutional network (DCN)** for classifying orthodontic images, achieving a **99.4% accuracy rate**. Similarly, AI is being used to create **digital impressions and orthodontic simulations**, streamlining the fabrication of **customized aligners and appliances** [85-87].

Beyond diagnosis and treatment planning, AI is also being utilized for **patient engagement**. Chatbots powered by **natural language processing (NLP)** are helping clinics **schedule appointments, answer patient inquiries, and provide real-time treatment updates** [88-90].

Conclusion

The application of **artificial intelligence in prosthodontics, implantology, and orthodontics** is revolutionizing modern dentistry. AI-driven technologies such as **machine learning, neural**

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networks, and 3D modeling are enhancing diagnostic accuracy, optimizing treatment outcomes, and streamlining the fabrication of dental prosthetics.

As AI continues to evolve, it is expected to further refine digital workflows, improve patient experiences, and minimize procedural risks. The integration of AI with CAD/CAM, CBCT, and augmented reality will likely define the future of precision dentistry, ensuring more personalized and efficient treatments for patients worldwide.

AI Applications in Oral Medicine and Pathology

AI's Role in Early Oral Cancer Detection

A significant challenge in oral cancer management is that many patients present with advanced-stage disease, which contributes to high morbidity and mortality rates. The prognosis of oral cancer is heavily dependent on early detection, accurate classification, and personalized treatment planning, while also minimizing human error and ensuring cost-effectiveness. AI has emerged as a powerful tool in improving these aspects of oral cancer care.

One of the earliest uses of AI in oral cancer diagnosis dates back to the late 1990s, when neural networks were utilized to distinguish between benign and malignant lesions based on both clinical and histologic features [91]. Since then, AI-assisted diagnostic systems have gained widespread attention, aiming to automate early lesion detection with accuracy comparable to that of experienced specialists.

A systematic review of 36 studies utilizing various machine learning models for early oral cancer detection found that AI significantly enhances diagnostic speed and precision. However, while AI shows promising results, current evidence is insufficient to validate certain algorithms for diagnosing precancerous lesions [92]. According to Baniulyte et al., the average sensitivity of AI for oral cancer detection stands at 83%, with an average specificity of 87%, meaning it effectively identifies patients without the disease [93].

Beyond diagnostics, AI is also being integrated into prognostic models, where machine learning algorithms analyze past clinical data, risk factors, and systemic conditions to predict the likelihood of malignant transformations [94–96]. AI-powered predictive models are now capable of identifying high-risk individuals based on their demographic profile, lifestyle, and other contributing factors, even in the absence of symptoms [97].

Recent AI Innovations in Oral Cancer Detection

Several deep-learning studies have focused on AI applications in oral cancer screening and risk assessment. Table 4 provides an overview of recent studies employing AI techniques to enhance cancer detection and prognosis.

Applications of AI in oral cancer.

Application	Diagnostic tool	Input data	Framework	Results	Ref
Cancer detection	Visual examination	Photographic images	CNN-ResNet	Accuracy 78 % Sensitivity78.5 % Precision 77.1 % F1 score 77 %	[98]
		Optical coherence tomography	ANN-SVM	Sensitivity 93–96 % Specificity 49–74 %	[99]
		Smartphone-based imaging	HRNet	Sensitivity 83 % Specificity 96.6 % Precision 84.3 % F1 score 83.6 %	[100]
		Autofluorescence imaging	ANN	Sensitivity 86 % Specificity 100 %	[91]
		Fluorescence visualization	ANN	Sensitivity 96.5 % Specificity 100 %	[101]
		MRI	CNN	Accuracy 96.5 %	[102]
		Hyperspectral imaging	CNN	Accuracy 91.4 % Sensitivity 94 % Specificity 91 %	[4]
		Confocal laser endomicroscopy	SVM	Accuracy 74 % Specificity 85 % Sensitivity 72 %	[104]
	Saliva	Metatranscriptomics Microbiome	Logistic regression	Specificity 94 % Sensitivity 90 %	[105]
		DNA methylation	SVM	Recall 0.94 Specificity 93 % Precision 94 %	[106]
		Impedance spectroscopy	SVM	Accuracy 80 %	[107]
	Oral smear	Cytology assay	k-Nearest Neighbor	Early disease with AUCs of 0.82 Late disease with AUCs of 0.93	[108]
		Papanicolaou stained cytology sample	R-CNN, ResNet 34	F1 score: 0.86	[109]
	Tissue biopsy	FTIR[a]	SVM	Sensitivity 81.3 % Specificity 95.7 % Accuracy 89.7 %	[110]
		PESI-MS[b]	PLS-LR	Accuracy 90.48 % and 95.35 % in positive- and negative-ion modes	[111]
		^{1}H HRMAS NMR[c]	Statistical model	Accuracy 90 %	[112]
Prognostic prediction	Medical records	Clinical characteristics	Deep learning	higher performance compared to the classic statistical method	[113]
		Gene expression profiling	SVM, DNN	Accuracy 96.5 % Sensitivity 98.1 % Specificity 94.2 %	[114]
		comprehensive, feature selection, nomogram	logistic regression, decision tree, SVM, ANN	Accuracy 80.08 %	[115]
Risk determination	Blood sample	Serum total malondialdehyde, serum proton donor capacity	Fuzzy logic	The risk was estimated as a concrete numerical value on a scale from 1 to 10	[116]

PLS-LR: Partial least squares-logistic regression.
[a] Fourier-transform-infrared-spectroscopy.
[b] Probe electrospray ionization mass spectrometry.
[c] Magnetic resonance imaging.

The Growth of AI in Dentistry

AI's Expanding Market in Dental Care

AI technology has revolutionized modern dentistry by improving **diagnosis, treatment planning, and patient care**. The dental AI market is witnessing **rapid expansion**, fueled by:

- **Growing reliance on digital technologies** in dental practice.
- **Increased demand for precise and efficient diagnostic tools**.
- **A strong focus on improving patient outcomes**.

Current projections estimate that the **global dental AI market** will reach **$1.3 billion by 2028**, growing at a **compound annual growth rate (CAGR) of 27.4%** between **2023 and 2028** .

The AI-driven dental market can be segmented based on **application type**, including:

1. **Diagnostic assistance** (the largest segment).
2. **Treatment planning** (expected to grow at the highest CAGR).
3. **Patient management**.

From an **end-user perspective**, dental AI adoption is highest in **clinics**, followed by **dental schools and research institutions**.

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Regional Market Trends:

- **North America** leads the AI-driven dental market due to **high-tech adoption and a strong presence of AI-based dental firms**.
- **Europe** ranks second, with increasing AI adoption in **dental clinics and research institutions**.

AI-Powered Innovations in Dentistry

Notable AI Platforms in the Dental Industry

Several AI-based systems have already received **regulatory approval** and are making a significant impact in clinical dentistry.

1. **Overjet (https://www.overjet.ai/)**
   - Received **FDA clearance in 2020**.
   - Uses AI to analyze **digital radiographs**, assisting in **decay detection and bone loss quantification**.
   - Helps dentists make **more consistent and accurate diagnoses**, improving treatment outcomes.

2. **VideaHealth (https://www.videa.ai/)**
   - AI-powered system trained on **large databases of dental X-rays**.
   - Assists in detecting **cavities, cysts, and tumors**.
   - Reduced **missed caries diagnoses by 43%** and decreased **incorrect diagnoses by 15%** in clinical trials.

3. **Diagnocat (https://eu.diagnocat.com/)**
   - AI-driven analysis of **dental X-rays** and **CBCT scans**.
   - Creates **3D models of maxilla and mandible** in **STL file format**, aiding in **precise implant planning**.
   - Reduces diagnostic errors and enhances efficiency, particularly for **inexperienced clinicians**.

As AI continues to advance, **automated radiographic analysis** is expected to further **improve diagnostic reliability and streamline treatment workflows**.

Challenges Hindering AI Adoption in Dentistry

Key Barriers to AI Integration in Dental Care

1. Limited Access to High-Quality Datasets

AI algorithms require **large and diverse datasets** for training. However, dental datasets often suffer from **incompleteness, small sample sizes, and lack of standardization**. Access to **medical and dental records** is further restricted due to **privacy laws and organizational barriers**, making AI model training difficult.

2. Interoperability Issues

Many dental practices use **non-standardized software and imaging systems**, which may not be compatible with AI platforms. **Seamless data integration** between AI systems and existing dental software requires the development of **standardized protocols and interfaces**.

3. Ethical and Legal Considerations

The implementation of AI in dentistry raises concerns regarding **patient privacy, data security, and liability**. Regulations such as **HIPAA (Health Insurance Portability and Accountability Act)** require strict **data governance and encryption** to protect patient information.

4. High Implementation Costs

For many smaller dental practices, acquiring AI-based **hardware, software, and training programs** is financially challenging. The **cost of AI integration** remains a major deterrent to widespread adoption.

5. Resistance to Change

Traditional dental practices may be hesitant to adopt AI due to:

- **Concerns about accuracy and reliability**.
- **Reluctance to shift from manual to automated workflows**.
- **Lack of AI literacy among dental professionals**.

6. Shortage of AI Expertise in Dentistry

The dental industry has **not prioritized AI research**, leading to a **lack of AI expertise** among practitioners. To bridge this gap, collaboration between **AI specialists and dental professionals** is essential. **Incorporating AI-focused education** into dental curricula can help build a **tech-savvy workforce**.

Overcoming these **challenges** is crucial for AI to fully transform **dental diagnostics, treatment planning, and patient care**.

Conclusion

AI has the potential to revolutionize **oral healthcare** by automating **routine tasks**, enhancing **diagnostic accuracy**, and streamlining **treatment workflows**. However, AI should be seen as a **supplementary tool rather than a replacement for human expertise**.

Despite existing challenges—such as **data limitations, ethical concerns, cost constraints, and resistance to change**—AI remains a **valuable asset** in dentistry. Long-term **clinical validation and careful algorithm design** are essential to ensure **fair, unbiased, and reproducible results**.

Future advancements should continue to **prioritize human oversight** while harnessing AI's capabilities to process **large datasets, optimize diagnostics, and enhance patient care**. Although AI is reshaping modern dentistry, **the final decision will always rest with the clinician**.

References

[1]Skeggs LT, Hochstrasser H. Multiple automatic sequential analysis. Clin. Chem. 1964;10:918–36. https://doi.org/10.1093/clinchem/10.10.918.

[2] Yu VL. Antimicrobial selection by a computer: a blinded evaluation by infectious diseases experts. JAMA 1979;242:1279. https://doi.org/10.1001/ jama.1979.03300120033020.

[3] Chen A, Brown R, Esposito D, Schore J, Shapiro R. Report to congress on the evaluation of medicare disease management programs. Washingt. Math. Policy Res. 2008.

Web of Medicine: Journal of Medicine, Practice and Nursing
webofjournals.com/index.php/5

[4] Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nat. Med. 2022;28:31–8. https://doi.org/10.1038/s41591-021-01614-0.

[5] Ecenbarger W. How dentists rip us off. Readers Dig. Interact. Arch. Available Online. Retrieved Febr. 1997;10:1999.

[6] Nguyen KTP, Medjaher K, Tran DT. A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines. Artif. Intell. Rev. 2023;56:3659–709. https://doi.org/10.1007/ s10462-022-10260-y.

[7] I. Logunova, Random Forest Classifier: basic Principles and Applications, (2022). https://serokell.io/blog/random-forest-classification.

[8] Qu Y, Lin Z, Yang Z, Lin H, Huang X, Gu L. Machine learning models for prognosis prediction in endodontic microsurgery. J. Dent. 2022;118:103947. https://doi. org/10.1016/j.jdent.2022.103947.

[9] Mortaheb P, Rezaeian M. Metal artifact reduction and segmentation of dental computerized tomography images using least square support vector machine and mean shift algorithm. J. Med. Signals Sensors. 2016;6:1. https://doi.org/ 10.4103/2228-7477.175867.

[10] Sohil F, Sohali MU, Shabbir J, James Gareth, Witten Daniela, Hastie Trevor, Tibshirani Robert. An introduction to statistical learning with applications in R: by. New York: Springer Science and Business Media; 2013. $41.98, eISBN: 978-1- 4614-7137-7, (2022).

[11] R. Pramoditha, Overview of a Neural Network's Learning Process, (n.d.). https: //rukshanpramoditha.medium.com/overview-of-a-neural-networks-learning-p rocess-61690a502fa.

[12] Anaya-Isaza A, Mera-Jim´enez L, Zequera-Diaz M. An overview of deep learning in medical imaging. Info. Med. Unlocked 2021;26:100723. https://doi.org/ 10.1016/j.imu.2021.100723.

[13] Ossowska A, Kusiak A, S´wietlik D. Artificial intelligence in dentistry—narrative review. Int. J. Environ. Res. Public Health 2022;19:3449. https://doi.org/ 10.3390/ijerph19063449.

[14] Chang HJ, Lee SJ, Yong TH, Shin NY, Jang BG, Kim JE, Huh KH, Lee SS, Heo MS, Choi SC, Kim TI, Yi WJ. Deep learning hybrid method to automatically diagnose periodontal bone loss and stage periodontitis. Sci. Rep. 2020;10:7531. https:// doi.org/10.1038/s41598-020-64509-z.

[15] Preshaw PM. Detection and diagnosis of periodontal conditions amenable to prevention. BMC Oral Health 2015;15:S5. https://doi.org/10.1186/1472-6831- 15-S1-S5.

[16] Revilla-Leo´n M, Go´mez-Polo M, Barmak AB, Inam W, Kan JYK, Kois JC, Akal O. Artificial intelligence models for diagnosing gingivitis and periodontal disease: a systematic review. J. Prosthet. Dent. 2022:1–9. https://doi.org/10.1016/j. prosdent.2022.01.026.

[17] You W, Hao A, Li S, Wang Y, Xia B. Deep learning-based dental plaque detection on primary teeth: a comparison with clinical assessments. BMC Oral Health 2020; 20:141. https://doi.org/10.1186/s12903-020-01114-6.

[18] Li S, Pang Z, Song W, Guo Y, You W, Hao A, Qin H. Low-Shot learning of automatic dental plaque segmentation based on local-to-global feature fusion. In: IEEE; 2020. p. 664–8. https://doi.org/10.1109/ISBI45749.2020.9098741.

[19] Alalharith DM, Alharthi HM, Alghamdi WM, Alsenbel YM, Aslam N, Khan IU, Shahin SY, Dianiˇskova´ S, Alhareky MS, Barouch KK. A deep learning-based approach for the detection

of early signs of gingivitis in orthodontic patients using faster region-based convolutional neural networks. Int. J. Environ. Res. Public Health. 2020;17:8447. https://doi.org/10.3390/ijerph17228447.

[20] Mansoor A, Patsekin V, Scherl D, Robinson JP, Rajwa B. A statistical modeling approach to computer-aided quantification of dental biofilm. IEEE J. Biomed. Heal. Informatics. 2015;19:358–66. https://doi.org/10.1109/ JBHI.2014.2310204.

[21] Moriyama Y, Lee C, Date S, Kashiwagi Y, Narukawa Y, Nozaki K, Murakami S. A mapreduce-like deep learning model for the depth estimation of periodontal pockets. In: Proc. 12th Int. Jt. Conf. Biomed. Eng. Syst. Technol. SCITEPRESS - Science and Technology Publications; 2019. p. 388–95. https://doi.org/10.5220/ 0007405703880395.

[22] Lee JH, Kim D, Jeong SN, Choi SH. Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm. J. Periodontal Implant Sci. 2018;48:114. https://doi.org/10.5051/ jpis.2018.48.2.114.

[23] Lin PL, Huang PW, Huang PY, Hsu HC. Alveolar bone-loss area localization in periodontitis radiographs based on threshold segmentation with a hybrid feature fused of intensity and the H-value of fractional Brownian motion model. Comput. Methods Programs Biomed. 2015;121:117–26. https://doi.org/10.1016/j. cmpb.2015.05.004.

[24] Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, Do¨rfer C, Schwendicke F. Deep learning for the radiographic detection of periodontal bone loss. Sci. Rep. 2019;9:8495. https://doi.org/10.1038/s41598-019-44839-3.

[25] Kim J, Lee HS, Song IS, Jung KH. DeNTNet: deep Neural Transfer Network for the detection of periodontal bone loss using panoramic dental radiographs. Sci. Rep. 2019;9:17615. https://doi.org/10.1038/s41598-019-53758-2.

[26] Setzer FC, Shi KJ, Zhang Z, Yan H, Yoon H, Mupparapu M, Li J. Artificial intelligence for the computer-aided detection of periapical lesions in cone-beam computed tomographic images. J. Endod. 2020;46:987–93. https://doi.org/ 10.1016/j.joen.2020.03.025.

[27] Mudrov VP. Artificial intelligence in the immunodiagnostics of chronic periodontitis. Russ. J. Infect. Immun. 2022;12:1186–90. https://doi.org/ 10.15789/2220-7619-AII-1999.

[28] Idrees M, Farah CS, Shearston K, Kujan O. A machine-learning algorithm for the reliable identification of oral lichen planus. J. Oral Pathol. Med. 2021;50:946–53. https://doi.org/10.1111/jop.13226.

[29] Idrees M, Shearston K, Farah CS, Kujan O. Immunoexpression of oral brush biopsy enhances the accuracy of diagnosis for oral lichen planus and lichenoid lesions.
J. Oral Pathol. Med. 2022;51:563–72. https://doi.org/10.1111/jop.13301.

[30] Keser G, Bayrakdar I˙S¸ , Pekiner FN, Çelik O¨ , Orhan K. A deep learning algorithm for classification of oral lichen planus lesions from photographic images: a retrospective study. J. Stomatol. Oral Maxillofac. Surg. 2023;124:101264. https://doi.org/10.1016/j.jormas.2022.08.007.

[31] Young DA, Nový BB, Zeller GG, Hale R, Hart TC, Truelove EL, Ekstrand KR, Featherstone JDB, Fontana M, Ismail A, Kuehne J, Longbottom C, Pitts N, Sarrett DC, Wright T, Mark AM, Beltran-Aguilar E. The American Dental Association caries classification system for clinical practice. J. Am. Dent. Assoc. 2015;146:79–86. https://doi.org/10.1016/j.adaj.2014.11.018.

[32] Lee S, Oh S, Jo J, Kang S, Shin Y, Park J. Deep learning for early dental caries detection in bitewing radiographs. Sci. Rep. 2021;11:16807. https://doi.org/ 10.1038/s41598-021-96368-7.

[33] Chen X, Guo J, Ye J, Zhang M, Liang Y. Detection of proximal caries lesions on bitewing radiographs using deep learning method. Caries Res. 2022;56:455–63. https://doi.org/10.1159/000527418.

[34] Mohammad-Rahimi H, Motamedian SR, Rohban MH, Krois J, Uribe SE, Mahmoudinia E, Rokhshad R, Nadimi M, Schwendicke F. Deep learning for caries detection: a systematic review. J. Dent. 2022;122:104115. https://doi.org/ 10.1016/j.jdent.2022.104115.

[35] Hung M, Voss MW, Rosales MN, Li W, Su W, Xu J, Bounsanga J, Ruiz-Negro´n B, Lauren E, Licari FW. Application of machine learning for diagnostic prediction of root caries. Gerodontology 2019;36:395–404. https://doi.org/10.1111/ ger.12432.

[36] Reyes LT, Knorst JK, Ortiz FR, Ardenghi TM. Machine learning in the diagnosis and prognostic prediction of dental caries: a systematic review. Caries Res. 2022; 56:161–70. https://doi.org/10.1159/000524167.

[37] Kühnisch J, Meyer O, Hesenius M, Hickel R, Gruhn V. Caries detection on intraoral images using artificial intelligence. J. Dent. Res. 2022;101:158–65. https://doi.org/10.1177/00220345211032524.

[38] Duong DL, Kabir MH, Kuo RF. Automated caries detection with smartphone color photography using machine learning. Health Informatics J. 2021;27: 146045822110075. https://doi.org/10.1177/14604582211007530.

[39] Estai M, Tennant M, Gebauer D, Brostek A, Vignarajan J, Mehdizadeh M, Saha S. Evaluation of a deep learning system for automatic detection of proximal surface dental caries on bitewing radiographs. Oral Surg. Oral Med. Oral Pathol. Oral Radiol. 2022;134:262–70. https://doi.org/10.1016/j.oooo.2022.03.008.

[40] Ramos-Gomez F, Marcus M, Maida CA, Wang Y, Kinsler JJ, Xiong D, Lee SY, Hays RD, Shen J, Crall JJ, Liu H. Using a machine learning algorithm to predict the likelihood of presence of dental caries among children aged 2 to 7. Dent. J. 2021;9:141. https://doi.org/10.3390/dj9120141.

[41] Park YH, Kim SH, Choi YY. Prediction models of early childhood caries based on machine learning algorithms. Int. J. Environ. Res. Public Health. 2021;18:8613. https://doi.org/10.3390/ijerph18168613.

[42] Pang L, Wang K, Tao Y, Zhi Q, Zhang J, Lin H. A new model for caries risk prediction in teenagers using a machine learning algorithm based on environmental and genetic factors. Front. Genet. 2021;12:636867. https://doi. org/10.3389/fgene.2021.636867.

[43] G. Alferez, J. Jime´nez, H. Herna´ndez, M. Gonza´lez, R. Domínguez, A. Briones, Application of data science to discover the relationship between dental caries and diabetes in dental records, (2022). https://doi.org/10.36227/techrxiv.20311734. v1.

[44] Butcher MC, Short B, Veena CLR, Bradshaw D, Pratten JR, McLean W, Shaban SMA, Ramage G, Delaney C. Meta-analysis of caries microbiome studies can improve upon disease prediction outcomes. APMIS 2022;130:763–77. https://doi.org/10.1111/apm.13272.

[45] De-Deus G, Souza EM, Silva EJNL, Belladonna FG, Simo˜es-Carvalho M, Cavalcante DM, Versiani MA. A critical analysis of research methods and experimental models to study root canal fillings. Int. Endod. J. 2022;55:384–445. https://doi.org/10.1111/iej.13713.
[46] Li S, Liu J, Zhou Z, Zhou Z, Wu X, Li Y, Wang S, Liao W, Ying S, Zhao Z. Artificial intelligence for caries and periapical periodontitis detection. J. Dent. 2022;122: 104107. https://doi.org/10.1016/j.jdent.2022.104107.
[47] Saghiri MA, Asgar K, Boukani KK, Lotfi M, Aghili H, Delvarani A, Karamifar K, Saghiri AM, Mehrvarzfar P, Garcia-Godoy F. A new approach for locating the minor apical foramen using an artificial neural network. Int. Endod. J. 2012;45: 257–65. https://doi.org/10.1111/j.1365-2591.2011.01970.x.
[48] Saghiri MA, Garcia-Godoy F, Gutmann JL, Lotfi M, Asgar K. The reliability of artificial neural network in locating minor apical foramen: a cadaver study.
J. Endod. 2012;38:1130–4. https://doi.org/10.1016/j.joen.2012.05.004.
[49] Herbst SR, Herbst CS, Schwendicke F. Preoperative risk assessment does not allow to predict root filling length using machine learning: a longitudinal study. J. Dent. 2023;128:104378. https://doi.org/10.1016/j.jdent.2022.104378.
[50] Qiao X, Zhang Z, Chen X. Multifrequency impedance method based on neural network for root canal length measurement. Appl. Sci. 2020;10:7430. https://doi. org/10.3390/app10217430.
[51] Jeon SJ, Yun JP, Yeom HG, Shin WS, Lee JH, Jeong SH, Seo MS. Deep-learning for predicting C-shaped canals in mandibular second molars on panoramic radiographs. Dentomaxillofacial Radiol. 2021;50:20200513. https://doi.org/ 10.1259/dmfr.20200513.
[52] Zheng L, Wang H, Mei L, Chen Q, Zhang Y, Zhang H. Artificial intelligence in digital cariology: a new tool for the diagnosis of deep caries and pulpitis using convolutional neural networks. Ann. Transl. Med. 2021;9:763. https://doi.org/ 10.21037/atm-21-119. –763.
[53] Chauhan R, Shah T, Shah D, Gohil T. A novel convolutional neural
network–Fuzzy-based diagnosis in the classification of dental pulpitis. Adv. Hum. Biol. 2022;13:79. https://doi.org/10.4103/aihb.aihb_50_22.
[54] Maharani MP, Daely PT, Lee JM, Kim D. Machine learning classification with GLCM and watershed for detecting pulpitis. 한국통신학회 학술대회논문집 2020: 1205–6.
[55] Kurniawan R, Hasana W, Negara BS, Zakree Ahmad Nazri M, Lestari F, Iskandar I. Prediction model for diagnosis of pulpitis diseases using learning vector quantization 3. In: Proc. 2021 4th Int. Conf. Comput. Informatics Eng. IEEE; 2021. p. 9–12. https://doi.org/10.1109/IC2IE53219.2021.9649223.
[56] Orhan K, Bilgir E, Bayrakdar IS, Ezhov M, Gusarev M, Shumilov E. Evaluation of artificial intelligence for detecting impacted third molars on cone-beam computed tomography scans. J. Stomatol. Oral Maxillofac. Surg. 2021;122: 333–7. https://doi.org/10.1016/j.jormas.2020.12.006.
[57] Zadroz˙ny Ł, Regulski P, Brus-Sawczuk K, Czajkowska M, Parkanyi L, Ganz S, Mijiritsky E. Artificial intelligence application in assessment of panoramic radiographs. Diagnostics 2022;12:224. https://doi.org/10.3390/ diagnostics12010224.

Volume 3, Issue 3, March 2025 **ISSN (E):** 2938-3765
[58] Xu T, Zhu Y, Peng L, Cao Y, Zhao X, Meng F, Ding J, Liang S. Artificial intelligence assisted identification of therapy history from periapical films for dental root canal. Displays 2022;71:102119. https://doi.org/10.1016/j.displa.2021.102119.

[59] Kirnbauer B, Hadzic A, Jakse N, Bischof H, Stern D. Automatic detection of periapical osteolytic lesions on cone-beam computed tomography using deep convolutional neuronal networks. J. Endod. 2022;48:1434–40. https://doi.org/ 10.1016/j.joen.2022.07.013.

[60] Javed S, Zakirulla M, Baig RU, Asif SM, Meer AB. Development of artificial neural network model for prediction of post-streptococcus mutans in dental caries. Comput. Methods Programs Biomed. 2020;186:105198. https://doi.org/ 10.1016/j.cmpb.2019.105198.

[61] Yuce F, O¨ ziç MÜ, Tassoker M. Detection of pulpal calcifications on bite-wing radiographs using deep learning. Clin. Oral Investig. 2022;27:2679–89. https:// doi.org/10.1007/s00784-022-04839-6.

[62] Haddad DS, Brioschi ML, Luchetti MAB, Civiero N, Moreira MA, Arita ES. Thermographic toothache screening by artificial intelligence. In: Proc. MICCAI Work. Med. Image Assist. Blomarkers' Discov. MICCAI Work. Artif. Intell. over Infrared Images Med. Appl. Springer; 2022. p. 45–56. https://doi.org/10.1007/ 978-3-031-19660-7_5.

[63] Saghiri MA, Saghiri AM, Samadi E, Nath D, Vakhnovetsky J, Morgano SM. Neural network approach to evaluate the physical properties of dentin. Odontology 2023;111:68–77. https://doi.org/10.1007/s10266-022-00726-4.

[64] Singi SR, Sathe S, Reche AR, Sibal A, Mantri N. Extended arm of precision in prosthodontics: artificial intelligence. Cureus 2022;14.

[65] Abduo J, Lyons K, Bennamoun M. Trends in computer-aided manufacturing in prosthodontics: a review of the available streams. Int. J. Dent. 2014;2014:1–15. https://doi.org/10.1155/2014/783948.

[66] PASRICHA N, AGGARWAL K. Digitalization of conventional removable prosthesis: cad-cam dentures. Univ. J. Dent. Sci. 2021;7.

[67] L.A. Dobrzan´ski, L.B. Dobrzan´ski, Dentistry 4.0 Concept in the Design and Manufacturing of Prosthetic Dental Restorations, Processes. 8 (2020) 525. http s://doi.org/10.3390/pr8050525.

[68] Ercoli C, Caton JG. Dental prostheses and tooth-related factors. J. Periodontol. 2018;89:S223–36. https://doi.org/10.1002/JPER.16-0569.

[69] Revilla-Leo´n M, Go´mez-Polo M, Vyas S, Barmak AB, Gallucci GO, Att W, O¨ zcan M, Krishnamurthy VR. Artificial intelligence models for tooth-supported fixed and removable prosthodontics: a systematic review. J. Prosthet. Dent. 2021.

[70] Chau RCW, Chong M, Thu KM, Chu NSP, Koohi-Moghadam M, Hsung RT-C, McGrath C, Lam WYH. Artificial intelligence-designed single molar dental prostheses: a protocol of prospective experimental study. PLoS ONE 2022;17: e0268535.

[71] Chau RCW, Hsung RT-C, McGrath C, Pow EHN, Lam WYH. Accuracy of artificial intelligence-designed single-molar dental prostheses: a feasibility study.
J. Prosthet. Dent. 2023. https://doi.org/10.1016/j.prosdent.2022.12.004.

[72] Bianchi J, Mendonca G, Gillot M, Oh H, Park J, Al Turkestani N, Gurgel M, Cevidanes L. Three-dimensional digital applications for implant space planning in orthodontics: a narrative review. J. World Fed. Orthod. 2022;11:207–15. https:// doi.org/10.1016/j.ejwf.2022.10.006.

[73] Lahoud P, EzEldeen M, Beznik T, Willems H, Leite A, Van Gerven A, Jacobs R. Artificial intelligence for fast and accurate 3-dimensional tooth segmentation on cone-beam computed tomography. J. Endod. 2021;47:827–35.

[74] Shujaat S, Riaz M, Jacobs R. Synergy between artificial intelligence and precision medicine for computer-assisted oral and maxillofacial surgical planning. Clin. Oral Investig. 2022:1–10.

[75] Bodhe R, Sivakumar S, Raghuwanshi A. Design and development of deep learning approach for dental implant planning. In: Proc. 2022 Int. Conf. Green Energy, Comput. Sustain. Technol. IEEE; 2022. p. 269–74.

[76] Y. Liu, Z. Chen, C. Chu, F.L. Deng, Transfer Learning via Artificial Intelligence for Guiding Implant Placement in the Posterior Mandible: an in vitro Study, (2021).

[77] Lee DW, Kim SY, Jeong SN, Lee JH. Artificial intelligence in fractured dental implant detection and classification: evaluation using dataset from two dental hospitals. Diagnostics 2021;11:233.

[78] Moiduddin K, Al-Ahmari A, Al Kindi M, Nasr ESA, Mohammad A, Ramalingam S. Customized porous implants by additive manufacturing for zygomatic reconstruction. Biocybern. Biomed. Eng. 2016;36:719–30. https://doi.org/ 10.1016/j.bbe.2016.07.005.

[79] Memon AR, Li J, Egger J, Chen X. A review on patient-specific facial and cranial implant design using Artificial Intelligence (AI) techniques. Expert Rev. Med. Devices. 2021;18:985–94.

[80] Wang J, Suenaga H, Yang L, Kobayashi E, Sakuma I. Video see-through augmented reality for oral and maxillofacial surgery. Int. J. Med. Robot. Comput. Assist. Surg. 2017;13:e1754.

[81] Mine Y, Suzuki S, Eguchi T, Murayama T. Applying deep artificial neural network approach to maxillofacial prostheses coloration. J. Prosthodont. Res. 2020;64: 296–300.

[82] Kurt M, Kurt Z, Is¸ık S¸ . Using deep learning approaches for coloring silicone maxillofacial prostheses: a comparison of two approaches. J. Indian Prosthodont. Soc. 2023;23:84.

[83] Monill-Gonz´alez A, Rovira-Calatayud L, D'Oliveira NG, Ustrell-Torrent JM. Artificial intelligence in orthodontics: where are we now? A scoping review. Orthod. Craniofac. Res. 2021;24:6–15. https://doi.org/10.1111/ocr.12517.

[84] Li S, Guo Z, Lin J, Ying S. Artificial intelligence for classifying and archiving orthodontic images. Biomed Res. Int. 2022;2022:1–11. https://doi.org/10.1155/ 2022/1473977.

[85] Faber J, Faber C, Faber P. Artificial intelligence in orthodontics. APOS Trends Orthod. 2019;9:201. https://doi.org/10.25259/APOS_123_2019.

[86] Tanikawa C, Yamashiro T. Development of novel artificial intelligence systems to predict facial morphology after orthognathic surgery and orthodontic treatment in Japanese patients. Sci. Rep. 2021;11:15853. https://doi.org/10.1038/s41598- 021-95002-w.

[87] Tsolakis IA, Gizani S, Tsolakis AI, Panayi N. Three-Dimensional-Printed customized orthodontic and pedodontic appliances: a critical review of a new era for treatment. Children 2022;9:1107. https://doi.org/10.3390/children9081107.

[88] Saccomanno S, Saran S, Vanella V, Mastrapasqua RF, Raffaelli L, Levrini L. The potential of digital impression in orthodontics. Dent. J. 2022;10:147. https://doi. org/10.3390/dj10080147.

[89] AKDENİZ BS, AYKAÇ V, TURGUT M, ÇETİN S. Digital dental models in orthodontics: a review. J. Exp. Clin. Med. 2022;39:250–5. https://doi.org/ 10.52142/omujecm.39.1.48.

[90] Hansa I, Katyal V, Semaan SJ, Coyne R, Vaid NR. Artificial intelligence driven remote monitoring of orthodontic patients: clinical applicability and rationale. Semin. Orthod. 2021;27:138–56. https://doi.org/10.1053/j.sodo.2021.05.010.

[91] Van Staveren HJ, Van Veen RLP, Speelman OC, Witjes MJH, Star WM, Roodenburg JLN. Classification of clinical autofluorescence spectra of oral leukoplakia using an artificial neural network: a pilot study. Oral Oncol. 2000;36: 286–93.

[92] García-Pola M, Pons-Fuster E, Su´arez-Fern´andez C, Seoane-Romero J, Romero-M´endez A, Lo´pez-Jornet P. Role of artificial intelligence in the early diagnosis of oral cancer. a scoping review. Cancers 2021;13:4600. https://doi.org/10.3390/ cancers13184600.

[93] Baniulyte G, Ali K. Artificial intelligence - can it be used to outsmart oral cancer? Evid. Based. Dent. 2022;23:12–3. https://doi.org/10.1038/s41432-022-0238-y.

[94] Alhazmi A, Alhazmi Y, Makrami A, Masmali A, Salawi N, Masmali K, Patil S. Application of artificial intelligence and machine learning for prediction of oral cancer risk. J. Oral Pathol. Med. 2021;50:444–50. https://doi.org/10.1111/ jop.13157.

[95] Ilhan B, Lin K, Guneri P, Wilder-Smith P. Improving oral cancer outcomes with imaging and artificial intelligence. J. Dent. Res. 2020;99:241–8. https://doi.org/ 10.1177/0022034520902128.

[96] Hung M, Park J, Hon ES, Bounsanga J, Moazzami S, Ruiz-Negro´n B, Wang D. Artificial intelligence in dentistry: harnessing big data to predict oral cancer survival. World J. Clin. Oncol. 2020;11:918–34. https://doi.org/10.5306/wjco. v11.i11.918.

[97] Kar A, Wreesmann VB, Shwetha V, Thakur S, Rao VUS, Arakeri G, Brennan PA. Improvement of oral cancer screening quality and reach: the promise of artificial intelligence. J. Oral Pathol. Med. 2020;49:727–30. https://doi.org/10.1111/ jop.13013.

[98] Tobias MAS, Nogueira BP, Santana MCS, Pires RG, Papa JP, Santos PSS. Artificial intelligence for oral cancer diagnosis: what are the possibilities? Oral Oncol. 2022;134:106117. https://doi.org/10.1016/j.oraloncology.2022.106117.

[99] James BL, Sunny SP, Heidari AE, Ramanjinappa RD, Lam T, Tran AV, Kankanala S, Sil S, Tiwari V, Patrick S, Pillai V, Shetty V, Hedne N, Shah D, Shah N, Chen Z, Kandasarma U, Raghavan SA, Gurudath S, Nagaraj PB, Wilder- Smith P, Suresh A, Kuriakose MA. Validation of a point-of-care optical coherence tomography device with machine learning algorithm for detection of oral potentially malignant and malignant lesions. Cancers 2021;13:3583. https://doi. org/10.3390/cancers13143583.

[100] Lin H, Chen H, Weng L, Shao J, Lin J. Automatic detection of oral cancer in smartphone-based images using deep learning for early diagnosis. J. Biomed. Opt. 2021;26:86007. https://doi.org/10.1117/1.JBO.26.8.086007.

[101] Nayak GS, Kamath S, Pai KM, Sarkar A, Ray S, Kurien J, D'Almeida L, Krishnanand BR, Santhosh C, Kartha VB, Mahato KK. Principal component analysis and artificial neural network

analysis of oral tissue fluorescence spectra: classification of normal premalignant and malignant pathological conditions. Biopolymers 2006;82:152–66. https://doi.org/10.1002/bip.20473.

[102] Bhandari B, Alsadoon A, Prasad PWC, Abdullah S, Haddad S. Deep learning neural network for texture feature extraction in oral cancer: enhanced loss function. Multimed. Tools Appl. 2020;79:27867–90. https://doi.org/10.1007/ s11042-020-09384-6.

[103] Dittberner A, Rodner E, Ortmann W, Stadler J, Schmidt C, Petersen I, Stallmach A, Denzler J, Guntinas-Lichius O. Automated analysis of confocal laser endomicroscopy images to detect head and neck cancer. Head Neck 2016;38: E1419–26. https://doi.org/10.1002/hed.24253.

[104] Banavar G, Ogundijo O, Julian C, Toma R, Camacho F, Torres PJ, Hu L, Kenny L, Vasani S, Batstone M. Detecting salivary host-microbiome RNA signature for aiding diagnosis of oral and throat cancer. MedRxiv 2022:2007–22.

[105] Adeoye J, Wan CCJ, Zheng LW, Thomson P, Choi SW, Su YX. Machine learning- based genome-wide salivary DNA methylation analysis for identification of noninvasive biomarkers in oral cancer diagnosis. Cancers 2022;14:4935. https:// doi.org/10.3390/cancers14194935.

[106] Braz DC, Neto MP, Shimizu FM, S´a AC, Lima RS, Gobbi AL, Melendez ME,
Arantes LMRB, Carvalho AL, Paulovich FV, Oliveira Jr ON. Using machine learning and an electronic tongue for discriminating saliva samples from oral cavity cancer patients and healthy individuals. Talanta 2022;243:123327. https://doi.org/10.1016/j.talanta.2022.123327.

[107] McRae MP, Kerr AR, Janal MN, Thornhill MH, Redding SW, Vigneswaran N, Kang SK, Niederman R, Christodoulides NJ, Trochesset DA, Murdoch C, Dapkins I, Bouquot J, Modak SS, Simmons GW, McDevitt JT. Nuclear F-actin cytology in oral epithelial dysplasia and oral squamous cell carcinoma. J. Dent. Res. 2021;100: 479–86. https://doi.org/10.1177/0022034520973162.

[108] Matias AV, Cerentini A, Macarini LAB, Amorim JGA, Daltoe´ FP, von Wangenheim A. Segmentation, detection, and classification of cell nuclei on oral cytology samples stained with papanicolaou. SN Comput. Sci. 2021;2:285. https://doi.org/10.1007/s42979-021-00676-8.

[109] Banerjee S, Pal M, Chakrabarty J, Petibois C, Paul RR, Giri A, Chatterjee J. Fourier-transform-infrared-spectroscopy based spectral-biomarker selection towards optimum diagnostic differentiation of oral leukoplakia and cancer. Anal. Bioanal. Chem. 2015;407:7935–43. https://doi.org/10.1007/s00216-015-8960- 3.

[110] Ashizawa K, Yoshimura K, Johno H, Inoue T, Katoh R, Funayama S, Sakamoto K, Takeda S, Masuyama K, Matsuoka T, Ishii H. Construction of mass spectra database and diagnosis algorithm for head and neck squamous cell carcinoma. Oral Oncol 2017;75:111–9. https://doi.org/10.1016/j. oraloncology.2017.11.008.

[111] Paul A, Srivastava S, Roy R, Anand A, Gaurav K, Husain N, Jain S, Sonkar AA. Malignancy prediction among tissues from Oral SCC patients including neck invasions: a 1H HRMAS NMR based metabolomic study. Metabolomics 2020;16:
38. https://doi.org/10.1007/s11306-020-01660-8.

[112] Kim DW, Lee S, Kwon S, Nam W, Cha IH, Kim HJ. Deep learning-based survival prediction of oral cancer patients. Sci. Rep. 2019;9:6994. https://doi.org/ 10.1038/s41598-019-43372-7.

[113] Shams WK, Htike ZZ. Oral cancer prediction using gene expression profiling and machine learning. Int. J. Appl. Eng. Res. 2017;12:4893–8.

[114] Bourdillon AT, Shah HP, Cohen O, Hajek MA, Mehra S. Novel machine learning model to predict interval of oral cancer recurrence for surveillance stratification. Laryngoscope 2023;133:1652–9. https://doi.org/10.1002/lary.30351.

[115] Scrobotaˇ I, Bˇaciuț G, Filip AG, Todor B, Blaga F, Bˇaciuț MF. Application of fuzzy logic in oral cancer risk assessment. Iran. J. Public Health. 2017;46:612.

[116] Artificial Intelligence in Healthcare Market by Offering (Hardware, Software, Services), Technology (Machine Learning, NLP, Context-aware Computing, Computer Vision), Application, End-use, and Region - Golobal Forecast to 2028, 2023. https://www.marketsandmarkets.com/Market-Reports/artificial-intelli gence-healthcare-market-54679303.html?gclid=Cj0KCQiAxbefBhDfARIsAL4 XLRrN271KbjyZ7TpXXVhtgZiTqjjaKw3q6UjQBMPFN_c8tIhTOkEzLmYaAi4 1EALw_wcB.

[117] Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry: chances and challenges. J. Dent. Res. 2020;99:769–74. https://doi.org/10.1177/ 0022034520915714.

[118] Ducret M, Mo¨rch CM. Focus on artificial intelligence ethics in dentistry. J. Dent. Sci. 2023;18:1409–10. https://doi.org/10.1016/j.jds.2022.12.003.

[119] Khandare L, Sreekantha DK, Sairam K. A study on encryption techniques to protect the patient privacy in health care systems. In: Proc. 2019 Innov. Power Adv. Comput. Technol. IEEE; 2019. p. 1–5.

[120] Schwendicke F, Chaurasia A, Wiegand T, Uribe SE, Fontana M, Akota I, Tryfonos O, Krois J. Artificial intelligence for oral and dental healthcare: core education curriculum. J. Dent. 2023;128:104363. https://doi.org/10.1016/j. jdent.2022.104363.