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SYSTEMATIC REVIEW
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Artificial Intelligence and its Implications in the Management of Orofacial Diseases - A Systematic Review

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Abstract:

Objective: This study aimed to evaluate artificial intelligence's integration into dental practice and its impact on clinical outcomes.

Material and Methods: Research papers titled "Artificial Intelligence and its Implications in Dentistry" were searched on PubMed, ResearchGate, Sci-Hub, and Crossref from 2018 onwards. The selected publications were independently evaluated, reviewed for eligibility, and meticulously analyzed to meet all inclusion criteria.

Results: This mini-review of 46 studies (2018-2024) explored AI applications in dentistry, particularly machine learning and deep learning. AI was applied for diagnosis in 19 studies, treatment planning in 3 studies, and both diagnosis and treatment in 18 studies. It was used for detection in 15 studies, segmentation in 7 studies, and classification in 4 studies, with the largest sample size being 7,245 patients focused on oral cancer detection. The studies used diverse imaging modalities, underscoring AI's broad applicability in the field.

Conclusion: Artificial intelligence in dentistry holds significant promise, particularly in the realm of diagnosis. The significant patient sample sizes and diverse imaging techniques further validate AI's potential to enhance diagnostic accuracy and treatment efficiency. As AI continues to evolve, its integration into dental practice is likely to become increasingly essential, where it should complement rather than replace human clinical expertise with more research needed before it can be widely used in clinical settings.

Keywords: Artificial intelligence, Machine learning, Deep learning, Convolutional neural networks, Deep neural networks, Virtual reality.

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1. INTRODUCTION

Artificial intelligence (AI) aims to enable machines to mimic intelligent human behavior, a concept that traces back to Aristotle and was further developed by Alan Turing. In August 1955, John McCarthy began advocating the term "AI", which was formalized during workshops in 1956, establishing AI as an academic field [1].

AI is rapidly evolving, focusing more on future applications. For example, Okayama University developed "Zerobot", a remote-controlled robot for needle insertion in computed tomography (CT)-guided interventional radiology, minimizing doctors' radiation exposure [2].

AI includes subcategories, like machine learning (ML), deep learning (DL), and robotics. ML enables automated learning without explicit programming, using current observations to forecast future occurrences [3]. DL is a recent advancement in AI systems in dentistry, using multiple neural network layers to analyze input data and make predictions from unstructured and unlabeled data [4].

AI's impact spans multiple fields, including medicine and engineering. In dentistry, AI enhances efficiency and accuracy, as well as manages routine tasks, like appointment scheduling. It can also identify malocclusions, detect maxillofacial abnormalities, and classify dental restorations. Radiography is the most popular diagnostic use [5]. In endodontics, AI accurately detects periapical pathologies and predicts disease outcomes [6].

Over the past 20 years, AI applications in dentistry have grown. One of the earliest was ML, aiming to build systems that learn and function without explicit human direction. Artificial neural networks (ANNs) emerged simultaneously, mimicking the human brain's neural network to help computers react appropriately to events [4, 7].

The objective of this review was to systematically evaluate and synthesize the current evidence on the applications, effectiveness, and implications of AI in the diagnosis, treatment, and management of orofacial diseases, with a focus on identifying its potential benefits, limitations, and areas for future research.

1.1. Application of AI in Disease Management

AI is widely applied in disease management to analyze treatment outcomes and enable precision medicine. These ML algorithms are robust analytical tools that aid medical professionals in evaluating patterns and trends, thereby reducing errors and improving diagnosis accuracy. In dentistry, DL applications are particularly promising, creating high-performance systems with superior decision-making by identifying configurations from vast image datasets.

AI's self-driven applications have gained interest in the pharmaceutical and medical industries, with advancements in medical image interpretation. Wearable technology can also provide early and effective therapy by anticipating life-threatening emergencies, like strokes [8].

According to the Canadian Dental Association, there are 9 acknowledged specialties in the field of dentistry, including dental public health, endodontics, oral and maxillofacial surgery, oral medicine and pathology, orthodontics and dentofacial orthopedics, pediatric dentistry, oral and maxillofacial radiology, periodontics, and prosthodontics [8]. This article further explains the role of AI in each of these subspecialties in detail.

1.2. Endodontics

1.2.1. Periapical Lesions

Diagnosing and treating teeth with periapical lesions can be challenging. Apical periodontitis, which accounts for about 75% of radiolucent jaw lesions, requires early detection to prevent disease spread and improve treatment outcomes [9]. While panoramic and intraoral periapical radiographs (IOPA) are commonly used, their reliability is limited due to the reduction of 3D anatomy into a 2D image. Cone-beam computed tomography (CBCT) imaging, a 3D technique, more accurately identifies periapical lesions' location and size, with a meta-analysis reporting accuracy values of 0.96 for CBCT, 0.73 for traditional periapical radiography, and 0.72 for digital periapical radiography. However, CBCT is less accurate for diagnosing apical periodontitis in teeth with root fillings [9].

Ruben *et al.* highlighted a DL model with superior diagnostic accuracy, with 0.87 sensitivity, 0.98 specificity, and 0.93 area under the curve (AUC), outperforming experienced oral radiologists [10]. Vo *et al.* and Maria *et al.* also introduced AI models with remarkable diagnostic performance, though limited by dataset size [11, 12]. These advancements highlight AI's potential to enhance diagnostic precision and efficiency in endodontics, pending further development and validation.

1.2.2. Working Length Determination

Choosing the correct working length is crucial for successful root canal treatment, reducing insufficient cleaning and shaping, and maintaining root-filling material in the canal. Xiaoyue *et al*. reported an AI model for measuring root canal length with exceptional accuracy, surpassing the dual frequency impedance ratio method, which had 85% accuracy. Future research can improve performance by increasing the sample size [13].

1.2.3. Vertical Root Fractures

Vertical root fractures (VRF) can occur in treated or untreated teeth and are often diagnosed late due to their subtle nature. AI models can help clinicians diagnose VRF more quickly and accurately [14]. Ziyang *et al*. found the ResNet50 AI model to have the best sensitivity and accuracy for diagnosing VRF [15]. Hina *et al*. reported an AI model detecting tooth cracks with a mean ROC of 0.97 [16].

1.2.4. Morphology of Root and Root Canal System

Evaluating the shape of tooth roots and canals is critical in endodontics, especially for complex variations, like C-shaped canals. Adithya *et al*. reported superior performance of Xception U-Net and residual U-Net AI technologies in categorizing C-shaped canal anatomy in mandibular second molars, though limited by small sample size and exclusive focus on C-shaped anatomy [17].

1.2.5. Prognosis of Root Canal Treatment

Chantal *et al*. developed an AI model to predict variables linked to root canal treatment failure, showing good performance in forecasting tooth-level factors. Yunxiang *et al.* found a model with 91.39% sensitivity, 95.63% AUC, and 57.96-90.20% accuracy. These automated models assist clinicians with decision-making, providing quick, accurate results without extensive clinical experience and reducing inter-observer variability [18, 19].

1.3. Orthodontics

Diagnosis in orthodontics involves cephalometric examination, facial and dental evaluation, skeletal development assessment, and inspection of upper respiratory congestion. DL and convolutional neural networks (CNNs) are effective for 3D cephalometric landmark identification, such as Web Ceph. Sameh *et al.* used the you only look once (YOLO) technique on intraoral images to detect malocclusions, like overjet, overbite, crossbite, crowding, and spacing, achieving 99.99% accuracy. Advances in computerized technology have led to the development of 3D intraoral scanners in dental practice [20].

AI also accurately detects skeletal age using cervical vertebral maturation and wrist X-rays, with CNN models achieving over 90% precision. The Dental Monitoring (DM) system, comprising a mobile app, web doctor, and detection algorithms, aims to reduce chair time, enable early orthodontic issue detection, and improve aligner fit [21].

1.4. Imaging

AI is considered one of the fastest-expanding tools of application in dentistry with regards to imaging and diagnosis. AI and DL could benefit medical radiography by automating data mining using the vast data from digital radiographs in clinical settings. Several studies have concluded the efficiency of AI in oral and maxillofacial radiology, in which numerous algorithms have been programmed to localize cephalometric landmarks, detect periapical disease and diseases of the periodontium, segment and classify cysts and tumors, and diagnose osteoporosis [22]. The accuracy and performance of different systems, however, have not been constant and dependent on the type of algorithm used.

1.4.1. Identifying Dental Anatomy and Detecting Caries

CNN identification software show potential in detecting anatomical structures. Usually, periapical radiographs are the training apparatus to locate and name teeth, where the CNN scans them and provides an accuracy rating of 95.8-99.45%, which is comparable to clinical professionals' accuracy score of 99.98% on detecting and classifying teeth [23]. A deep CNN algorithm detected carious lesions in 3000 posterior teeth periapical radiographs with a sensitivity of 74.5-97.1% and an accuracy of 75.5-93.3%. This is a substantial advancement over medical professionals using radiographs alone for diagnosis, with sensitivity ranging from 19 to 94% [24].

1.4.2. CBCT

With wide applications in dentistry, CBCT imaging is considered one of the most crucial diagnostic criteria in many instances to differentiate teeth and their surrounding structures. In a study conducted by Kuofeng *et al*. (2019) at the University of Hong Kong, China, they concluded that the number of 3D imaging modalities has grown nine times between 1995 and 2019 [25]. This being said, it is important to understand the reasoning behind its growth and popular demand in the industry.

The 3D component of CBCT helps medical professionals precisely identify diseased regions, specifically in the buccolingual aspect, which other radiological modalities, like panoramic X-rays, cannot provide. However, assessing each landmark and measuring parameters is time-consuming. Automation can resolve these issues. DL enables the entire process, from input images to final classification, without the need for human intervention. This is achieved by advanced software capable of handling vast data volumes and performing complex tasks, like predictive modeling, natural language processing, and image recognition.

Image recognition and analysis of specific diseases usually follow a course of 3 steps: pre-processing, segmentation, and post-processing. CNNs are the most frequently employed neural networks for segmenting and analyzing medical images in recent days. They contain three parameters consisting of input, output, and hidden layers, where the hidden layers are made up of several pooling, convolutional, and fully connected layers [26].

Hierarchical features are extracted and learned *via* convolutional filters, while the pooling layer connects nearby pixels to the average of all features that have been obtained [27]. One of the most significant CNN frameworks is U-Net, which is also employed in image segmentation. This can help reduce the discrepancy of multiple factors, like the ability of new and experienced clinicians to interpret the same images can be more closely matched, and the disparity in imaging diagnosis between wealthy and impoverished communities can be lessened.

1.4.2.1. Inferior Alveolar Nerve

Inferior alveolar nerve (IAN) injury is a common adverse effect of implant surgery, molar extraction, and orthognathic surgery. The prognostic value of CBCT is higher than that of panoramic X-rays prior to surgery. Therefore, identifying and segmenting the IAN on CBCT images before surgery is crucial, primarily using CNNs. Both the studies conducted by Pierre *et al.* and Mu-Qing *et al.* have discovered CNN as highly accurate at detecting the association between the IAN and the third molar in addition to detecting the IAN itself [28, 29]. Although the automation of this process is time-saving and efficient, the accuracy remains only acceptable and requires improvement.

1.4.2.2. Tooth Segmentation and Endodontics

Many studies on the use of DL in dentistry have been centered on tooth segmentation, which can be classified into partial segmentation and global segmentation. Specifically, global segmentation approaches based on DL and CBCT can yield more detailed dental information than contemporary oral scans that simply display the position and axis of the crown without revealing the position of the root. Conversely, partial segmentation methods are used to help diagnose conditions related to the teeth, including pulpitis, periapical disease, and root fractures.

A method for automatically segmenting teeth based on CBCT imaging was published by Kang *et al*. They started by converting 3D images into 2D images, and then recording 2D regions of interest (ROIs). Ultimately, ROIs were used to segment the 3D teeth with 93.35% accuracy. Moreover, the detection of periapical pathosis on CBCT images was investigated using the CNN approach, achieving an accuracy of 92.8%. The data showed no difference between DL and manual segmentation [30]. Additionally, U-Net was able to identify unobturated MB2 canals on endodontically obturated maxillary molars and C-shaped root canals of the second molar [31].

1.4.2.3. TMJ and Sinus Disease

CBCT images can be segmented using U-Net to show the mandibular ramus and condyles. A web-based approach based on a neural network and shape variation analyzer can be used to classify temporomandibular joint osteoarthritis. Apart from osteoarthritis and condyle morphology, CBCT can demonstrate the joint space, effusion, and mandibular fossa, all of which can support a diagnosis of temporomandibular joint dysfunction syndrome [32]. Sinusitis has also been diagnosed using CNNs. Similar studies have been conducted by other investigators, who have segmented the sinus lesion, air, and bone using 3D U-Net. Still, there is room for improvement in the sinus lesion algorithm [33].

1.4.2.4. Dental Implant

Together, CBCT and DL can help with evaluation prior to surgery for issues related to the area of tooth loss, such as height, thickness, IAN placement, and alveolar bone density. They also provide postoperative stability analysis, which is convenient for examination later.

CNNs can be utilized to assist in the planning of the implant's initial location. A new end-to-end technology for CBCT image analysis only requires 0.001 seconds to perform. A multi-task CNN technique that can classify implant stability, extract zones of interest, and segment implants was presented by Liping *et al.* It evaluated each implant in 3.76 seconds and had an accuracy of above 92% [34].

1.4.2.5. Landmark Localization

In surgical navigation systems, accurate cranio-maxillofacial landmark localization is essential for surgical precision. Traumatic defects and abnormalities pose challenges for DL in this field. However, DL techniques enable precise surgical planning, and despite its challenges, DL has been reported to perform well in CMF landmark localization. Neslisah *et al.* presented a three-step DL technique to segment anatomy and automate landmarks, producing excellent outcomes [35].

Orthodontic analysis is another application for this technique. Jonghun *et al.* were able to identify 23 landmarks and compute 13 parameters using a mask region-based convolutional neural network (R-CNN), which completed tasks equivalent to manual analysis in 30 seconds, whereas manual analysis took 30 minutes [36].

1.4.3. Cyst and Tumor Classification

A computer-aided classification system for cysts and tumors based on image textures on panoramic radiographs and CBCT has been developed. Multiple DL techniques, particularly CNN-based techniques, have been developed to identify and categorize lesions on panoramic radiographs and CBCT into tumors and cyst lesions. Using panoramic radiographs, Kwon *et al*. and Hyunwoo *et al*. detected and classified ameloblastoma and other cysts using the YOLO network, a deep CNN model for detection tasks [37]. The performance of the studied trials, including ML and DL models, revealed variability despite encouraging results. These findings were understandable as cystic and tumor lesions can exhibit similar radiographic signs and manifest in various manners, like shape, location, and internal structure differences. For use in clinical settings, AI models that identify and categorize tumor and cyst lesions must be further developed.

1.5. Periodontal Bone Loss

CNN has been applied to bone loss detection and periodontal condition categorization. A DL hybrid AI model was recently built by Hyuk-Joon *et al.* to diagnose periodontal disease and stage it in accordance with the 2017 World Workshop on the Classification of Periodontal and Peri-implant Illnesses and Conditions [38]. These studies have revealed promising results, with AI models delivering findings being on par with or even better than manual periodontal bone loss analysis.

1.6. Restorative Dentistry

AI's ability to detect caries is one of its most impressive applications in restorative dentistry. For instance, V. *et al.* demonstrated that ANNs could distinguish between dental caries and normal tooth anatomy using patient oral images, achieving 97.1% accuracy in identifying interproximal caries. However, no studies have shown AI's capability to predict caries severity [39].

Ragda *et al.* found that AI models could identify and differentiate between various dental restorations based on gray values on dental radiographs. Additionally, AI's use of sophisticated algorithms, like neural networks and decision tree models, has significantly improved the accuracy of dental shade matching [3, 40]. According to a review by Sthithika *et al.* [41], a decision tree regression AI model for specific dental ceramics achieved 99.7% accuracy. The type of technology and lighting conditions impact AI's shade-matching accuracy, enhancing the aesthetic results of dental restorations.

ANN has also been used to determine the shade, light-curing unit, and composite Vickers hardness ratio of bottom-to-top composites in an *in vitro* study [42] and assist in predicting the debonding probability of composite restorations [43]. A study created a CNN AI model to identify the crown tooth preparation finishing line, achieving an accuracy of 90.6% to 97.4% [44]. AI also helps predict post-operative sensitivity and dental restoration failure. A controversial study trained AI to predict post-operative sensitivity using data from 213 dentist questionnaires [45]. Despite promising results, the reliability of AI outcomes is influenced by the quality of the training data.

1.7. Periodontics

AI has advanced much in the field of periodontology recently. According to studies, AI systems are useful for assessing periodontal health and making medical diagnoses. For example, Nguyen *et al*. discovered that DL technology detects periodontally damaged teeth on periapical radiographs more reliably than ANN [46-48].

A study conducted by Gregory *et al*. [49] demonstrated that ML models could be trained to correlate data obtained from dental radiographs, clinical examinations, and patient medical histories in order to automatically diagnose the disease in the future. The capacity of this system to gauge the severity of periodontal disease is one of the most recent developments in AI in periodontology. ANN was shown to be able to differentiate between aggressive and chronic periodontitis in patients by evaluating immunologic parameters, with accuracy ranging from 90 to 98%, having statistical significance [50].

According to a recent systematic review study, AI applications can identify dental plaque with an accuracy of 73.6% to 99%. However, based on IOPAs, the accuracy of this technology in detecting periodontitis is reported to be between 74% and 78.20%. Dental implant design is optimized through the application of AI technology. Here, AI models adjust the porosity, length, and diameter of the dental implant, resulting in reduced stress at the implant-bone interface and enhanced dental implant design [51]. However, several studies conducted by Henggou *et al*., Seung-Ryong *et al*., and Chia-Hui *et al.* have reported that models can forecast the success and osteointegration of dental implants [52-54].

1.8. Prosthodontics

1.8.1. CAD/CAM

The digital imaging of prepared teeth and the milling of restorations utilizing ceramic blocks are made easier by computer-aided design and computer-aided manufacturing (CAD/CAM). They have reduced the possibility of human mistakes in the finished prosthesis while displacing the laborious and lengthy traditional casting procedure [55].

1.8.2. Fixed and Removable Prosthetics Supported by Teeth

When it comes to fixed prostheses, technologies can be used to analyze and suggest different treatment alternatives after the original tooth anatomy has been scanned. When designing a removable partial denture (RPD), a computing device should initially collect data linked to the intraoral situation, including the site of the teeth missing, the prosthetic state of the teeth existing, and occlusion [55].

One study showed a philosophy of existence (ontology) and case-based software for motorized programmed RPD designs, with 96% success for patients using RPDs. Another study adapted the model into a 2-dimensional format for fully computerized design, achieving 100% accuracy for the mandible and 75% for the maxilla [56]. AiDental software automates customized RPD generation, enhancing preclinical learning and student education [57].

1.8.3. Maxillofacial Prosthesis

Before the development of CAD/CAM, wax was used for carving to regenerate the facial form. The first step is to take X-ray, MRI, or CT scans, and then utilize computer software. The information is then transported to a rapid prototyping (RP) model. However, RP models cannot accurately follow skin curvature, so the wax cast is adapted and the final steps must be carved. CAD/CAM technology showed better results in the replacement of lost structures than traditional methods [58].

1.9. Oral Surgery

1.9.1. Tooth Impaction

A common pathological dental condition occurring due to local and systemic etiological factors, such as genetics, is tooth impaction. The range of these etiological factors affects 0.8% to 3.6% of the world population and the impact of third molars ranges from 16.7% to 68.6% [59, 60]. Infections, such as pericoronitis, periodontitis, orofacial discomfort, TMJ issues, fractures, cysts, and neoplasms, can arise from untreated tooth impaction. In most cases, impacted teeth need to be extracted, but not before other anatomical structures and root morphology are assessed [59, 61-63].

When it comes to dental surgeries, ANNs have proven their importance. It is emphasized that the application of AI technology has the potential to significantly transform orthognathic surgeries. For instance, it was observed that ANN models increased the accuracy of the outcome of orthognathic surgery which oral surgeons took into consideration in a study by Raphael *et al*. To achieve this goal, 30 pre-treatment facial images of patients undergoing orthognathic surgery were assessed by doctors, and anticipated post-surgery facial images were generated. The projected post-surgery outcomes were then altered using trained ANN models. AI intervention increased the accuracy by more than 80% by comparing the pre and post-AI-modified predicted facial images with the actual post-surgery facial images. Consequently, the use of AI in orthognathic surgery can have a significant impact on treatment planning and decision-making [64].

Due to nerve injury, paresthesia is a common side effect after third molar extraction. By using panoramic photos to locate the nerve, this can be prevented. These images are presently used by DL algorithms to forecast the risk of IAN injury. Based on the nerve's proximity to the mandibular third molar, they can precisely locate and forecast the possibility of nerve damage. According to reports, AI technologies can anticipate the likelihood of nerve injury after tooth extractions with 82% accuracy [65].

AI has helped to increase the success rate of treatment by accurately locating oral lesions on panoramic radiographs prior to surgery. In one study, AI exhibited 90.36% accuracy in identifying odontogenic keratocysts and ameloblastoma on dental images [66, 67].

1.9.2. Implantology

Dental implant therapies are improved when intraoral scanners and CBCT images are combined. With AI integration in implantology, several limitations on fixed and removable prostheses could be lifted, such as occlusal or interproximal adjustment errors, cementation mistakes, and positional faults. An AI model was proposed by Shriya *et al.* to lessen these inaccuracies, where AI was employed to help identify subgingival margins of abutments for implants using monolithic zirconia crowns. This technique reduced mistakes and time spent [55, 68].

1.10. Oral Medicine

AI has significantly advanced the detection and diagnosis of oral cancer. ANNs have shown 98.3% accuracy and 100% specificity using laser-induced autofluorescence, which is a non-invasive technology that distinguishes normal from premalignant tissue. CNNs have also excelled in recognizing cancerous and precancerous lesions through autofluorescence images. CNNs, used for hyperspectral image analysis, demonstrated the potential for unsupervised image-based classification and diagnosis of oral cancer. Deep neural networks (DNNs) predicted the development of oral cancer from potentially malignant lesions with 96% accuracy, surpassing other computer systems [69].

The gold standard for identifying oral cancer lesions remains histopathologic analysis, where AI has enhanced image efficacy and reduced errors. CNNs efficiently identified cancer stages by recognizing the keratinization layer. Additionally, segmentation methods detecting keratin pearls in patients were proposed [70]. AI also improved radiological interpretations, aiding clinicians in achieving accurate and effective diagnoses [71].

1.11. Pediatric Dentistry

1.11.1. Augmented Reality and Virtual Reality

Virtual reality (VR) is a computer-generated 3D simulation enhancing interaction with electronic devices and the real environment. In dentistry, the inclination toward VR has increased due to the demand for clinical practice and motor skills training, enabling trainees to practice and learn without the risk of endangering patients. This is particularly beneficial for pediatric patients who are often more hyperactive, requiring clinicians to be vigilant against sudden movements. Furthermore, VR aids pediatric care by providing self-distraction techniques through games and entertainment applications, diminishing anxiety and pain perception, which enhances the experience and encourages the youth to perform frequent dental visits. Augmented reality (AR) also enables parents to visually see intra-oral remarks made by dentists, improving patient education and compliance with children's oral hygiene measures [72].

1.11.2. Pediatric Airway Management

SmartScope is an ML-based algorithm proposed by Clyde *et al.*, which applies pediatric anesthesia airway management *via* endotracheal intubation. It recognizes the airway/tracheal anatomy and the position of the vocal cords, confirming the intubation using bronchoscopy and video-laryngoscopy. As stated in a study, the segmentation module output can be used as a tracheal GPS to enable the localization of the tracheal rings [73].

2. MATERIALS AND METHODS

This review, designated by IRB code IRB-COD-STD-19-JULY-2024, was formally approved on July 22, 2024.

2.1. Search Strategy

PubMed was searched for recent papers (from 2018 onwards) on "Artificial Intelligence and its Implications in Dentistry". Additional related studies were explored *via* ResearchGate, Sci-Hub, and Crossref.

2.2. Eligibility Criteria

To be included in the systematic review, studies must meet the specified inclusion criteria: articles using AI models in various dental sub-specialties, such as endodontics, prosthodontics, periodontics, orthodontics, oral medicine, oral surgery, pediatric dentistry, and imaging. Exclusion criteria were case reports/series, letters to editors, inaccessible full-text articles, and older studies.

2.3. Study Selection

The research title, abstract, and keywords of the pertinent publications were reviewed by the investigators to determine their eligibility. Then, all possibly eligible papers' full texts were retrieved and carefully reviewed to find research that matched all inclusion requirements. The risk of bias in the included studies was addressed by two reviewers independently assessing each study, ensuring unbiased evaluation. Any discrepancies were resolved through discussion or consultation with a third reviewer.

2.4. Data Extraction

Titles and abstracts of the chosen studies were independently evaluated by authors who screened the titles and selected the abstracts for full-text inclusion. The following categories of information were extracted: Author, year of publication, type of study, sample size, AI tool, data set used, AI usage (for diagnosis, treatment, or both), imaging modality, detailed usage (classify, detect, segment), performance, validation technique, and accuracy (Fig. **1**).

3. RESULTS

This systematic review included articles from 2018-2024 where AI was implemented in various fields of dentistry. The primary AI tools utilized were ML and DL, with subcategories of DL, including CNNs and ANNs. Other branches, like fuzzy logic [26], deep geodesic learning [35], and VR [72] were also included. AI architectures, such as U-net and its branches [17], logistic regression, random forests, gradient boosting [18], YOLO [20], and Sparse Octree (S-Octree) [44], were mentioned, as displayed in Table **1**.

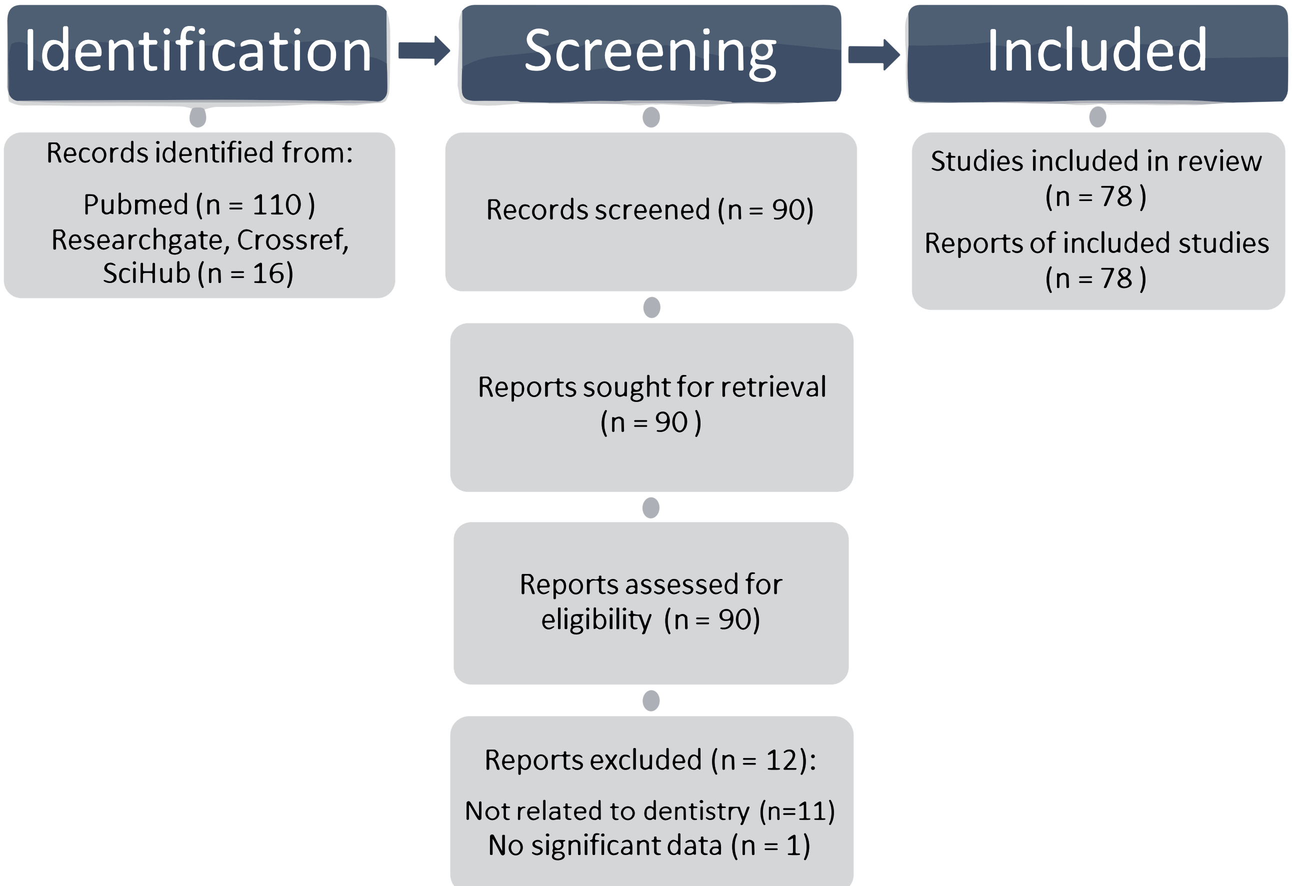

Fig. (1). Literature search process using the PRISMA search strategy.

Table 1. Characteristics of articles representing AI in various disciplines in dentistry.

Author, Year/Refs.	Type of Study	AI Tool*	Imaging Modality†	Usage Modality‡	Application§	Sample Size
Endodontics						
Kruse C (2019) [9]	*Ex vivo* histopathological study	N/A	CBCT	Diagnosis	Assessment of apical periodontitis	223 teeth with 340 roots
Pauwels (2021) [10]	Comparison study	DL	IOPA	Diagnosis	Detection of periapical lesions	10 sockets
Qiao X (2020) [13]	Prospective study	DL	N/A	Treatment	Detection of the correct length of the root canal	21 extracted teeth
Fukuda M (2019) [14]	Evaluation study	DL	OPG	Diagnosis	Detection of vertical root fractures (VRF)	330 VRF teeth
Sherwood AA (2021) [17]	Evaluation study	DL	CBCT	Diagnosis	Segment and classify C-shaped canal morphologies	135 CBCT images
Herbst CS (2022) [18]	Retrospective longitudinal study	ML	IOPA	Diagnosis	Association analysis between various factors and treatment failure	591 permanent teeth

(Table 1) contd.....

Author, Year/Refs.	Type of Study	AI Tool*	Imaging Modality+	Usage Modality‡	Application§	Sample Size
Li Y (2022) [19]	Prospective study	DL	IOPA	Diagnosis and treatment evaluation	Automated evaluation of root canal therapy	245 root canal treated X-ray images
Orthodontics						
Talaat S (2021) [20]	Retrospective study	DL	N/A	Diagnosis and treatment plan	intraoral images for the detection of malocclusions	intraoral images of 700 subjects
Kazimierczak N (2024) [21]	A comprehensive review	DL, ML	Lateral cephalogram	Diagnosis and treatment plan	Detecting skeletal age, patient monitoring, establishing a treatment plan	139 articles
Imaging						
Tuzoff (2019) [23]	Retrospective study	DL	OPG	Diagnosis: teeth detection and numbering	Classifies detected teeth images according to the FDI notation	1574 images
Hung (2020) [25]	Systematic review	DL, ML	IOPA, OPG, CBCT, cephalometrics, MRI	Diagnosis of multiple dental and maxillofacial diseases	Localization of landmarks, classification/segmentation of maxillofacial cysts and/or tumors, identification of periodontitis/periapical disease	50 electronic search titles
Carrillo-Perez (2022) [26]	Systematic review	DL, ML	IOPA, OPG, CBCT	Diagnosis and treatment planning of multiple dental procedures	Disease identification, image segmentation, image correction, and biomimetic color analysis and modeling	120 eligible papers
Abdou MA (2022) [27]	Systematic review	DL, ML	IOPA, OPG, CBCT, CT, MRI, Ultrasound, PET, Fluorescence Angiography, and even photographic images	Diagnosis and treatment planning using CAD systems	Classification, detection, localization, segmentation, and automatic diagnosis	105 articles
Liu MQ (2022) [29]	Retrospective study	DL	CBCT	Diagnosis: automatic detection of the mandibular third molar (M3) to the mandibular canal (MC)	Training, detection, segmentation, classification, and validation, testing of lower M3	254 CBCT scans
de Dumast (2018) [32]	Prospective study	DL	CBCT	Diagnosis: classification of temporomandibular joint osteoarthritis	Classification: web-based system for deep neural network classifier of 3D condylar morphology, computation and integration of high dimensional imaging, clinical, and biological data	Training dataset consisted of 259 condyles
Huang (2022) [24]	Retrospective study	DL	CBCT	Diagnosis: assessment and classification of implant stability	Training and testing of image processing algorithm for implant denture segmentation, volume of interest (VOI) extraction, and implant stability classification	779 implant coronal section images
Torosdagli (2019) [35]	Retrospective study	DL	CBCT	Diagnosis	Segmentation and anatomical landmarking	250 images
Ahn (2022) [36]	Retrospective study	DL	CBCT	Diagnosis and treatment planning: analysis of facial profile processing in relation to CBCT images for diagnosis and treatment planning of orthodontic patients	Detection of 23 landmarks, partitioning, detecting regions of interest, and extracting the facial profile in automated measurements of 13 geometric parameters from CBCT images taken in natural head position	30 CBCTs with multiple views

(Table 1) contd.....

Author, Year/Refs.	Type of Study	AI Tool*	Imaging Modality+	Usage Modality‡	Application§	Sample Size
Yang (2020) [37]	Retrospective study	DL	OPG	Diagnosis: Automated Detection of Cyst and Tumors of the Jaw in Panoramic Radiographs	Detection, classification, and labeling of images into 4 categories: dentigerous cysts, odontogenic keratocyst, ameloblastoma, and no cyst	1602 lesions on panoramic radiographs
Chang (2020) [38]	Retrospective study	DL	OPG	Diagnosis and prognosis: automatic method for diagnosing periodontal bone loss and staging periodontitis of each individual tooth	Detection of bone loss and conventional CAD processing for classification used for periodontitis staging according to the new 2017 criteria classification	518 images
Restorative dentistry						
Shetty S (2023) [41]	Systematic review	ML, DL	N/A	Diagnosis	Utilizes AI for enhancing the precision and consistency of dental shade selection in restorative and cosmetic dentistry.	15 articles selected for review
Deniz Arısu H (2018) [42]	Experimental study	DL	N/A	Examination of material properties	Analysis of the effect of different light curing units and composite parameters on the hardness of dental composites.	60 specimens
Yamaguchi S (2019) [43]	Prospective study	DL	3D Stereolithography models from a 3D oral scanner	Diagnosis	Predict debonding of CAD/CAM composite resin crowns using 2D images from 3D models	24 cases with a total of 8640 images
Bei Zhang (2019) [44]	Prospective study	DL	3D dental model data	Diagnosis and treatment	Classification, detection, segmentation of tooth preparation margin line	380 oral patients' dental preparation models
Marta ct Revilla-León *et al.* (2022) [45]	Systematic review	ML, DL	IOPA, near-infrared transillumination techniques, CBCT,	Diagnosis and treatment	Diagnosing dental caries, vertical tooth fractures; detecting tooth preparation margins; predicting restoration failure	34 articles analyzed
Periodontics						
Sachdeva S (2021) [46]	Systematic review	DL	Radiographs, CAD/CAM	Diagnosis, treatment planning	Aids in screening, diagnosis, and treatment planning of periodontal diseases by early detection	25 articles included
Nguyen TT (2021) [47]	Systematic review	ML, DL	Radiographs, CBCT, CAD/CAM	Diagnosis and treatment planning	Directs treatment to make informed decisions in dentistry	32 articles included
Reddy MS (2019) [48]	Retrospective study	ML	OPG	Diagnosis	Aid in the diagnostics in medical and dental fields	2482 panoramic radiographs
Yauney G (2019) [49]	Prospective study	ML	IOPA	Diagnosis	Correlate information derived from clinical examination, dental radiographs, and patient's medical history to diagnose the disease automatically in the future	1215 intraoral fluorescent images
Revilla-León M (2023) [50]	Systemic review	ML, DL	Intraoral clinical images, IOPA's, OPG's, bitewing	Diagnosis	Detecting dental plaque, diagnosis of gingivitis, diagnosis of periodontal disease from intraoral images, and diagnosis of alveolar bone loss from periapical, bitewing, and panoramic radiographs	24 articles were included
Prosthodontics						
Singi SR (2022) [55]	Systematic review	DL	CAD/CAM	Diagnosis and treatment planning utilizing CAD/CAM in prosthesis fabrication	Application in fixed and removable prosthesis along with maxillofacial prosthesis to reduce errors	380 dental preparations

(Table 1) contd.....

Author, Year/Refs.	Type of Study	AI Tool*	Imaging Modality+	Usage Modality‡	Application§	Sample Size
Ali IE (2023) [56]	Literature review	DL	CAD/CAM	Diagnosis and treatment planning in prosthodontic workflow	Collecting information of the patient oral condition to enhance the prosthetic treatment	15 articles
Mahrous A (2023) [57]	Comparative study	ML	N/A	Treatment planning and aiding in removable prosthesis study design	An app that aids in treatment planning and the design of the RPD	73 RPD designs
Oral surgery						
Patcas (2019) [64]	Prospective	ML, DL	Extraoral and intraoral pictures	Treatment plan and prognosis	Score the patient's age appearance and facial attractiveness based on pre- and post-orthodontic treatment photographs	2164 Pre- and post-treatment photographs
KIM bs (2021) [65]	Preliminary study	DL	OPG	Treatment planning	Determine whether CNNs can predict paresthesia of the IAN using panoramic radiographic images before extraction of the mandibular third molar	300 preoperative OPGs
Liu Z (2021) [66]	Retrospective study	ML, DL	OPG	Diagnosing and treatment planning for surgical procedures	CNN algorithm that significantly improves the classification accuracy	420 OPGs
Ghods K (2023) [40]	Systematic review	ML, DL	Intraoral clinical images, IOPA's, OPG's, bitewing	Diagnosis, treatment planning	Detection of dental abnormalities and oral malignancies based on radiographic view and histopathological features	116 articles included
Mahmoud H (2021) [67]	Systematic review	ML	Intraoral clinical images, IOPA's, OPG's, bitewing	Diagnosis, treatment planning	Methods for diagnostic evaluation of head and neck cancers using automated image analysis.	32 articles were included
Patel P (2020) [59]	Prospective	ML, DL	OPG, CBCT	Diagnosis and treatment planning	Determining the specific signs of close relationship between impacted mandibular third molar	120 individuals
Oral medicine						
Patil S (2022) [69]	Systematic review	DL	CT	Diagnosis of oral cancer	Detection of precancerous and cancerous lesions	9 articles
Al-Rawi N (2022) [70]	Systematic review	DL, ML	N/A	Diagnosis and detection of oral cancer	Uses AI in histopathologic images for the diagnosis and detection of oral cancer.	17 studies with a total of 7245 patients and 69,425 images
Moosa Y (2023) [71]	Survey research	ML	N/A	Diagnosis and treatment planning	AI detection and collection of patient data, medical history, imaging and clinical features	200 dentists answered questionnaire
Pediatric dentistry						
Barros (2023) [72]	Systematic review	VR	N/A	Treatment plan: anxiety reduction among children	Behavior management	22 randomized control trials included
Matava (2020) [73]	Systematic review	ML, DL	N/A	Diagnosis Treatment planning: pediatric anesthesia airway management Prognosis: predicting outcomes during pediatric airway management	Diagnosis, monitoring, procedure assistance, and predicting outcomes during pediatric airway manage	27 articles

Note: * ML, DL, VR.
+ IOPA, OPG, CBCT, Cephalometrics, *etc*.
‡ diagnosis, treatment, or both.
§ classify, detect, segment.

Table 2. AI articles, datasets, performance, and results.

Author, Year\Refs	Dataset Used	Performance	Validation	Accuracy of the Results
Orhan (2020) [30]	153 CBCTs with periapical lesions obtained from 109 patients	Only one tooth was incorrectly identified/numbered 142 of a total of 153 periapical lesions were detected	92.8% reliability	No significant difference between manual and CNN measurement methods (p > 0.05)
Serindere (2022) [33]	148 healthy and 148 inflamed sinus images	Diagnosis of sinusitis in OPGs was moderately high, whereas it was clearly higher with CBCT images, being recognoized as the "gold standard" for diagnosis	By average accuracy, sensitivity, and specificity of the CNN model	-

Note: OPG: 75.7% accuracy, 75.7% sensitivity, and 75.7% specificity of the model in diagnosing sinusitis
CBCT: 99.7% accuracy, 100% sensitivity, and 99.3% specificity in diagnosing sinusitis.

Of the 44 studies presented in Table **1**, 15 were systematic reviews, 11 retrospective studies, 8 prospective studies, 2 evaluation studies, 2 comparative studies, 1 survey research, 1 preliminary study, 1 experimental study, and 1 *ex vivo* histopathological study.

As displayed in Table **1**, various imaging modalities were used, including IOPA, orthopantomogram (OPG), bitewing, CBCT, cephalometrics, magnetic resonance imaging (MRI), CT, ultrasound, positron emission tomography (PET), fluorescence angiography, 3D stereolithography models, near-infrared transillumination techniques, CAD/CAM, and intraoral/extraoral photographs. One study by Xiaoyue *et al.* focused on an impedance method instead of traditional imaging [13].

AI tools aimed at diagnosis, treatment planning, or both were evaluated. Nineteen studies used AI for diagnosis alone, 3 for treatment alone, and 18 for both diagnosis and treatment. AI was used for detection in 15 studies, segmentation in 7 studies, and classification in 4 studies. 3 studies utilized AI for detection, classification, and segmentation.

Sample sizes varied across the studies. The largest sample size was 7245 patients for detecting and diagnosing oral cancer using histopathologic analysis [70]. Ruben *et al*. used the smallest sample size of 10 sockets in bovine ribs to identify periapical lesions [10]. Samples included teeth, roots, sockets, X-ray pictures, publications, intraoral images, CBCT scans, preparation models, lateral cephalograms, and OPGs. Three studies used patients as samples, four used teeth, three used CBCT scans, and four used OPGs.

As per Table **2**, 449 different sinus and periapical images were obtained from a total of 405 patients. The performance of AI tools for both was efficient, with only one incorrectly identified tooth in Kaan *et al.'s* study with 92.8% reliability, and CBCT being recognized as the gold standard in Serindere *et al.'s* study with high accuracy, sensitivity, and specificity.

4. DISCUSSION

The main aim of this study was to evaluate whether AI could be applied in dental clinical practice to enhance diagnoses, patient care, and treatment outcomes. AI has been successfully employed in multiple fields of dentistry, but it is essential to delve further into its uses and outcomes to evaluate its continuous reliability in dentistry.

In endodontics, Ruben *et al.* constructed a DL model with high sensitivity (0.87), specificity (0.98), and ROC-AUC (0.93) [10]. Vo *et al.* generated another tool with similar diagnostic accuracy [11]. Maria *et al.* unveiled an AI solution with a superior accuracy of 70% and a specificity of 92.39%, surpassing the performance of some human experts in the field [12].

Detecting VRF can be challenging for dentists. Ziyang *et al.* suggested that the AI ResNet50 displayed the highest accuracy and sensitivity for VRF diagnosis [15]. Hina *et al.* proposed a similar model with a mean ROC of 0.97 in detecting cracked teeth [16].

In orthodontics, CNNs have been found to be successful in 3D cephalometric landmark identification. Sameh *et al.* utilized intraoral pictures with the YOLO technique, an AI model detecting malocclusions, such as overjet, overbite, crossbite, crowding, and spacing with an exceptional accuracy rate of 99.99% [20].

The use of AI in imaging has flourished in previous years. From identifying dental anatomy [23] to detecting caries [24], CNN models have proven accuracy as high as 95.8-99.45% and 75.5-93.3%, respectively [23, 24]. CBCT imaging is the most applicable imaging module in AI. One of the most significant CNN frameworks is U-Net, which is employed in image segmentation to identify landmarks, anatomy, and pathologies [31].

Pierre *et al.* [28] and Mu-Qing *et al.* [29] found that CNNs can accurately detect the association between the IAN and the third molar, as well as the IAN itself on CBCT images. Although CNNs facilitate this process, the accuracy remains only acceptable and requires improvement.

Kang *et al.* proposed a technique to detect ROIs from CBCT images to segment precise 3D teeth with a 93.35% accuracy, allowing the identification of various dental diseases within or around the tooth structure [30]. U-Net identified unobturated MB2 canals on endodontically obturated maxillary molars and C-shaped root canals of the second molar [31]. Pulp segmentation was also achievable through the same procedure.

CBCT could also be utilized for dental implant placement. A new CNN technology was able to plan an implant's initial location within 0.001 seconds. Liping *et al.*

found that it could classify implant stability, extract zones of interest, and segment implants, each within 3.76 seconds and with an accuracy of above 92% [34].

A DL technique presented by Neslisah *et al.* was able to segment anatomy and automate landmarks through 3 steps, specifically benefitting orthodontics [35]. In agreement, Jonghun *et al.* utilized mask R-CNN to identify 23 landmarks, completing tasks equivalent to that of manual analysis in 30 seconds, whereas manual analysis took 30 minutes [36].

AI in oral surgery uses similar principles for CBCT to relate the position of the tooth to be extracted or the lesion to be removed to other important anatomical structures, like the IAN or maxillary sinus, reducing complications to a minimum [28, 29].

Kwon *et al.* and Hyunwoo *et al.* showed promising results with YOLO, a DL model aiding in cyst and tumor classification. This tool detected and classified ameloblastomas [37] and bone-related diseases, like periapical cysts, dentigerous cysts, keratocystic odontogenic tumors (KCOT), bone fractures, jaw abnormalities, and even bone cancers, with an overall accuracy close to 80% [74-77]. Despite encouraging results, these models revealed variability due to the different radiologic features of pathologies, such as shape, location, and internal structure differences. Consequently, CNNs for cyst and tumor classification need further development before being employed in dental practice.

AI's role in imaging also includes bone loss detection and periodontal condition categorization. Hyuk-Joon *et al.* developed a DL model to diagnose and stage periodontal disease, proving to be equivalent, if not superior, to manual detection and diagnosis. Clinicians may overlook periodontal bone loss on panoramic imaging, where computer-assisted diagnosis has proven efficient in early detection and intervention [38].

In restorative dentistry, AI has shown promise. V. *et al.* proposed an ANN-based technology for oral images to identify caries, which can be revolutionary for growing dentists to aid in interproximal caries diagnosis [39]. However, no algorithm exists yet for caries severity detection. In agreement, Ragda *et al.* concluded that AI could also differentiate dental restorations based on extent, distribution, and gray values on dental radiographs [40].

In prosthodontics, AI tools assist in designing prostheses, especially RPDs, where dentists struggle to select the best therapy for patients. AI optimizes given information, like the amount and location of lost teeth, occlusion, and the state of remaining teeth, to aid in patient-specific treatment planning. AiDental software auto-generates customized RPDs, highly implemented in dental education systems [57]. Maxillofacial prostheses design and fabrication with CAD/CAM systems is also possible.

A case-based software for pre-existing programmed RPD designs displayed 96% accuracy, indicating its potential for patients using RPDs. In disagreement, another study modifying the documented RPD design into a 2D form achieved 100% accuracy for the mandible and 75% for the maxilla [56].

In oral medicine, ANN-based systems using hyperspectral images or laser-induced autofluorescence, a non-invasive diagnostic technique that uses laser light to detect abnormal tissue changes, differentiated between normal and premalignant tissues, exhibiting 98.3% accuracy and 100% specificity. Yet, their performance for the diagnosis was not significant. Prediction of lesion development and prognostic features was achieved using DNNs with a high accuracy rate of 96% [69].

CNNs also aid in histopathologic analysis to stage cancer through the level of keratinization or detecting keratin pearls *via* image segmentation [70].

In pediatrics, both Ta-Ko *et al.* [74] and Barros *et al.* [72] agree that VR serves as a major aiding tool. Distraction techniques ensure workflow efficiency by diverting children's attention from the otherwise “scary” procedure. In agreement, Osama *et al.* confirmed this through their randomized clinical trial [75].

Additionally, SmartScope, an AI-based technology proposed by Clyde *et al*., assists in pediatric airway management and endotracheal intubation. Segmentation of tracheal anatomy and vocal cords *via* a GPS localizes the tracheal rings for intubation using bronchoscopy and video-laryngoscopy. This is especially useful as pediatric airways differ in shape and size from adult airways [73].

The limitations of this review include geographical variability in study selection, reliance on a limited number of databases, and a focus on articles published only from 2018 onwards, which may not capture foundational research. Additionally, the inclusion criteria emphasized AI applications in specific dental fields, potentially overlooking emerging areas. The variation in sample sizes across studies may have further impacted the generalizability and reliability of the findings.

The implications of this study highlight the transformative potential of AI in enhancing diagnostic accuracy, treatment planning, and clinical decision-making across various dental specialties. As AI technologies continue to evolve, they are poised to complement human expertise, streamline workflows, and potentially improve access to high-quality dental care globally. However, further research is needed to address data privacy concerns and validate AI models in diverse clinical settings. A comprehensive evaluation is needed before making decisions to ensure patient well-being and maximize success rates [8, 78].

CONCLUSION

AI has the potential to improve patient outcomes, preventive care, workflow efficiency, dental disease treatment, and diagnosis accuracy. Treatment planning may be enhanced by its capacity for pattern recognition and data analysis. The complexity of dental cases, the requirement for a variety of excellent datasets, and uncertainties regarding the interpretability and dependability of AI algorithms are obstacles, though. AI has the potential to enhance dental specialists' knowledge and enhance patient care in contemporary dentistry through continued research, interdisciplinary collaboration, and ethical considerations.

AUTHORS' CONTRIBUTION

M.M.M.M.: Study conception and design; M.B.D.: Data collection; H.A.: Data analysis or interpretation; Y.A.: Writing of the paper; S.A.A.F.A.B.: Writing, review, and editing. All authors have reviewed the results and approved the final version of the manuscript.

LIST OF ABBREVIATIONS

AI	=	Artificial intelligence
ML	=	Machine learning
CNNs	=	Convolutional neural networks
DL	=	Deep learning
CAD/CAM	=	Computer-aided design and computer-aided manufacturing
ANNs	=	Artificial neural networks
DNNs	=	Deep neural networks
CBCT	=	Cone-beam computed tomography
VRF	=	Vertical root fracture
YOLO	=	You only look once technique
DM	=	Dental monitoring
IAN	=	Inferior alveolar nerve
CT	=	Computed tomography
KCOT	=	Keratocystic odontogenic tumors
ROI	=	Regions of interest
R-CNN	=	Region-based convolutional neural network
RPD	=	Removable partial denture
MRI	=	Magnetic resonance imaging
RP	=	Rapid pro typing
AR	=	Augmented reality
VR	=	Virtual reality
IOPA	=	Intra-oral periapical radiograph
PET	=	Positron emission tomography
OPG	=	Orthopantomogram
ROC-AUC	=	Receiver operating characteristics-area under the curve
PET	=	Positron emission tomography

CONSENT FOR PUBLICATION

Not applicable.

STANDARDS OF REPORTING

PRISMA guidelines were followed.

AVAILABILITY OF DATA AND MATERIALS

The data and supporting information are provided within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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SUPPLEMENTARY MATERIAL

PRISMA checklist is available as supplementary material on the publisher's website along with the published article.

REFERENCES

[1] Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. Gastrointest Endosc 2020; 92(4): 807-12. http://dx.doi.org/10.1016/j.gie.2020.06.040 PMID: 32565184

[2] Hiraki T, Kamegawa T, Matsuno T, Komaki T, Sakurai J, Kanazawa S. Zerobot®: A remote-controlled robot for needle insertion in CT-guided interventional radiology developed at Okayama university. Acta Med Okayama 2018; 72(6): 539-46. PMID: 30573907

[3] Abdalla-Aslan R, Yeshua T, Kabla D, Leichter I, Nadler C. An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surg Oral Med Oral Pathol Oral Radiol 2020; 130(5): 593-602. http://dx.doi.org/10.1016/j.oooo.2020.05.012 PMID: 32646672

[4] Meghil MM, Rajpurohit P, Awad ME, McKee J, Shahoumi LA, Ghaly M. Artificial intelligence in dentistry. Dent Rev 2022; 2: 10009.

[5] Chen YW, Stanley K, Att W. Artificial intelligence in dentistry: Current applications and future perspectives. Quintessence Int 2020; 51(3): 248-57. PMID: 32020135

[6] Karobari MI, Adil AH, Basheer SN, *et al.* Evaluation of the diagnostic and prognostic accuracy of artificial intelligence in endodontic dentistry: A comprehensive review of literature. Comput Math Methods Med 2023; 2023(1): 7049360. http://dx.doi.org/10.1155/2023/7049360 PMID: 36761829

[7] Bini SA. Artificial intelligence, machine learning, deep learning, and cognitive computing: What do these terms mean and how will they impact health care? J Arthroplasty 2018; 33(8): 2358-61. http://dx.doi.org/10.1016/j.arth.2018.02.067 PMID: 29656964

[8] Bonny T, Al Nassan W, Obaideen K, Al Mallahi MN, Mohammad Y, El-damanhoury HM. Contemporary role and applications of artificial intelligence in dentistry. F1000 Res 2023; 12: 1179. http://dx.doi.org/10.12688/f1000research.140204.1 PMID: 37942018

[9] Kruse C, Spin-Neto R, Evar Kraft DC, Væth M, Kirkevang LL. Diagnostic accuracy of cone beam computed tomography used for assessment of apical periodontitis: An *ex vivo* histopathological study on human cadavers. Int Endod J 2019; 52(4): 439-50. http://dx.doi.org/10.1111/iej.13020 PMID: 30267421

[10] Pauwels R, Brasil DM, Yamasaki MC, *et al.* Artificial intelligence for detection of periapical lesions on intraoral radiographs: Comparison between convolutional neural networks and human observers. Oral Surg Oral Med Oral Pathol Oral Radiol 2021; 131(5): 610-6.

http://dx.doi.org/10.1016/j.oooo.2021.01.018 PMID: 33653645

[11] Ngoc VTN, Viet DH, Anh LK, *et al.* Periapical lesion diagnosis support system based on X-ray images using machine learning technique. World J Dent 2021; 12(3): 189-93. http://dx.doi.org/10.5005/jp-journals-10015-1820

[12] Calazans MAA, Ferreira FABS, Alcoforado MLMG, Santos A, Pontual AA, Madeiro F. Automatic classification system for periapical lesions in cone-beam computed tomography. Sensors (Basel) 2022; 22(17): 6481. http://dx.doi.org/10.3390/s22176481 PMID: 36080940

[13] Qiao X, Zhang Z, Chen X. Multifrequency impedance method based on neural network for root canal length measurement. Appl Sci (Basel) 2020; 10(21): 7430. http://dx.doi.org/10.3390/app10217430

[14] Fukuda M, Inamoto K, Shibata N, *et al.* Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol 2020; 36(4): 337-43. http://dx.doi.org/10.1007/s11282-019-00409-x PMID: 31535278

[15] Hu Z, Cao D, Hu Y, *et al.* Diagnosis of *in vivo* vertical root fracture using deep learning on cone-beam CT images. BMC Oral Health 2022; 22(1): 382. http://dx.doi.org/10.1186/s12903-022-02422-9 PMID: 36064682

[16] Shah H, Hernandez P, Budin F, *et al.* Automatic quantification framework to detect cracks in teeth. Proc SPIE Int Soc Opt Eng 2018; 10578: 105781K. http://dx.doi.org/10.1117/12.2293603 PMID: 29769755

[17] Sherwood AA, Sherwood AI, Setzer FC, *et al.* A deep learning approach to segment and classify C-shaped canal morphologies in mandibular second molars using cone-beam computed tomography. J Endod 2021; 47(12): 1907-16. http://dx.doi.org/10.1016/j.joen.2021.09.009 PMID: 34563507

[18] Herbst CS, Schwendicke F, Krois J, Herbst SR. Association between patient-, tooth- and treatment-level factors and root canal treatment failure: A retrospective longitudinal and machine learning study. J Dent 2022; 117: 103937. http://dx.doi.org/10.1016/j.jdent.2021.103937 PMID: 34942278

[19] Li Y, Zeng G, Zhang Y, *et al.* AGMB-transformer: Anatomy-guided multi-branch transformer network for automated evaluation of root canal therapy. IEEE J Biomed Health Inform 2022; 26(4): 1684-95. http://dx.doi.org/10.1109/JBHI.2021.3129245 PMID: 34797767

[20] Talaat S, Kaboudan A, Talaat W, *et al.* The validity of an artificial intelligence application for assessment of orthodontic treatment need from clinical images. Semin Orthod 2021; 27(2): 164-71. http://dx.doi.org/10.1053/j.sodo.2021.05.012

[21] Kazimierczak N, Kazimierczak W, Serafin Z, Nowicki P, Nożewski J, Janiszewska-Olszowska J. AI in orthodontics: Revolutionizing diagnostics and treatment planning—a comprehensive review. J Clin Med 2024; 13(2): 344-4. http://dx.doi.org/10.3390/jcm13020344 PMID: 38256478

[22] Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry: Chances and challenges. J Dent Res 2020; 99(7): 769-74. http://dx.doi.org/10.1177/0022034520915714 PMID: 32315260

[23] Tuzoff DV, Tuzova LN, Bornstein MM, *et al.* Tooth detection and numbering in panoramic radiographs using convolutional neural networks. Dentomaxillofac Radiol 2019; 48(4): 20180051. http://dx.doi.org/10.1259/dmfr.20180051 PMID: 30835551

[24] Tadinada A. Artificial intelligence, machine learning, and the human interface in medicine: Is there a sweet spot for oral and maxillofacial radiology? Oral Surg Oral Med Oral Pathol Oral Radiol 2019; 127(4): 265-6. http://dx.doi.org/10.1016/j.oooo.2018.12.024 PMID: 30922539

[25] Hung K, Montalvao C, Tanaka R, Kawai T, Bornstein MM. The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review. Dentomaxillofac Radiol 2020; 49(1): 20190107. http://dx.doi.org/10.1259/dmfr.20190107 PMID: 31386555

[26] Carrillo-Perez F, Pecho OE, Morales JC, *et al.* Applications of artificial intelligence in dentistry: A comprehensive review. J Esthet Restor Dent 2022; 34(1): 259-80. http://dx.doi.org/10.1111/jerd.12844 PMID: 34842324

[27] Abdou MA. Literature review: Efficient deep neural networks techniques for medical image analysis. Neural Comput Appl 2022; 34(8): 5791-812. http://dx.doi.org/10.1007/s00521-022-06960-9

[28] Lahoud P, Diels S, Niclaes L, *et al.* Development and validation of a novel artificial intelligence driven tool for accurate mandibular canal segmentation on CBCT. J Dent 2022; 116: 103891. http://dx.doi.org/10.1016/j.jdent.2021.103891 PMID: 34780873

[29] Liu MQ, Xu ZN, Mao WY, *et al.* Deep learning-based evaluation of the relationship between mandibular third molar and mandibular canal on CBCT. Clin Oral Investig 2022; 26(1): 981-91. http://dx.doi.org/10.1007/s00784-021-04082-5 PMID: 34312683

[30] Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J 2020; 53(5): 680-9. http://dx.doi.org/10.1111/iej.13265 PMID: 31922612

[31] Hsu K, Yuh DY, Lin SC, *et al.* Improving performance of deep learning models using 3.5D U-Net *via* majority voting for tooth segmentation on cone beam computed tomography. Sci Rep 2022; 12(1): 19809. http://dx.doi.org/10.1038/s41598-022-23901-7 PMID: 36396696

[32] de Dumast P, Mirabel C, Cevidanes L, *et al.* A web-based system for neural network based classification in temporomandibular joint osteoarthritis. Comput Med Imaging Graph 2018; 67: 45-54. http://dx.doi.org/10.1016/j.compmedimag.2018.04.009 PMID: 29753964

[33] Serindere G, Bilgili E, Yesil C, Ozveren N. Evaluation of maxillary sinusitis from panoramic radiographs and cone-beam computed tomographic images using a convolutional neural network. Imaging Sci Dent 2022; 52(2): 187-95. http://dx.doi.org/10.5624/isd.20210263 PMID: 35799961

[34] Huang Z, Zheng H, Huang J, *et al.* The construction and evaluation of a multi-task convolutional neural network for a cone-beam computed-tomography-based assessment of implant stability. Diagnostics (Basel) 2022; 12(11): 2673. http://dx.doi.org/10.3390/diagnostics12112673 PMID: 36359516

[35] Torosdagli N, Liberton DK, Verma P, Sincan M, Lee JS, Bagci U. Deep geodesic learning for segmentation and anatomical landmarking. IEEE Trans Med Imaging 2019; 38(4): 919-31. http://dx.doi.org/10.1109/TMI.2018.2875814 PMID: 30334750

[36] Ahn J, Nguyen TP, Kim YJ, Kim T, Yoon J. Automated analysis of three-dimensional CBCT images taken in natural head position that combines facial profile processing and multiple deep-learning models. Comput Methods Programs Biomed 2022; 226: 107123. http://dx.doi.org/10.1016/j.cmpb.2022.107123 PMID: 36156440

[37] Yang H, Jo E, Kim HJ, *et al.* Deep learning for automated detection of cyst and tumors of the jaw in panoramic radiographs. J Clin Med 2020; 9(6): 1839. http://dx.doi.org/10.3390/jcm9061839 PMID: 32545602

[38] Chang HJ, Lee SJ, Yong TH, *et al.* Deep learning hybrid method to automatically diagnose periodontal bone loss and stage periodontitis. Sci Rep 2020; 10(1): 7531. http://dx.doi.org/10.1038/s41598-020-64509-z PMID: 32372049

[39] Geetha V, Aprameya KS, Hinduja DM. Dental caries diagnosis in digital radiographs using back-propagation neural network. Health Inf Sci Syst 2020; 8(1): 8. http://dx.doi.org/10.1007/s13755-019-0096-y PMID: 31949895

[40] Ghods K, Azizi A, Jafari A, Ghods K. Application of artificial intelligence in clinical dentistry: A comprehensive review of literature. J Dent (Shiraz) 2023; 24(4): 356-71. PMID: 38149231

[41] Shetty S, Gali S, Augustine D, Sv S. Artificial intelligence systems in dental shade-matching: A systematic review. J Prosthodont 2024; 33(6): 519-32. http://dx.doi.org/10.1111/jopr.13805 PMID: 37986239

[42] Deniz Arısu H, Eligüzeloglu Dalkilic E, Alkan F, Erol S, Uctasli MB, Cebi A. Use of artificial neural network in determination of

shade, light curing unit, and composite parameters' effect on bottom/top vickers hardness ratio of composites. BioMed Res Int 2018; 2018: 1-9.
http://dx.doi.org/10.1155/2018/4856707 PMID: 30539012

[43] Yamaguchi S, Lee C, Karaer O, Ban S, Mine A, Imazato S. Predicting the debonding of CAD/CAM composite resin crowns with AI. J Dent Res 2019; 98(11): 1234-8.
http://dx.doi.org/10.1177/0022034519867641 PMID: 31379234

[44] Zhang B, Dai N, Tian S, Yuan F, Yu Q. The extraction method of tooth preparation margin line based on S-Octree CNN. Int J Numer Methods Biomed Eng 2019; 35(10): e3241.
http://dx.doi.org/10.1002/cnm.3241 PMID: 31329358

[45] Revilla-León M, Gómez-Polo M, Vyas S, *et al*. Artificial intelligence applications in restorative dentistry: A systematic review. J Prosthet Dent 2022; 128(5): 867-75.
http://dx.doi.org/10.1016/j.prosdent.2021.02.010 PMID: 33840515

[46] Sachdeva S, Mani A, Vora H, Saluja H, Mani S, Manka N. Artificial intelligence in periodontics: A dip in the future. Journal of Cellular Biotechnology 2021; 7(2): 119-24.
http://dx.doi.org/10.3233/JCB-210041

[47] Nguyen TT, Larrivée N, Lee A, Bilaniuk O, Durand R. Use of artificial intelligence in dentistry: Current clinical trends and research advances. Dent News 2021; 28(2): 50-7.
http://dx.doi.org/10.12816/0059360 PMID: 34343070

[48] Reddy MS, Shetty SR, Shetty RM, Vannala V, Sk S. Future of periodontics lies in artificial intelligence: Myth or reality? J Investig Clin Dent 2019; 10(4): e12423.
http://dx.doi.org/10.1111/jicd.12423 PMID: 31120578

[49] Yauney G, Rana A, Wong LC, Javia P, Muftu A, Shah P. Automated process incorporating machine learning segmentation and correlation of oral diseases with systemic health. Annu Int Conf IEEE Eng Med Biol Soc 2019; 2019: 3387-93.
http://dx.doi.org/10.1109/EMBC.2019.8857965 PMID: 31946607

[50] Revilla-León M, Gómez-Polo M, Barmak AB, *et al.* Artificial intelligence models for diagnosing gingivitis and periodontal disease: A systematic review. J Prosthet Dent 2023; 130(6): 816-24.
http://dx.doi.org/10.1016/j.prosdent.2022.01.026 PMID: 35300850

[51] Roy S, Dey S, Khutia N, Roy Chowdhury A, Datta S. Design of patient specific dental implant using FE analysis and computational intelligence techniques. Appl Soft Comput 2018; 65: 272-9.
http://dx.doi.org/10.1016/j.asoc.2018.01.025

[52] Zhang H, Shan J, Zhang P, Chen X, Jiang H. Trabeculae microstructure parameters serve as effective predictors for marginal bone loss of dental implant in the mandible. Sci Rep 2020; 10(1): 18437.
http://dx.doi.org/10.1038/s41598-020-75563-y PMID: 33116221

[53] Ha SR, Park HS, Kim EH, *et al.* A pilot study using machine learning methods about factors influencing prognosis of dental implants. J Adv Prosthodont 2018; 10(6): 395-400.
http://dx.doi.org/10.4047/jap.2018.10.6.395 PMID: 30584467

[54] Liu CH, Lin CJ, Hu YH, You ZH. Predicting the failure of dental implants using supervised learning techniques. Appl Sci (Basel) 2018; 8(5): 698.
http://dx.doi.org/10.3390/app8050698

[55] Singi SR, Sathe S, Reche AR, Sibal A, Mantri N. Extended arm of precision in prosthodontics: Artificial intelligence. Cureus 2022; 14(11): e30962.
http://dx.doi.org/10.7759/cureus.30962 PMID: 36465202

[56] Ali IE, Tanikawa C, Chikai M, Ino S, Sumita Y, Wakabayashi N. Applications and performance of artificial intelligence models in removable prosthodontics: A literature review. J Prosthodont Res 2024; 68(3): 358-67.
http://dx.doi.org/10.2186/jpr.JPR_D_23_00073 PMID: 37793819

[57] Mahrous A, Botsko DL, Elgreatly A, Tsujimoto A, Qian F, Schneider GB. The use of artificial intelligence and game-based learning in removable partial denture design: A comparative study. J Dent Educ 2023; 87(8): 1188-99.
http://dx.doi.org/10.1002/jdd.13225 PMID: 37186466

[58] Alshadidi AAF, Alshahrani AA, Aldosari LIN, *et al.* Investigation on the application of artificial intelligence in prosthodontics. Appl Sci (Basel) 2023; 13(8): 5004.
http://dx.doi.org/10.3390/app13085004

[59] Patel PS, Shah JS, Dudhia BB, Butala PB, Jani YV, Macwan RS. Comparison of panoramic radiograph and cone beam computed tomography findings for impacted mandibular third molar root and inferior alveolar nerve canal relation. Indian J Dent Res 2020; 31(1): 91-102.

[60] Yates EJ, Yates LC, Harvey H. Machine learning "red dot": open-source, cloud, deep convolutional neural networks in chest radiograph binary normality classification. Clin Radiol 2018; 73(9): 827-31.
http://dx.doi.org/10.1016/j.crad.2018.05.015 PMID: 29898829

[61] Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. Artificial intelligence: Applications in orthognathic surgery. J Stomatol Oral Maxillofac Surg 2019; 120(4): 347-54.
http://dx.doi.org/10.1016/j.jormas.2019.06.001 PMID: 31254637

[62] Lee JH, Han SS, Kim YH, Lee C, Kim I. Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol 2020; 129(6): 635-42.
http://dx.doi.org/10.1016/j.oooo.2019.11.007 PMID: 31992524

[63] Kang F, Sah MK, Fei G. Determining the risk relationship associated with inferior alveolar nerve injury following removal of mandibular third molar teeth: A systematic review. J Stomatol Oral Maxillofac Surg 2020; 121(1): 63-9.
http://dx.doi.org/10.1016/j.jormas.2019.06.010 PMID: 31476533

[64] Patcas R, Bernini DAJ, Volokitin A, Agustsson E, Rothe R, Timofte R. Applying artificial intelligence to assess the impact of orthognathic treatment on facial attractiveness and estimated age. Int J Oral Maxillofac Surg 2019; 48(1): 77-83.
http://dx.doi.org/10.1016/j.ijom.2018.07.010 PMID: 30087062

[65] Kim BS, Yeom HG, Lee JH, *et al.* Deep learning-based prediction of paresthesia after third molar extraction: A preliminary study. Diagnostics (Basel) 2021; 11(9): 1572.
http://dx.doi.org/10.3390/diagnostics11091572 PMID: 34573914

[66] Liu Z, Liu J, Zhou Z, *et al.* Differential diagnosis of ameloblastoma and odontogenic keratocyst by machine learning of panoramic radiographs. Int J CARS 2021; 16(3): 415-22.
http://dx.doi.org/10.1007/s11548-021-02309-0 PMID: 33547985

[67] Mahmood H, Shaban M, Rajpoot N, Khurram SA. Artificial Intelligence-based methods in head and neck cancer diagnosis: An overview. Br J Cancer 2021; 124(12): 1934-40.
http://dx.doi.org/10.1038/s41416-021-01386-x PMID: 33875821

[68] Miragall MF, Knoedler S, Kauke-Navarro M, *et al.* Face the future—artificial intelligence in oral and maxillofacial surgery. J Clin Med 2023; 12(21): 6843.
http://dx.doi.org/10.3390/jcm12216843 PMID: 37959310

[69] Patil S, Albogami S, Hosmani J, *et al.* Artificial intelligence in the diagnosis of oral diseases: Applications and pitfalls. Diagnostics (Basel) 2022; 12(5): 1029.
http://dx.doi.org/10.3390/diagnostics12051029 PMID: 35626185

[70] Al-Rawi N, Sultan A, Rajai B, *et al.* The effectiveness of artificial intelligence in detection of oral cancer. Int Dent J 2022; 72(4): 436-47.
http://dx.doi.org/10.1016/j.identj.2022.03.001 PMID: 35581039

[71] Moosa Y, Alizai MHK, Tahir A, Zia S, Sadia S, Fareed MT. Artificial Intelligence in oral medicine. Int J Health Sci 2023; 7(S1): 1476-88. [IJHS].
http://dx.doi.org/10.53730/ijhs.v7nS1.14369

[72] Barros Padilha DX, Veiga NJ, Mello-Moura ACV, Nunes Correia P. Virtual reality and behaviour management in paediatric dentistry: A systematic review. BMC Oral Health 2023; 23(1): 995.
http://dx.doi.org/10.1186/s12903-023-03595-7 PMID: 38087294

[73] Matava C, Pankiv E, Ahumada L, Weingarten B, Simpao A. Artificial intelligence, machine learning and the pediatric airway. Paediatr Anaesth 2020; 30(3): 264-8.
http://dx.doi.org/10.1111/pan.13792 PMID: 31845543

[74] Huang TK, Yang CH, Hsieh YH, Wang JC, Hung CC. Augmented

reality (AR) and virtual reality (VR) applied in dentistry. Kaohsiung J Med Sci 2018; 34(4): 243-8.
http://dx.doi.org/10.1016/j.kjms.2018.01.009 PMID: 29655414

[75] Felemban OM, Alshamrani RM, Aljeddawi DH, Bagher SM. Effect of virtual reality distraction on pain and anxiety during infiltration anesthesia in pediatric patients: A randomized clinical trial. BMC Oral Health 2021; 21(1): 321.
http://dx.doi.org/10.1186/s12903-021-01678-x PMID: 34172032

[76] Shan T, Tay FR, Gu L. Application of artificial intelligence in dentistry. J Dent Res 2021; 100(3): 232-44.
http://dx.doi.org/10.1177/0022034520969115 PMID: 33118431

[77] Zhou X, Wang H, Feng C, *et al.* Emerging applications of deep learning in bone tumors: Current advances and challenges. Front Oncol 2022; 12: 908873.
http://dx.doi.org/10.3389/fonc.2022.908873 PMID: 35928860

[78] Asgary S. The potential of AI-based clinical decision making in dentistry. Int J Oral Health Dent Manag 2023; 1(1): 1-2. Available from:
https://www.wecmelive.com/peer-review/the-potential-of-aibased-clinical-decision-making-in-dentistry-39.html