Concise Review

Development of Artificial Intelligence Models for Tooth Numbering and Detection: A Systematic Review

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A B S T R A C T

Dental radiography is widely used in dental practices and offers a valuable resource for the development of AI technology. Consequently, many researchers have been drawn to explore its application in different areas. The current systematic review was undertaken to critically appraise developments and performance of artificial intelligence (AI) models designed for tooth numbering and detection using dento-maxillofacial radiographic images. In order to maintain the integrity of their methodology, the authors of this systematic review followed the diagnostic test accuracy criteria outlined in PRISMA-DTA. Electronic search was done by navigating through various databases such as PubMed, Scopus, Embase, Cochrane, Web of Science, Google Scholar, and the Saudi Digital Library for the articles published from 2018 to 2023. Sixteen articles that met the inclusion exclusion criteria were subjected to risk of bias assessment using QUADAS-2 and certainty of evidence was assessed using GRADE approach. AI technology has been mainly applied for automated tooth detection and numbering,

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to detect teeth in CBCT images, to identify dental treatment patterns and approaches. The AI models utilised in the studies included exhibited a highest precision of 99.4% for tooth detection and 98% for tooth numbering. The use of AI as a supplementary diagnostic tool in the field of dental radiology holds great potential.

Introduction

Artificial intelligence (AI) is the wondrous innovation that constitutes the core of fourth industrial revolution. With the power to emulate human-like cognitive thinking, intuitive reasoning, and intelligent behaviour, it revolutionised the domain of computer technology.[1,2] Neural network is an incredibly potent component of AI that can learn from a given dataset and generate matrices to represent learning patterns which simulate the functions of the human brain,[3] enabling it to perform tasks similarly to a human being. This technology forms the core of advanced intelligence.

The field of AI is experiencing rapid growth and expansion in all industries and health care sector is not an exception to this trend.AI techniques have showcased their remarkable prowess in unravelling crucial data patterns, paving the way for extensive exploration of their potential as clinical trial aids.[4,5] These advanced technologies prove to be invaluable in aiding decision-making processes pertaining to prognosis, forecasting, and various stages of diagnosis of disease and subsequent treatment. Harnessing the power of AI has proven to enhance accuracy, effectiveness, and precision, rivalling that of seasoned medical professionals, while operating at a quicker pace and at a fraction of the cost.[6]

In the realm of medicine, AI is mostly used for machine learning and, more recently, deep learning. Machine learning is a subset of AI where systems are able to learn and carry out intelligent tasks and analyse patterns within a vast dataset without prior knowledge or manually created rules.[7] On the other hand, deep learning is a subfield within machine learning that focuses on learning not only individual patterns but also a hierarchy of interconnected patterns. By combining and layering these patterns, deep learning systems become much more powerful compared to simpler, shallow systems.[8]

Artificial neural networks (ANNs) are an incredibly popular class of deep learning algorithms. They are composed of neurons organised in layers, allowing for communication between these units.[7,9] In the field of medicine and dentistry, one subclass of ANN that is widely used is the convolutional neural network (CNN). CNNs interpret digital information like photos and videos by using a special design of neuron connections and the mathematical action of convolution.[10] The field of radiology has witnessed a significant impact since the introduction of neural networks, especially through the utilisation of digital picture archiving and communication systems. These systems have provided a wealth of imaging data that can be used to train AI algorithms.[11,12]

Dento-maxillofacial radiography assists in diagnosing oral diseases, strategising therapy, and follow patient progress. Numerous maxillofacial radiographs are taken every day since they are a crucial adjuvant diagnostic tool in dentistry.[13] Tooth detection and numbering, identifying dental treatment patterns and approaches through radiographs proves invaluable in the dental world. Tooth detection involves determining whether a tooth is a prosthesis and on the other hand, tooth numbering refers to assigning specific numbers or codes to individual teeth. Dentists employ this technique for a myriad of purposes, such as keeping comprehensive clinical records, diagnosing dental abnormalities, devising personalised treatment plans, alleviating the burden on human experts, facilitating seamless communication among dental professionals, and simplifying overall charting processes.[14] When a dentist mentions a tooth number, it's comparable to flipping through pages in a dental history book. These numbers hold a plethora of information, from previous treatments to possible problems. With this knowledge, dentists can create precise treatment plans, making the dental process easier and more personalised for each patient. It's similar to having a dental roadmap that directs efficient oral care.[15]

Dentists spend a significant amount of time on radiographic interpretation, which can be affected by personal factors like fatigue, emotions, and lack of experience, leading to possible misdiagnosis or underdiagnoses.[16] The use of automated tools for radiographic interpretation can help reduce the workload of dentists and decrease the occurrence of misdiagnosis.[17] There are 32 teeth in standard human dentition. Instead of comparing all the teeth at once, it would be more efficient and accurate to number each tooth from the X-ray image. This way, we can limit our database comparisons to only the teeth with matching numbers, greatly improving computational efficiency and accuracy.[18]

AI has made its mark in the world of dental radiology, detecting various conditions like dental caries,[19] gingival and periodontal disease,[20-22] odontogenic cysts and tumors,[23] Oral cancer[24] and conditions affecting maxillary sinus and temporomandibular joints.[25,26] In addition, AI has been extensively studied to improve the detection of cephalometric landmarks,[27] segmentation of teeth structures,[28] and classification of teeth.[29] These efforts have shown promising results, but there is still much untapped potential waiting to be explored in this field. Hence, this paper aims to thoroughly examine the available literature on effectiveness of AI models exclusively in tooth numbering and detection using dento-maxillofacial radiographic images and provide an up-to-date overview of their diagnostic development and performance.

Materials and methods

To ensure the quality of their methodology, the authors of this systematic review adhered to the diagnostic test accuracy criteria specified in the Preferred Reporting Items for

Table 1 – Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcomes) elements.

Research question	What are the applications and performance of the artificial intelligence models that have been widely used in tooth numbering and detection?
Population	Digital panoramic radiographs
Intervention	AI-based models for tooth numbering and detection
Comparison	Expert opinions and reference standards.
Outcome	Measurable or predictive outcomes such as accuracy, sensitivity, specificity, precision, recall, receiver operating characteristic curve (ROC), ROI—region of interest area under the curve (AUC), statistical significance, F1 scores, object inclusion ratio (OIR), mAP—mean average precision, mAR—mean average recall, IoU—intersection of union

Systematic Reviews and Meta-Analyses Extension (PRISMA-DTA).[30] Table 1 provides the PICO (Problem/Patient, Intervention/Indicator, Comparison, and Outcome) criteria that were used in the search for papers. The protocol for this review was registered with PROSPERO under the ID record number CRD42022331221.

Search strategy

Using an array of reputable databases, including PubMed, Scopus, Embase, Cochrane, Web of Science, Google Scholar, and the Saudi Digital Library, we conducted a digital search to gather data. Our unwavering search spanned across the years 2018 to 2023. In order to search for articles in electronic databases, we used English language filters and Boolean operators (AND, OR). “Deep learning” OR “Artificial intelligence” OR “Machine learning” OR “CNN” OR “ANN” AND “Dental” OR “ Panaromic radiographs” OR “Digital radiographs” OR “CBCT” OR “Cone Beam Computed tomography” OR “Periapical radiography” OR “Radiographs” OR “ tooth” OR “numbering” OR “detection” were the following words to search for the articles. We conducted a manual review of pertinent research publications and citations in addition to our electronic search. This entailed reviewing the reference lists of previously collected articles in the college library where hard copies of journals were accessible. The search was carried out by 2 independent authors who were trained to conduct the same.

Study selection

The selection process was based on the relevance of the articles to the research area, as well as the title and abstract. Two authors (S.V. and V.M.) independently carried out the search process and total of 486 articles were included in the initial consideration, with 484 obtained through the electronic database search and 2 found through manual search. To ensure there were no duplicates, 2 members not involved in the initial search checked all articles, resulting in 287 duplicates being removed. Comprehensive assessment of the remaining 199 papers was conducted for meeting eligibility criteria.

Inclusion and exclusion criteria

The papers chosen for this systematic review had to fulfil the following requirements: (1) they had to be original studies centred on AI; (2) they had to offer quantitative data that could be assessed and analysed; and (3) they had to refer to the data that was used to assess AI-based models. There were no restrictions on the study design for inclusion in this review. Articles that did not address AI innovation, conference papers that were uploaded online or never published, articles lacking full-text versions, and articles written in languages other than English were excluded.

Data extraction

After conducting an initial evaluation of the chosen papers using their titles and abstracts, and removing any duplicates, the authors proceeded to thoroughly analyse the full texts. Based on this assessment, the total number of articles deemed suitable for inclusion in this systematic review decreased to 19. In order to ensure an impartial assessment, we eliminated the journal and author information from the articles and had 2 independent authors (P.C.M. and M.M.), who were not involved in the original search, assess them. Data from the papers that were selected was retrieved and entered into a Microsoft Excel sheet. The data included information about the authors, the year of publication, the study’s goals, the kinds of AI algorithms that were applied, and the data that was used to train, validate, and test the model. Results, findings, and suggestions derived from the investigation were also supplied. Conflicting views over the inclusion of 3 articles resulted from the lack of sufficient evidence to support their results and conclusions. Following consultation with another qualified author, the decision was made to exclude these works of literature. As a result, a total of 16 articles were included in the qualitative analysis for this systematic review, as shown in Figure 1. These 16 articles were considered potentially eligible and underwent a critical analysis.

Using QUADAS-2[31] which examined several aspects of research design and reporting, including patient selection, index test, reference standard, flow, and timing, the included papers were evaluated for quality. This analysis evaluated the data’ generalisability to various clinical settings and patient populations as well as possible sources of bias. The 2 reviewers demonstrated substantial agreement, with an 86% level of agreement as measured by Cohen’s kappa.

Results

Following an extensive review of 16 articles, qualitative information was gleaned. The bulk of the research, which were published over the previous 4 years, showed a growing pattern of articles discussing the application of AI models for tooth numbering and detection.

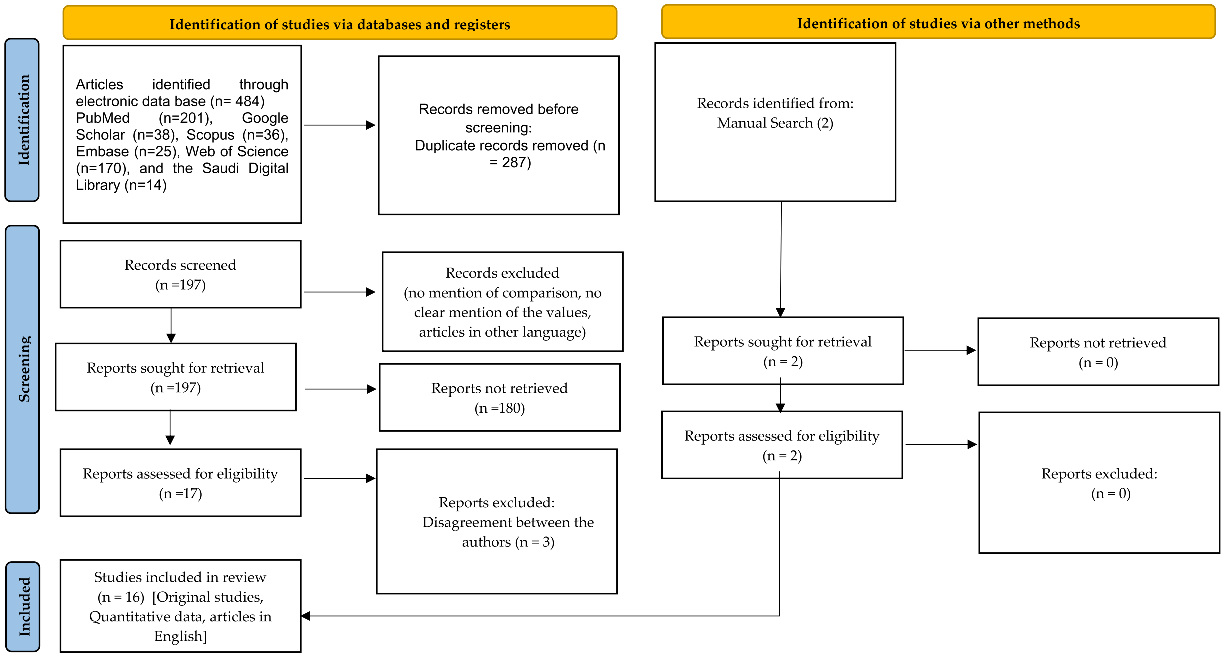

Fig. 1 – PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources.

Qualitative synthesis of the included studies

AI technology has been mainly applied for automated tooth detection and numbering in intraoral and panoramic radiographs,[14,18,32-42] to detect teeth in CBCT images,[43] to detect natural teeth and identification of dental treatment approaches and patterns.[44,45] Out of the 16 studies analysed in this review, 9 studies used[32-36,39,41,42,44,45] dental panoramic radiographs for testing and training the AI system, while 5 studies[18,37,38,40,42] utilised intraoral radiographs (periapical and bitewing) and CBCT scans[43] were utilised in one of the included study. Additionally, 2 of the included studies focused automated tooth detection and numbering on paediatric panoramic radiographs.[35,39]

We collected data from the included articles, but we could not perform a meta-analysis due to the heterogeneity in the extracted data. The heterogeneity mainly came from the different types of data samples used to evaluate the performance of AI models. Therefore, this systematic review only presents descriptive data from the included studies.as depicted in Table 2

Study characteristics

The study features that were extracted from the included studies contained details about the authors, year of publication, objectives of the study, types of AI model development algorithms used, sources of data used for training, validation, and testing of the models, accuracy of model evaluation, conclusions drawn from the study, and any recommendations made by the authors.

Outcome measures

Efficiency in task performance was evaluated using different outcome measures, which included quantifiable or predictive results like accuracy, sensitivity, specificity, precision, recall, receiver operating characteristic curve, region of interest (ROI), area under the curve, statistical significance, F1 scores, object inclusion ratio, mean average precision (mAP), mean average recall, and intersection of union.

Risk of bias assessment and applicability concern

The included studies were assessed for their quality and risk of bias using the QUADAS-2 assessment tool (Table S1). All studies used patient-derived information in the form of dento-maxillofacial radiographic images as input for the CNNs. This resulted in a low risk of bias (100%) in both arms for the patient-selection domain. Similarly, a low risk of bias was reported in both arms for the index test domain, as a steady training system was employed in all studies. Furthermore, the implementation of standardised methods for inputting data in AI technology has also contributed to minimising bias in the flow and timing domain. However, it is worth noting that one of the studies,[39] included in the analysis did not explicitly define the reference standard used to interpret the results of the index test. This gives rise to questions about possible bias in terms of both risk of bias and application in the index test, reference standard, flow, and timing domains.

Another set of 5 studies[35,38,40,44,45] relied on annotations made by a single observer as a reference standard. As a result, 37.5% of the studies had a high risk of bias in both arms.

Table 2 – Qualitative synthesis of included studies.

S. no	Authors	Year of publication	Study design	Algorithm Architecture	Objective of the study	No. of patients/ images/ photographs for testing	Study factor	Modality	Comparison if any	Evaluation accuracy/average accuracy/statistical significance	Results (+)effective, (-)non effective (N) neutral	Outcomes	Authors suggestions/ conclusions
1	Kabir et al[14]	2022	Observational study	CNN	To recognise tooth numbers in intraoral radiographs	1240 intraoral radiographs	Tooth detection and numbering	Intraoral radiography (periapical and bitewing)	Three specialists: a resident in the periodontics program and 2 board-certified periodontists.	Precision and recall 96% and 96% (via panoramic view) and 87% and 87% (via repository match)	(+) effective	Without the need for human assistance, the suggested tooth numbering approach is reliable, self-contained, and able to be connected with other dental diagnostic modules.	Dentists will benefit from improved documentation, precise treatment planning, and improved communication thanks to AI-based tooth recognition and tooth number assignment in dental radiographs.
2	Chen et al[18]	2019	Observational study	CNN	To automate tooth detection and numbering	1250 digitised periapical radiographs.	Tooth detection and numbering	Periapical radiography	Three expert dentists [3,2 and 4 years of experience]	Recalls and progression are more than 90%, and the average IOU value was 91%.	(+) effective	The machine system performed exceptionally well with teeth detection, but concerned to each numbering was unsatisfactory. The machine performed very close to the level of junior dentist [2 years of experience]	If a sophisticated neural network system can be employed to support dental x-ray diagnosis, that will be a big aid.
3.	Bilgir et al[32]	2021	Observational study	CNN	To detect and number teeth using CNN	2482 anonymised panoramic radiographs	Tooth detection and numbering	Panoramic radiography	Oral and maxillofacial radiologists [10 years of experience and 3 years of experience]	TP, FP, and FN had the following numbers: 1388, 50, and 64. Sensitivity, precision, and F- measure were 95.59%, 96.52%, and 96.06 % respectively	(+) effective	The system was successful in detecting and numbering the teeth	AI systems can be used by clinicians to identify and count teeth in panoramic radiographs, which could potentially replace human observers' evaluation and aid in decision-making.

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Table 2. (*Continued*)

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4.	Tuzoff et al[33]	2019	Observational study	CNN	To train and detect as well as number teeth	1574 Panoramic radiographs [1352 training group; 222 testing group]	Tooth detection and numbering	Panoramic radiography	Five Experts [Dento- -max-illofacial radi-ology]	Teeth detection System: Precision & Sensitivity =.99.4 % Expert Precision =99.9% Sensitivity:99.8% Teeth Numbering System: Specificity:99.94% Sensitivity :98% Expert: Specificity:99.97% Sensitivity:98.93%	(+) effective	Expert performance is comparable to that of the suggested computer-aided diagnosis solution. The system continues to perform lower than experts in both detection and numbering tasks.	This simplifies the process of filling out digital dental charts
5.	Prados-Privado et al[34]	2021	Observational study	CNN	To automate tooth Numbering and detection in panoramic images	8,000 panoramic radiographs	Tooth detection and numbering	Panoramic radiography	Three Expert dentist	99.24% accuracy in identifying teeth and 93.83% accuracy in counting teeth	(+) effective	The model architecture attained 99.24% accuracy in detecting teeth and 93.83% accuracy in numbering teeth.	Proposed CNN can be used in real clinical practice.
6.	Kılıc et al[35]	2021	Observational study	CNN	To automate detection and numbering of deciduous teeth in children	421 panoramic radiographs	Tooth detection and numbering	Panoramic radiography	Pedodontist with 10 years of clinical experience	Sensitivity, precision, and F1 score were 98.04% 95.71%, and 96.86%	(+) effective	The AI system was successful in detecting and numbering the deciduous teeth of children as depicted on DPRs.	AI plays a valuable role in forensic identification, in addition to serving as a time-saving aid to clinicians.
7.	Kim et al[36]	2020	Observational study	CNN	To detect and number the teeth and implants with only fixtures in a DPR image	303 panoramic radiographs	Teeth detection and numbering	Panoramic radiography	Three dentists	Sensitivity, specificity, and accuracy were 84.2%, 75.5%, and 84.5%,	(+) effective	The algorithm that performed the best in dental detection, RCNN + heuristics, was used.	Using the RCNN and CNN algorithms, dental objects may be identified in a DPR image, and each tooth can be given a number based on its location and shape.

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Table 2. (*Continued*)

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8.	Görürgöz et al[37]	2022	Observational study	CNN	To evaluate the (R-CNN) algorithm for tooth detection and numbering	1686 anonymised periapical radiographs	Tooth detection and numbering	Periapical radiography	Two dento maxillofacial radiologists	F1 score, precision, and sensitivity were 87.20%, 78.12%, and 98.67%, respectively.	(+) effective	When it came to identifying and numbering teeth in periapical pictures, the AI algorithm built on the Faster R-CNN Inception v3 architecture worked admirably.	Clinicians can benefit from the deep learning-based techniques by having less work to do, better dental records, and quicker turn-around times for urgent cases.
9.	Yasa et al[38]	2020	Observational study	CNN	To propose an automatic method for detection and numbering of teeth	1125 bitewing radiographs	Tooth detection and numbering	Bitewing radiographs	A specialist with 9 years of experience	Sensitivity, Precision and F-measure values was 0.9748, 0.9293 and 0.9515, respectively.	(+) effective	There is potential for identifying and numbering teeth using a CNN method for bitewing image processing.	By enabling the automatic creation of dental charts and electronic dental records, the automatic detection by CNN technique can save time.
10.	Kaya et al[39]	2022	Observational study	CNN	To automate Tooth detection and numbering on paediatric panoramic radiographs.	4545 paediatric panoramic radiographs	Teeth detection and numbering	Panoramic radiography	Unclear	YOLO V4 mAP value of 92.22 %, mAR value of 94.44% and weighted-F1 score of 91%	(+) effective	The model was successful in detecting and numbering both primary and permanent teeth on paediatric panoramic radiographs	In addition to saving time, automatic tooth detection can be used as a pre-processing technique to identify dental diseases.
11.	Mahdi et al[40]	2020	Observational study	CNN	To recognise teeth in DPRs	1000 panoramic radiographs	Tooth detection and numbering	Panoramic radiography	Expert dentist	It achieves 97.4% and 98.1 % mAPs for ResNet-50 and ResNet-101, respectively w5ith faster R-CNN technique. The optimisation technique further improved the results i.e. F1 score improves from 97.8% to 98.2% for ResNet-101.	(+) effective	The suggested model's performance level is comparable to that of a skilled dentist, making it suitable for clinical use.	We intend to add automatic prosthetic detection and dental condition evaluation to the present model in the future.

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Table 2. (*Continued*)

S. no	Authors	Year of publication	Study design	Algorithm Architecture	Objective of the study	No. of patients/ images/ photographs for testing	Study factor	Modality	Comparison if any	Evaluation accuracy/average accuracy/statistical significance	Results (+)effective, (-)non effective (N) neutral	Outcomes	Authors suggestions/ conclusions
12.	Zhang et al[41]	2018	Observational study	CNN	To detect teeth and classify dental periapical radiographs for medical curing and post-mortem identification	1000 panoramic radiographs	Tooth detection and numbering	Dental periapical radiography	State -of-the-art CNN	High precision and recall of 95.8% and 96.1%	(+) effective	We may observe that our method performs significantly better than the most advanced deep learning technique.	With prior information, our MOD4 module significantly improved the system's performance by fixing numerous teeth detection errors.
13.	Estai M et al .[42]	2022	Observational study	CNN	To evaluate an automated detection system to detect and classify permanent teeth	591 OPGs	Tooth detection and numbering	OPG images	Three qualified dentists	ROI detection module IoU=70% Tooth detection module - recall and precision of 99% Tooth numbering module - recall, precision and F1 score of 98%	(+) effective	For automatic tooth detection and numbering from OPG pictures, the resulting automated technique performed well..	The automatic filing of dental charts in forensic and general dentistry can benefit from deep learning.
14.	Du et al[43]	2022	Observational study	CNN	To propose a teeth-detection method to avoid complex noises and metal artefacts and to accelerate the operation speed for processing CBCT images.	25 dental CBCT scans	Teeth-detection	CBCT scans	FasterR-CNN	Training and prediction time were shortened by 80% and 62% in our method, The OIR metric of our method was 96.27%, while for the faster R-CNN method, it was 91.40%.	(+) effective	With single-layer CBCT, all of these works promise improved tooth detecting performance.	Our method's primary features are its robust detection and high prediction speed.
15.	Choi et al[44]	2022	Observational study	CNN	To automate detection of natural teeth and dental treatment patterns based on DPRs to promote its applicability as human identifiers	1638 panoramic radiographs	Natural teeth detection and identification of dental treatment patterns	Panoramic radiography	An Oral and maxillofacial radiologist	Average precision were 99.1% for natural teeth, 80.6% for prostheses, 81.2% for treated root canals, and 96.8% for implants, respectively. Average recall were 99.6%, 84.3%, 89.2%, and 98.1%, in the same order, respectively.	(+) effective	CNN performed exceptionally well in automatically detecting natural teeth, prosthetics, treated root canals, and implants using dental panoramic radiographs.	Complete automation of the DVI process might be achieved by building a large database and incorporating an automated detection information calculation.

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Table 2. (Continued)

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16.	Yüksel et al[45]	2021	Observational study	CNN	To detect 5 different dental treatment approaches and simultaneously number the dentition on panoramic X-ray images	1005 panoramic radiographs	Natural teeth detection and identification of dental treatment patterns	Panoramic radiography	Professional Endodontist	This framework carries out enumeration with an average precision (AP) score of 89.4% and performs treatment identification with a 59.0% AP score.	(+) effective	DENTECT is a useful and scalable clinical tool that expedites treatment planning at a rate of accuracy that may match that of dental professionals..	In this work, we proposed a deep learning based framework on a panoramic dental radiograph that simultaneously numbers the teeth and diagnoses numerous disorders.

CBCT, cone beam computerised tomography; DPR, dental panoramic radiographs; DVI, disaster victim identification; IoU, intersection of union; mAP, mean average precision; mAR, mean average recall; OIR, object inclusion ratio; OPG, orthopantomogram; ROI, region of interest.

Overall, both research arms had a low risk of bias when considering all criteria in the included studies. Please refer to Supplementary Table S1 and Figure 2 for detailed information on the risk of bias assessment and applicability concerns in the included studies.

Assessment of strength of evidence

Using the Grading of Recommendations Assessment Development and Evaluation (GRADE) technique, the degree of evidence certainty in this systematic review was evaluated.[46] There are 4 levels of certainty of evidence: very low, low, moderate, and high. The level of certainty of evidence is determined by evaluating 5 factors: risk of bias, inconsistency, indirectness, imprecision, and publication bias. The included papers in this systematic review reported a moderate level of certainty of evidence, based on this assessment (Table 3).

Discussion

Dental and maxillofacial imaging procedures play a crucial role in the early detection of diseases. They are also effective for imaging dental and maxillofacial structures, allowing for the identification of dental decay, bone infections, root pathologies, and other dental issues. These procedures are instrumental in diagnosing injuries and managing patient conditions.[47,48] Interpreting radiographs quickly and accurately is challenging for dentists due to the intricate anatomy and evolving nature of diseases. Currently, dental professionals have to manually analyse and annotate these images, which adds to their workload.[48] However, AI has demonstrated the ability to greatly enhance workflow efficiency and accuracy in dental imaging.[49] Presently, dental images are often digitised and easily converted into computer data.[50]

Utilising an AI system that can automatically label and identify teeth can potentially reduce the incidence of incorrect dental treatment. This would help to avoid situations where the wrong therapy is performed, or the wrong tooth is treated.[45] For instance, a study revealed that around 21.1% of tooth extractions are performed on the wrong tooth due to issues like miscommunication and fatigue among dentists who are overworked.[50] Thus combining AI technology with dental radiology can effectively address the challenges faced by dental practitioners in the clinical setting and improve the precision and accuracy of dental procedures.[45,50] Hence, it is important to explore and evaluate the advancements and performance of AI models specifically designed for tooth numbering and detection using dento-maxillofacial images

Effectiveness of AI in automated tooth detection and numbering in intraoral and panoramic radiographs

CNNs have various applications in the field of radiology, including classification, detection, and segmentation tasks. In radiographic image analysis, detection is crucial for identifying and localising regions with lesions or specific anatomical structures. Among the studies analysed, a total of thirteen

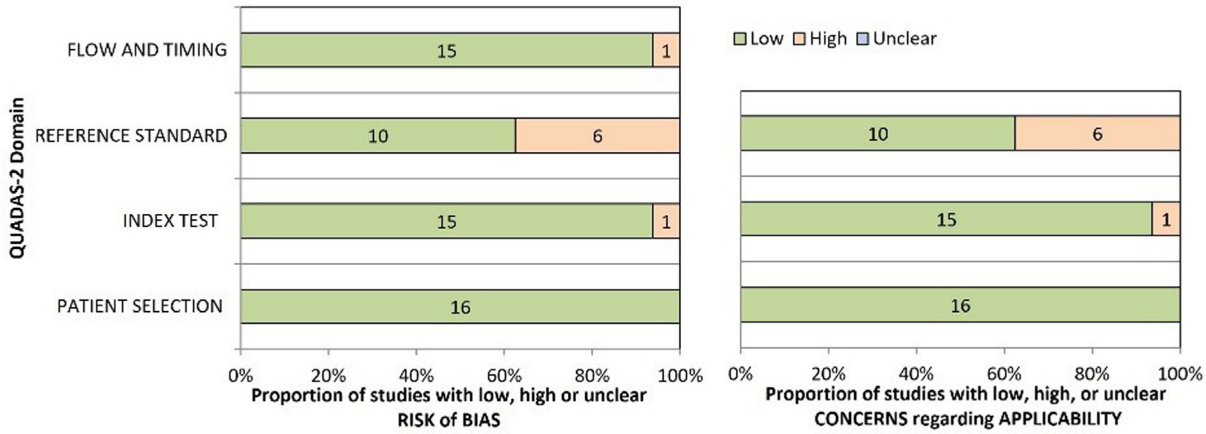

Fig. 2 – QUADAS-2 assessment of the individual risk of bias domains and applicability.

have explored the use of AI models for automated tooth detection and numbering. Two notable studies conducted by Chen et al[18] and Tuzoff et al[33] stand out in this area. Chen et al[18] reported that the system achieved excellent results in tooth detection but had unsatisfactory performance in tooth numbering. The machine's performance was comparable to that of a junior dentist with 2 years of experience. The neural network had a tooth detection precision of 98.8%, but the precision had even decreased to 71.5% for tooth numbering. This system was unable to accurately number teeth in certain complex cases, such as severely decayed teeth, extensive overlaps, extensive dental restorations, and cases where orthodontic treatment was completed after tooth extraction, making it impossible to use the standard FDI teeth numbering template. There were instances where 2 "half teeth" were incorrectly recognised as a single intact tooth. This is a limitation of CNNs, as they are unable to consider the spatial relationship between image features.

In another research conducted by Tuzoff et al,[33] system demonstrated exceptional accuracy in both tooth detection and numbering, comparable to expert performance. The tooth detection module performed exceptionally well in various scenarios, including images with normal teeth arrangement and more complex cases. Analysing the errors made by the system revealed that both the system and the experts encountered challenges in accurately numbering the teeth. The main reasons for numbering errors were due to lack of nearby teeth, small remaining tooth fragments, and extensive dental work. Molars were the most commonly misclassified.

Kılıc et al[35] and Kaya et al[39] employed paediatric panoramic radiographs to develop an automated tooth diagnosis and numbering system. Using a combination of a Faster R-CNN model and Google Net Inception v2 architecture, Kilic et al[35] created a ground-breaking model capable of detecting and numbering deciduous teeth in children. This successfully identified and assigned numbers to each primary tooth on paediatric panoramic radiographs and demonstrated excellent performance. Kaya et al[35] opted for YOLO V4 to detect and number teeth due to its fast speed and exceptional accuracy in object detection. The mAP score of 92.22% further confirmed the model's remarkable success in automating tooth

Table 3 – Assessment of strength of evidence.

Outcome	Inconsistency	Indirectness	Imprecision	Risk of bias	Publication bias	Strength of evidence
Application of AI in automated tooth detection and numbering in intraoral and panoramic radiographs[14,18,32-42]	Not present	Not present	Not present	Present	Not present	⊕⊕⊕○
Application of AI to propose a teeth detection method in CBCT images[43]	Not present	Not present	Not present	Not present	Not present	⊕⊕⊕⊕
Application of AI to detect natural teeth and identification of dental treatment patterns and approaches[44,45]	Not present	Not present	Not present	Present	Not present	⊕⊕⊕○

⊕⊕⊕⊕ - High evidence ⊕⊕⊕○-Moderate evidence
The certainty of the studies included in this systematic review was evaluated using the Grading of Recommendations Assessment Development and Evaluation (GRADE) approach. Inconsistency, indirectness, imprecision, risk of bias and publication bias were the 5 domains that determines the certainty of evidence and can be categorises as very low, low, moderate, or high evidence. The overall certainty of evidence from the included studies in this review was found to be moderate.

enumeration. Out of the remaining studies, the model utilised by Prados-Privado et al[28] attained the highest accuracy of 99.24% for tooth detection and 93.83% for numbering teeth. This achievement was accomplished by analysing over 8000 panoramic images encompassing a wide range of dental health conditions.

This review provides evidence of the excellent performance of tooth number recognition in both intraoral and panoramic radiographs, as demonstrated by Kabir et al.[14] Their proposed framework successfully assigned tooth numbers in periapical and bitewing images with minimal error rates. Moreover, the tooth numbering model could be easily incorporated into other dental diagnostic models, allowing for the generation of comprehensive clinical reports. These reports could greatly assist clinicians in making accurate diagnoses and verifying clinical chartings. He also found that the current framework could not handle intraoral radiographs that were incorrectly oriented, like being upside-down or mirrored and suggested the need for improvement in identifying anatomical landmarks, such as the maxillary sinus and mental foramen, in order to correctly reorient and assign tooth numbers for these types of images.

Another study conducted by Mahdi et al[40] demonstrated effectiveness of using ResNet-50 and ResNet-101 as base networks for faster R-CNN. The combination of these networks achieved an impressive mAP of 98% in dental recognition tasks. This model holds promise as a reliable tool for dental care professionals. Future plans include expanding the model to include automatic evaluation of dental conditions and detection of prosthetics.

In the study by Zhang et al,[41] a cascaded CNN model was devised to accurately identify tooth numbers in periapical radiographs, yielding impressive precision of 95.8% and recall of 96.1%. He presented a unique approach that combines label tree with cascade network structure, along with several key strategies, to achieve outstanding results in teeth detection and classification. This MOD4 module rectified numerous teeth detection errors and significantly enhanced the overall performance of the system through the utilisation of prior knowledge. Furthermore, the proposed method demonstrated impressive performance even with limited training data, effectively handling complex scenarios such as tooth loss, decayed teeth, and dental fillings. There were also some cases where radiographs with only one or 2 teeth resulted in a misdiagnosis due to the algorithm's inability to distinguish between the left and right sides. The proposed system seemed to struggle when faced with such scenarios. In another research, tooth detection was carried out using Faster R-CNN, while tooth numbering relied on the VGG-16 architecture. The system assigned confidence scores for tooth classification, and based on these scores, tooth numbers were assigned. Training and validation of the system used a 3-step procedure, resulting in high-performance tooth detection and numbering comparable to experts suggested by Estai et al.[42]

Effectiveness of AI to propose a teeth detection method in CBCT images

The use of CBCT imaging provides enhanced accuracy in diagnosis, treatment planning, and ultimately, prognosis when compared to traditional 2D radiography methods such as bitewings, periapical radiographs, and OPGs.[43] Medical images often suffer from noise due to the process of image acquisition and transmission. CBCT, in particular, is susceptible to noise because of its geometrical nature. However, deep learning techniques, such as CNN architectures, have emerged as effective solutions for mitigating noise and enhancing image quality.[51] The method proposed by Du M et al.[43] is characterised by its fast prediction speed and strong detection capabilities. It achieved high precision and consistently outperformed simple object detection networks on average. Its unique feature was its ability to maintain stable detection even in highly noisy images, making it more reliable than traditional object detection methods. The result was not affected by the absence of a tooth because the predicted location will be determined through combined detection, and the overall number of teeth will remain the same. The faster prediction speed and lower device requirements make it feasible to use in various clinical scenarios.[43] Though the results are promising, we need more studies to arrive at a definitive conclusion.

Effectiveness of AI to detect natural teeth and identification of dental treatment patterns and approaches

The study's suggested model demonstrated promising results overall, with the highest precision and recall achieved for the identification of natural teeth (99.1% and 99.6%, respectively). However, it is worth noting that the model's performance was limited in identifying certain dental treatment patterns, such as prostheses and treated root canals. This indicates that dental panoramic radiographs could be useful for disaster victim identification.[44]

A powerful new deep learning framework, called DENTECT, was created to quickly detect 5 different dental treatment approaches. The framework consisted of quadrant segmentation, enumeration, and treatment detection models. The enumeration model could accurately label teeth with a mAP score of 89.1%, which can be a valuable tool for dentists in clinical settings. The treatment detection model achieved a mAP score of 59.0%. As the dataset size increases, DENTECT's performance is expected to improve significantly.[45] According to Yuskel et al,[45] small datasets can make a model more sensitive to noise and data imperfections. In the dataset used, almost every image had its own inherent flaws. In such cases, the model becomes highly sensitive to these flaws, making the significance of each data point even more crucial. However, if the dataset size were increased, the impact of each data point on the model would decrease, resulting in a more robust and effective model.

Challenges and future considerations in AI

Even though studies that have examined performance of AI models designed for tooth numbering and detection using dento-maxillofacial radiographic images revealed encouraging findings, several other factors need to be considered for the successful implementation of AI in clinical practice. One feature that contributes to the successful development of automatic interpretation systems is the need for a large amount of data, which can be addressed by using data augmentation techniques. Also, it is important that the training data sets have to be accurate and consistent, with minimal errors.[52] Therefore, experienced oral and maxillo-facial (OMF) radiologists/experts should be involved in these efforts. Additionally, it is crucial to develop precise and efficient tools for annotation, labelling, and drawing in order to perform these tasks effectively. It is important to provide information about the number of human annotators and their qualifications. Measures should be taken to reduce inter- and intrarater variability and ensure the reliability of the reference standard. A substantial collection of data, which includes detailed labels provided by OMF radiologists/experts, is required for building a comprehensive data set reservoir.[53]

A relatively small number of dental radiograph datasets were used in some of the studies included, especially when compared to AI studies in the medical field. This may give rise to AI models that are excessively tailored and yield outcomes that are unrealistically positive.[11] The reason behind this lies in the fact that AI algorithms generally necessitate a significant volume of data in order to effectively extrapolate to diverse situations. To address this issue, it is important to justify the sample size and, if possible, statistically calculate it to ensure that the results can be applied to a larger population.[54,55] It is challenging to comprehend the reason behind incorrect judgements made by AI. This creates a problem as it is not easy to rectify the logic used by AI in making these judgements.[52]

Conclusions

In conclusion AI models performed better in tooth numbering and detection using dento-maxillofacial radiographic images, with higher sensitivity, specificity, precision, and recall rates. Considering this scenario, AI is poised to serve as a valuable companion in bolstering the efforts of dental practitioners by enabling them to manage multiple images concurrently. Nevertheless, it is important to acknowledge that the findings of AI radiographic readings are not inherently infallible, as their accuracy relies on the quality of the training data and the efficacy of model selection and training processes. Hence, it is imperative that experts offer their ultimate assessment as the final arbiter in all cases.

Conflict of interest

None disclosed.

Author contributions

PCM, SV, MM, SBK and VM: the conception and design, acquisition of data, analysis of the data, interpretation of the data and drafting the article; ASA, AR, TA, BA, KMA, SB, NM: acquisition of the data, analysis and revising it critically for important intellectual content and final approval of the version to be submitted. All authors have approved the final article.

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