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REVIEW

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Accuracy of artificial intelligence in caries detection: a systematic review and meta-analysis

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Abstract

Introduction Artificial intelligence (AI) has significantly transformed the diagnosis and treatment of dental caries, a prevalent issue in oral health care. Traditional diagnostic procedures such as eye inspection and radiography have limitations in detecting early-stage degradation. Artificial intelligence (AI) provides a viable alternative to improve diagnostic precision and effectiveness. This systematic review examines the diagnostic precision of artificial intelligence systems in identifying dental caries using X-ray images.

Methodology The literature search utilized electronic web resources such as PubMed, Scopus, Web of Science, IEEE Explore, Google Scholar, Embase, and Cochrane. We conducted the search using specific MeSH key phrases and collected data up to January 2024. The QUADAS-2 assessment method was used to assess the risk of bias using a graph and a heat map. We conducted the statistical analysis using R v 4.3.1 software, which included the "meta," "metafor," "metaviz," and "ggplot2" packages. We displayed the results using odds ratios (OR) and forest plots with a 95% confidence interval (CI).

Results We used a comprehensive search approach in accordance with the PRISMA guidelines to find appropriate studies. The meta-analysis incorporates fourteen of the 21 articles included in this review. The research mostly uses convolutional neural networks (CNNs) for analyzing images, showing outstanding accuracy, sensitivity, and specificity in detecting caries. Significant variability in study results highlights the need for additional research to comprehend the components affecting AI effectiveness.

Conclusion Despite challenges in implementation and data availability, this systematic review provides essential information about AI and shows great potential caries detection, improve diagnostic consistency, and ultimately enhance patient care in dentistry.

Keywords Artificial Intelligence, Dental caries, Machine learning, Caries detection

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Introduction

Dentistry is not an exception to the new paradigm in diagnosis and treatment brought about by the introduction of Artificial Intelligence (AI) [1]. The development of AI technology has substantially aided in the diagnosis and treatment of dental caries, a frequent but difficult issue in oral health care [2]. Dental caries is still a common condition throughout the world, affecting a large percentage of people in all age categories [3]. While visual inspection and radiographic interpretation are excellent approaches for detecting caries, they are not always reliable in capturing the early stages of decay, especially when it is hidden or below the cavosurface [1, 3]. These constraints should be overcome by the introduction of AI and machine learning in dentistry, which will provide a new standard for diagnostic precision and effectiveness [1].

In the past, dental professionals' knowledge has been crucial in detecting dental caries through the use of instruments like dental explorers, visual exams, and traditional radiography [4]. Despite their widespread use, these techniques have certain inherent drawbacks. Due to the high degree of subjectivity in the manual procedure, practitioners' diagnosis accuracy varies greatly depending on their background and level of skill [5]. Additionally, even though they are essential, traditional radiographs can occasionally miss early-stage caries, particularly if they are occlusal or interproximal, where visual access is restricted [2, 5].

The invention of laser fluorescence equipment, which may identify changes in tooth structure suggestive of caries, and the introduction of digital radiography, which provides improved imaging capabilities, have both marked key turning points in the evolution of caries detection [6]. Even though these developments strengthen diagnostic capacities, they still need to be interpreted, and artificial intelligence can help improve them even more [5, 6].

AI has played a leading role in revolutionizing caries detection, particularly in the areas of machine learning and deep learning models like convolutional neural networks (CNNs) [7]. With the use of enormous datasets of dental imaging, these systems may learn to recognize patterns and abnormalities that might point to the existence of caries. AI's strength is its ability to process and interpret data at a speed and scale significantly faster than that of humans, which lessens the subjectivity involved in conventional diagnostic techniques [1, 7].

Annotated datasets, which classify dental photos for the presence or absence of caries, are used to train AI models. These models are trained to recognize subtle characteristics of dental caries on radiographs, such as alterations in tooth structure and density that might not be immediately noticeable to the human eye. This skill is especially helpful for managing dental caries early on because it enables treatments that can stop or reverse the spread of decay, protecting tooth structure and enhancing oral health [8].

Recent research has shown that artificial intelligence (AI) is highly sensitive, specific, and accurate at identifying dental caries [8, 9]. These studies evaluate how well AI algorithms perform in comparison to the diagnostic judgments of skilled dental experts. The results frequently show that AI is just as good as or better than humans at identifying dental caries. These findings have significant ramifications since they imply that artificial intelligence (AI) could be a useful supplementary instrument in dental diagnostics, offering a second opinion that improves caries detection accuracy and lowers the possibility of oversight [10, 11].

Furthermore, AI's capacity to reliably interpret radiographs and other diagnostic pictures may standardize the identification of dental caries, lowering practitioner variability and possibly producing more consistent treatment results [12]. Dentists may be able to streamline workflows and concentrate more on patient care and less on diagnostic uncertainty by using AI in dental practices.

AI's precision in detecting dental cavities is more than simply a technical marvel; it also directly improves patient care and clinical results. Early and precise caries detection can result in prompt intervention, stopping the spread of decay, protecting the natural structure of the tooth, and eventually lowering the need for more involved and expensive treatments [13]. AI-enhanced diagnostics can also promote a proactive approach to dental care by enhancing patient education and engagement by enabling patients to view and comprehend their oral health state [1].

There are obstacles to the broad use of AI-assisted caries diagnosis, despite the encouraging developments in this field [14]. These include protecting patient privacy and security, integrating AI tools into current dentistry office operations, and requiring large datasets for the purpose of training AI models [15]. Further research is required to confirm AI's effectiveness in a variety of contexts and demographics, as well as to investigate how it might be used in tandem with other cutting-edge technologies [14, 15].

As time goes on, artificial intelligence has more applications in dentistry than only detecting cavities. AI has the potential to completely transform a number of dental care processes, including individualized treatment planning and predictive analytics for identifying risk factors for oral illnesses [1, 2, 8]. The application of artificial intelligence (AI) in dentistry is a convergence of technology and healthcare that has the potential to improve patient care globally in terms of accuracy, effectiveness, and quality [14, 15]. The objective of this meta-analysis and systematic review is to examine how well deep learning algorithms and convolutional neural networks (CNNs), two cutting-edge AI techniques, can identify dental caries. Through a systematic examination of data from many sources, such as bitewing, panoramic, and periapical radiographs, this systematic review aims to offer a thorough evaluation of AI's diagnostic precision, sensitivity, and specificity in caries discovery. In addition, it looks into the consequences of integrating AI into clinical practice, covering both the potential benefits and potential drawbacks. AI has the ability to completely transform dental diagnoses and treatment planning as it develops, ushering in a new age in dental healthcare.

Methodology

Protocol of the study

The present systematic review followed the PRISMA guidelines presented for systematic review and quantitative analysis. This systematic review is registered in PROSPERO with the registration number: CRD42023482739.

Research questions

Studies regarding the diagnostic accuracy of artificial intelligence for dental X-ray in caries detection were chosen based on the "PICOS" (PRISMA-P 2016) technique with following research question:

1. What is the overall diagnostic accuracy of artificial intelligence systems for dental X-ray images?
2. How does the accuracy of artificial intelligence systems vary depending on the type of dental structure or lesion being assessed?
3. How does the accuracy of artificial intelligence systems vary depending on the type of dental radiograph being used?
4. What are the factors that influence the accuracy of artificial intelligence systems for dental X-ray images?
5. What is the impact of using artificial intelligence systems on the clinical workflow of dental professionals?

PICOS

P (population): Patients undergoing dental X-ray imaging.

I (intervention): AI systems for the detection and segmentation of dental structures and lesions on X-ray images. These systems typically use machine learning algorithms to analyze dental X-ray images and identify dental structures and lesions. Convolutional neural networks (CNNs), Deep neural networks (DNNs), Support vector machines (SVMs), Decision trees, Random forests.

C (comparison): Human dentists or traditional methods of dental X-ray image interpretation.

O (outcome): The accuracy, sensitivity, and specificity of AI in detecting dental caries.

S (study design): Prospective and retrospective cohort studies and case–control studies etc.

Search strategy

We conducted an electronic database search to find papers that discuss the use of artificial intelligence in caries detection, identification, and protocol creation. Up until January 2024, the search encompassed all pertinent research, with no limitations on the year of publication. We searched PubMed, Scopus, Web of Science, and Embase among other databases. We obtained articles using MeSH terms and keywords. We also investigated supplementary databases such as Cochrane, IEEE Xplore, and Google Scholar in addition to the search.

The search strategy employed MeSH terms and relevant keywords combined with Boolean operators "OR" and "AND" to ensure comprehensive coverage. The search used keywords such as "artificial intelligence," "machine learning," "deep learning," "caries," "dental caries," "panoramic radiography," "peripical radiography," "bitewing radiography," "diagnosis," "diagnosis time," "treatment planning," "bias," and "algorithm bias," among others. These terms were combined using appropriate boolean operators to refine the search, as detailed in Table 1.

Study selection

We imported the search results into EndNote X8 software, where we identified and removed duplicate records. We determined the eligibility of the articles through a two-step screening process, first reviewing the abstracts and then examining the full-text articles. This systematic approach ensured that only studies meeting the predefined inclusion criteria were considered for the review.

Eligibility criteria

Three examiners utilised the PICOS approach to review the entire text of papers and eliminate animal experiments and research published in languages other than English. Figure 1 illustrates the criteria for inclusion and exclusion set by the examiners.

Data extraction

The authors, A.M.L. and N.N.F.R., undertook a thorough data extraction process following an electronic literature search completed on May 19, 2023. The final search included research up to January 2024. Specific criteria guided the selection of the articles, ensuring the inclusion of only relevant studies on the application of artificial intelligence in caries detection.

We deemed the involvement of a third reviewer necessary to address any inconsistencies or misunderstandings that may arise during the selection process. The third reviewer was instrumental in reconciling any discrepancies among the primary reviewers, guaranteeing the inclusion of only studies that fulfilled all eligibility requirements in the final analysis.

Data extracted from the selected studies included key characteristics such as the following:

Table 1 Search strategies using MeSH keywords

Database	Search Terms	Results
PubMed	((Artificial Intelligence [MeSH] OR Machine Learning [MeSH] OR Deep Learning) AND (caries [MeSH] OR dental caries[MeSH])) AND ((Panoramic Radiography[MeSH] OR Periapical Radiography[MeSH] OR Bitewing Radiography[MeSH])) AND (diagnosis[MeSH] OR diagnosis time OR treatment planning[MeSH]) AND (bias[MeSH] OR algorithm bias)	474
Cochrane Library	(artificial intelligence OR machine learning OR deep learning) AND (caries OR dental caries) AND (panoramic OR periapical OR bitewing) AND (diagnosis OR diagnosis time OR treatment planning) AND (bias OR algorithm bias)	8
Web of Science	TS= (("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "convolutional neural network") AND ("panoramic radiograph" OR "periapical radiograph" OR "bitewing radiograph" OR "dental X-ray" OR "oral radiograph")) AND (TS=("caries" OR "dental caries" OR "periodontal disease" OR "periodontitis")) AND (TS=("diagnosis" OR "diagnosis time" OR "treatment planning" OR "bias" OR "algorithmic bias"))	32
IEEE Explore	("artificial intelligence" OR "machine learning" OR "deep learning") AND ("caries" OR "dental caries") AND ("panoramic" OR "periapical" OR "bitewing") AND (diagnosis OR "diagnosis time" OR "treatment planning") AND (bias OR "algorithm bias")	12
Google Scholar	("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("dental caries") AND ("Panoramic Radiography" OR "Periapical Radiography" OR "Bitewing Radiography") AND ("diagnosis" OR "diagnosis time" OR "treatment planning") AND ("bias" OR "algorithm bias")	226
Scopus	(TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning") AND TITLE-ABS-KEY("caries" OR "dental caries") AND TITLE-ABS-KEY("panoramic" OR "periapical" OR "bitewing") AND TITLE-ABS-KEY(diagnosis OR "diagnosis time" OR "treatment planning") AND TITLE-ABS-KEY(bias OR "algorithm bias"))	22
Embase	(artificial intelligence OR machine learning OR deep learning) AND (caries OR dental caries) AND (panoramic OR periapical OR bitewing) AND (diagnosis OR exp diagnosis/ OR "diagnosis time" OR treatment planning) AND (bias OR exp bias/)	09
	Total studies found	783

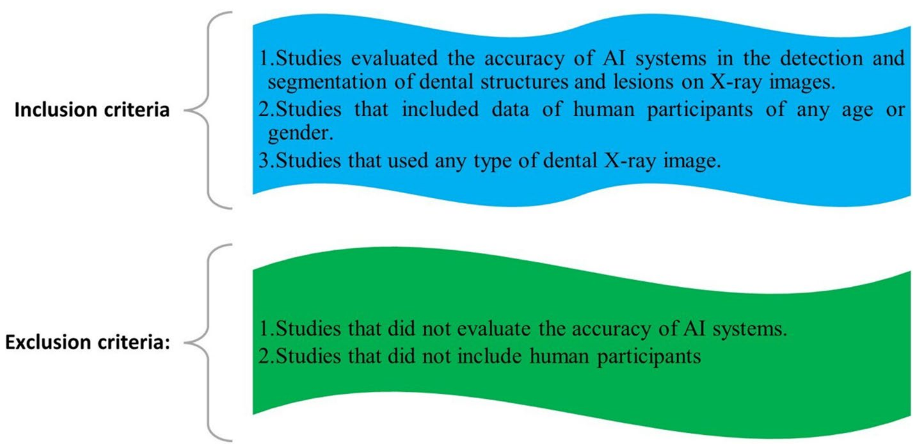


Fig. 1 Inclusion and exclusion criteria of the studies

- *Authors*: Names of the study authors.
- *Year*: Year of publication.
- *Study Design*: Type of study design used (e.g., retrospective, cross-sectional, randomized controlled trial).
- *AI Algorithm*: The specific AI algorithm or model employed (e.g., CNNs, DNNs, SVMs etc.).
- *Number of Samples*: Total number of samples or participants included in the study.
- *X-ray Type*: Type of radiographic images used (e.g., panoramic, periapical, bitewing).
- *Comparator*: The reference standard or comparator used in the study (e.g., trained dental professionals, other AI models).
- Evaluation Metrics: Metrics used to evaluate AI performance (e.g., accuracy, sensitivity, specificity, AUC).
- *Outcomes*: The main findings or outcomes of the study.

This systematic and inclusive approach guaranteed the precise and comprehensive retrieval of data, establishing a strong basis for the further examination and integration of the findings.

Risk of bias and quality assessment of research articles

The authors (A.M.L. and N.N.F.R) evaluated the total number of included studies based on the revised version of the earlier published risk of bias assessment tool [16]. This quality assessment was done by the QUADAS-2 Assessment Bar Graph and heat map. This graph provides a visual representation of the risk levels across different assessment domains for each study. The domains evaluated include patient selection, index tests, reference standards, flow and timing, and applicability concerns. The color gradient in the bar graph ranges from green to red, indicating a risk level from low (1) to high (3). This visual format allows for a quick assessment of which areas might be problematic or which studies generally exhibit higher risks of bias.

Statistical analysis

The statistical study was performed using R v 4.3.1 software along with the "meta", 'metafor", "metaviz", and " ggplot2" packages. We presented the findings using odds ratios (OR) and the percentage of forest plots within a 95% confidence interval (CI).

Results

Study selection outcomes

MeSH keywords were utilized to retrieve articles from various databases. The PRISMA flowchart (Fig. 2) illustrates the study selection procedure. Initially, the database search yielded 783 documents. We excluded 562 records before screening because they were duplicates

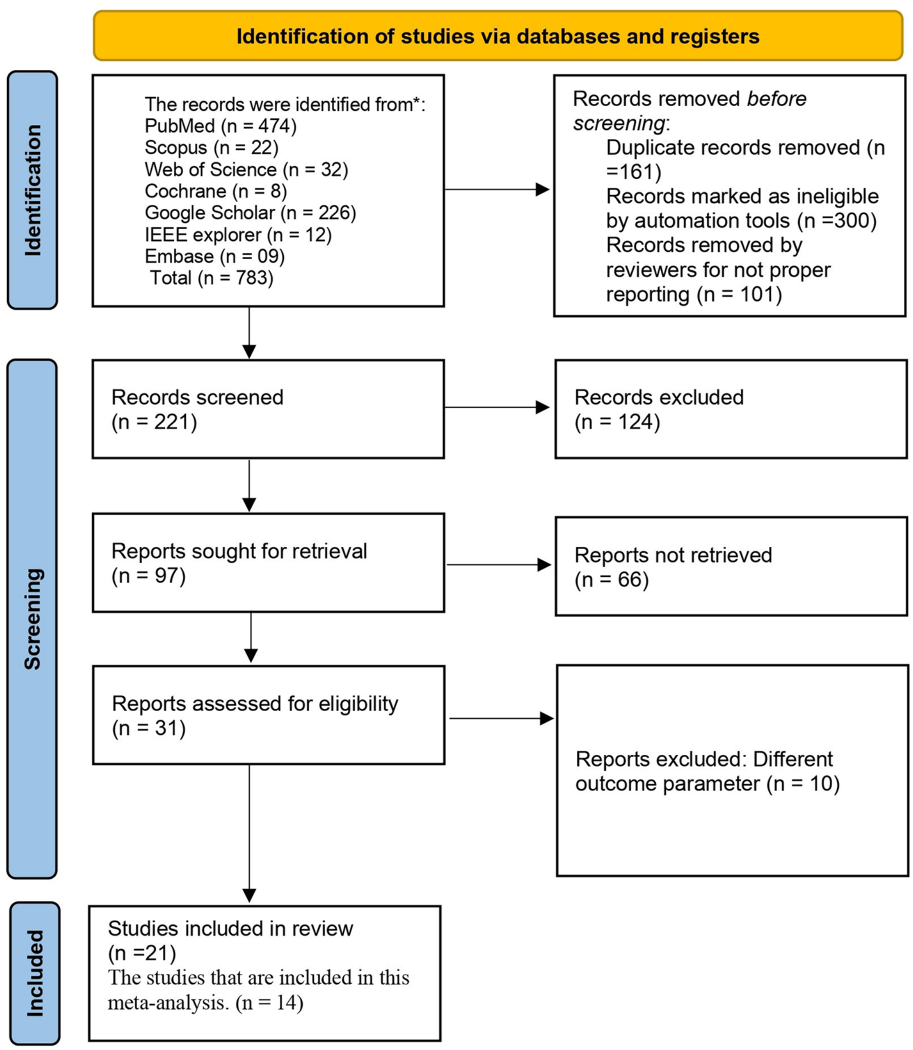


Fig. 2 PRISMA flowchart

or irrelevant, leaving 221 records available for screening. After conducting a thorough evaluation, we eliminated 124 records that did not meet the inclusion criteria, based on a review of their titles and abstracts. After evaluating 97 full-text papers for suitability, we removed 76 due to factors such as missing data, incorrect study design, or outcomes that did not align with the review's objectives. The qualitative synthesis included 21 studies. Of these, 14 papers met the criteria for inclusion in the quantitative meta-analysis.

Study features

Tables 2 and 3 provide a comprehensive overview of the basic features of the 21 studies included in the systematic review. The studies span from 2017 to 2023 and involve a diverse range of populations with a notable number of studies conducted in Asian and European contexts. Studies conducted across various populations including China, South Korea, Brazil, Turkey, France, USA, UK, Taiwan, Germany, and India. There are 21 studies listed, the majority of which were published between 2021 and 2023.

Journals varied across fields like Bioengineering, Neural Computing, and Clinical Oral Investigations.

The majority of the studies are either retrospective or analyze historical data to assess the efficacy of AI models. The studies are either retrospective or cross-sectional, with the aim of evaluating the current accuracy of AI systems. This implies that the field prefers observational research designs. These study types are conducive to analyzing existing datasets and are commonly used in medical research, where prospective trials may be impractical or unnecessary.

Convolutional Neural Networks (CNNs) are the predominant algorithm used across the studies [18–21, 24–32, 34, 35]. This reflects CNN's strengths in handling image data, making them ideal for radiographic image analysis in dental settings. Studies by Chen et al. [17] and Srivastava et al. [37] talked about similar AI tools, such as the EfficientNet and ResNet models, which showed a preference for strong neural network architectures when dealing with large amounts of complex image data.

In all studies, accuracy is a commonly reported metric, with several studies highlighting AI models achieving accuracy rates of over 90%. High Accuracy Levels: Several studies, such as Chen et al. [17] with an accuracy of 95.44% and Zhu et al. [18] with 93.64%, demonstrate that CNNs consistently achieve high accuracy. Bayraktar et al. [19] and Huang et al. [20] reported similar high accuracy

Table 2 Studies included in systematic review

No	Study reference	Journal	Population	Year of publication
1	Chen et al., [17]	Bioengineering	Taiwan	2023
2	Zhu et al., [18]	Neural Computing and Applications	China	2022
3	Bayraktar et al. [19],	Clinical Oral Investigations	Turkey	2022
4	Huang et al., [20]	Medrxiv	Taipei	2021
5	Mao et al., [21]	Sensors	Taiwan	2021
6	De Araujo Faria et al. [22],	Journal of Digital Imaging	Brazil -France	2021
7	Hur et al., [23]	Scientific Reports	South Korea	2021
8	Lee et al. [24],	Scientific Reports	South Korea	2021
9	Vinayahalingam et al. [25]	Scientific Reports	Netherlands	2021
10	Mertens S et al. [26]	Journal of Dentistry	Germany	2021
11	Moran et al. [27]	Sensors	Brazil	2021
12	Lian et al. [28]	Diagnostics	China	2021
13	Zheng et al. [29]	Annals of Translational Medicine	China	2021
14	Bayrakdar et al. [30]	Oral Radiology	Turkey	2021
15	Devlin et al. [31]	British Dental Journal	UK	2021
16	Chen et al., [32]	International Journal of Computer Assisted Radiology and Surgery	China	2021
17	Geetha et al. [33],	Health Information Science and Systems	India	2020
18	Cantu et al., [34]	Journal of Dentistry	Germany	2020
19	Choi et al. [35],	Journal of Signal Processing System	South Korea	2018
20	Lee et al., [36]	Journal of Dentistry	South Korea	2018
21	Srivastava *et al.*, [37]	Arxiv: Computer Vision and Pattern Recognition	USA	2017

Table 3 Characteristics of the included studies are as follows

Sl	Authors Year	Study Design	AI algorithm	No. of sample	X-ray type	Comparator	Evaluation	Outcomes
1	Chen et al 2023 [17]	Retrospective	CNNs, Efficient Net	11,000	Digital periapical radiographs	Trained dental professionals	Accuracy of 95.44%, sensitivity 94.15%, specificity 95.47%, ROC AUC 98.31%	With convolutional neural networks (CNNs), the EfficientNet-B0 model outperforms the status quo
2	Zhu et al 2022 [18]	Retrospective	CNNs	1159	Panoramic radiographs	Reference models	Accuracy: 93.64%, precision: 94.09%, mean dice coefficient: 93.64%, F1 score: 92.87%, and recall: 86.01%	The CNN model successfully separated the caries from the panoramic x-rays
3	Bayraktar et al 2022 [19]	Cross sectional	CNNs	1000	Digital bitewing radiographs	2 Trained dental professionals	Accuracy of 94.59%, sensitivity was 72.26, specificity was 98.19%, PPV was 86.58%, NPV was 95.64% and overall AUC was 87.19%	With respectable accuracy rates, this CNN-based model performed admirably
4	Huang et al 2021 [20]	Cross sectional	CNNs	748	OCT and micro-CT images	Dental surgeons	Accuracy 95.21%, Sensitivity of 98.85% specificity of 89.83%, PPV of 93.48% and NPV was 98.15%,	ResNet-152 When comparing OCT pictures of teeth, CNNs models outperform physicians in identifying abnormal structures
5	Mao et al 2021 [21]	Cross sectional	CNNs	278	Bitewing radiographs	Reference models GoogleNet, Vgg19, and ResNet50	Accuracy 95.56%	AlexNet model demonstrated high accuracy in comparison to other models
6	De Araujo Faria et al. 2021 [22]	Retrospective	ANNs	15	Digital Panoramic radiographs	2 Expert dental surgeon	Accuracy of 98.8% AUC = 0.9869	The model's ability to detect and diagnose caries was highly accurate
7	Hur et al 2021 [23]	Retrospective	ANNs	2642	Panoramic radiographs and CBCT images	Single predictors as reference	ROC of 0.88 to 0.89	ANNs have better accuracy
8	Lee et al 2021 [24]	Cross sectional	CNNs	354	Bitewing radiographs	dental surgeon	Precision 63.29%; recall 65.02%; F1-score 64.14%	This CNNs model displayed significant performance in detecting caries lesion
9	Vinayahalingam et al. 2021 [25]	Retrospective	CNNs	500	Panoramic radiographs	Reference standards	Accuracy of 0.87, sensitivity of 0.86, specificity of 0.88, AUC of 0.90, F1 score of 0.86	This AI model displayed skilled performance in detecting caries in third molars

Table 3 (continued)

Sl	Authors Year	Study Design	AI algorithm	No. of sample	X-ray type	Comparator	Evaluation	Outcomes
10	Mertens S et al 2021 [26]	Randomized control trial	CNNs	140	Bitewing radiographs	dental surgeon	ROC of 0.89 sensitivity of 0.81	AI model demonstrated statistically significant performance compare to dentist
11	Moran et al 2021 [27]	Cross sectional	CNNs	112	Digital bitewing radiographs	ResNet model	Accuracy of 73.3%	Better accuracy compare to the reference model
12	Lian et al 2021 [28]	Cross sectional	CNNs	1160	Panoramic radiographs	dental surgeon	IoU 0.785, Dice coefficient values of 0.663 Accuracy of 0.986 recall rate of 0.821	These models displayed similar results to that of expert dentists
13	Zheng et al 2021 [29]	Cross sectional	CNNs	844	Radiographs	VGG19, Inception V3, dental surgeon	Accuracy = 0.82, precision = 0.81, sensitivity = 0.85 specificity = 0.82, AUC = 0.89,	CNN model ResNet18 showed good performance
14	Bayrakdar et al 2021 [30]	Retrospective	CNNs	621 patients (2325 images, 2072 for training, 200 for validating and 53 for testing)	Bitewing radiographs	dental surgeon	For caries detection sensitivity 0.84, precision 0.81, and F-measure rates 0.84 and for caries segmentation were sensitivity 0.86, precision 0.84, and F-measure rates 0.84	These models can accurately detect DC. There were also beneficial in the segmentation of DC
15	Devlin et al 2021 [31]	Randomized control trial	CNNs	24	Bitewing radiographs	dental surgeon	High accuracy of diagnosis with sensitivity of 71% and decrease in specificity of 11% are statistically significant ($p < 0.01$) in comparison with expert dentists	This model significantly improved dentists' ability to detect enamel-only proximal caries

Table 3 (continued)

SI	Authors Year	Study Design	AI algorithm	No. of sample	X-ray type	Comparator	Evaluation	Outcomes
16	Chen et al 2021 [32]	Retrospective	CNNs	2900	Digital periapical radiographs	Reference models with dental surgeon	DC and PDL were detected with precision, recall, and average precision values less than 0.25 for mild level, 0.2–0.3 for moderate level and 0.5–0.6 for severe level Lesions were generally detected with precision and recall between 0.5–0.6 at all levels	This models can detect caries using periapical radiographs
17	Geetha et al 2020 [33]	Cross sectional	ANNs	145	Digital periapical radiographs	dental surgeon	Accuracy of 97.1%, false positive (FP) rate of 2.8%, ROC area of 0.987 and PRC area of 0.987	This AI model can predict caries more accurately
18	Cantu et al 2020 [34]	Retrospective	CNNs	3293	Bitewing radiographs	4 dental surgeon	Accuracy of 0.80; sensitivity of 0.75, specificity of 0.83	This CNN-based model was significantly more accurate than the experienced dentists
19	Choi et al 2018 [35]	Retrospective	CNNs	475	Digital periapical radiographs	Dental surgeon and raw CNN reference models	*F1max* 0.74 with False Positives 0.88	This model was superior to the system using a naïve CNN
20	Lee et al 2018 [36]	Retrospective	DCNNs	2400	Digital periapical radiographs	Not mentioned	Accuracy of 89.0%, 88.0%, 82.0% and AUC of 0.917, 0.890, 0.845	This CNNs-based model demonstrated good performance in detecting DC
21	Srivastava et al 2017 [37]	Retrospective	FCNN	3000	Digital periapical radiographs	3 experienced dentists	F1-score 70%, accuracy 80.5–61.5%	Better performance than comparator dentist

CNNs Convolutional neural networks, *ANNs* Artificial neural networks, *DCNNs* Deep neural networks, *CT* Computed tomography scans, *CBCT* Cone-beam computed tomography levels, reinforcing the reliability of CNNs in dental diagnostics. This high level of accuracy suggests that AI could play a crucial role in improving diagnostic precision in dental radiography. The reported sensitivity rates vary, but they are generally high, with many studies noting rates above 80%. This implies that AI models excel at accurately identifying patients with the condition under examination. High specificity rates indicate a strong ability of AI models to correctly identify those patients who do not have the condition, reducing the risk of false positives. The sensitivity and specificity metrics were particularly notable in studies such as Mao et al. [21], who achieved a sensitivity of around 94% and a specificity close to 95%. The findings of Lee et al. [24] and Bayraktar et al. [19] closely mirrored these rates, demonstrating consistent detection capabilities of AI across different studies.

Overall prevalence of accuracy of the caries detection

Figure 3 displays a forest plot showing the prevalence of accuracy in AI for caries detection, including data from fourteen studies conducted between 2017 and 2023 (Table 4). The studies had sample sizes ranging from 15 to 11,000 people, with stated accuracy varying from 73.3% to 98.8%. Each study's outcome contains the odds ratio (OR) and the p-value, indicating the statistical significance of the data in comparison to a standard value.

Most of the research has high accuracy rates, with six studies achieving 95% accuracy. Lian et al. [28] and De Araujo Faria et al. [22] both achieved accuracies of 99%. Moran et al. [27] showed the lowest accuracy at 73.3%, with a broad confidence interval (CI) ranging from 65.11% to 81.49%, suggesting a less exact estimate likely due to a smaller sample size.

The odds ratios (ORs) differ significantly among the researchers, suggesting variations in the impact of artificial intelligence (AI) on caries detection relative to a control group or expected standard. Lian et al. [28] found an OR of 1.469, showing a large positive effect, whereas Moran et al. [22] reported an OR of 0.052, suggesting a much smaller effect compared to other studies. The paper presents an odds ratio of around 2.72, with a 95% confidence interval of 14.65 to 14.65, indicating the significant effectiveness of AI in detecting caries in several investigations.

The I^2 value of 88.0% indicates significant heterogeneity among the study outcomes, likely stemming from variations in study designs, AI technologies employed, sample sizes, or other study-specific factors. Most research provides statistically significant results with p-values significantly lower than 0.05, except for Lee et al. [24], who reported a p-value of 0.08, showing results that are not statistically significant at the customary 5% level.

Accuracy of caries detection by different Xray technique

Forest plot (Fig. 4) appears to be some variation in the accuracy of AI in caries detection depending on the type of x-ray used. Overall, the studies included in the forest

Forest plot of prevalence of accuracy of AI in caries detection

Sl No.	Authors Year	Total sample	Accuracy (%)	Lower 95% CI	Upper 95% CI	OR	*P* value
1	**Chen *et al.* 2023 [17]**	11000	95.44%	0.99	1.00	1.000	< 0.001
2	**Zhu *et al.* 2022 [18]**	1159	93.61%	0.94	0.97	0.959	< 0.001
3	**Bayraktar *et al.* 2022 [19]**	1000	94.59%	0.96	0.99	0.982	< 0.001
4	**Huang *et al.* 2021 [20]**	748	95.21%	0.98	1.01	0.997	< 0.001
5	**Mao *et al.* 2021 [21]**	278	95.56%	0.98	1.03	1.008	< 0.001
6	**De Araujo Faria *et al.* 2021 [22]**	15	98.8%	1.25	1.34	1.303	0.001
7	**Vinayahalingam *et al.* 2021 [25]**	500	87.0%	0.36	0.39	0.381	0.046
8	**Moran *et al.* 2021 [27]**	112	73.3%	0.046	0.058	0.052	< 0.001
9	**Lian *et al.* 2021 [28]**	1160	98.6%	1.45	1.47	1.469	< 0.001
10	**Zheng *et al.* 2021 [29]**	844	82.0%	0.29	0.30	0.300	< 0.001
11	**Geetha *et al.* 2020 [33]**	145	97.1%	1.21	1.28	1.246	< 0.001
12	**Cantu *et al.* 2020 [34]**	3293	80.0%	0.30	0.31	0.312	< 0.001
13	**Lee *et al.* 2018 [36]**	3000	89.0%	0.47	0.48	0.479	0.080
14	**Srivastava *et al.* 2017 [37]**	3000	80.5%	0.29	0.30	0.303	< 0.001

Overall OR: 0.59; 95% CI: 0.46 to 0.77.
I^2: 89.98%

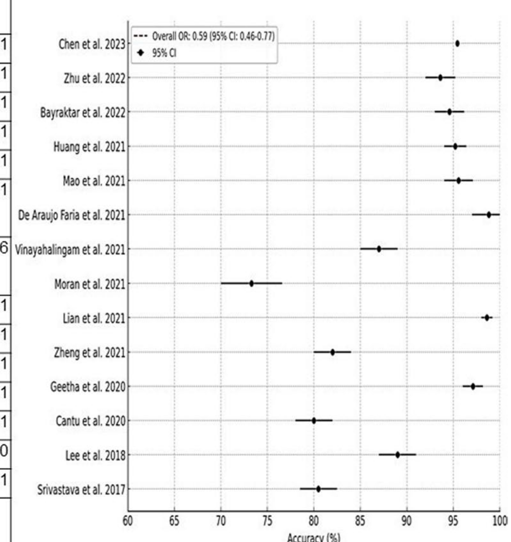


Fig. 3 Forest plot of prevalence of accuracy of AI in caries detection. Overall Odds Ratio: 2.718; 95% CI: 14.649452269170583 - 14.649452269170595; I^2: 88.0 %

Table 4 Characteristics of the prevalence of accuracy of AI in caries detection

Sl No	Authors Year	Total sample	Accuracy (%)	Lower 95% CI	Upper 95% CI	OR	*P* value
1	**Chen et al. 2023** [17]	11,000	95.44%	0.99	1.00	1.000	< 0.001
2	**Zhu et al. 2022** [18]	1159	93.61%	0.94	0.97	0.959	< 0.001
3	**Bayraktar et al. 2022** [19]	1000	94.59%	0.96	0.99	0.982	< 0.001
4	**Huang et al. 2021** [20]	748	95.21%	0.98	1.01	0.997	< 0.001
5	**Mao et al. 2021** [21]	278	95.56%	0.98	1.03	1.008	< 0.001
6	**De Araujo Faria et al. 2021** [22]	15	98.8%	1.25	1.34	1.303	0.001
7	**Vinayahalingam et al. 2021** [25]	500	87.0%	0.36	0.39	0.381	0.046
8	**Moran et al 2021** [27]	112	73.3%	0.046	0.058	0.052	< 0.001
9	**Lian et al 2021** [28]	1160	98.6%	1.45	1.47	1.469	< 0.001
10	**Zheng et al 2021** [29]	844	82.0%	0.29	0.30	0.300	< 0.001
11	**Geetha et al 2020** [33]	145	97.1%	1.21	1.28	1.246	< 0.001
12	**Cantu et al 2020** [34]	3293	80.0%	0.30	0.31	0.312	< 0.001
13	**Lee et al 2018** [36]	3000	89.0%	0.47	0.48	0.479	0.080
14	**Srivastava et al 2017** [37]	3000	80.5%	0.29	0.30	0.303	< 0.001

Overall OR: 0.59; **95% CI**: 0.46 to 0.77; I^2: 89.98%

plot suggest that AI can be accurate in caries detection with different x-ray types, but some methods may be more accurate than others. The accuracy for digital bitewing x-rays appears to be high (possibly around 80% based on one study), with a narrow confidence interval, which suggests a precise estimate (Fig. 4a). The accuracy for digital panoramic x-rays appears to be lower than for bitewing x-rays, with one study showing an accuracy around 70% and a wide confidence interval, indicating less precision in the estimate. (Fig. 4b) Periapical x-rays show an accuracy around 76%, but the confidence interval is wide, so the estimate is not very precise. More research is needed to draw conclusions about periapical x-rays (Fig. 4c).

Overall sensitivity of AI accuracy in caries detection

We conducted a forest plot and meta-analysis to evaluate the sensitivity of AI in caries detection across multiple studies (Fig. 5/Table 5). The meta-analysis encompassed nine studies conducted between 2020 and 2023, with a total of 17,190 participants. Sensitivity ranged from 71% to 98.85%, with corresponding odds ratios (OR) ranging from 2.448 to 85.957 across the studies. The pooled analysis yielded an overall OR of 1.258 (95% CI: 0.493—2.540), indicating no significant association between the examined factor and the outcome. However, substantial heterogeneity was observed among the studies ($I^2 = 86.03\%$, $p < 0.05$), suggesting variability in effect sizes beyond chance. These findings underscore the importance of considering factors contributing to heterogeneity in future research and clinical practice.

Figure 6 and Table 6 displays the forest plot, which shows the specificity percentages, odds ratios (OR), and 95% confidence intervals (CI) from seven studies that looked at how well artificial intelligence (AI) systems could find cavities in teeth. The specificity values vary widely, from 0.82% to 98.19%, among different researchers. The weighted mean specificity across studies is around 87.90%, showing the great overall performance of AI in accurately recognising non-caries instances. The heterogeneity analysis shows a high Q statistic of 144,926.65 and an I^2 statistic of 96.03%, showing substantial variability among trials beyond chance. Other variables, besides random sampling error, may be influencing the discrepancies in specificity estimates. The p-value of less than 0.001 confirms the existence of statistically significant heterogeneity. It is important to carefully examine study design, AI model properties, and other causes of variability when evaluating and applying results from AI studies to dental caries diagnosis.

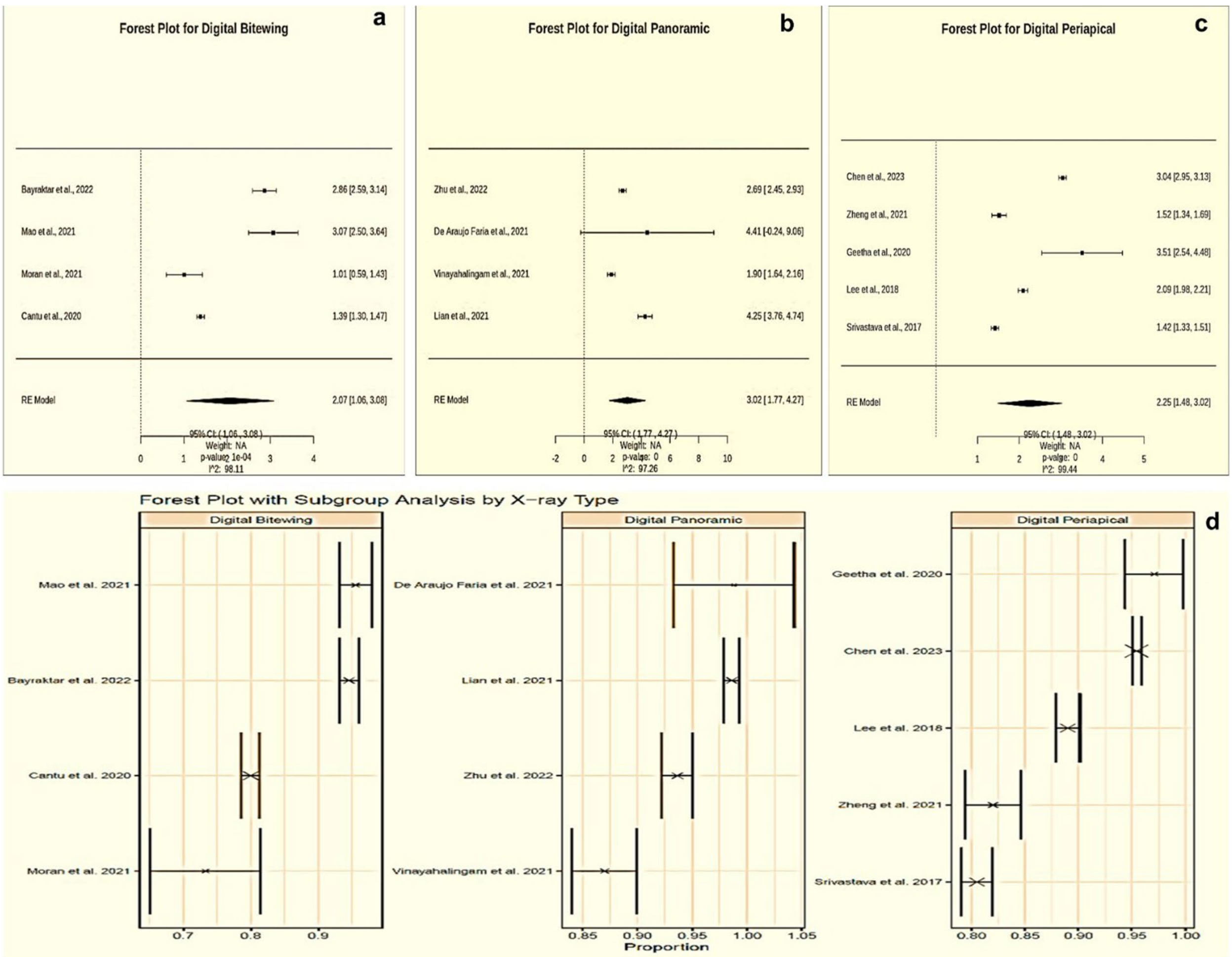


Fig. 4 Forest plot of subgroup analysis to determine the accuracy of AI in caries detection by **a** digital bitewing, **b** digital panoramic, and **c** digital periapical radiograph **d**) overall differences

Forest plot of overall sensitivity of AI in caries detection					
Sl No.	**Authors Year**	**N**	**Sensitivity (%)**	**95% CI (Lower, Upper)**	**OR**
1	**Chen *et al.* 2023 [17]**	11000	94.15%	92.70% to 95.60%	16.09 (16.02, 16.17)
2	**Bayraktar *et al.* 2022 [19]**	1000	72.26%	69.49% to 75.03%	2.60 (2.53, 2.68)
3	**Huang *et al.* 2021 [20]**	748	98.85%	98.19% to 99.51%	85.95 (85.30, 86.62)
4	**Vinayahalingam *et al.* 2021 [25]**	500	86.0%	83.85% to 88.15%	6.14 (5.96, 6.33)
5	**Mertens S *et al.* 2021 [26]**	140	81.0%	78.57% to 83.43%	4.26 (3.99, 4.55)
6	**Zheng *et al.* 2021 [29]**	844	85.1%	82.89% to 87.31%	5.71 (5.58, 5.85)
7	**Bayrakdar *et al.* 2021 [30]**	621	84%	81.73% to 86.27%	5.25 (5.10, 5.40)
8	**Devlin *et al.* 2021 [31]**	24	71%	68.19% to 73.81%	2.44 (2.04, 2.94)
9	**Cantu *et al.* 2020 [34]**	3293	75.0%,	72.32% to 77.68%	3.00 (2.96, 3.05)
95% CI for Overall Odds Ratio: (0.493, 2.540), Overall Odds Ratio (OR): 1.258					
I^2 Statistic: 86.03%, p-value for Heterogeneity: <0.05					

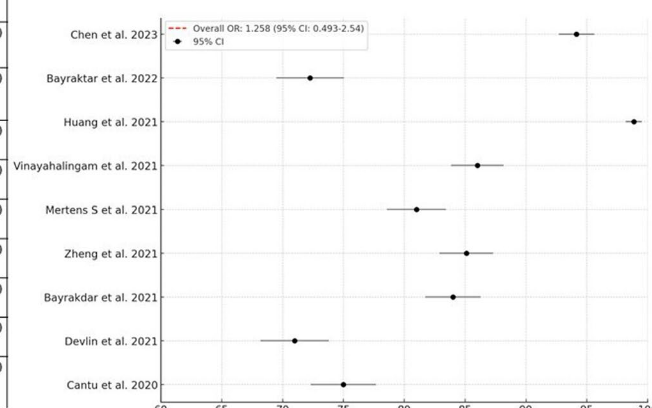


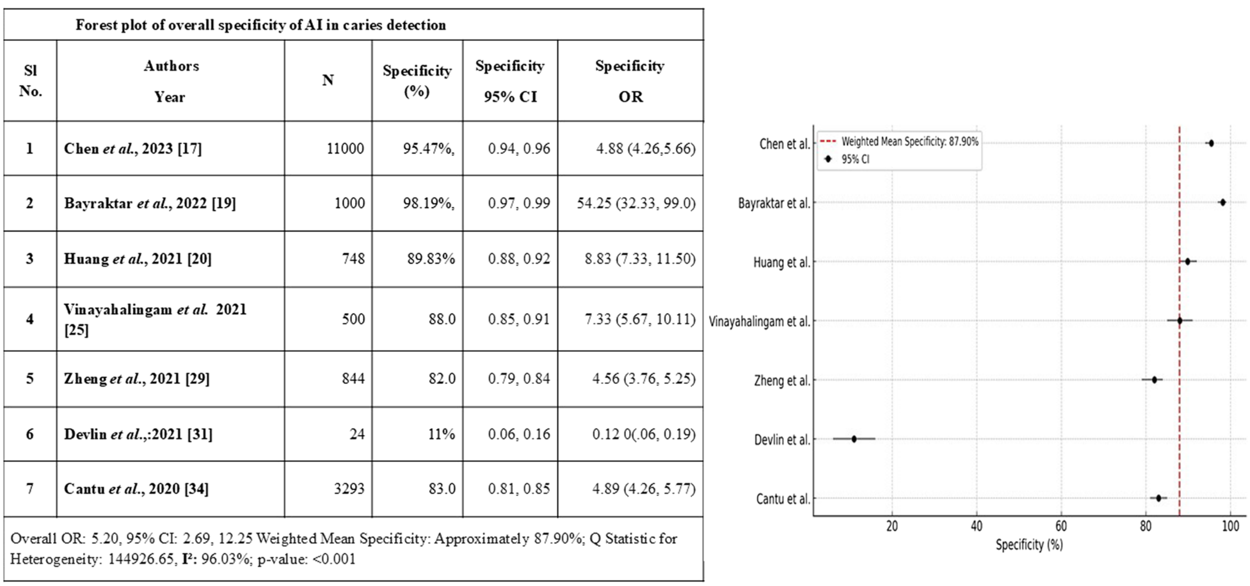
Fig. 5 Forest plot of overall sensitivity of AI in caries detection. 95% CI for Overall Odds Ratio: (0.493, 2.540), Overall Odds Ratio (OR): 1.258. I. 2 Statistic: 86.03%, p-value for Heterogeneity: < 0.05

Table 5 Characteristics of overall sensitivity of AI in caries detection

Sl No	Authors Year	N	Sensitivity (%)	95% CI (Lower, Upper)	OR
1	**Chen et al. 2023** [17]	11,000	94.15%,	92.70% to 95.60%	16.09 (16.02, 16.17)
2	**Bayraktar et al. 2022** [19]	1000	72.26%	69.49% to 75.03%	2.60 (2.53, 2.68)
3	**Huang et al. 2021** [20]	748	98.85%	98.19% to 99.51%	85.95 (85.30, 86.62)
4	**Vinayahalingam et al. 2021** [25]	500	86.0%	83.85% to 88.15%	6.14 (5.96, 6.33)
5	**Mertens S et al. 2021** [26]	140	81.0%	78.57% to 83.43%	4.26 (3.99, 4.55)
6	**Zheng et al. 2021** [29]	844	85.1%	82.89% to 87.31%	5.71 (5.58, 5.85)
7	**Bayrakdar et al. 2021** [30]	621	84%	81.73% to 86.27%	5.25 (5.10, 5.40)
8	**Devlin et al. 2021** [31]	24	71%	68.19% to 73.81%	2.44 (2.04, 2.94)
9	**Cantu et al. 2020** [34]	3293	75.0%,	72.32% to 77.68%	3.00 (2.96, 3.05)

95% CI for Overall Odds Ratio: (0.493, 2.540), Overall Odds Ratio (OR): 1.258

I^2 Statistic: 86.03%, p-value for Heterogeneity: < 0.05



Forest plot of overall specificity of AI in caries detection

Sl No.	Authors Year	N	Specificity (%)	Specificity 95% CI	Specificity OR
1	Chen *et al.*, 2023 [17]	11000	95.47%,	0.94, 0.96	4.88 (4.26,5.66)
2	Bayraktar *et al.*, 2022 [19]	1000	98.19%,	0.97, 0.99	54.25 (32.33, 99.0)
3	Huang *et al.*, 2021 [20]	748	89.83%	0.88, 0.92	8.83 (7.33, 11.50)
4	Vinayahalingam *et al.* 2021 [25]	500	88.0	0.85, 0.91	7.33 (5.67, 10.11)
5	Zheng *et al.*, 2021 [29]	844	82.0	0.79, 0.84	4.56 (3.76, 5.25)
6	Devlin *et al.*,:2021 [31]	24	11%	0.06, 0.16	0.12 0(.06, 0.19)
7	Cantu *et al.*, 2020 [34]	3293	83.0	0.81, 0.85	4.89 (4.26, 5.77)

Overall OR: 5.20, 95% CI: 2.69, 12.25 Weighted Mean Specificity: Approximately 87.90%; Q Statistic for Heterogeneity: 144926.65, I^2: 96.03%; p-value: <0.001

Fig. 6 Forest plot of overall specificity of AI in caries detection. Weighted Mean Specificity: Approximately 87.90%; Q Statistic for Heterogeneity: 144926.65, I. 2 Statistic: 96.03%, p -value: < 0.001

Table 6 Characteristics of overall specificity of AI in caries detection

Sl No	Authors Year	N	Specificity (%)	Specificity 95% CI	Specificity OR
1	**Chen et al., 2023** [17]	11,000	95.47%,	0.94, 0.96	4.88 (4.26,5.66)
2	**Bayraktar et al., 2022** [19]	1000	98.19%,	0.97, 0.99	54.25 (32.33, 99.0)
3	**Huang et al., 2021** [20]	748	89.83%	0.88, 0.92	8.83 (7.33, 11.50)
4	**Vinayahalingam et al. 2021** [25]	500	88.0	0.85, 0.91	7.33 (5.67, 10.11)
5	**Zheng et al., 2021** [29]	844	82.0	0.79, 0.84	4.56 (3.76, 5.25)
6	**Devlin et al.,:2021** [31]	24	11%	0.06, 0.16	0.12 0(.06, 0.19)
7	**Cantu et al., 2020** [34]	3293	83.0	0.81, 0.85	4.89 (4.26, 5.77)

Overall OR: 5.20, 95% CI: 2.69, 12.25 Weighted Mean Specificity: Approximately 87.90%; Q Statistic for Heterogeneity: 144,926.65, I^2: 96.03%; p-value: < 0.001

Risk of bias

QUADAS-2 assessment bar graph observations (Fig. 7)

- *Patient Selection:* Most studies show moderate to high risk, with more studies appearing in the orange and red zones.
- *Index Test:* This domain also displays a range of risk, with several studies showing higher risk levels.
- *Reference Standard:* Here, the risk seems varied, with some studies showing low risk (green) and others high risk (red).
- *Flow and Timing:* Most studies are in the low-risk category for this domain, as indicated by the green color.
- *Applicability Concerns:* The risks are generally low in this domain across the studies, with most bars colored green.

QUADAS-2 assessment heatmap (Fig. 8)

The heatmap offers a detailed view of the risk assessment for each study across the same domains. Each cell in the heatmap is colored based on the risk level:

- 1 (Low Risk): Green; 2 (Moderate Risk): Yellow; 3 (High Risk): Red

Observations

- *Patient Selection:* Some studies demonstrate a high risk (red cells) due to concerns over patient selection and representativeness [24, 25, 33].
- *Index Test:* Some studies [23, 35] have identified a high risk, suggesting that the index test may not have been completed according to a defined methodology or interpreted without knowledge of the reference standard.
- *Reference Standard:* Multiple studies [28, 33] indicate a high danger, implying that the reference standard may not have been properly implemented.
- *Flow and Timing:* While most studies in this field demonstrate low hazards, some exceptions [21, 22] exhibit moderate risks.
- *Applicability Concerns:* Few studies show high concern for applicability [25], suggesting that the results might not apply to the intended patient population.

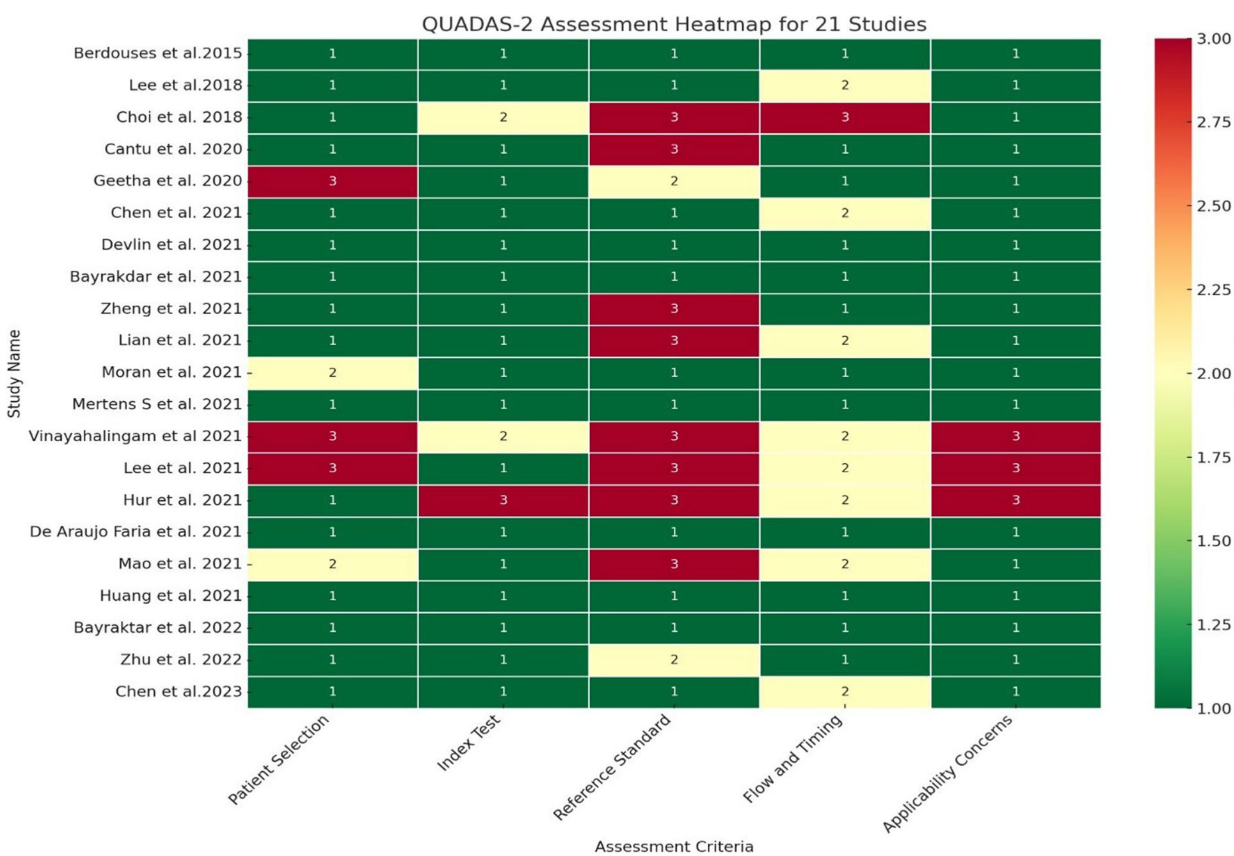


Fig. 7 QUADAS risk of bias assessment in bar graph

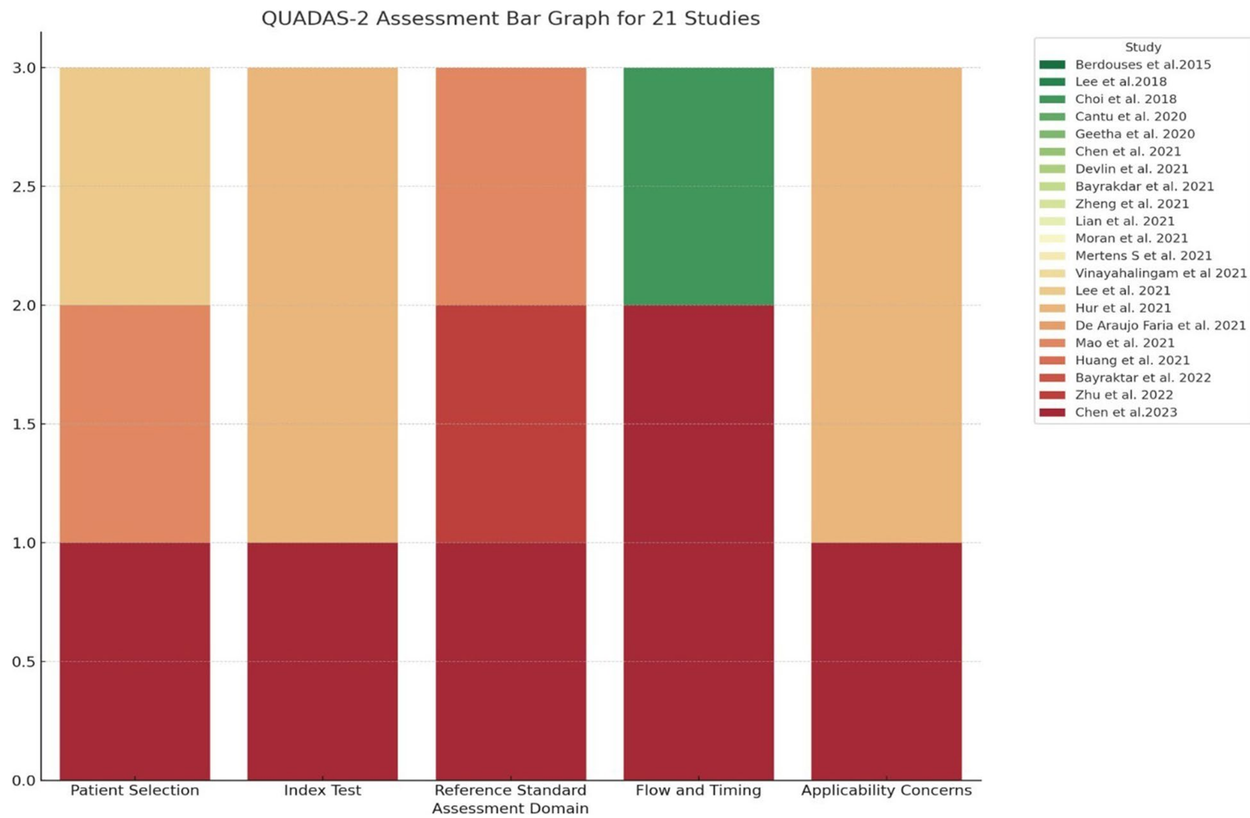


Fig. 8 QUADAS risk of bias assessment in heatmap

Discussion

Artificial intelligence (AI) has been used in dental diagnostics, revolutionizing caries detection by enhancing accuracy and efficiency. This systematic review and meta-analysis are intended to assess the sensitivity, specificity, and overall diagnosis accuracy of AI systems on various types of dental X-rays. Our research shows that AI routinely achieves high levels of diagnostic accuracy, frequently outperforming conventional methods and providing substantial promise for improving clinical results.

Advancements in AI and caries detection

AI technologies, namely machine learning models like CNNs, have demonstrated exceptional ability to recognize patterns in intricate datasets that surpass human vision [38]. Even experienced dentists find it challenging to identify minor changes in dental X-rays that could signal the initial phases of dental caries using conventional technologies [39]. Our results correspond with the umbrella review of Dashti et al. (2024), which indicated accuracy rates between 73.3% and 98.6% across several datasets. Both studies show that convolutional neural networks (CNNs) can help with dental diagnoses. However, the umbrella review stresses how unpredictable results can be because of different datasets and different methods used. This variability aligns with our findings of significant heterogeneity ($I^2 = 88.0\%$) among the included studies [40]. The sensitivity and specificity statistics obtained from the multiple trials included in our meta-analysis demonstrate the strong performance of AI. Specificity rates of up to 98.19% and sensitivity rates of up to 98.85% have been found in studies [19, 20]. This shows that AI can cut down on both false negatives and false positives, making dental caries diagnostics more reliable [18].

Clinical implications of AI in dentistry

When it comes to clinical applications, the incorporation of AI into dental practices has significant implications. By enhancing the diagnosis process, artificial intelligence has the potential to lessen the mental burden placed on dental practitioners, enabling them to provide more focused patient engagement and care [41]. Furthermore, the high accuracy rates offered by cost-effective AI systems could result in early detection of dental caries, potentially enabling interventions to halt or even reverse the progression of decay [42]. Alternative technologies such as optical coherence tomography (OCT), laser fluorescence, and transillumination systems have been introduced as alternatives to traditional radiography [43]. These modalities can provide different types of information about caries lesions, such as subsurface structure and demineralization, which radiographs might miss. The application of AI in radiograph interpretation could complement and enhance these technologies, creating a more comprehensive diagnostic toolkit. By integrating AI with these approaches, dental practitioners can benefit from more accurate and early detection of caries, improving overall patient outcomes [42, 43]. This not only helps to maintain the natural structure of the teeth, but it also lessens the likelihood that more, more comprehensive, and more expensive treatments may be required in the future [1, 7, 37, 42]. According to Lee et al. (2021), the capability of artificial intelligence to deliver diagnostic outputs that are consistent and trustworthy can also help to standardize the quality of treatment that patients receive, thereby minimizing the variability that is caused by human variables such as fatigue or subjective determination [24].

Enhancing patient outcomes and trust

One of the most important advantages of artificial intelligence in dental diagnostics is the possibility that it may improve patient outcomes [44]. It is possible that more effective treatments and an overall improvement in oral health could result from the accurate and early identification of caries [11, 15, 17]. On top of that, the use of artificial intelligence has the potential to instill a higher level of faith in diagnostic procedures among patients. This is due to AI's potential to serve as an unbiased second opinion, thereby enhancing patients' trust in their dentists' suggested treatment plans [7, 8, 44].

Sources of heterogeneity

In this systematic review, we found substantial variation among the studies that were included, as evidenced by high I^2 values in the different meta-analyses. This heterogeneity indicates that the differences in research outcomes are not only random, but rather, are impacted by multiple significant factors that require additional examination.

a One of the primary sources of heterogeneity is the diversity of A) models employed across the studies. The studies included in this review utilized different machine learning algorithms, such as CNNs, DNNs, and SVMs, each with its own architecture, training dataset, and performance characteristics. The performance of these models can vary significantly depending on factors such as the size and quality of the training data, the specific algorithmic parameters, and the type of image preprocessing used. As a result, studies using different AI models may report varying levels of accuracy, sensitivity, and specificity, contributing to the observed heterogeneity.

b Another significant factor contributing to variation arises from the diverse categories of radiographic images examined in the research included. The studies analyzed in this study utilized periapical, bitewing, and panoramic radiographs, each of which provides distinct difficulties and advantages in detecting caries. Another systematic review also reported that, Bitewing radiographs are highly efficient in identifying interproximal caries, whereas panoramic radiographs offer a wider perspective of the dental arch but with reduced precision. The diverse diagnostic accuracy of AI models in different imaging modalities is likely a factor in the observed variability in the study results [45].

c The studies included in the analysis exhibited variations in their design and the populations they investigated. Differences in study design, such as retrospective versus prospective cohort studies, along with variations in sample numbers, demographic features, and clinical settings, can influence the generalizability and applicability of the findings. Research conducted in specific groups with different levels of dental caries or in different geographical areas may show varying levels of accuracy in diagnosis, which adds to the overall diversity.

d Furthermore, variations in the evaluation and documentation of results among different research may also contribute to the presence of heterogeneity. The main goal of most of the studies was to test how well AI models could diagnose problems. However, there were differences in the exact metrics used (like accuracy, sensitivity, specificity, and area under the curve [AUC]) and the levels set for finding cavities. Variability in the results can arise from inconsistent reporting of outcomes and potential biases in the selection of cases or controls, making it difficult to directly compare research.

Challenges

Despite the above advantages, a number of obstacles hinder the widespread implementation of artificial intelligence in dental diagnostics. Protection of personal information is of the utmost importance, particularly with regard to the management of sensitive patient data [46]. Additionally, the incorporation of AI technologies into pre-existing clinical workflows presents a number of important hurdles, all of which require an investment of both time and money [47]. AI needs to be incorporated with regard for demographic risk, social determinants, health care service, and economic variables to value dentistry practice. Therefore, the development of AI systems with great specificity should be given top priority independent of the frequency context. High specificity helps to reduce overtreatment and directs focus on lesions that truly call for attention, therefore assuring more efficient use of resources [48].

Limitations

We should acknowledge several limitations, even though our systematic review and meta-analysis offer valuable insights into the diagnostic accuracy of artificial intelligence (AI) systems in detecting dental caries.

First, the heterogeneity among the included studies is significant, stemming from variations in AI models, radiographic techniques, and study designs. This variability may affect the generalizability of our findings across different clinical settings.

Second, the studies included in our analysis predominantly focused on specific types of radiographic images (such as bitewing or panoramic radiographs), which may limit the applicability of AI models to other imaging modalities or newer technologies that were not covered.

Third, the potential for publication bias exists, as studies with positive outcomes are more likely to be published, which could skew the overall results of our meta-analysis. Additionally, while we employed the QUADAS-2 tool for assessing the risk of bias in individual studies, we did not utilize QUADAS-C, which might be more suitable for comparative analyses.

Finally, particularly in populations with low disease frequency, inadequate specificity artificial intelligence systems could cause unwarranted interventions. Future studies should thus give top priority to the creation of highly specific artificial intelligence models capable of precisely differentiating between circumstances needing intervention and those not so demanding. Furthermore, taken into account in the integration of artificial intelligence into clinical practice should be demographic risk, socioeconomic determinants of health, and financial limitations to guarantee fair and efficient application [48].

Future directions

As we look to the future, it is vital to continuously create and validate AI models in order to handle these difficulties. The development of standardized protocols for artificial intelligence training is necessary. These protocols should include a diversity of training datasets in order to improve the robustness and usability of AI systems across a variety of clinical situations and individual populations. Additionally, future research should concentrate on the incorporation of artificial intelligence tools that can supplement conventional diagnostic procedures. This would lead to the development of a comprehensive diagnostic framework that capitalizes on the strengths of both human expertise and AI capabilities.

Furthermore, regulatory frameworks need to be adapted in order to keep up with the rapid advancements in technology. This is necessary in order to guarantee that artificial intelligence products are both safe and effective for clinical usage. When it comes to developing standards that govern the ethical use of artificial intelligence in healthcare, collaborations between researchers, doctors, and policymakers are absolutely necessary. These guidelines will ensure that patients benefit from these technologies without having their privacy or autonomy compromised.

Conclusions

AI has the ability to greatly improve the diagnosis process in dentistry, especially in detecting dental caries. This review emphasizes the high sensitivity and specificity rates of AI, showcasing its potential to enhance diagnostic accuracy, ultimately resulting in improved patient outcomes and streamlined clinical workflows. Dental professionals must address difficulties such as maintaining data privacy, incorporating AI into clinical practices, and improving AI models through comprehensive research to fully utilize AI in dentistry. It is crucial for the dental profession to adopt and apply innovations in a conscientious and ethical manner to improve patient care as we progress. This review anticipates increased collaboration between human skills and artificial intelligence in dentistry in the future, leading to remarkable enhancements in the quality and effectiveness of dental treatment.

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None.

Authors' contributions
A.M.L was responsible for conceptualization, resources, supervision, validation, and writing the original draft. Both A.M.L and N.N.F.R contributed to data curation, formal analysis, methodology, supervision, and writing review and editing. Additionally, N.N.F.R handled the visualization tasks.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

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Not applicable.

Consent for publications
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Competing interests
The authors declare no competing interests.

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