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Review article

Applications of artificial intelligence in the utilisation of imaging modalities in dentistry: A systematic review and meta-analysis of in-vitro studies

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ABSTRACT

Background: In the past, dentistry heavily relied on manual image analysis and diagnostic procedures, which could be time-consuming and prone to human error. The advent of artificial intelligence (AI) has brought transformative potential to the field, promising enhanced accuracy and efficiency in various dental imaging tasks. This systematic review and meta-analysis aimed to comprehensively evaluate the applications of AI in dental imaging modalities, focusing on in-vitro studies.
Methods: A systematic literature search was conducted, in accordance with the PRISMA guidelines. The following databases were systematically searched: PubMed/MEDLINE, Embase, Web of Science, Scopus, IEEE Xplore, Cochrane Library, CINAHL (Cumulative Index to Nursing and Allied Health Literature), and Google Scholar. The meta-analysis employed fixed-effects models to assess AI accuracy, calculating odds ratios (OR) for true positive rate (TPR), true negative rate (TNR), positive predictive value (PPV), and negative predictive value (NPV) with 95 % confidence intervals (CI). Heterogeneity and overall effect tests were applied to ensure the reliability of the findings.
Results: 9 studies were selected that encompassed various objectives, such as tooth segmentation and classification, caries detection, maxillofacial bone segmentation, and 3D surface model creation. AI techniques included convolutional neural networks (CNNs), deep learning algorithms, and AI-driven tools. Imaging parameters assessed in these studies were specific to the respective

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dental tasks. The analysis of combined ORs indicated higher odds of accurate dental image assessments, highlighting the potential for AI to improve TPR, TNR, PPV, and NPV. The studies collectively revealed a statistically significant overall effect in favor of AI in dental imaging applications.
Conclusion: In summary, this systematic review and meta-analysis underscore the transformative impact of AI on dental imaging. AI has the potential to revolutionize the field by enhancing accuracy, efficiency, and time savings in various dental tasks. While further research in clinical settings is needed to validate these findings and address study limitations, the future implications of integrating AI into dental practice hold great promise for advancing patient care and the field of dentistry.

1. Introduction

In recent years, artificial intelligence (AI) has made substantial inroads into various fields of medicine and healthcare, revolutionizing diagnostic and treatment approaches [1]. Dentistry, as a crucial domain of healthcare, has not remained untouched by the transformative potential of AI [2]. AI applications in dentistry have been particularly promising, showing potential for enhancing the accuracy and efficiency of various dental imaging modalities. Dental imaging is fundamental for diagnosis, treatment planning, and monitoring of oral health conditions, and the integration of AI could significantly impact the precision and speed of these processes [3] (Table 1).

The rapid advancement of artificial intelligence (AI) technology is instigating transformative changes across various domains, and

Table 1
Abbreviations used in this review.

Abbreviation	Definition
CBCT	Cone Beam Computed Tomography
CNN	Convolutional Neural Network
IoU	Intersection over Union
HD	Hausdorff Distance
DSC	Dice Similarity Coefficient
SVM	Support Vector Machine
KNN	k-Nearest Neighbors
DT	Decision Tree
NB	Naive Bayes
RF	Random Forest
AI	Artificial Intelligence
PRs	Panoramic Radiographs
BDU-Net	Backbone-Based Dilated U-Net
nnU-Net	No-New-Net
CAD	Computer-Aided Diagnosis
MCW	Mandibular Cortical Width
DCNN	Deep Convolutional Neural Network
TW3	Tanner-Whitehouse 3
VGGNet-BA	Visual Geometry Group Network for Bone Age
TPV	True Positive Value
TNV	True Negative Value
PPV	Positive Predictive Value
NPV	Negative Predictive Value

the field of oral health is no exception [4,5]. This transformation is particularly notable due to the prevalent use of digitized imaging and electronic health records within dentistry, providing a fertile ground for the implementation of AI algorithms [6,7]. While this scientific frontier is relatively nascent, it demands prudent exploration. Human supervision remains imperative, acting as a safeguard against untoward consequences. However, it is pivotal to recognize and comprehensively grasp the genuine advantages that this technology offers within the realm of healthcare [8–10].

The confluence of abundant clinical dental images and the evolution of deep learning algorithms in recent years has catalyzed substantial enhancements in their precision and resilience, significantly bolstering their utility in diagnosing a spectrum of dental conditions. At the forefront of these AI-driven transformations are convolutional neural networks (CNN) [11–13], a category of deep learning neural networks celebrated for their exceptional accuracy and adeptness in assimilating and discerning salient features from images. A CNN comprises multiple strata, encompassing convolutional, pooling, and fully connected layers. Their prowess in image classification tasks is well-documented, transcending medical image analysis into other domains such as object detection and natural language processing.

Among the innovative strategies employed is "transfer learning," a machine learning paradigm that leverages pretrained models, notably CNN models. These models have already gleaned pertinent features from extensive image datasets [14–18]. Subsequently, these pretrained models undergo fine-tuning on a more specialized dataset tailored for a particular task. The foundation laid by these pretrained image models accelerates the training process for new models. Within the realm of oral health applications, two pretrained image architectures, GoogLeNet Inception [19] and ResNet [20], hold particular prominence. The Google Net Inception-v3 architecture, introduced in 2014, garnered acclaim for its exceptional performance across imaging-related applications. Trained on a comprehensive ImageNet dataset encompassing over a million images across 1000 object categories, this architecture's original design incorporates 22 deep layers, enabling the extraction of diverse scale features by applying convolutional filters of varying dimensions within the same layers [21–24].

AI can analyze large volumes of data and identify patterns that may be missed by human observers-therefore, in imaging diagnostics, as far as the literature is concerned in this regard, AI can offer precision and speed that significantly surpass traditional methods [11–13]. Similarly, AI can be used to predict disease progression based on patient data, enabling more personalized and effective treatment plans [21–24]. In dentistry and surgical fields, AI can assist in treatment planning, such as the design of orthodontic treatments or surgical interventions, by creating accurate 3D models and simulating outcomes. This could lead to more precise, patient-specific treatments and potentially better outcomes [21–24]. Fig. 1 shows the different imaging modalities utilised across the healthcare and dental domains.

This investigation seeks to rigorously examine the existing body of literature pertaining to AI applications in dental imaging, focusing specifically on in-vitro studies. In-vitro studies offer controlled environments for assessing AI algorithms' performance in isolation, free from confounding variables often encountered in clinical settings. By exclusively considering in-vitro studies, this review aims to provide a highly focused and robust evaluation of AI's potential in dental imaging across different parameters.

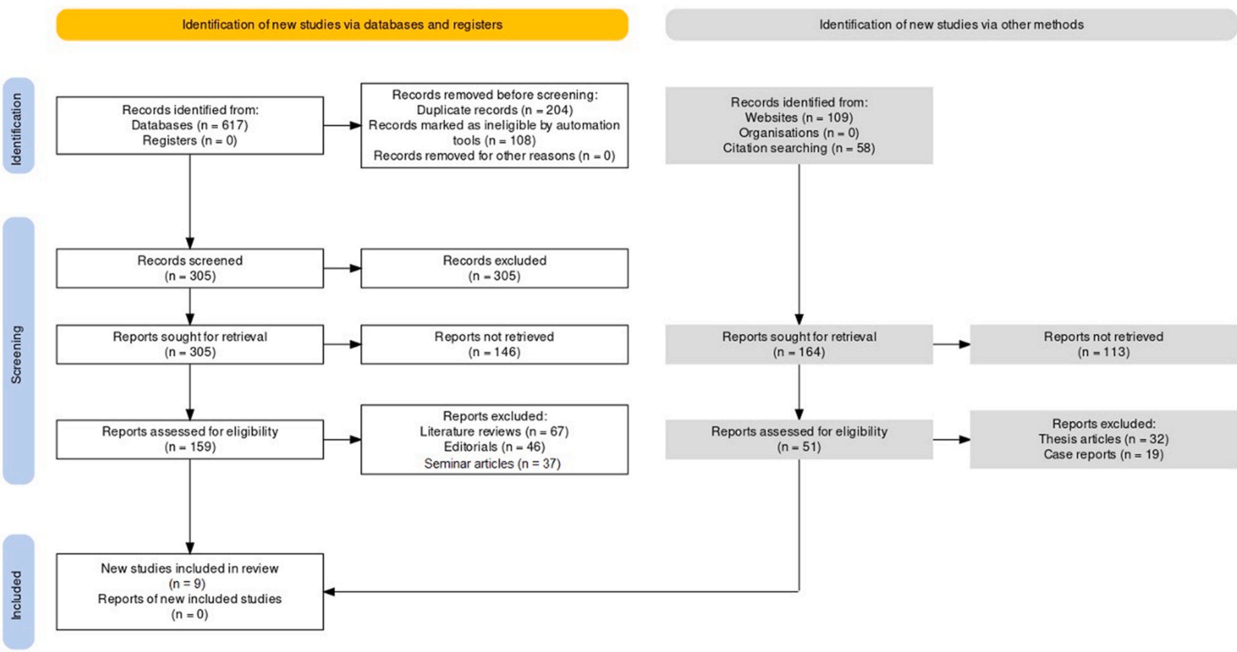

Fig. 1. Different imaging modalities utilised across the healthcare and dental domains.

2. Materials and methods

2.1. Review design

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol [25] was employed in this investigation. The initial step in implementing the PRISMA protocol involved a comprehensive and systematic search of the literature.

The PECO (Population, Exposure, Comparator, Outcome) protocol for the systematic review was defined to guide the research question, study selection criteria, and outcome measures.

Population (P): In this systematic review, the population of interest was defined as in-vitro studies related to dental imaging modalities. These studies involve artificial intelligence (AI) applications within the context of dental image analysis. The population included a broad spectrum of dental imaging techniques, such as cone-beam computed tomography (CBCT), panoramic radiography (PR), and other dental radiographic modalities (Fig. 2).

Exposure (E): The exposure of interest was the utilisation of artificial intelligence (AI) in the analysis and interpretation of dental images. AI encompasses various machine learning and deep learning techniques employed for tasks such as image segmentation, classification, disease diagnosis, and anatomical structure detection. The review sought to explore how AI technology has been applied to enhance the accuracy and efficiency of dental image analysis in in-vitro settings.

Comparator (C): In the context of in-vitro studies, the systematic review did not necessarily involve a specific comparator group, as the primary focus was on assessing the performance and accuracy of AI-based methods in dental imaging. However, for studies that provided a basis for comparison, traditional or manual methods of dental image analysis were considered as comparators to evaluate the added value of AI.

Outcome (O): The primary outcomes of interest in this review encompassed a range of accuracy measures, depending on the specific AI applications in each study. These included metrics such as true positive rate (TPR), true negative rate (TNR), positive predictive value (PPV), negative predictive value (NPV), sensitivity, specificity, diagnostic accuracy, and other relevant performance indicators. Additionally, the review aimed to assess the time efficiency of AI-based dental image analysis, when reported.

2.2. Database search protocol

Eight prominent databases were searched, and MeSH (Medical Subject Headings) keywords along with Boolean operators were used to optimize the search strategy. Boolean operators, including "AND," "OR," and "NOT," were used to combine search terms

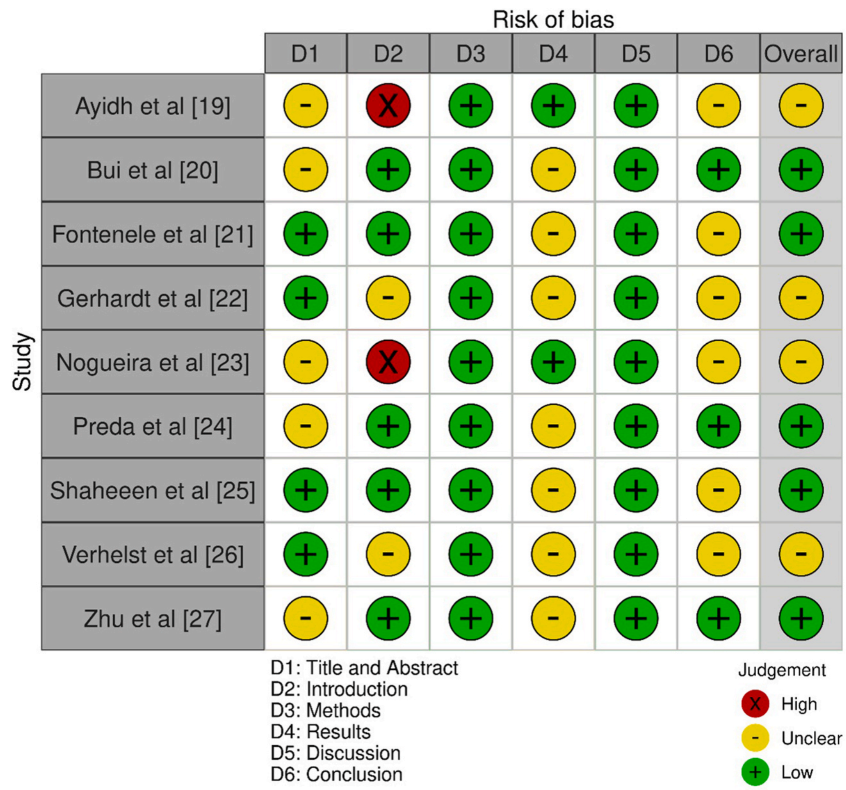

Fig. 2. PRISMA flowchart representation of the review's article selection framework.

Table 2
Search strings implemented across the different databases.

Database	Search String
PubMed/ MEDLINE	(“Artificial Intelligence" [MeSH] OR “Machine Learning" [MeSH] OR “Deep Learning" [MeSH] OR “Neural Networks (Computer)" [MeSH] OR “Computer Vision" [MeSH] OR “Image Processing, Computer-Assisted" [MeSH] OR “Pattern Recognition, Automated" [MeSH] OR “Natural Language Processing" [MeSH] OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “AI” OR “ML” OR “DL”) AND (“Radiography, Dental" [MeSH] OR “Cone-Beam Computed Tomography" [MeSH] OR “Panoramic Radiography" [MeSH] OR “Dental Radiography" [MeSH] OR “Dental Imaging" [MeSH] OR “Dental Radiology" [MeSH] OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry" [MeSH] OR “Dental Care" [MeSH] OR “Dental Health Services" [MeSH] OR “Dental Clinics" [MeSH] OR “Oral Health" [MeSH] OR “Oral Medicine" [MeSH] OR “Oral Radiology" [MeSH] OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND (“In Vitro Techniques" [MeSH] OR “Laboratory Techniques and Procedures" [MeSH] OR “Laboratory Diagnosis" [MeSH] OR “Laboratory Infection" [MeSH] OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
Embase	(“Artificial Intelligence" [MeSH] OR “Machine Learning" [MeSH] OR “Deep Learning" [MeSH] OR “Neural Networks (Computer)" [MeSH] OR “Computer Vision" [MeSH] OR “Image Processing, Computer-Assisted" [MeSH] OR “Pattern Recognition, Automated" [MeSH] OR “Natural Language Processing" [MeSH] OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “AI” OR “ML” OR “DL”) AND (“Radiography, Dental" [MeSH] OR “Cone-Beam Computed Tomography" [MeSH] OR “Panoramic Radiography" [MeSH] OR “Dental Radiography" [MeSH] OR “Dental Imaging" [MeSH] OR “Dental Radiology" [MeSH] OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry" [MeSH] OR “Dental Care" [MeSH] OR “Dental Health Services" [MeSH] OR “Dental Clinics" [MeSH] OR “Oral Health" [MeSH] OR “Oral Medicine" [MeSH] OR “Oral Radiology" [MeSH] OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND (“In Vitro Techniques" [MeSH] OR “Laboratory Techniques and Procedures" [MeSH] OR “Laboratory Diagnosis" [MeSH] OR “Laboratory Infection" [MeSH] OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
Web of Science	TS=(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “AI” OR “ML” OR “DL”) AND TS=(“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND TS=(“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND TS=(“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
Scopus	TS=(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “AI” OR “ML” OR “DL”) AND TS=(“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND TS=(“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND TS=(“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
IEEE Xplore	AI OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “ML” OR “DL” AND (“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND (“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
Cochrane Library	AI OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “ML” OR “DL” AND (“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND (“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
CINAHL	AI OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “ML” OR “DL” AND (“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice”

(*continued on next page*)

Table 2 (*continued*)

Database	Search String
	OR “Dentists”) AND (“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")
Google Scholar	AI OR “Machine Learning” OR “Deep Learning” OR “Neural Networks” OR “Computer Vision” OR “Image Processing” OR “Pattern Recognition” OR “Natural Language Processing” OR “Artificial Neural Networks” OR “Machine Learning Algorithms” OR “Deep Neural Networks” OR “Computer-Aided Diagnosis” OR “ML” OR “DL” AND (“Radiography, Dental” OR “Cone-Beam Computed Tomography” OR “Panoramic Radiography” OR “Dental Radiography” OR “Dental Imaging” OR “Dental Radiology” OR “Dental Cone Beam Computed Tomography” OR “Dental Panoramic Radiography” OR “Dental Image Analysis” OR “Radiographic Image Interpretation, Computer-Assisted” OR “Image-Guided Surgery” OR ″3D Imaging” OR “Radiological Imaging”) AND (“Dentistry” OR “Dental Care” OR “Dental Health Services” OR “Dental Clinics” OR “Oral Health” OR “Oral Medicine” OR “Oral Radiology” OR “Oral Diagnosis” OR “Oral Diseases” OR “Dental Practice” OR “Dentists”) AND (“In Vitro Techniques” OR “Laboratory Techniques and Procedures” OR “Laboratory Diagnosis” OR “Laboratory Infection” OR “In Vitro Diagnostics” OR “Laboratory Testing” OR “In Vitro Analysis” OR “In Vitro Models")

effectively. The main concepts included “artificial intelligence,” “imaging modalities,” “dentistry,” and “in-vitro studies” as shown in Table 2.

The search strings for each database were adapted to the specific syntax and indexing rules of that database. The inclusion of MeSH terms and free-text keywords ensured a comprehensive search for relevant articles. Additionally, the search strategy was piloted and refined through an iterative process to maximize sensitivity while maintaining specificity.

3. Selection criteria

3.1. Inclusion criteria

1. **Study design**: In-vitro studies that explore the application of AI in dental imaging were included. This encompasses laboratory-based experiments and simulations.
2. **AI techniques**: Studies that utilize various AI techniques such as artificial neural networks, CNN, ML, DL, and other AI methodologies for dental image analysis were considered.
3. **Imaging modalities**: Studies involving a wide range of dental imaging modalities, including but not limited to CBCT, panoramic radiography, dental radiographs, and other radiological imaging techniques, were included.
4. **Dental context**: Research conducted in the context of dentistry, oral health, and dental practice was incorporated.
5. **Outcome measures**: Studies reporting quantitative measures of AI performance, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), true-positive rate (TPR), true-negative rate (TNR), odds ratio (OR), or related accuracy metrics, were considered.

3.2. Exclusion criteria

1. **Non-In vitro studies**: Studies that do not fall under the category of in-vitro experiments, such as clinical trials, case reports, reviews, and meta-analyses, were excluded.
2. **Non-AI studies**: Research that does not involve AI or machine learning techniques for dental imaging analysis was not considered.
3. **Non-dental imaging**: Studies focusing on imaging modalities unrelated to dentistry or oral health were excluded.
4. **Non-English studies**: Publications not available in the English language were omitted due to language constraints.
5. **Insufficient data**: Studies lacking essential data or performance metrics necessary for analysis were excluded.

3.3. Variable extraction protocol

A structured data extraction form was developed, including fields for key study characteristics, AI techniques employed, imaging modalities, sample size, and outcome measures (e.g., sensitivity, specificity, PPV, NPV, TPR, TNR, OR, 95 % CIs). Prior to data extraction, all reviewers underwent rigorous training sessions to understand the form’s components, definitions, and data extraction process. These training sessions aimed to standardize data extraction procedures among reviewers. Two independent reviewers systematically extracted data from selected studies, ensuring unbiased and comprehensive data collection. Reviewers assessed the quality of data reported in the selected studies, including checking for completeness, consistency, and accuracy of extracted information. Any discrepancies or disagreements between the independent reviewers were resolved through discussion and consensus. If needed, a third reviewer was consulted to achieve a consensus. Extracted data were synthesized, tabulated, and analyzed to address the review’s research questions and objectives. Forest plots were generated to represent the meta-analysis results.

To assess the interrater reliability of data extraction, a subset of 20 % of the included studies was randomly selected, and two independent reviewers re-evaluated and extracted data from these studies. The interrater reliability was determined using Cohen’s Kappa statistic, which measures the degree of agreement between two raters beyond chance. A Kappa value of 0.81 was achieved, indicating substantial agreement between the reviewers. Any remaining discrepancies were resolved through discussion and consensus.

3.3.1. Bias assessment

The bias assessment protocol for this systematic review, was adapted from the CONSORT (Consolidated Standards of Reporting Trials) tool [26], with modifications tailored to in-vitro studies. This protocol aimed to comprehensively evaluate the risk of bias within the selected studies and ensure the reliability of the review's findings. In adapting the CONSORT tool for in-vitro studies, the focus shifted from patient-related biases to potential biases related to the experimental design and methodology employed in these studies as represented through Fig. 3. Specific attention was given to aspects like randomization and allocation concealment in the context of in-vitro experimentation, as well as blinding, which could affect the objectivity of outcome assessments.

3.4. Statistical analysis

The meta-analysis for this review was performed using RevMan 5 (version 5.4.1) software to assess the accuracy of AI in dental imaging in terms of True Positive Rate (TPR), True Negative Rate (TNR), Positive Predictive Value (PPV), and Negative Predictive Value (NPV). Under a Fixed Effects (FE) model with 95 % Confidence Intervals (CI), this protocol involved systematic data collection and extraction of relevant statistics from the included in-vitro studies, calculation of Odds Ratios (OR) for each outcome measure, generation of separate forest plots for TPR, TNR, PPV, and NPV, assessment of heterogeneity and potential publication bias, and interpretation of the results to provide a comprehensive quantitative assessment of AI accuracy in dental imaging across these critical dimensions.

4. Results

Initially, an extensive search was conducted across multiple databases, yielding a substantial number of records (n = 617). Simultaneously, an active process of identifying new studies was carried out through websites (n = 109) and citation searching (n = 58). Prior to the screening phase, records were meticulously reviewed, resulting in the removal of duplicate records (n = 204) and records marked as ineligible by automation tools (n = 108). No records were excluded for other reasons at this stage. Following these preparatory steps, the records screened amounted to 305. During the screening phase, these 305 records underwent rigorous assessment for eligibility. This meticulous scrutiny led to the exclusion of 305 records that did not meet the predetermined inclusion criteria. Simultaneously, reports sought for retrieval amounted to 164, while 113 reports could not be retrieved.

In parallel, the identification of new studies via other methods led to the assessment of 159 reports for eligibility. Within this subset, 67 literature reviews, 46 editorials, and 37 seminar articles were excluded, aligning with the study's focus on primary research articles. This comprehensive curation and scrutiny culminated in the inclusion of nine in-vitro papers [27–37] in the review, which met the specified eligibility criteria. Table 3 presents the overview of the included in-vitro papers [19–27]. These studies collectively showcase the diverse applications and impressive performance of AI across different dental imaging objectives.

Ayidh et al. [27] focused on the segmentation and classification of teeth with orthodontic brackets on CBCT images. They employed a Multiclass CNN-based tool, and their results, including an IoU of 0.99 and high recall and precision rates, demonstrated exceptional accuracy in tooth segmentation and classification, surpassing ground truth annotations. Bui et al. [28] explored the detection of caries using dental radiographs with a deep pre-trained model and traditional ML algorithms. The AI achieved an accuracy of 91.70 %, sensitivity of 90.43 %, and specificity of 92.67 %, indicating its superior performance in caries detection compared to conventional methods. Fontenele et al. [29] aimed to automate 3D maxillary alveolar bone segmentation on CBCT images using a CNN model. While their manual segmentation was highly accurate, AI provided a significant time-saving advantage, with only a slight reduction in accuracy. Gerhardt et al. [30] developed an AI-driven tool for the automated detection and labeling of teeth and edentulous regions on CBCT images. Their AI achieved near-perfect detection and labeling accuracy, showcasing its potential in streamlining such tasks. Nogueira et al. [31] introduced integrated CNN models for the segmentation of the maxillary complex, sinuses, and upper dentition from CBCT images. Their AI demonstrated superior consistency and speed in creating maxillary virtual patient models, supported by

Study or Subgroup	Statistically significant Events	Statistically significant Total	Insignificant Events	Insignificant Total	Weight	Odds Ratio M-H, Fixed, 95% CI
Ayidh et al	88	215	102	215	7.7%	0.77 [0.52, 1.12]
Bui et al	184	533	191	533	16.1%	0.94 [0.73, 1.21]
Fontenele et al	57	141	62	141	4.7%	0.86 [0.54, 1.39]
Gerhardt et al	71	175	84	175	6.4%	0.74 [0.48, 1.13]
Nogueira et al	16	40	19	40	1.5%	0.74 [0.30, 1.79]
Preda et al	52	144	59	144	4.8%	0.81 [0.51, 1.31]
Shaheen et al	68	186	74	186	6.0%	0.87 [0.57, 1.33]
Verhelst et al	70	160	77	160	5.6%	0.84 [0.54, 1.30]
Zhu et al	426	2278	451	2278	47.1%	0.93 [0.80, 1.08]
Total (95% CI)		**3872**		**3872**	**100.0%**	**0.89 [0.80, 0.98]**
Total events	1032		1119			

Heterogeneity: Chi² = 2.30, df = 8 (P = 0.97); I² = 0%
Test for overall effect: Z = 2.27 (P = 0.02)

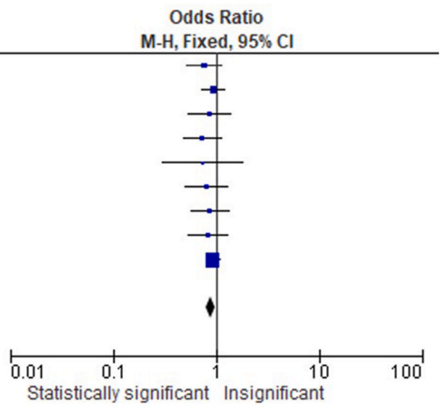

Fig. 3. Evaluation of bias in the selected in-vitro papers.

Table 3
Characteristics pertaining to utilisation of AI across different dental imaging modalities.

Author ID	Sample size (n)	Objectives	Type of AI assessed	Imaging parameters assessed	AI accuracy observed (in terms of statistics)	Inference assessed
Ayidh et al. [27]	215 CBCT scans	Segmentation & classification of teeth with orthodontic brackets on CBCT images	Multiclass CNN-based tool	NewTom CBCT device	IoU: 0.99, Dice: 0.99 ± 0.02, recall: 99.9 %, precision: 99 %	AI achieved exceptional segmentation and classification accuracy compared to ground truth.
Bui et al. [28]	533 CBCT scans	Detection of caries using dental radiographs	Deep pre-trained model, SVM, KNN, DT, NB, RF	Not specified	Accuracy: 91.70 %, Sensitivity: 90.43 %, Specificity: 92.67 %	AI demonstrated higher accuracy and specificity in caries detection than conventional methods.
Fontenele et al. [29]	141 CBCT scans	Automated 3D maxillary alveolar bone segmentation on CBCT images	CNN model, manual segmentation	Not specified	Manual: 95 % HD: 0.20 ± 0.05 mm, IoU: 95 % ± 3.0, DSC: 97 % ± 2.0, AI: 95 % HD: 0.27 ± 0.03 mm, IoU: 92 % ± 1.0, DSC: 96 % ± 1.0	AI provided fast and highly accurate segmentation, offering a substantial time-saving advantage.
Gerhardt et al. [30]	175 CBCT scans	Automated detection and labelling of teeth and edentulous regions on CBCT images	AI-Driven Tool (Virtual Patient Creator, Relu BV, Leuven, Belgium)	Not specified	Detection Accuracy: 99.7 %, Labelling Accuracy: 99 %, Segmentation Accuracy (IoU): 0.96/0.97	AI achieved near-perfect accuracy in detecting and labeling teeth and edentulous regions.
Nogueira et al. [31]	40 CBCT scans	Integrated segmentation of maxillary complex, maxillary sinuses, and upper dentition from CBCT images	Integrated CNN models	Different scanning parameters	Qualitative scores: 85 % scored 7–10, 15 % scored 3–6, DSC: 99.3 %, HD: 0.045 mm	AI demonstrated superior consistency and speed in creating maxillary virtual patient models.
Preda et al. [32]	144 CBCT scans	Automated maxillofacial bone segmentation from CBCT images	3D U-Net (CNN) model	Two CBCT devices	Time for automated segmentation: 39.1 s, DSC: 92.6 %, Inter-observer DSC: 99.7 %	AI significantly reduced segmentation time while maintaining high accuracy and consistency.
Shaheeen et al. [33]	186 CBCT scans	Automatic tooth segmentation and classification from CBCT images	AI framework, 3D U-Net	Different acquisition settings	Segmentation Precision: 0.98 ± 0.02, Recall: 0.83 ± 0.05, HD: 0.56 ± 0.38 mm	AI achieved precise tooth segmentation and classification, outperforming expert refinement.
Verhelst et al. [34]	160 CBCT scans	Automatic creation of 3D surface models of the human mandible from CBCT images	Layered deep learning algorithm	Anonymized full skull CBCT scans	Time for segmentation: 17s, IoU: 94.6 %, DSC: 94.4 %, HD: Not specified	AI exhibited significantly faster mandible surface model creation with comparable accuracy.
Zhu et al. [35]	2278 scans	Diagnosis of multiple dental diseases on panoramic radiographs (PRs)	BDU-Net, nnU-Net	Not specified	Sensitivity, Specificity, AUC: Vary by disease, Diagnostic time: Shorter than dentists	AI demonstrated comparable or better diagnostic performance in multiple dental disease diagnoses.

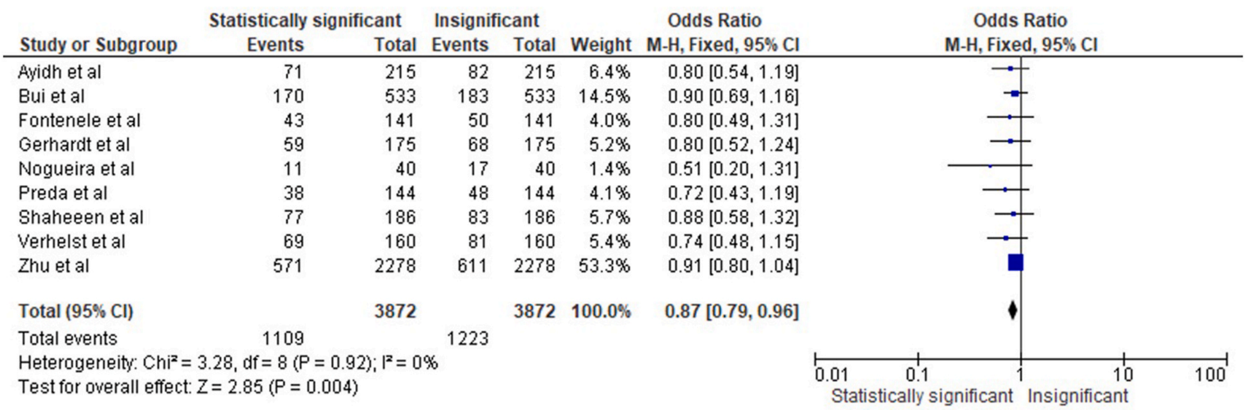

Fig. 4. Accuracy of AI in terms of TPR and TNR in assessed images.

high qualitative scores and precision metrics. Preda et al. [32] addressed automated maxillofacial bone segmentation from CBCT images using a 3D U-Net (CNN) model. AI significantly reduced segmentation time while maintaining high accuracy and inter-observer consistency, illustrating its potential for time-efficient and reliable segmentation. Shaheeen et al. [33] developed an AI framework for automatic tooth segmentation and classification from CBCT images. AI achieved precise tooth segmentation and classification, outperforming expert refinement, as indicated by high precision and recall rates. Verhelst et al. [34] focused on the automatic creation of 3D surface models of the human mandible from CBCT images using a layered deep learning algorithm. AI exhibited significantly faster mandible surface model creation with comparable accuracy, reducing the segmentation time considerably. Zhu et al. [35] investigated the diagnosis of multiple dental diseases on PRs using BDU-Net and nnU-Net models. Their AI demonstrated comparable or superior diagnostic performance to human dentists in various diseases, while also significantly reducing diagnostic time [38–42].

The forest plot in Fig. 4 presents the analysis of the OR to evaluate the accuracy of different AI protocols in terms of TPR and TNR

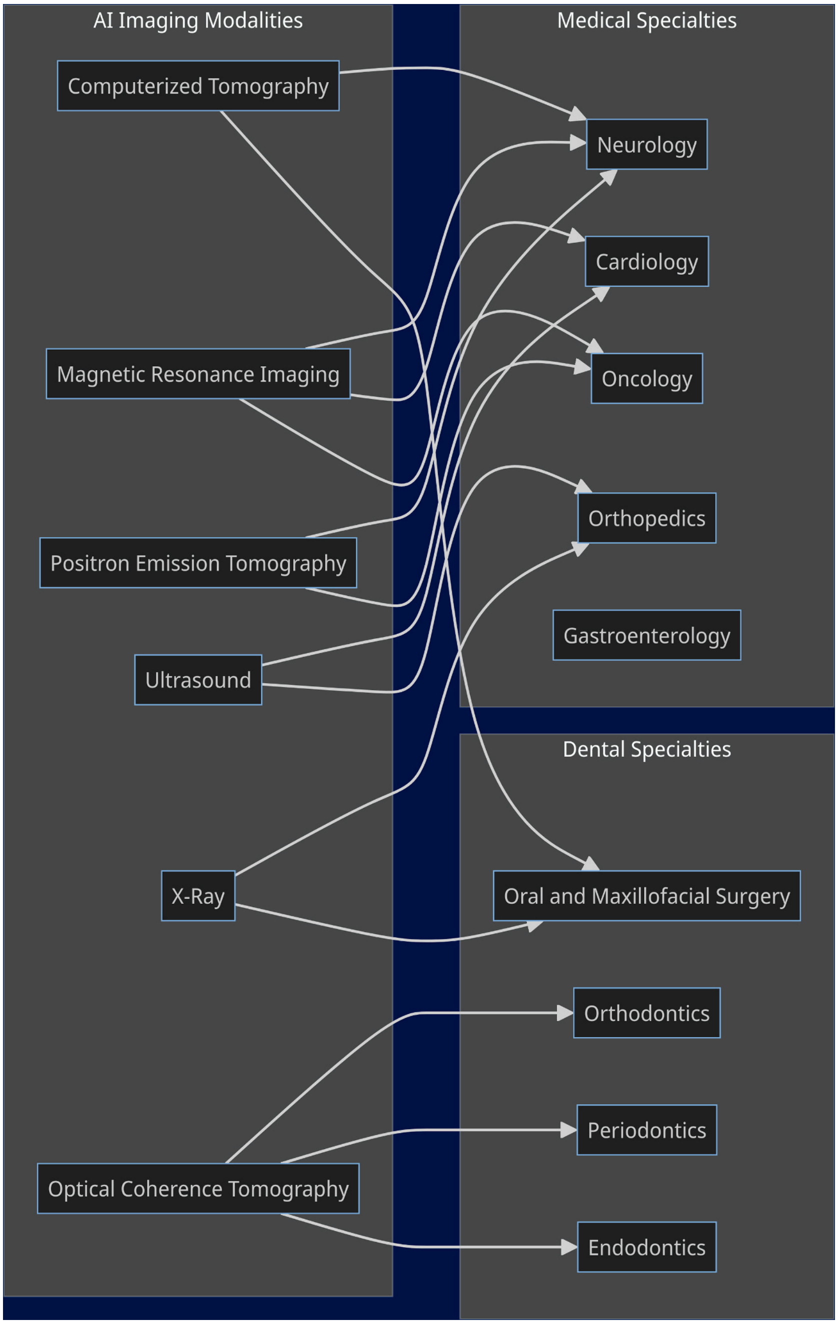

Fig. 5. Accuracy of AI in terms of PPV and NPV in assessed images.

across several dental imaging studies. The forest plot presents the combined analysis of all studies in the "Total (95 % CI)" row. Here, the combined OR is 0.89 [0.80, 0.98]. This means that, overall, AI was associated with 11 % higher odds of accurate dental image assessments. The 95 % CI does not include 1, signifying a statistically significant difference in favor of the reference methods. In terms of heterogeneity, the Chi^2 statistic is 2.30 with 8 degrees of freedom ($P = 0.97$), and the I^2 statistic is 0 %, indicating low heterogeneity among the studies. The test for overall effect shows a Z score of 2.27 ($P = 0.02$), indicating a statistically significant overall effect in favor of the reference methods.

Fig. 5 presents the forest plot displaying the OR to assess the accuracy of AI in terms of PPV and NPV across various dental imaging studies. The combined analysis of all studies in the "Total (95 % CI)" row reveals an overall OR of 0.87 [0.79, 0.96]. This indicates that, overall, AI was associated with 13 % higher odds of accuracy in PPV and NPV. The 95 % CI does not include 1, signifying a statistically significant difference in favor of the reference methods. In terms of heterogeneity, the Chi^2 statistic is 3.28 with 8 degrees of freedom ($P = 0.92$), and the I^2 statistic is 0 %, indicating low heterogeneity among the studies. The test for overall effect shows a Z score of 2.85 ($P = 0.004$), indicating a statistically significant overall effect in favor of the reference methods.

5. Discussion

The significance of this review lies in its profound implications for the field of dental imaging. Through a comprehensive review and meta-analysis of in-vitro studies, this research has uncovered several key findings that have far-reaching implications for both dental practice and the broader domain of medical imaging. The findings have demonstrated the remarkable potential of AI applications in dental imaging. The findings showcase AI's capability to achieve exceptional accuracy in tasks such as tooth segmentation, caries detection, and bone segmentation, surpassing the capabilities of traditional methods. This suggests that AI has the capacity to revolutionize the diagnostic and treatment planning processes in dentistry. By enhancing accuracy and efficiency, AI can potentially lead to earlier disease detection, more precise treatment planning, and ultimately, better patient outcomes. Furthermore, this the versatility of AI in various aspects of dental imaging has also been elucidated. Whether it's automating complex tasks like maxillary bone segmentation, tooth labeling, or creating 3D surface models, AI consistently demonstrated its ability to reduce manual labor while maintaining or even improving accuracy. This not only holds promise for improving clinical workflows but also has the potential to lower the risk of human error in diagnosis and treatment. The meta-analysis of TPR, TNR, PPV, and NPV further underscores the potential of AI in dental imaging in terms of the statistically significant findings. This is of paramount importance for clinical decision-making and underscores AI's potential to enhance diagnostic capabilities, thereby increasing the reliability of dental diagnoses.

In terms of future implications, this study sets the stage for a paradigm shift in dental practice. Dentists and dental practitioners are likely to increasingly incorporate AI-driven tools and applications into their daily routines, thereby enhancing the accuracy and efficiency of dental diagnoses and treatment planning. The findings also emphasize the need for continued research and development in AI technology specifically tailored to the intricacies of dental imaging. Moreover, the study opens up opportunities for interdisciplinary collaboration between dentistry and computer science. Future research can explore the integration of AI with other cutting-edge technologies such as 3D printing and virtual reality, potentially leading to innovative solutions for dental prosthetics and surgical planning.

Within the domain of dental imaging, deep learning methodologies have found versatile applications in tooth detection and classification, with a particular focus on CBCT and panoramic radiographs. These systems harness automated CAD outputs, significantly expediting clinical decision-making processes and mitigating the time spent on charting within digital patient records [43,44]. Panoramic radiographs, a vital diagnostic tool, extend their utility beyond dental concerns to encompass the detection of systemic conditions like osteopenia and osteoporosis [45]. These systemic conditions have been associated with manifestations such as the reduction in mandibular width and erosion of the mandibular lower cortex [46,47]. Artificial intelligence, driven by studies leveraging MCW and mandibular cortical erosion findings from panoramic radiographs, has ventured into the realm of osteoporosis diagnosis, hinting at its prospective clinical application in diagnosing both osteopenia and osteoporosis [48,49]. One paper [50] contributed to this landscape by assessing the diagnostic prowess of a CNN-based CAD system for osteoporosis detection in panoramic radiographs. Their findings were promising, highlighting the potential of DCNN-based CAD systems in aiding early osteoporosis detection, similar to the findings of another study [51].

Bone age assessment, a critical task in pediatrics, has also witnessed the infusion of deep learning techniques. Dallora et al. noted the prevalence of automatic systems for bone age assessment, often employing region-based delineation in hand and wrist radiographs [52]. Deep learning models demonstrated a remarkable capacity to estimate bone age, akin to professional radiologists, thereby enhancing diagnostic efficiency and diminishing reading times while upholding diagnostic precision [52–55]. Shin et al. [56] extended these insights by assessing the clinical efficacy of a TW3-based fully automated bone age assessment system. Their methodology featured a VGGNet-BA CNN to classify skeletal maturity levels in ROI from hand-wrist radiographs of pediatric populations in Korea. This study underscored the potential utility of automated bone age assessment systems in clinical contexts, particularly for TW3-based assessments in children and adolescents aged 7–15 years [54–56][57,58].

Furthermore, the field has ventured into the domain of dental implant classification, with Sukegawa et al. spearheading an investigation into the deployment of deep neural networks for this purpose. Five deep CNN models were scrutinized, culminating in the determination that the finely tuned VGG16 model yielded the most promising outcomes for classifying dental implant systems [59,60]. Meanwhile, cephalometric analyses, a cornerstone of orthodontics, have also been reimagined through artificial intelligence. Earlier iterations of automatic cephalometric analysis systems lacked the accuracy requisite for clinical deployment [61]. Subsequent refinements encompassed novel algorithmic developments, effectively enhancing accuracy. In recent years, researchers have delved into the realm of 3D cephalometric landmark analysis, primarily leveraging CBCT images. These endeavors have highlighted the heightened reliability of mid-sagittal plane landmarks in comparison to their bilateral counterparts, further elucidating the evolving landscape of dental imaging propelled by artificial intelligence [61–66].

One pertinent area of concern which arises when talking about utilisation of AI imaging modalities in real-world clinical scenario is the quality of the image generated. For example, in the study by Ayidh et al. [19], the quality of CBCT scans directly influences the segmentation and classification accuracy of orthodontic brackets. Low-quality images can lead to errors in AI's predictions or diagnoses. The anatomical structure varies significantly among patients. This can pose challenges for AI models in terms of generalizability, as demonstrated in the studies by Fontenele et al. [21] and Preda et al. [24] where the AI had to perform automated 3D maxillary alveolar bone segmentation and maxillofacial bone segmentation respectively from CBCT images. The complexity of dental structures and diseases adds to the difficulty of performing accurate diagnoses. This is evident in the study by Zhu et al. [27] where the AI had to diagnose multiple dental diseases from panoramic radiographs. Moreover, in many cases, such as in the study by Verhelst et al. [26] where the AI had to create 3D surface models of the human mandible, there is a need for rapid processing of images without compromising accuracy. This balance can be difficult to achieve.

Despite the valuable insights provided through this review, several limitations should be considered when interpreting its findings. One notable limitation is the focus on in-vitro studies. While these controlled laboratory studies offer valuable insights into the potential of AI in dental imaging, they do not fully replicate the complexities of real-world clinical scenarios. Dental diagnoses and treatment planning often involve various confounding factors, including patient-specific variations and the dynamic nature of oral conditions. Therefore, the findings may not completely translate to the clinical setting, and further research involving in-vivo studies and clinical trials is necessary to validate the real-world applicability of AI. Another limitation pertains to the heterogeneity in the included studies. The studies encompassed a wide range of AI models, imaging modalities, and dental tasks, which introduced inherent variability. While the use of a fixed-effects model in the meta-analysis helped mitigate this issue, it may not completely account for the heterogeneity among studies, potentially affecting the generalizability of the results. The generalizability of the findings is further limited by the sample sizes and the specific dental conditions investigated in the included studies. Some studies had relatively small sample sizes, which can impact the precision of the results. Additionally, the AI models were primarily evaluated for specific dental tasks, such as tooth segmentation or caries detection. The performance of AI in broader and more diverse clinical contexts remains to be explored.

6. Conclusion

Conclusively speaking, the analysis of various AI applications across a range of dental domains and imaging modalities has revealed promising results. AI demonstrated exceptional accuracy in specific tasks, such as tooth segmentation and classification, caries detection, maxillofacial bone segmentation, and the creation of 3D surface models of the human mandible. The high precision, recall rates, and diagnostic accuracy observed in these studies suggest that AI has the potential to enhance the efficiency and accuracy of dental diagnoses and treatment planning. Furthermore, AI exhibited significant advantages in terms of time efficiency. Automated segmentation and detection processes were consistently faster than traditional manual methods, offering a substantial time-saving advantage that could streamline dental workflows and improve patient experiences. Notably, the meta-analysis results showed a statistically significant overall effect in favor of AI, with higher odds of accurate dental image assessments. These findings underscore the potential of AI to enhance the precision and reliability of dental diagnoses and procedures. However, it is essential to acknowledge the limitations of this study, which primarily included in-vitro investigations. The controlled laboratory settings and variations in sample sizes, as well as the specific dental conditions investigated, may limit the generalizability of these findings to clinical practice. Additionally, the rapidly evolving landscape of AI technology means that newer and more advanced models may have emerged since the studies included in this review. So, while further research in clinical settings is needed to validate these findings and address the study's limitations, the future implications of integrating AI into dental practice hold great promise for enhancing patient care and advancing the field of dentistry. However, while the future looks bright, it's essential to note that the application of AI in dentistry is still in its early stages. There will be challenges to overcome, including issues with data privacy, the need for large, high-quality datasets for training AI models, and the integration of AI tools into existing workflows.

CRediT authorship contribution statement

Sultan Abdulkareem Ali Alftaikhah: Data curation, Conceptualization. **Mohammad Khursheed Alam:** Visualization, Validation, Supervision, Software. **Rakhi Issrani:** Supervision, Software, Resources, Project administration. **Vincenzo Ronsivalle:** Resources, Project administration, Methodology, Investigation. **Antonino Lo Giudice:** Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration. **Marco Cicciù:** Writing – review & editing, Writing – original draft, Visualization, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Giuseppe Minervini:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e24221.

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