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SYSTEMATIC REVIEW

Advancements in artificial intelligence algorithms for dental implant identification: A systematic review with meta-analysis

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ABSTRACT

Statement of problem. The evidence regarding the application of artificial intelligence (AI) in identifying dental implant systems is currently inconclusive. The available studies present varying results and methodologies, making it difficult to draw definitive conclusions.

Purpose. The purpose of this systematic review with meta-analysis was to comprehensively analyze and evaluate articles that investigate the application of AI in identifying and classifying dental implant systems.

Material and methods. An electronic systematic review was conducted across 3 databases: MEDLINE/PubMed, Cochrane, and Scopus. Additionally, a manual search was performed. The inclusion criteria consisted of peer-reviewed studies investigating the accuracy of AI-based diagnostic tools on dental radiographs for identifying and classifying dental implant systems and comparing the results with those obtained by expert judges using manual techniques—the search strategy encompassed articles published until September 2023. The Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool was used to assess the quality of included articles.

Results. Twenty-two eligible articles were included in this review. These articles described the use of AI in detecting dental implants through conventional radiographs. The pooled data showed that dental implant identification had an overall accuracy of 92.56% (range 90.49% to 94.63%). Eleven studies showed a low risk of bias, 6 demonstrated some concern risk, and 5 showed a high risk of bias.

Conclusions. AI models using panoramic and periapical radiographs can accurately identify and categorize dental implant systems. However, additional well-conducted research is recommended to identify the most common implant systems. (J Prosthet Dent xxxx;xxx:xxx-xxx)

Dental implants have high long-term success and survival rates, making them a popular choice for the oral rehabilitation of partially and completely edentulous patients.[1–6] With the increased number of patients rehabilitated with implant-supported prostheses, complications are inevitable.[7–10]

The frequency of significant mechanical complications, such as screw or implant fracture, and biological complications, such as peri-implantitis, is progressively and unavoidably rising, impacting long-term success.[11,12] Hence, the dental community is increasingly concerned about dental implant-related complications, which pose a significant public health issue and are associated with substantial socio-economic costs.[13,14]

The dental implant manufacturer, system, design, and width must be determined before these complications can be resolved or a replacement implant-supported prosthesis provided. Identifying dental implant types can be challenging because dentists may have placed different implant brands for the same patient, and information may need to be shared across countries.[15,16] Implant identification difficulty could be attributed to dentists not providing relevant documents, patients misplacing these documents, or the lack of information from the dentist or manufacturer.[16] Consequently, when complications occur, dentists may

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Clinical Implications

In clinical settings, AI technology may enable the accurate distinction of various implant brands using periapical and panoramic radiographs.

struggle to identify implant systems, leading to more invasive treatment methods.[17–19] Moreover, dental implant identification can be beneficial for forensic purposes.[20]

Despite the widespread use of radiographs to identify implant systems, their distortion, haziness, and noise make it difficult to distinguish implants with a similar shape and structure.[21–23] Many implant systems are available in the market, complicating their recognition.[24] Thus, a reliable technique of identifying implant systems is needed.

Artificial intelligence (AI) and deep learning methods are beneficial in healthcare; they can analyze and classify complex data using sophisticated algorithms that imitate human neurological activities.[25] Convolutional neural networks (CNNs) are computer models trained to recognize stored photographs through computer calculations and have been recognized as the most recent fundamental models of artificial neural networks and deep learning.[26–31] CNNs have been applied to several domains of dentistry,[32–34] have demonstrated efficacy in the identification and categorization of visual patterns inside images, and can undergo training to detect particular patterns without the need for human participation.[33,34]

Systematic reviews have been published to explore the use of AI in prosthodontics, including its applications as an automated diagnostic tool, predictive measure, and classification tool.[35,36] Regarding implant dentistry, a systematic review revealed the role of AI applications in optimizing implant design and developing prediction models to determine osteointegration success from patient risk factors.[37] However, regarding the application of AI in the identification of dental implants, a previous review assessed only 7 studies with limited types of implants analyzed.[37] As there has been a rise in the dissemination of information concerning this topic and its application, the present systematic study was performed.

This systematic review aimed to identify the available efficacy of AI algorithms for identifying and classifying dental implant systems. The research hypothesis was that AI can help identify different dental implant designs with an accuracy of not less than 90%.

MATERIAL AND METHODS

This systematic review used a systematic approach to assess the current state of the effectiveness of AI algorithms in identifying and classifying dental implant systems. The review followed the Joanna Briggs Institute (JBI) methodology for diagnostic test accuracy[38] and the preferred reporting items for systematic reviews and meta-analyses of diagnostic test accuracy (PRISMA-DTA) guidelines.[39] The systematic review protocol is available in the International Prospective Register of Systematic Reviews (PROSPERO): CRD42023479106.

A search for relevant studies was conducted without time or language restrictions; the most recent search was conducted in September 2023. The search results were imported to a software program (EndNote; Clarivate) to eliminate duplicate records. The review question, population, index test, reference test, diagnosis of interest criteria (PIRD) framework, eligibility criteria, online databases searched, keywords used for searching, and manual search sources are presented in Table 1.

Two reviewers (A.Y.A., R.A.) screened the titles and abstracts of identified articles using predetermined eligibility criteria. If additional information was required, the reviewers assessed the full text of the articles. The reviewers examined potentially relevant articles and agreed on the final selection for further analysis. In the event of divergent opinions between the 2 reviewers at any point during the process, a third reviewer, (W.I.) facilitated conflict resolution through discourse.

Based on the JBI recommendation, the quality assessment of diagnostic accuracy studies-2 (QUADAS-2) tool was used to assess the quality of included articles against the predefined criteria to consider individual sources of risk of bias. The QUADAS-2 evaluates the risk of bias and applicability concerns in 4 key domains: patient selection, index test, reference standard, and flow and timing (Supplemental Table 1, available online). The QUADAS-2 questions were answered by “Yes,” “No,” or “Some concern,” helping to evaluate the quality of the included studies and the risk of bias in each domain. A reviewer (R.A.) conducted the initial assessment in the data extraction process, followed by a separate evaluation by a second reviewer (A.Y.A.). A third reviewer (D.E.) resolved any conflicts or discrepancies during the assessment.

The data from the included studies were extracted by using a standardized data extraction form. Information included study identity, radiographic modalities, data set size (training, validation, test), and the individuals responsible for executing and interpreting the index tests (including numbers and expertise). Additionally, dental implant systems and AI models sensitivity, specificity, and accuracy of the AI model and data related to quality assessment were extracted.

For meta-analyses across descriptive studies, accuracy was expressed as a percentage with the 95% confidence interval (CI) for every study and the weighted accuracy percentage with the 95% CI across all studies. Meta-analysis for descriptive studies was done using a statistical software program (Jamovi version 2.3.21 for MS Windows; https://www.jamovi.org).[40]

Table 1. Review question, PIRD framework, eligibility criteria, online databases searched, and keywords used for searching and manual search sources

Item	Description
Review question	What is the accuracy of artificial intelligence models in identifying dental implant systems using periapical and panoramic radiographs?
PIRD framework (Population, Index test, Reference test, Diagnosis of interest)	Population: Periapical and panoramic radiographs of patients who underwent dental implant treatment; Index test: a diagnostic tool based on AI; Reference test: experts' judgment; and Diagnosis of interest; accuracy of identification and classification of dental implant systems.
Eligibility criteria	– Inclusion criteria: diagnostic clinical, retrospective, or cross-sectional studies that examined the accuracy of diagnostic tools utilizing artificial intelligence algorithms on dental radiographs. These studies focused on identifying and classifying dental implant systems and compared the performance of these AI-based tools to manual techniques conducted by expert judges. – Exclusion criteria: review articles, letters, expert opinions, and articles discussing AI applications in dental fields other than dental implant identification.
Database searched	PubMed, Web of Science, and Cochrane
Keywords used for searching	The search terms were developed based on MeSH keywords related to AI and dental implants: "algorithm" OR" algorithm*" OR "artificial intelligence" OR "AI" OR "automatic" OR "automated" OR "semi-automatic" OR "semi-automated" OR "deep learning" OR "Convolutional neural network" OR CNN OR "machine learning" AND "Dental implant" OR "oral implant" OR "osseointegrated implant.", and the search strategy was customized for each database after a limited primary search.
Additional manual searches	– The reference lists of all related articles – Relevant journals, including Journal of Prosthetic Dentistry, International Journal of Prosthodontics, Journal of Dentistry, Journal of Oral Rehabilitation, Journal of Prosthodontics, Journal of Prosthodontic Research, Journal of Periodontology, Journal of Clinical Periodontology, Journal of Oral Implantology, International Journal of Oral Maxillofacial Surgery, International Journal of Oral Maxillofacial Surgery, International Journal of Oral Maxillofacial Implants, Implant Dentistry, International Journal of Implant Dentistry, European Journal of Oral Implantology, Clinical Oral Investigations, Clinical Implant Dentistry and Related Research, Journal of Biomechanics, Journal of Clinical Medicine, and applied sciences. – The System for Information on Grey Literature in Europe (OpenGrey)

RESULTS

Of the 4009 references obtained through an electronic database search, 2444 remained after removing duplicates. After title and abstract screening, 48 articles were selected; a second screening resulted in 24 eligible records, of which 3 were excluded after full-text screening and 1 article was added via hand searching, resulting in 22 eligible articles.[16,19,20,41–59] These articles described the use of AI in identifying dental implants through either periapical[16,20,41–44,57,58] or panoramic[19,45–50,56] radiographs, and some studies used both types of radiographs.[51–55,59] The number of articles identified at the various review stages can be seen in the PRISMA flowchart (Fig. 1).

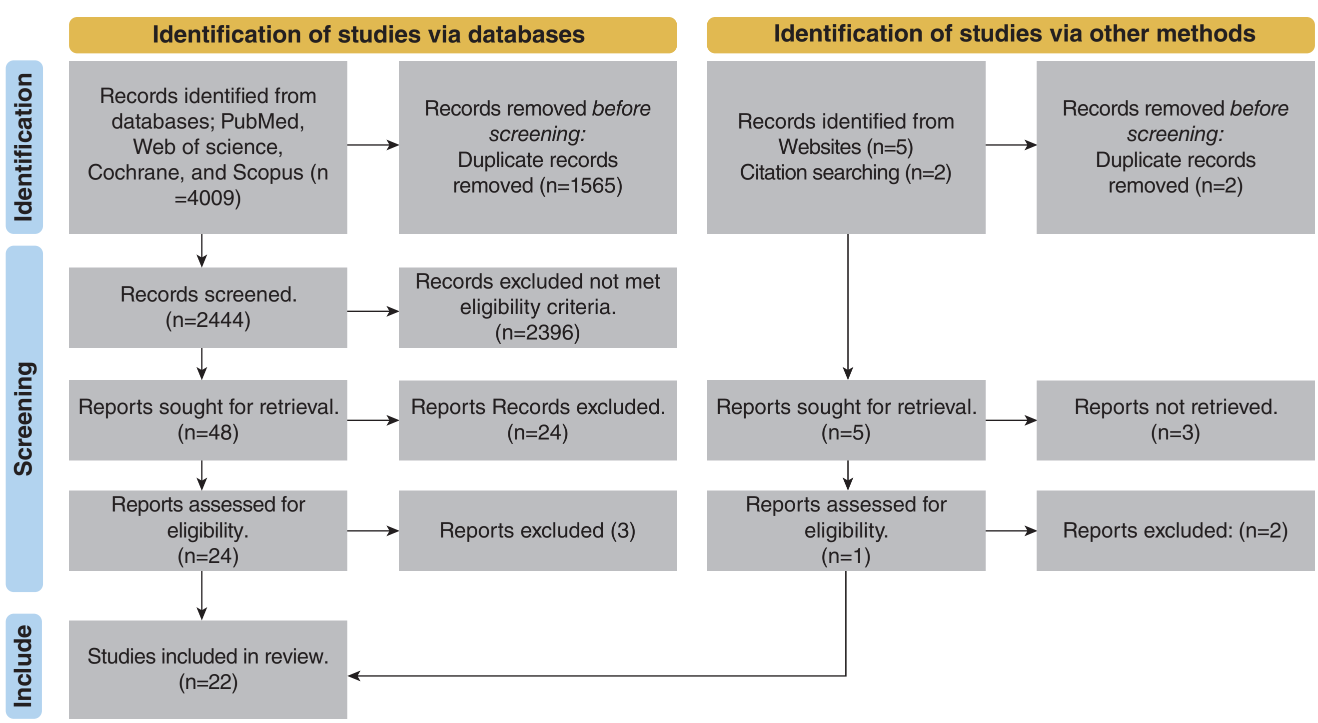

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) flow indicating number of studies at different review stages.

The characteristics of the included studies are summarized in chronological order from 2015 to 2023 in Table 2. The total number of implants included in 20 studies,[16,19,20,41,42,44,45,47–59] was 287 676; in 2 studies,[43,46] the exact number of implants was not specified. Of the included 22 studies, 9 studies reported the individuals who interpreted the reference tests,[20,45,47,51–53,57–59] including periodontists, surgeons, prosthodontists, residents, general dentists, and board-certified oral and maxillofacial radiologists. The implant systems identified and the AI models tested are presented in Table 3. The validation techniques consisted of a machine learning approach,[41] training validation process and cross-entropy curves,[20,53] CPUs,[54] 4-fold,[19,50] 5-fold,[55,56] and 10-fold,[51] Google Cloud's n1-standard-8 machine with NVIDIA Tesla V100,[58] and custom automated DL engine,[59] cross-validation protocols.

A risk of bias assessment of each domain for every involved study is presented in Figure 2, and Supplemental Table 2 (available online) reveals the detailed assessment. The QUADAS-2 tool critical appraisal checklist for diagnostic accuracy studies showed a low risk of bias among the studies. Regarding index tests and reference standard and test, flow, and timing domains, all studies had a 100% low risk of bias. Conversely, 5 studies[41,43,44,49,56] showed a high risk of bias in the patient selection domain, and 6 studies demonstrated some concern risk.[16,19,45,47,50,55] The overall risk of bias is shown in Supplemental Figure 1 (available online).

Concerning the article selection procedure by evaluating titles and abstracts, a high degree of concordance was seen between the 2 reviewers (Cohen kappa =.95, $P<.001$). Similarly, upon examining the complete texts of the articles, high agreement was observed between the 2 reviewers (Cohen kappa =1, $P<.001$).

Sensitivity and specificity across the studies ranged from 33% to 100% and 70 to 98.7%, respectively. The area under curve (AUC) varied among the studies, ranging from 71% to 100%. The meta-analysis encompassed 10 studies,[16,19,20,42,45,48,50–53,] that collectively examined the accuracy of dental implant identification had an overall accuracy of 92.56% (range 90.49% to 94.63%) (Fig. 3).

DISCUSSION

AI-based models may offer a solution to identifying dental implant systems from radiographs, particularly in patients where clinical information is unavailable. By using object-detection algorithms, AI algorithms can efficiently analyze images and assist dentists in resolving complications and prosthetic difficulties associated with dental implants, thus reducing human error and improving treatment workflows.[33,34]

This systematic review aimed to assess the efficiency of AI algorithms in identifying and classifying dental implant systems, including the 22 studies,[16,19,20,41–59] that assessed the accuracy of AI algorithms and provided valuable insights into the potential of AI technology in this context. Based on the findings of this review, the utilization of AI algorithms to identify and classify dental implant systems has shown promising results.

An overall accuracy of dental implant identification of 92.56% (range 90.49% to 94.63%) was determined, thus supporting the hypothesis that AI can achieve an accuracy of not less than 90% in identifying various designs of dental implants. Six studies,[16,50,51,53] reported high accuracy rates, highlighting the robust performance and reliability of AI algorithms for this application. Notably, Lee et al[53] reported an accuracy rate exceeding 98.4% by using a deep convolutional neural network architecture. Similarly, Kim et al[16] focused on classifying implant fixtures in periapical radiographs and reported an accuracy rate of 95.5%. These findings underscore the effectiveness of AI algorithms in identifying dental implants precisely.

However, some studies in the meta-analysis reported relatively lower accuracy rates,[19,42,45,52] possibly because of dataset limitations, radiograph quality variations, and challenges associated with differentiating between similar implant shapes. To enhance the reliability and accuracy of AI algorithms, future research should address these limitations and explore strategies to mitigate their impact.

Twelve studies[41,43,44,46,47,49,54–59] were excluded from the meta-analysis because insufficient information was provided regarding essential statistical measures. Reporting all necessary statistical measures, including confidence intervals, is recommended to enhance the precision and reliability of study findings and improve the overall quality and transparency of research in this field.

The included studies encompassed diverse methodologies and algorithms, encompassing image processing techniques and deep learning models. Image processing-based frameworks such as the one developed by Morais et al[49] have demonstrated promise in accurately identifying dental implants. As explored by Kong et al,[49] Kohlakala et al,[55] and Kim et al,[44] deep learning algorithms have exhibited reasonable accuracy rates and highlighted the potential for effective implant classification.

While most studies primarily used periapical or panoramic radiographs, 1 study provided insights into the accuracy of an automated deep-learning algorithm using a large-scale multicenter dataset.[59] This adds to the reliability and generalizability of the findings and suggests that both panoramic and periapical radiographs can be

Table 2. Characteristics of included studies

Study ID	Dental Implant Systems	Radiographic Modality	AI Method	Data Set Size (Training, Validation, Test)	Reference Test. Interpretation No. (Expertise)	Results (Sensitivity, Specificity, Accuracy)	AUC
Morais et al, 2015[41]	NR	Periapical	k-NN classifier	601 (1.8%, 20.7%, 77.5%)	NR	NR,NR, 91%	NR
Kim et al, 2020[16]	Brånemark MK, TiUnite; Dentium Implantium; Straumann BLT	Periapical	Pretrained CNN (SqueezeNet, GoogLeNet, ResNet-18, MobileNet-v2, and ResNet-50)	801 (60%, 20%, 20%)	NR	NR, NR, 98%	NR
Lee and Jeong, 2020[51]	Osstem TSIII; Dentium Superline; Straumann BL	Periapical, Panorama	Fine-tuned and pre-trained deep CNN architecture (GoogLeNet Inception-v3)	10,770 (40%, 40%, 20%)	1 (Periodontist)	95.3%, 97.6%, 99.5%	97%
Lee et al, 2020[52]	Astra OsseoSpeed TX; Dentium Implantium; Superline; TSIII; SLActive BL; SLActive BLT	Panoramic, periapical	Trained automated DCNN using Neuro-T version 2.0.1 (Neurocle Inc.)	11,980 (80%, NR, 20%)	25 (Periodontists, periodontology residents, and residents from other disciplines)	95%, 85%, 91.1%	95%
Said et al, 2020[20]	Nobel Biocare NobelActive [NNA], Brånemark System [NBS]; Straumann BL, TL; Zimmer Biomet Dental, Tapered Screw-Vent [ZTSV], SwissPlus [ZSP]	Intraoral radiographs	Pretrained GoogLeNet Inception v3 CNN network	1206 (40%, 40%, 20%)	NR (Surgeons)	93.5%, 94.2%, 93.8%	93%
Sukegawa et al, 2020[19]	Zimmer Full Osseotite; Dentsply; Astra EV, TX, Microthread; NobelBiocare MKIII, Nobel Replace CC, Replace Select Tapered; Kyocera Finesia; Straumann TL	Panorama	CNN models (specifically, basic CNN with three convolutional layers, VGG16 and VGG19 transfer-learning models, and finely tuned VGG16 and VGG19)	8859 (75%, NR, 25%)	NR	92.8%, 90.7%, 93.5%	100%
Takahashi et al, 2020[45]	Nobel Biocare MK III, IIIG, MKIV, SG; Starumann BL; GC Genesio	Panorama	object detection algorithm (Yolov3) (TensorFlow and Keras deep-learning libraries)	1282 (80%, NR, 20%)	1 (Prosthodontist)	82%, NR, 85%	72%
Benakatti et al, 2021[46]	Osstem TS III SA Regular; TS III SA Medium; Noris Medical Tuff	Panorama	Hu and eigenvalues (Supervised machine learning, SVM, KNN, X boost, and logistic regression classifiers)	NR (80%, NR, 20%)	NR	NR, NR, 76%	NR
Lee et al, 2021[53]	NR	Panoramic, periapical	VGGNet-19, GoogLeNet Inception-v3, and automated DCNN	251 intact and 194 fractured (60%, 20%, 20%)	3 (Periodontists and prosthodontist)	100%, 96%, NR	97%
Lee et al, 2022[47]	Straumann SLActive BL, BLT; Dentium Implantium, Superline; Astra OsseoSpeed TX, Osstem TSIII	Panoramic	Auto-DL algorithm (Neuro-T 2.0.1, Neurocle Inc., Seoul, Korea).	7145 (80%, 20%, NR)	44 (Periodontists, periodontology residents, and general dentists)	100%, 98%, 98%	NR
Santos et al, 2021[42]	Straumann; SIN; Neodent	Periapical	deep CNNs, deployed by using "Keras" and "Tensorflow" frameworks (Google)	1860 (80%, NR, 20%)	NR	95.6%, 87.3%, 99%	NR
Sukegawa et al, 2021[48]	Brånemark Mk III; OSSEOTITE; Astra EV, TX; NobelBiocare Replace Select Tapered, Nobel Replace; Astra MicroThread; Straumann TL; Finesia; Straumann BL	digital panoramic radiographs	ResNet18, 34, 50, 101, and 152 deep convolutional neural network models.	9767 (60%, 20%, 20%)	NR	98%, NR, 99%	99%
Ayman et al, 2022[43]	Nucleoss; Implant Swiss; Implance; Bego	Periapical radiographs	Three CNN architectures Resnet50V2, Xception, and VGG16	NR (70%, 15%, 15%)	1 (NR)	100%, NR, 100%	
Guo et al, 2022[54]	Bego; Bicon; Straumann	Periapical, Panorama	VGG16, VGG16-GAP, and TVGG15	935 (59%, 19%, 21%)	NR	79%, NR, 89%	
Kim et al, 2022[44]	Dentium Superline; Osstem TS III; Straumann BL	Periapical	DCNN YOLOv3 (You Only Look Once version 3	355 (72%, 8%, 20%)	NR	94.4%, 97.9%, 96.7%	
Kohlakala et al, 2022[55]	Straumann Anthogyr; Astra; MIS; Nobel Biocare	Periapical, Panorama	fully convolutional network FCN-1	483 (70%, 13%, 17%)	NR	90.98%, NR, 94.06%	95%
Kong et al, 2022[49]	Bicon; BioHorizons Point Implant, LITSS410D; Zimmer BIOMET 3i LLC, Biotem Dental; Dentis; Dentium; Dentsply Xive S plus; Dio Implant; Hiossen Implant, IBS Implant; MegaGen Implant; Neobiotech; Nobel Biocare; Osstem Implant; Straumann; Thommen Medical; Zimmer Biomet Dental	Panoramic radiographs	Built using EfficientNet and Meta Pseudo Labels techniques. Submodels of EfficientNet included EfficientNet-B0 and EfficientNet-B4.	45396 (80%, 20%, NR)	NR	NR, NR, 89.4%	NR

Table 2 *(Continued)*

Study ID	Dental Implant Systems	Radiographic Modality	AI Method	Data Set Size (Training, Validation, Test)	Reference Test. Interpretation No. (Expertise)	Results (Sensitivity, Specificity, Accuracy)	AUC
Sukegawa et al, 2022[50]	Full OSSEOTITE; Astra EV, TX, MicroThread; Branemark Mk III; Kyocera Finesia, POIEX; NobelBiocare Replace Select Tapered, Nobel Replace CC; Straumann TL, Straumann BL	Digital dental panoramic radiograph	ResNet18, ResNet18+ABN, ResNet50, ResNet50+ABN, ResNet152, ResNet152+ABN	10191 (60%, 20%, 20%)	NR	96%, NR, 97%	99%
Tiryaki, et al, 2023[56]	Osstem Implant; Implance AGS; Implant Direct Envista; Nucleoss Implant; Bego Implant Systems	Panoramic Radiographs	CNN, VGG-16, VGG-19, ResNet-50, ResNet-101, and Google Network (GoogleNet)	11904 (NR, NR, NR)	NR	96.4%, 99.6%, 99.2%	NR
Hsiao et al, 2023[57]	BioHorizons Legacy implant, Tapered Pro; Straumann BL, BL Tapered, Standard Straumann, Tapered Effect; Nobel Biocare Active, Parallel CC, Replace CC, Replace Select Straight, Replace Select Tapered, Speedy Groovy, Speedy Replace	Periapical Radiograph	MnasNet, ShuffleNet, MobileNet, AlexNet, VGG, ResNet, DenseNet, SqueezeNet, ResNeXt, Wide ResNet	657 (75%, NR, 25%)	1 (Periodontist)	NR, NR, 90%	NR
Kong 2023[58]	Osstem TSIII and USII; Zimmer Osseotite EXternal Biomet 3i LLC; Dentsply Sirona Xive S plus	Periapical Radiographic	Cloud-based AutoML and fine-tuned CNN algorithms	4800 (80%, 10%, 10%)	1 (Prosthodontist)	NR, 96%, 98%	NR
Park et al, 2023[59]	Neobiotech; Nobel biocare; Dentsply; Dentium; Dioimplant; Megagen; Straumann; Shinhung; Osstem; Warantec	Panoramic and Periapical Radiographic Images	Automated DL algorithm	156,965 (80%, 10%, 10%)	1 (Oral and maxillofacial radiologist)	NR, NR, 88.53%	88%

AI, Artificial intelligence; AUC, Area under curve; BL, Bone Level; BLT, Bone level/Tissue level; CNN, Convolutional neural network; KNN, k-nearest neighbor; NR, Not reported; SVM, Support vector machine; TL, Tissue level; VGG, Visual Geometry Group.

Table 3. Implant systems identified and AI models tested in included studies

Dental Implant systems	Bicon (IITSS510D, POF 3008, POF3008Q)[49,54] BioHorizons (LITSS410D,[49,57] Point implant[49,57], Legacy implant,[57] Tapered Pro[57]) Dentium (Implantium,[16,47,49,52,59] Superline[44,47,51,52]) Dentsply (OsseoSpeed TX,[47,52] Astra EV, TX, Microthread,[19] Astra EV,[48,50] Astra TX,[48,50] Astra MicroThread[19,48,50] Xive S plus[49,58]) Dio Implant (SFN3808H,[49] MST 18104,[49] UF,[59] UF II[59]) Implant Direct (Envista)[56] Kyocera (Finesia,[19,48,50], POI EX[50]) MegaGen Implant (EF4011P, TS3M3508C),[49] (Any ridge, Anyone internal, Anyone external, Exfeel external)[59] Neobiotech (EB3513A, POF4007Q)[49], (IS I, IS II, IS III, EB)[59] NobelBiocare (NobelActive[20,57], MKIII, SG, CC,[19] MK III, IIIG, MKIV, SG,[45] Replace Select Tapered,[19,48,50,57] Nobel Replace CC[48,50,57], Brånemark Mk III[48,50] Brånemark MK TiUnite,[16] Brånemark system,[20,57] Parallel CC[57] Replace Select Straight[57] Speedy Groovy,[57] Speedy Replace[57]) Nucleoss (T6 Standard)[43,56] Osstem (TS III[44,46,47,49,51,56,58,59], US II[49,59], GS II,[59] US III[59]) Straumann (BLT,[16,47,52] BL,[20,44,45,47,48,50–52,57] TL,[19,20,48,50] Anthogyr[55] BL Tapered[57] Standard Straumann[42,54,57] Tapered Effect[57]) Shinhung (luna)[59] Zimmer (Biomet Dental,[20,49] Full Osseotite,[19,50] BIOMET 3i LLC[49,58] SwissPlus: (ZSP),[20] Tapered Screw-Vent [ZTSV][20]) Miscellaneous: Implant Swiss,[43] GC Genesio,[45] Noris Medical Tuff,[46] Neodent,[42] Implance AGS,[43,56] Implant Systems (Bego),[43,54,56] MIS,[55] Biotem.[49] Dentis,[49] Hiossen Implant,[49] IBS Implant,[49] SIN,[42] Thommen Medical,[49] Warantec.[59]
AI Models	Classical Machine Learning: k-nearest neighbor (kNN) classifier,[41,46] logistic regression classifiers,[46] Support Vector Machine (SVM),[46] XG Boost[46] Convolutional Neural Networks (CNNs): AlexNet,[57] Automated DL algorithm (Neuro-T)[47,59] Cloud-Based Automl,[58] DenseNet,[57] EfficientNet,[49] Fine-tuned CNN,[51,58] Fully convolutional network FCN-1[16] GoogLeNet,[16,20,51,53,56] Meta Pseudo Labels algorithms[49] MnasNet,[57] MobileNet,[57] ResNet,[50,56,57] ResNeXt,[57] ShuffleNet,[57] SqueezeNet,[57] object detection algorithm (Yolov3),[45] pre-trained deep CNN[16,20,42–44,48,51–54,56] VGGNet-19,[53] VGG,[16,19,43,54,56] VGG 19,[19,56] VGG 16-GAP,[54] TVGG,[54] Wide ResNet,[57]

AI, Artificial intelligence; BL, Bone Level; BLT, Bone level/Tissue level; CNN, Convolutional neural network; DL, Deep Learning; TL, Tissue level; VGG, Visual Geometry Group.

Risk of bias domains

Study	D1	D2	D3	D4	Overall
Morais et al. 2015	X	+	+	+	X
Kim et al. 2020	–	+	+	+	–
Lee and Jeong 2020	+	+	+	+	+
Lee et al. 2020	+	+	+	+	+
Said et al. 2020	+	+	+	+	+
Sukegawa et al. 2020	–	+	+	+	–
Takahashi et al. 2020	–	+	+	+	–
Benakatti et al. 2021	+	+	+	+	+
Lee et al. (a) 2021	+	+	+	+	+
Lee et al. (b) 2021	–	+	+	+	–
Santos et al. 2021	+	+	+	+	+
Sukegawa 2021	+	+	+	+	+
Ayman et al. 2022	X	+	+	+	X
Guo et al. 2022	+	+	+	+	+
Kim et al. 2022	X	+	+	+	X
Kohlakala et al. 2022	–	+	+	+	–
Kong et al. 2022	X	+	+	+	X
Sukegawa et al. 2022	–	+	+	+	–
Tiryaki et al. 2023	X	+	+	+	X
Hsiao et al. 2023	+	+	+	+	+
Kong 2023	+	+	+	+	+
Park et al. 2023	+	+	+	+	+

Domains:
D1: Patient selection.
D2: Index test.
D3: Reference standard.
D4: Flow & timing.

Judgement
X High – Some concerns + Low

Figure 2. Risk of bias summary: review authors judgments of each risk of bias item.

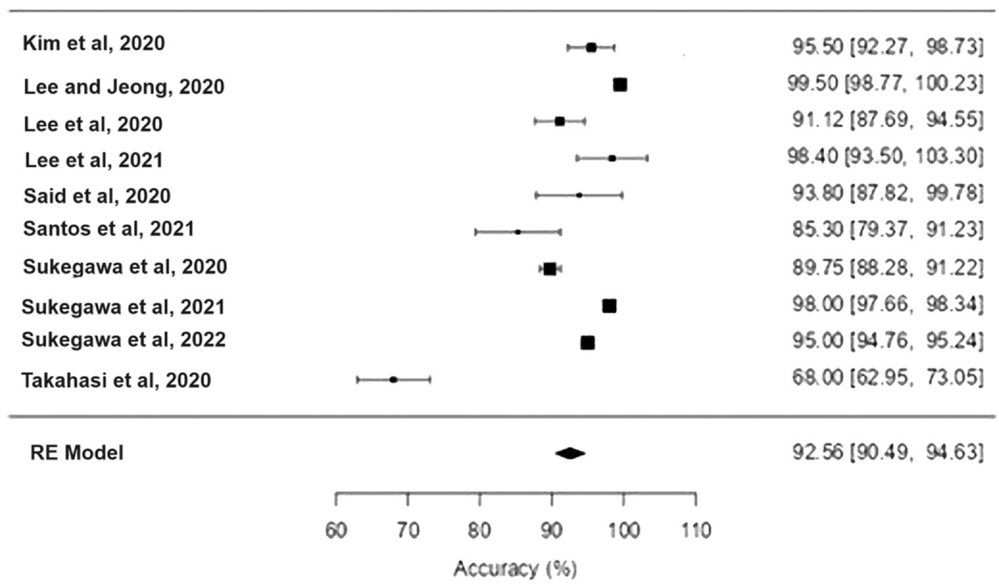

Figure 3. Forest plot of included studies showing accuracy and CI.

reliably used for the identification of dental implant systems.

The quality assessment of the studies included in this systematic review demonstrated adherence to recommended diagnostic accuracy studies guidelines. Most studies,[16,19,20,41,42,45–48,50–53,55,56,58,59] avoided a case-control design, minimizing the potential introduction of bias. Importantly, all the studies interpreted the index test results without knowledge of the reference standard results, ensuring unbiased interpretation.[16,19,20,41–53,55,56] The studies made appropriate choices for the reference standard used to accurately classify the target condition.[16,19,20,41–56] By selecting reliable and validated reference standards, the studies ensured accurate classification of the target condition, reducing the potential for misclassification bias and enhancing the accuracy of the results. Additionally, the reference standard results were interpreted independently of the index test results, minimizing the risk of incorporation bias.[16,19,20,41–56]

Most studies used a prespecified threshold, indicating transparent and objective criteria for classifying the target condition, enhancing the results' reliability and reproducibility.[16,19,20,41–56] The flow and timing between the index test and reference standard were maintained adequately in all studies, allowing for accurate comparison and minimizing potential changes in the target condition.[16,19,20,41–56] Furthermore, all patient radiographs received the same reference standard, reducing heterogeneity and ensuring consistency in the diagnostic evaluation process.[16,19,20,41–56]

However, the findings of the QUADAS-2 tool identified some concerns, particularly regarding patient selection and potential biases within the included studies. Certain studies demonstrated a high risk of bias in patient selection,[41,43,44,49,56] and some studies were identified as having some concern,[16,19,45,47,50,55] indicating limitations in the representativeness of their study populations. These biases should be carefully considered when interpreting the overall results as they may impact the generalizability and reliability of the findings.

Limitations of the reviewed studies included that some lacked validation by independent professional experts, which may have impacted the quality assessment of the evaluated characteristics.[16,19,41–43,56] The mixed-use of panoramic and periapical radiographs without the standardized region of interest (ROI) cropping posed challenges in comparing accuracy findings and managing the dataset.[51–55,59] The studies generally used relatively small sample sizes and a limited number of dental implant systems, which may limit the generalizability of the findings.[16,19,42,45,57] Additionally, the variation in deep learning algorithms used across the studies makes it challenging to compare the classification performance of different types of dental implant systems objectively.[16,19,41–43,56] The focus on 2D radiographs without exploring the potential benefits of 3D dental radiographic imaging, such as cone beam computed tomography, was another limitation.[16,19,41–43,56] Further research should address the limitations identified to maximize the clinical applicability of AI in dental implantology.

To enhance the clinical applicability of AI algorithms, future developments should focus on larger and more diverse datasets, training the algorithms on a wide range of implant designs and variations. Additional features like surface texture and connection type can improve the accuracy of implant identification. Evaluating algorithm performance using different radiographs or with multiple implant manufacturers would provide valuable insights into their ability to handle diverse clinical scenarios and increase confidence in their reliability and applicability.

This systematic review provides evidence supporting the efficacy of AI algorithms in accurately identifying and classifying dental implant systems. The high accuracy rates achieved by multiple studies highlight the potential of AI in this field. However, it is important to address the challenges and limitations identified.

By integrating AI technology into dental practice, implant dentistry can benefit from increased efficiency, reduced human error, and improved treatment planning. Continued research and development in this area will contribute to advancing computer-assisted systems, ultimately leading to better outcomes for clinicians and patients in achieving optimal dental implant outcomes.

CONCLUSIONS

Based on the findings of this systematic review with meta-analysis, the following conclusions were drawn:

1. With further advancements and refinements in methodology and technology, AI modes have the potential to identify dental implant systems from radiographs and improve patient care.
2. Based on the pooled results, an overall accuracy of dental implant identification of 92.56% (range 90.49% to 94.63%) was obtained.
3. Additional well-conducted research is recommended to identify the most common implant systems by addressing limitations such as limited datasets and variations in radiograph quality.

APPENDIX A. SUPPORTING INFORMATION

Supplemental data associated with this article can be found in the online version at doi:10.1016/j.prosdent.2023.11.027.

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