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SYSTEMATIC REVIEW

Evaluation of accuracy of deep learning and conventional neural network algorithms in detection of dental implant type using intraoral radiographic images: A systematic review and meta-analysis

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ABSTRACT

Statement of problem. With the growing importance of implant brand detection in clinical practice, the accuracy of machine learning algorithms in implant brand detection has become a subject of research interest. Recent studies have shown promising results for the use of machine learning in implant brand detection. However, despite these promising findings, a comprehensive evaluation of the accuracy of machine learning in implant brand detection is needed.

Purpose. The purpose of this systematic review and meta-analysis was to assess the accuracy, sensitivity, and specificity of deep learning algorithms in implant brand detection using 2-dimensional images such as from periapical or panoramic radiographs.

Material and methods. Electronic searches were conducted in PubMed, Embase, Scopus, Scopus Secondary, and Web of Science databases. Studies that met the inclusion criteria were assessed for quality using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool. Meta-analyses were performed using the random-effects model to estimate the pooled performance measures and the 95% confidence intervals (CIs) using STATA v.17.

Results. Thirteen studies were selected for the systematic review, and 3 were used in the meta-analysis. The meta-analysis of the studies found that the overall accuracy of CNN algorithms in detecting dental implants in radiographic images was 95.63%, with a sensitivity of 94.55% and a specificity of 97.91%. The highest reported accuracy was 99.08% for CNN Multitask ResNet152 algorithm, and sensitivity and specificity were 100.00% and 98.70% respectively for the deep CNN (Neuro-T version 2.0.1) algorithm with the Straumann SLActive BLT implant brand. All studies had a low risk of bias.

Conclusions. The highest accuracy and sensitivity were reported in studies using CNN Multitask ResNet152 and deep CNN (Neuro-T version 2.0.1) algorithms. (J Prosthet Dent 2025;133:137-146)

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Clinical Implications

Deep learning algorithms can accurately detect implant brands using 2D images such as periapical or panoramic radiographs.

Implant dentistry has advanced significantly in recent years, with more precise and efficient methods of implant placement and maintenance.[1] One area of interest is the use of machine learning algorithms for implant brand detection, which can aid in identifying and tracking implant components over time. Moreover, fast and precise identification of dental implants placed in patients are major factors in practice management and safety for dentists and forensic professionals.[2]

The accuracy of machine learning algorithms in implant brand detection has become a subject of research interest.[3] Recent studies have reported promising results for the use of machine learning in implant brand detection.[4] For instance, Lee et al[5] reported that a deep learning algorithm achieved a high level of accuracy in detecting implant brands from radiographic images, with more than 90% accuracy. Similarly, Santos et al[6] reported that a machine learning algorithm was able to accurately detect implant brands from implant surface images, achieving an accuracy of 99.78%.

However, despite these promising findings, a comprehensive evaluation of the accuracy of machine learning in implant brand detection is needed. Reviews regarding dental AI[7,8] have been published aiming to narrate the development of AI from incipient stages to the present and to summarize the current advanced research in dentistry. In particular, convolutional neural networks (CNNs) have developed rapidly in regard to image analysis such as detection, classification, and segmentation.[9] CNNs consist of convolution layers that are used to generate feature maps of input data using convolution kernels[10] and to classify images without the need to manually extract features.[11] Regularizing the CNN models with spatial dropout layers and replacing the convolutional layers with dense convolution blocks has been reported to further improve the segmentation performance. Experimental results showed that the proposed method compared favorably with existing methods.[12]

The aim of this systematic review was to evaluate and compare the accuracy performance of artificial intelligence algorithms in accurately identifying the brand and model of dental implant systems using deep learning algorithms. The null hypothesis was that the deep learning algorithms would not be able to accurately detect dental implant brands from radiographical images.

MATERIAL AND METHODS

A comprehensive search was conducted in PubMed, Embase, Scopus, Web of Science, and Cochrane databases to identify relevant articles published until March of 2023. The search was performed using a combination of keywords and medical subject heading (MeSH) terms, including "dental implants", "implant brand", "machine learning", "artificial intelligence", and "neural networks". The search was restricted to studies published in the English language, and the keywords for each database with the number of articles in each database is shown in Table 1.

Studies were included if they met the following criteria: original research article, investigated the use of deep learning algorithms for implant brand detection, reported on the accuracy, sensitivity, specificity, or other performance measures of the algorithm, conducted on human participants, used 2D images such as periapical or panoramic radiographs, and were published in peer-reviewed journals. Studies that were not in the English language or using cone beam computed tomography images, animal studies, conference abstracts, and review articles were excluded.

Table 1. Keywords for each data base

Database	Keyword	Result
PubMed	("Machine Learning"[Mesh] OR "Deep Learning"[Mesh] OR "Supervised Machine Learning"[Mesh] OR "Unsupervised Machine Learning"[Mesh] OR "Neural Networks, Computer"[Mesh]) AND ("Dental Implants"[Mesh])	32
Embase	('machine learning'/exp OR 'machine learning' OR 'deep learning'/exp OR 'deep learning' OR 'supervised machine learning'/exp OR 'supervised machine learning' OR 'unsupervised machine learning'/exp OR 'unsupervised machine learning' OR 'artificial neural network'/exp OR 'artificial neural network') AND ('tooth implant'/exp OR 'tooth implant' OR 'tooth implantation'/exp OR 'tooth implantation' OR 'dental implant'/exp OR 'dental implant')	121
Scopus	(TITLE-ABS-KEY ("Machine Learning") OR TITLE-ABS-KEY ("Deep Learning") OR TITLE-ABS-KEY ("Supervised Machine Learning") OR TITLE-ABS-KEY ("Unsupervised Machine Learning") OR TITLE-ABS-KEY ("Neural Network")) AND (TITLE-ABS-KEY ("Dental Implants") OR TITLE-ABS-KEY ("Dental Implant") OR TITLE-ABS-KEY ("tooth implant"))	112
Scopus Secondary	(TITLE-ABS-KEY ("Machine Learning") OR TITLE-ABS-KEY ("Deep Learning") OR TITLE-ABS-KEY ("Supervised Machine Learning") OR TITLE-ABS-KEY ("Unsupervised Machine Learning") OR TITLE-ABS-KEY ("Neural Network")) AND (TITLE-ABS-KEY ("Dental Implants") OR TITLE-ABS-KEY ("Dental Implant") OR TITLE-ABS-KEY ("tooth implant"))	5
WOS	(ALL=("Machine Learning" OR "Deep Learning" OR "Supervised Machine Learning" OR "Unsupervised Machine Learning" OR "Neural Network")) AND ALL=("dental implant" OR "tooth implant" OR "dental implantation" OR "dental implants" OR "tooth implants")	69

Table 2. Data extracted from selected articles

Author, Year	Country	Implant System	Architecture	Dataset and Image Type	Outputs (Accuracy (ACC) %, Precision (PRE) %, F1 score %, Sensitivity or Recall (REC) %, Specificity %, Area Under Curve (AUC))
da Mata Santos et al, 2021[13]	Brazil	1. Straumann 2. Neodent 3. SIN Implant	CNN (Deep CNNs)	360 periapical radiographs	Accuracy: 85.3 (78.4–90.5) Sensitivity: 89.9 (81.1–95.6) Specificity: 82.4 (73.7–87.3)
Guo et al, 2022[14]	China/ Australia	1. Bego 2. Bicon 3. Straumann	CNN (TVGG15)	600 digital radiographs	Accuracy: 78.7 Precision: 82 F1 score: 79 Sensitivity: 79
Hadj Saïd et al, 2020[15]	France	1. Nobel Biocare (NNA, NBS) 2. Straumann (SBL, STL) 3. Zimmer Biomet (ZTSV, ZSP)	CNN(GoogleNet)	241 digital radiographs	Accuracy: 93.8 (87.2–99.4) Sensitivity: 93.5 (84.2–99.3) Specificity: 94.2 (83.5–99.4)
Jang et al, 2022[16]	Republic of Korea		CNN (Faster R-CNN with Reset 101 backbone)	60 periapical radiographs	Precision: 97.7 F1 score: 98.4 Sensitivity: 99.2
Kim et al, 2020[17]	Republic of Korea	1. Branemark Mk TiUnite 2. Dentium Implantium 3. Straumann (BL, TL)	CNN (SqueezeNet)	80 periapical radiographs	Accuracy: 96 Precision: 96 F1 score: 96 Sensitivity: 96
			CNN (GoogLeNet)		Accuracy: 93 Precision: 92 F1 score: 93 Sensitivity: 94
			CNN (ResNet-18)		Accuracy: 98 Precision: 98 F1 score: 98 Sensitivity: 98
			CNN (MobileNet-v2)		Accuracy: 97 Precision: 96 F1 score: 96 Sensitivity: 96
			CNN (ResNet-50)		Accuracy: 98 Precision: 98 F1 score: 98 Sensitivity: 98
Kohlakala et al, 2022[18]	South Africa/ Belgium	1. Anthogyr 2. Astra 3. MIS 4. Nobel Biocare	CNN (fully convolutional network (FCN))	82 digital radiographs	Accuracy: 90.43 Precision: 74.38 F1 score: 80.73 Sensitivity: 90.98
				87 digital radiographs	Accuracy: 94.06 Precision: 68.31 F1 score: 84.48 Sensitivity: 78.64
Lee et al, 2020[19]	Republic of Korea	1. Osstem 2. Dentium 3. Straumann	CNN (Deep CNNs)	1076 periapical radiographs	Sensitivity: 97.1 Specificity: 99.5 AUC: 97.9 (00.40) (96.90–98–70)
				1078 panoramic radiographs	Sensitivity: 93.6 Specificity: 95.7 AUC: 95.6 (00.70) (94.20–96.70)
Lee et al, 2020[20]	Republic of Korea	1. Dentsply Astra 2. Dentium Implantium 3. Dentium Superline 4. Osstem 5. Straumann SLActive BL 6. Straumann SLActive BLT	CNN (Automated deep convolutional neural network (DCNN))	967 periapical radiographs	Sensitivity: 95.50 Specificity: 84.60 AUC: 96.10 (00.90) (94.10–97.60)
				1429 panoramic radiographs	Sensitivity: 92.20 Specificity: 88.20 AUC: 92.90 (00.18) (90.40–94.90)
Lee et al, 2022[21]	Republic of Korea	Dentsply Astra	Deep learning (Neuro-T version 2.0.1)	30 panoramic radiographs	Accuracy: 92.2 Sensitivity: 80.0 Specificity: 94.7
		Dentium Implantium		30 panoramic radiographs	Accuracy: 94.4 Sensitivity: 83.3 Specificity: 96.7
		Dentium Superline		30 panoramic radiographs	Accuracy: 89.4 Sensitivity: 56.7 Specificity: 96.0
		Osstem TSIII		30 panoramic radiographs	Accuracy: 90.0 Sensitivity: 70.0 Specificity: 94.0
		Straumann SLActive BL		30 panoramic radiographs	

Table 2 *(Continued)*

Author, Year	Country	Implant System	Architecture	Dataset and Image Type	Outputs (Accuracy (ACC) %, Precision (PRE) %, F1 score %, Sensitivity or Recall (REC) %, Specificity %, Area Under Curve (AUC))
					Accuracy: 96.1 Sensitivity: 93.3 Specificity: 96.7
		Straumann SLActive BLT		30 panoramic radiographs	Accuracy: 98.9 Sensitivity: 100.0 Specificity: 98.7
Saïd et al, 2020[22]	France	1. Nobel Biocare Nobleactive 2. Nobel Biocare Branhmark 3. Straumann bone level 4. Straumann tissue level 5. Zimmer biomet (ZTSV) 6. Zimmer biomet (ZSP)	CNN (Deep CNN (GoogleNet))	241 digital radiographs	Accuracy: 93.8 (87.2–99.4) Sensitivity: 93.5 (84.2–99.3) Specificity: 94.2 (83.5–99.4)
Sukegawa et al, 2021[23]	Japan	1. Full OSSEOTITE 4.0 2. Astra EV 4.2 3. Astra TX 4.0 4. Astra TX 4.5: 5. Astra MicroThread 4.0 6. Astra MicroThread 4.5 7. Brånemark Mk III 4.0 8. FINESIA 4.2 9. Replace Select Tapered 4.3 10. Nobel Replace CC 4.3 11. Straumann Tissue 4.1 12. Straumann Bone Level 4.1	CNN (Multitask ResNet18)	1950 panoramic radiographs	Accuracy: 98.03 Precision: 97.80 F1 score: 97.49 Sensitivity: 97.27 Specificity: AUC: 99.97
			CNN (Multitask ResNet34)		Accuracy: 98.51 Precision: 98.47 F1 score: 98.26 Sensitivity: 98.08 AUC: 99.98
			CNN (Multitask ResNet50)		Accuracy: 98.69 Precision: 98.70 F1 score: 98.38 Sensitivity: 98.12 AUC: 99.98
			CNN (Multitask ResNet101)		Accuracy: 98.99 Precision: 98.95 F1 score: 98.75 Sensitivity: 98.60 AUC: 99.99
			CNN (Multitask ResNet152)		Accuracy: 99.08 Precision: 99.14 F1 score: 98.99 Sensitivity: 98.86 AUC: 99.99
			CNN (singletask ResNet18)		Accuracy: 97.87 Precision: 97.37 F1 score: 97.24 Sensitivity: 97.26 AUC: 99.96
			CNN (singletask ResNet34)		Accuracy: 98.00 Precision: 97.90 F1 score: 97.62 Sensitivity: 97.43 AUC: 99.97
			CNN (singletask ResNet50)		Accuracy: 98.00 Precision: 98.16 F1 score: 97.76 Sensitivity: 97.46 AUC: 99.96
			CNN (singletask ResNet101)		Accuracy: 98.41 Precision: 98.22 F1 score: 98.05 Sensitivity: 97.98 AUC: 99.97
			CNN (singletask ResNet152)		Accuracy: 98.51 Precision: 98.39 F1 score: 98.20 Sensitivity: 98.09 AUC: 99.98

Table 2 (*Continued*)

Author, Year	Country	Implant System	Architecture	Dataset and Image Type	Outputs (Accuracy (ACC) %, Precision (PRE) %, F1 score %, Sensitivity or Recall (REC) %, Specificity %, Area Under Curve (AUC))
Sukegawa et al, 2022[24]	Japan	1. Full OSSEOTITE 4.0 2. Astra EV 4.2 3. Astra TX 4.0 4. Astra TX 4.5: 5. Astra MicroThread 4.0 6. Astra MicroThread 4.5 7. Brånemark Mk III 4.0 8. FINESIA 4.2 9. POI EX 42 10. Replace Select Tapered 4.3 11. Nobel Replace CC 4.3 12. Straumann Tissue 4.1 13. Straumann Bone Level 4.1	CNN (ResNet18)	2034 panoramic radiographs	Accuracy: 94.86 (00.26) (94.60–95.13) Precision: 94.41 (00.36) (94.04–94.77) F1 score: 93.82 (00.37) (93.45–94.18) Sensitivity: 93.33 (00.39) (92.93–93.72) AUC: 99.79 (00.03) (99.76–99.82)
			CNN (ResNet18 with attention branch network)		Accuracy: 97.19 (00.26) (96.96–97.41) Precision: 96.86 (00.36) (96.59–97.14) F1 score: 96.52 (00.37) (96.25–96.78) Sensitivity: 96.27 (00.39) (95.98–96.56) AUC: 99.93 (00.03) (99.91–99.94)
			CNN (ResNet50)		Accuracy: 95.78 (00.42) (95.36–96.19) Precision: 95.46 (00.47) (94.99–95.93) F1 score: 94.98 (00.48) (94.50–95.46) Sensitivity: 94.71 (00.50) (94.21–95.21) AUC: 99.83 (00.06) (99.77–99.89)
			CNN (ResNet50 with attention branch network)		Accuracy: 95.11 (00.28) (94.83–95.39) Precision: 94.77 (00.37) (94.40–95.14) F1 score: 94.16 (00.43) (93.74–94.59) Sensitivity: 93.82 (00.49) (93.33–94.31) AUC: 99.75 (00.02) (99.73–99.77)
			CNN (ResNet152)		Accuracy: 96.24 (00.39) (95.84–96.63) Precision: 95.75 (00.48) (95.20–96.30) F1 score: 95.30 (00.52) (94.70–95.90) Sensitivity: 95.09 (00.52) (94.40–95.80) AUC: 99.85 (00.09) (99.84–99.86)
			CNN (ResNet152 with attention branch network)		Accuracy: 95.64 (00.25) (95.39–95.88) Precision: 95.14 (00.32) (94.83–95.46) F1 score: 94.70 (00.28) (94.78–95.82) Sensitivity: 94.50 (00.30) (94.58–95.61) AUC: 99.55 (00.02) (99.50–99.57)
Sukegawa et al, 2020[25]	Japan	1. Full OSSEOTITE 4.0 2. Astra EV 4.2 3. Astra TX 4.0 4. Astra TX 4.5: 5. Astra MicroThread 4.0 6. Astra MicroThread 4.5 7. Brånemark Mk III 4.0 8. FINESIA 4.2 9. Replace Select Tapered 4.3 10. Nobel Replace CC 4.3 11. Straumann Tissue 4.1	CNN (Basic)	2214 panoramic radiographs	Accuracy: 86.00 Precision: 84.20 F1 score: 81.90 Sensitivity: 80.20
			CNN (VGG16-transfer)		Accuracy: 89.90 Precision: 88.80 F1 score: 87.40 Sensitivity: 86.40
			CNN (VGG16-fine tuning)		Accuracy: 93.50 Precision: 92.80 F1 score: 91.60 Sensitivity: 90.70
			CNN (VGG19-transfer)		Accuracy: 88.00 Precision: 87.30 F1 score: 85.30 Sensitivity: 84.00
			CNN (VGG19-fine tuning)		Accuracy: 92.70 Precision: 91.30 F1 score: 90.20 Sensitivity: 89.40

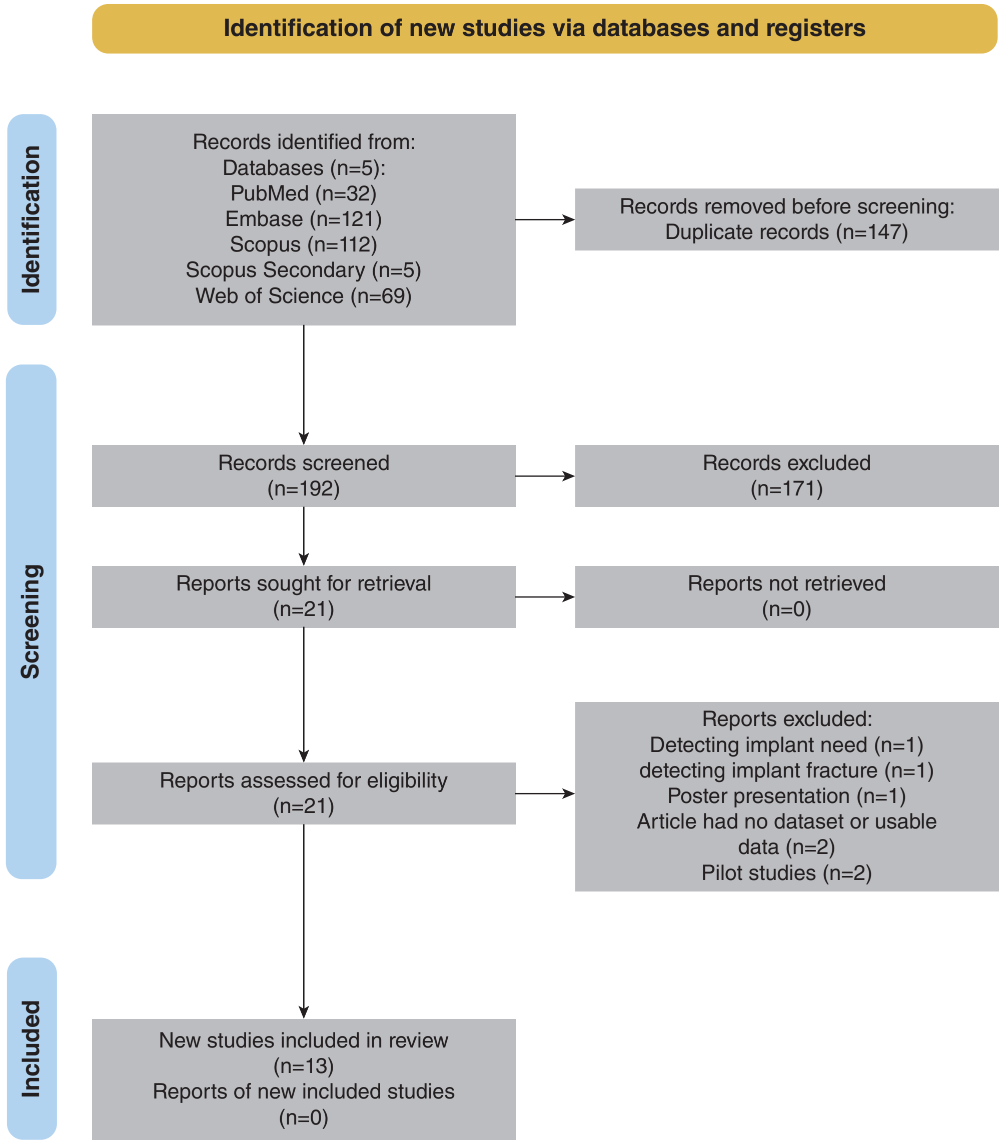

Figure 1. PRISMA flowchart. PRISMA, preferred reporting items for systematic reviews and meta-analyses.

Two independent reviewers (M.D., S.H.) (Cohen kappa=0.90) screened the titles and abstracts of the identified articles for eligibility; for any discrepancy in the eligibility of the articles, a third reviewer (J.L.) was asked to decide. Full-text articles were retrieved for further assessment. The reviewers independently extracted the following data from the eligible studies: author/year, country, image types, implant system, architecture, dataset, accuracy (ACC), precision (PRE), F1 score, sensitivity or recall (REC), and specificity area under curve (AUC) (Table 2). Discrepancies among the reviewers were resolved through discussion and consensus.

The quality of the included studies was assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool, assessing the risk of bias in the following domains: patient selection, index test, reference standard, and flow and timing. Any disagreements among the reviewers were resolved through discussion and consensus (1.0 kappa).

The primary outcomes of interest were the accuracy, sensitivity, and specificity of the machine learning algorithms in implant brand detection. A meta-analysis was performed using the random-effects model to estimate the pooled performance measures and the 95% confidence intervals (CI) using a software program (STATA v.17; StataCorp LLC). Heterogeneity was assessed with the I^2 statistic. Sensitivity analysis and publication bias assessment were also performed.

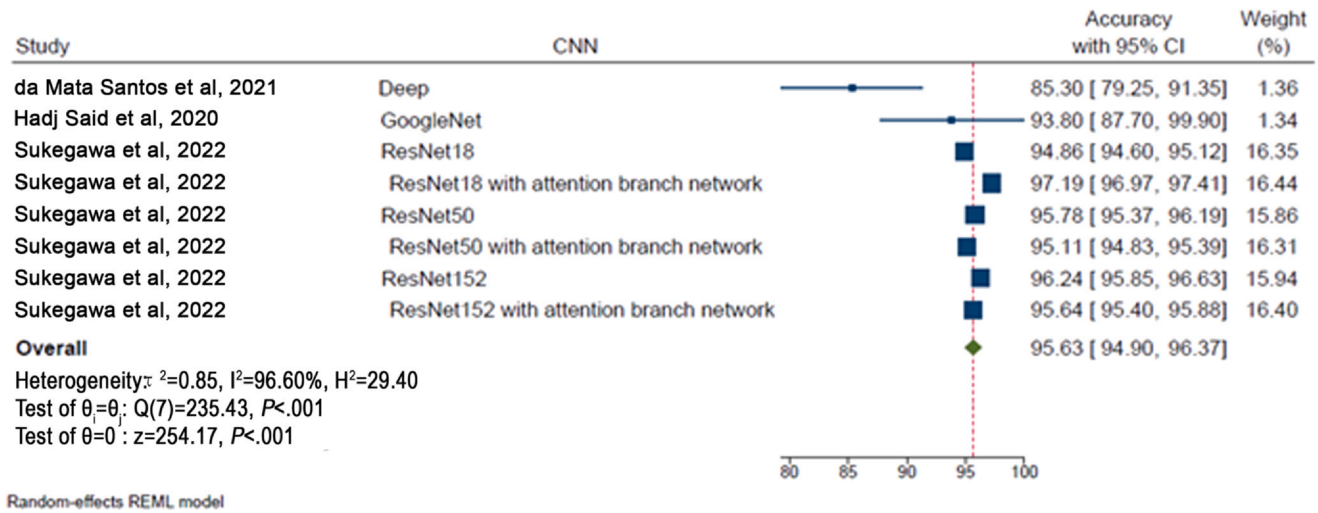

Figure 2. Random-effect meta-analysis of accuracy of implant brand detection.

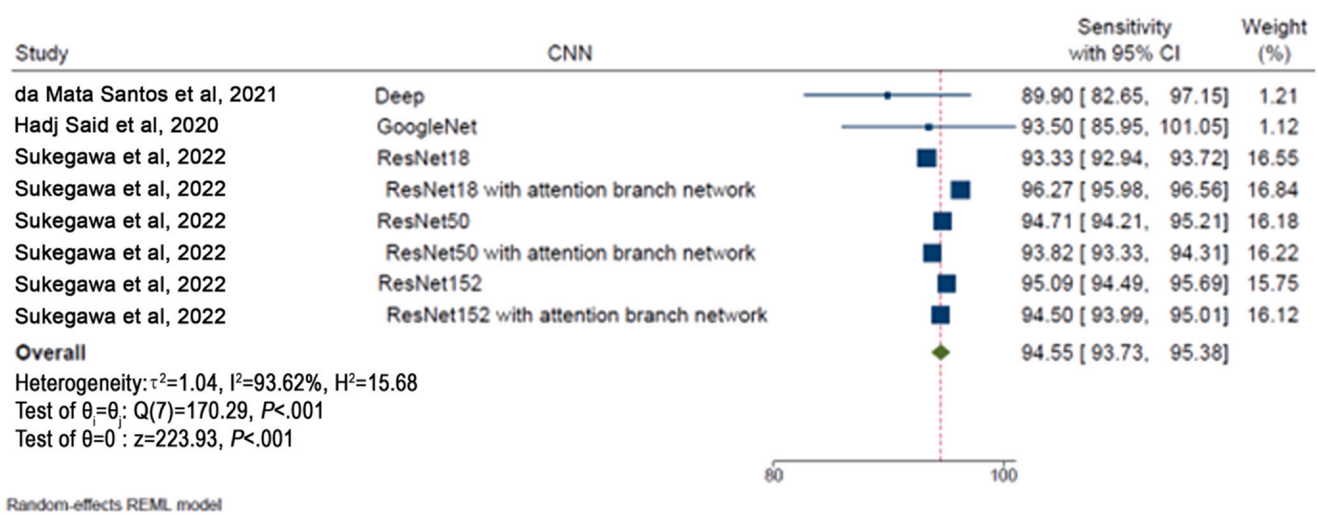

Figure 3. Random-effect meta-analysis of sensitivity of implant brand detection.

RESULTS

A total of 339 articles were identified through electronic searches. After removing duplicates and nonrelevant titles, 21 articles were selected for full-text review. Eight articles were excluded following the full-text review (1 detecting the need for implant treatment, 1 detecting implant fracture, 1 poster, 1 lacked a dataset, 1 omitted usable data, 2 were pilot studies). In total, 13 studies were selected for the systematic review, and 3 were included in the meta-analysis. (Fig. 1).

Descriptive statistics included studies using various imaging modalities, including periapical radiographs, panoramic radiographs, or a combination of both. Different brands of dental implants were used across studies, with the most common brands being Straumann, Dentium, Astra, Nobel, and Osstem. All studies used CNN with different algorithms, with the most common model structure being different types of ResNet.

The meta-analysis found that the overall accuracy of CNN algorithms in detecting dental implants in radiographic images was 95.63%, and the result of this analysis was significant ($P<.001$). However, a significant heterogeneity among the studies was observed ($I^2=96.60\%$, $P<.001$) (Fig. 2). The sensitivity of the CNN algorithms was 94.55%, and the result of this analysis was significant ($P<.001$), However, a significant heterogeneity among the studies was observed ($I^2=93.62\%$, $P<.001$) (Fig. 3). Specificity of the CNN algorithms was 97.91%. The result of this analysis was significant ($P<.001$), However, a significant heterogeneity among the studies was observed ($I^2=100\%$, $P<.001$) (Fig. 4). The highest reported accuracy was 99.08% for the CNN Multitask ResNet152 algorithm, and sensitivity and specificity were 100.00% and 98.70% respectively

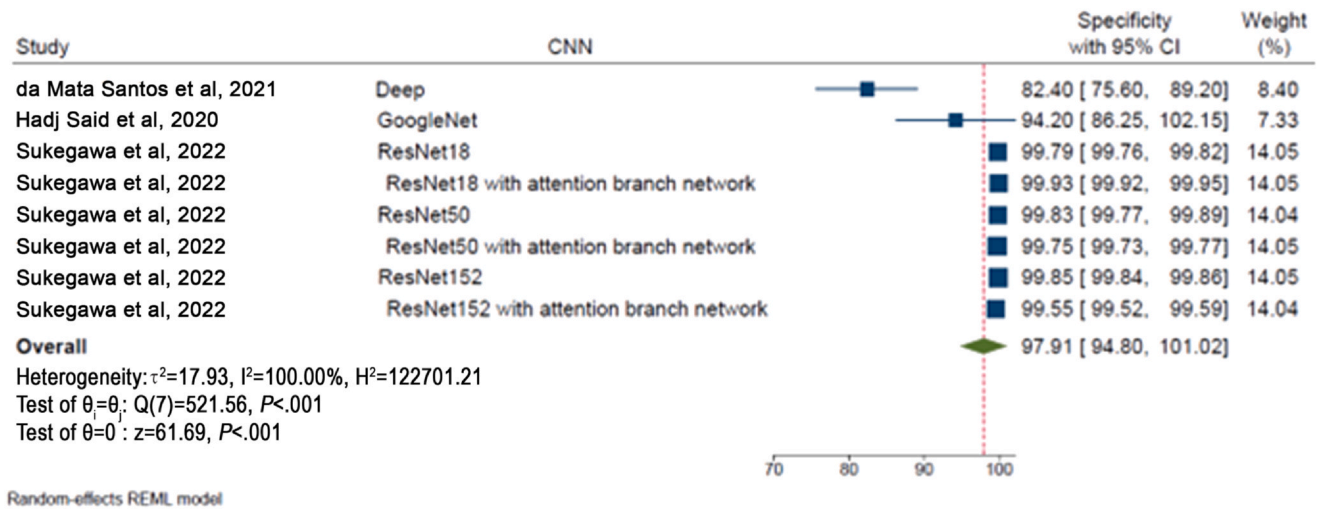

Figure 4. Random-effect meta-analysis of specificity of implant brand detection.

Table 3. Risk of bias assessment for selected articles

Study	Risk of Bias			Applicability Concerns			
	Data Selection	**Index Text**	**Reference Test**	**Flow and Timing**	**Data**	**Index Text**	**Reference Test**
da Mata Santos et al, 2021[13]	Low	Low	Low	Low	Low	Low	Low
Guo et al, 2022[14]	High	Low	Low	Low	Low	Low	Low
Hadj Saïd et al, 2020[15]	High	Low	Low	Low	Low	Low	Low
Jang et al, 2022[16]	Unclear	High	Low	Low	Low	low	Low
Kim et al, 2020[17]	Unclear	Low	Low	Low	Low	Low	Low
Kohlakala et al, 2022[18]	High	Low	High	Low	Low	Low	low
Lee et al, 2020[19]	Low	Low	Low	Low	Low	Low	Low
Lee et al, 2020[20]	Low	Low	Unclear	Low	Low	Low	low
Lee et al, 2022[21]	Unclear	Unclear	Unclear	Low	Low	Low	Low
Saïd et al, 2020[22]	High	Low	Low	Low	Low	Low	Low
Sukegawa et al, 2021[23]	Unclear	Low	Low	Low	Low	Low	Low
Sukegawa et al, 2022[24]	Unclear	Low	Low	Low	Low	Low	Low
Sukegawa et al, 2020[25]	Unclear	Low	Low	Low	Low	Low	Low

for the deep CNN (Neuro-T version 2.0.1) algorithm with the Straumann SLActive BLT implant brand. The quality assessment of the included studies showed a low risk of bias across all studies (Table 3, Fig. 5).

DISCUSSION

The aim of this systematic review and meta-analysis was to evaluate the accuracy, sensitivity, and specificity of deep learning algorithms in detecting dental implant brands using 2D radiographic images. This systematic review showed that current deep learning algorithms can help clinicians detect dental implant brands from panoramic images; therefore, the null hypothesis that the deep learning algorithms would not be able to provide accurate detection of dental implant brands from radiographical images was rejected. The meta-analysis of the studies

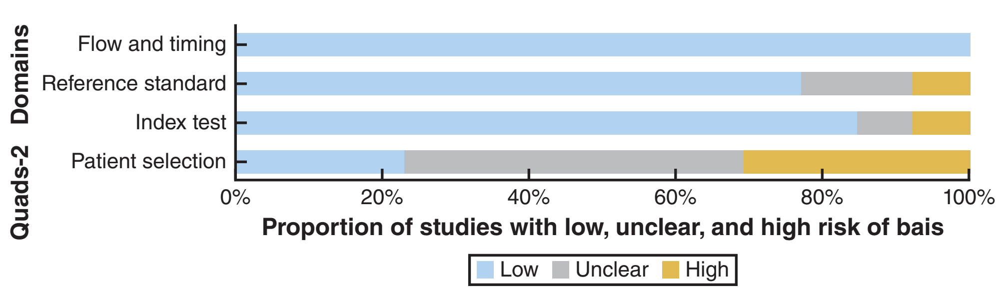

Figure 5. Risk of bias assessment for selected articles.

found that the overall accuracy of CNN algorithms in detecting dental implants in radiographic images was 95.63%, with a sensitivity of 94.55% and a specificity of 97.91%. The highest reported accuracy was 99.08% for the CNN Multitask ResNet152 algorithm, and sensitivity and specificity were 100.00% and 98.70% respectively for the deep CNN (Neuro-T version 2.0.1) algorithm with the Straumann SLActive BLT implant brand.

The studies included in this review[13–25] used different imaging modalities and brands of dental implants, which suggested that the accuracy of deep learning algorithms in detecting implant brands was not affected by these factors. However, all studies included in this review used a relatively small sample size and focused on a limited number of implant brands. Further studies are needed to assess the accuracy of deep learning algorithms across a wider range of implant brands and imaging modalities.

The findings suggested that deep learning algorithms, specifically CNNs, are highly accurate in detecting dental implant brands using 2D radiographic images. This accuracy is consistent with that of previous studies that have shown the effectiveness of CNNs in various dental applications, including caries detection, tooth segmentation, and landmark detection.[26–28] CNNs have also been shown to outperform other machine learning algorithms in dental applications due to their ability to extract features automatically from images, making them effective in detecting subtle patterns and abnormalities.[29]

One potential application of deep learning algorithms in implant dentistry is to improve the accuracy and efficiency of implant planning and placement. Accurately identifying the brand of dental implant can provide important information for the implant treatment plan, including implant size and placement, and can also aid in postoperative follow-up and maintenance. The high accuracy of deep learning algorithms in detecting implant brands using 2D radiographic images suggests that they may have clinical utility in this context.

However, the studies included in this review[13–25] were conducted on radiographic images and did not assess the accuracy of deep learning algorithms in detecting implants in vivo. Further studies are needed to assess the accuracy of deep learning algorithms in detecting implant brands in vivo and to compare the accuracy of deep learning algorithms with traditional methods of implant identification, such as visual inspection or implant records.

CONCLUSIONS

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

1. Deep learning algorithms, specifically CNNs, were found to be accurate in detecting dental implant brands using 2D radiographic images.
2. Accurate identification of implant brands can aid in treatment planning and follow-up.

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