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Review Article

Artificial intelligence innovations revolutionizing dental implant success

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Abstract

Artificial intelligence (AI) represents the latest trend in dentistry, offering precise tools that can reshape the outcomes of our treatments. Considering the need to support and enhance the clinical decision-making process, this systematic review provides insights into the effectiveness and accuracy of various AI models. The aim is to evaluate the evidence on the effectiveness of various AI models for implant dentistry in diagnosis, treatment planning, prognosis, and implant system classification. In accordance with the PRISMA-DTA guidelines, a comprehensive search was conducted across multiple databases, including PubMed/Medline, Google Scholar, and Cochrane from the year 2016 to 2024. During the article screening and selection process, the PICO guidelines were followed. The methodological quality and bias of the study were assessed using the Critical Appraisal Skills Programme (CASP) 2023 checklist for systematic review and the CASP checklist for clinical prediction rule. It has been found that AI models are highly effective in detecting anatomical landmarks, improving surgical planning for implant positioning, predicting the outcome based on alveolar bone patterns around the implant, and providing accurate classification in detecting implant systems. For clinicians to achieve the greatest benefits for their patients, a broader knowledge of AI applications in implant dentistry and a deeper understanding of its insights are essential.

Keywords: Artificial intelligence, Artificial neural networks, Convolutional neural networks, Deep learning, Machine learning

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1. Introduction

Artificial Intelligence (AI), a burgeoning discipline within computer science, is among the most recent areas of study exhibiting a form of intelligence that can mimic human cognitive skills. During the 1950s, John McCarthy, a mathematician, widely recognized as a father of AI, introduced the world to a technology or a machine that uses data to understand and tackle human challenges through learning.[1] Since then, AI has evolved into diverse networking capabilities such as deep learning, neural networks, machine learning, knowledge representation, and reasoning, contributing to various fields in dentistry, particularly diagnosis and planning treatment strategies, examining various forms of imaging data, periodontal diseases, surgical navigation, and dental education.[2].

Following the intensifying trend for oral health, utilizing technology to enhance the quality of dental treatment while managing costs in dental clinics is crucial. With continuous evolution and transition of dental implants, innovations are being added daily, and AI has transformative potential in the area of implant dentistry. A dental implant is a treatment approach that is reliable and consistently effective for replacing missing teeth.[3] It became increasingly popular in comparison to other treatment modalities because it conserves surrounding tooth structure and bone.[4]

Dental implant-based restoration for completely or partially edentulous patients improves masticatory function and overall quality of life.[5-6]. Since dental implants have become the benchmark for restoring missing teeth, an ideal treatment plan, clinical decision-making, survival prediction, prognosis, and meticulous assessment of the jawbone should be undertaken. AI can execute these interpretation processes faster than humans.

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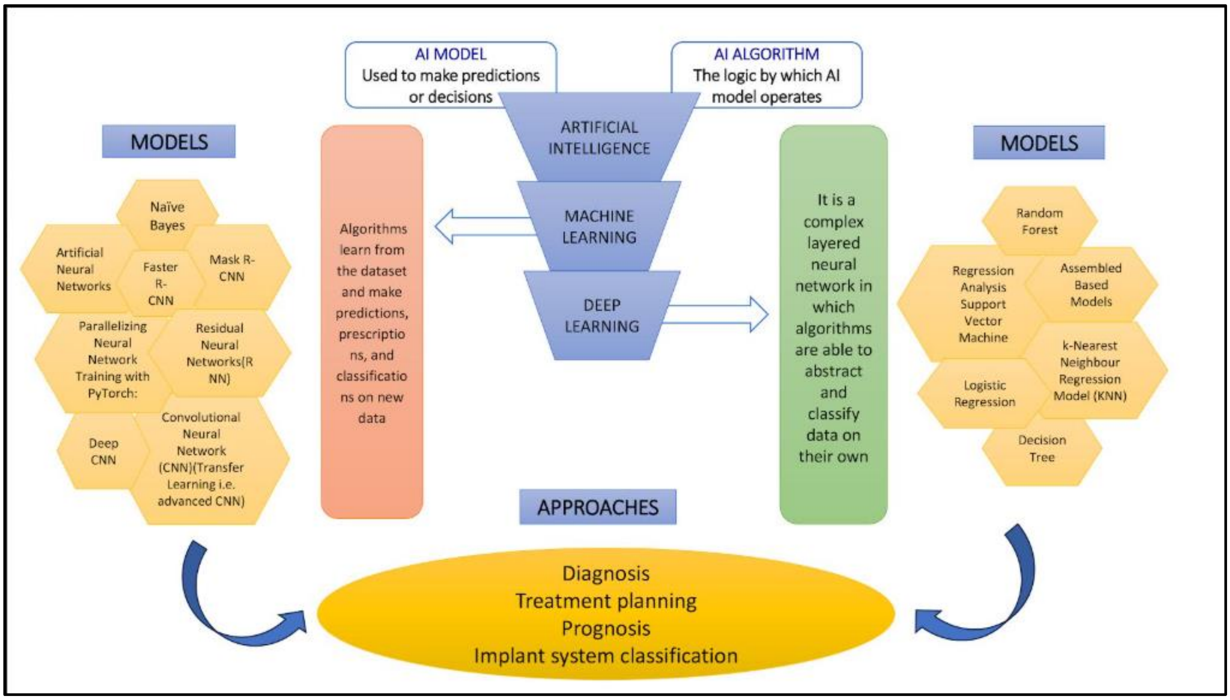


Figure 1: Core aspects of Artificial Intelligence

An AI model is a program that has been trained on a set of data to recognize certain patterns or make certain decisions without further human intervention. After briefly introducing various AI models and their uses, this systematic review aims to provide comprehensive data on how AI is implemented in implant dentistry and what doors it can open in assisting dentists (**Figure 1**)

2. Materials and Methods

2.1. Data sources

The systematic review adhered to the Guidelines for Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Diagnostic Test Accuracy (PRISMA-DTA). A comprehensive search of literature was conducted across electronic databases including PubMed/Medline, Google Scholar, and Cochrane spanning from 2016 to 2024. Keywords such as "artificial intelligence and implant dentistry", "deep learning and dental implants", "artificial neural networks and prognosis of dental implants", "machine learning for the success of dental implants", "convolutional neural networks and their use in implant dentistry", and "AI and dental implant system classification" were employed to identify relevant studies. The search methodology followed the PICO (patient/population, intervention, comparison, and outcome) framework.

2.2. Inclusion and exclusion criteria

The review considered studies centered on AI in implant dentistry, covering articles focusing on predictive or measurable outcomes that can be quantified. Included were studies employing diverse AI algorithms such as Regression Analysis, Random Forest Model, AdaBoost Model, Bayesian Network, PyTorch Networking, Convoluted Neural Networks, and other AI methodologies for dental image analysis, AI models which were trained on datasets and their approach is validated in terms of clinical decision making and implant system classification. Articles unrelated to AI and implant dentistry, publications not in English, and studies lacking crucial data or performance metrics for analysis were excluded.

A PICO question was crafted, encompassing the population or problem, intervention, comparison, and outcome. The population consists of advancements, performance, and applications of AI in implant dentistry, focusing on assessing anatomical landmarks, predicting dental implant success, identifying missing tooth regions, forecasting prognosis, and classifying dental implant systems. The intervention focused on AI models. No comparison was deemed applicable. Quantifiable or predictive findings such as Positive/Negative Predictive Values, sensitivity, specificity, Correlation Coefficient, and accuracy of the models were considered for the outcome.

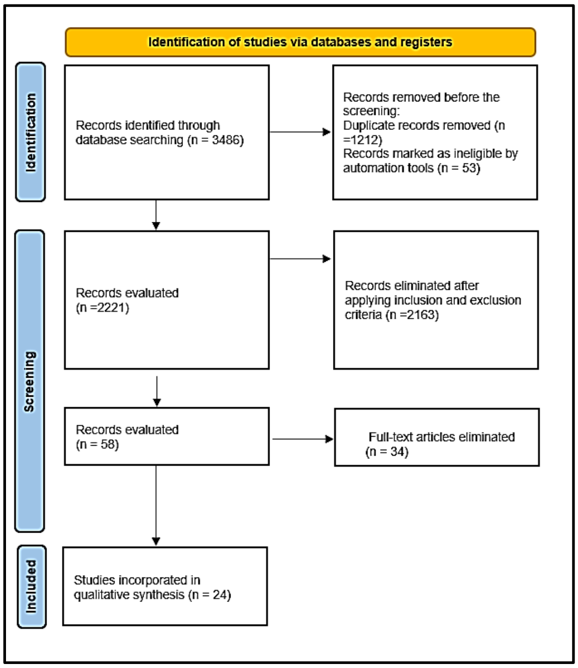
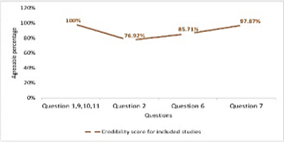


Figure 2: Flowchart for screening and selection of articles

Authors	Q1	Q2	Q6	Q7	Q9	Q10	Q11
Moayeri et al. (2016)	Y	Y	Y	Y	Y	Y	Y
Jaskari et al. (2020)	Y	Y	Y	Y	Y	Y	Y
Bayrakdar et al. (2021)	Y	N	Y	Y	Y	Y	Y
Roongruangsilp et al. (2021)	Y	N	Y	Y	Y	Y	Y
Alsomali et al. (2022)	Y	N	Y	Y	Y	Y	Y
Park et al. (2022)	Y	N	Y	Y	Y	Y	Y
Lyakhov et al. (2023)	Y	Y	Y	Y	Y	Y	Y
Kung et al. (2023)	Y	N	Y	Y	Y	Y	Y
Zhang et al. (2023)	Y	Y	N	Y	Y	Y	Y
Hwang et al. (2023)	Y	Y	N	Y	Y	Y	Y
Moufti et al. (2023)	Y	Y	N	Y	Y	Y	Y
Yang et al. (2024)	Y	Y	Y	Y	Y	Y	Y
Papantonopoulos et al. (2016)	Y	Y	Y	Y	Y	Y	Y
Liu CH et al. (2018)	Y	N	Y	Y	Y	Y	Y
Zhang et al. (2020)	Y	Y	N	Y	Y	Y	Y
Cha et al. (2021)	Y	N	Y	Y	Y	Y	Y
Liu et al. (2022)	Y	N	N	Y	Y	Y	Y
Chen et al. (2023)	Y	Y	Y	Y	Y	Y	Y
Kim et al. (2020)	Y	Y	Y	Y	Y	Y	Y
Lee JH et al. (2020)	Y	Y	Y	Y	Y	Y	Y
Sukegawa et al. (2020)	Y	N	Y	N	Y	Y	Y
Takahashi et al. (2020)	Y	Y	N	Y	Y	Y	Y
Hadj et al. (2020)	Y	Y	Y	Y	Y	Y	Y
Lee et al. (2021)	Y	Y	Y	Y	Y	Y	Y

a. Critical Appraisal Skills Programme (CASP) questions scoring-Y=Yes (2), CT=Can't Tell (1), N=No (0)



b. Line chart in accordance with CASP questionnaire table evaluating clinical prediction rule

Figure 3: CASP clinical prediction rule assessment guide

Table 1: Critical appraisal skills programme checklist for systematic review

Questions	Answers
1. Did the review address a clearly focused question?	Y
2. Did the authors look for the right type of papers?	Y
3. Do you think all the important, relevant studies were included?	CT
4. Did the review's authors do enough to assess quality of the included studies?	Y
5. If the results of the review have been combined, was it reasonable to do so?	Y
6. What are the overall results of the review?	Y
7. How precise are the results?	Y
8. Can the results be applied to the local population?	Y
9. Were all important outcomes considered?	Y
10. Are the benefits worth the harms and costs?	Y

Y=Yes, CT=Can't Tell, N=No

Table 2: Critical Appraisal Skills Programme checklist for clinical prediction rule

Questions
Q1. Is the clinical prediction rule (CPR) clearly defined?
Q2. Did the population from which the rule was derived include an appropriate spectrum of patients?
Q3. Was the rule validated in a different group of patients?
Q4. Were the predictor variables and the outcome evaluated in a blinded fashion?
Q5. Were the predictor variables and the outcome evaluates in the whole sample selected initially?
Q6. Are the statistical methods used to construct and validate the rule clearly described?
Q7. Can the performance of the rule be calculated?
88. How precise was the estimate of the treatment effect?
Q9. Would the prediction rule be reliable and the results interpretable if used for your patient?
Q10. Is the rule acceptable in your case?
Q11. Would the results of the rule modify your decision about the management of the patient, or the information you can give to him/her?

Table 3: AI in diagnosis and treatment planning of dental implants

S no	Authors	Year	Models	Datasets/patients taken	Radiographic techniques used	Approach	Evaluation of effectiveness/accuracy	Conclusion
1	Moayeri et al.	2016	Combined W-J48, SVM, Neural Network, K-NN and Naïve Bayes.	224 patients	CBCT	To predict success of dental implants	The hybrid model improves sensitivity to predict success rate up to 13.3%	Combined algorithm gives better performance and higher prediction accuracy[10]
2	Jaskari et al.	2020	CNN	594 patients	CBCT	To accurately locate mandibular canals for dental implant treatment planning	The model predicted the position of mandibular canal with an accuracy of about 0.5 mm for 90% of its length	Accurately identify the mandibular canal and is precise on sections where the canal's path is hard to see[11]
3	Bayrakdar et al.	2021	Deep CNN(U-Net)	75 patients	CBCT	To assess anatomical landmarks, bone thickness and bone height for successful dental implant planning	Successfully detected anatomical landmarks: 72.2% for canals, 66.4% for sinuses/fossa, and 95.3% for missing teeth	No significant difference seen in detection of bone height whereas notable difference in bone thickness exists between AI and manual measurements[12]
4	Roongruangsilp et al.	2021	Faster R-CNN	184 patients	CBCT	To evaluate developed AI performance in planning dental implants in the posterior maxillary region	The blurred augmented model's detection accuracy was improved by 12.5% but by 18.3% reduction in accuracy but sharpen, color and noise showed both improved accuracy and detection	Abundant and high-quality datasets are critical for both original and augmented models of AI to accurately and precisely help in implant treatment planning[13]
5	Alsomali et al.	2022	Deep learning	34 datasets	CBCT	To automatically identify and recognize radiographic markers of proposed dental implant site in new patients based on learned datasets	83% were correctly identified with only 2.8% of false positive results and 17% missed GP markers	The model accurately localizes the radiographic stent GP markers for proposing dental implant site and also showed that only axial images are not sufficient for an AI model to give satisfactory results[14]
6	Park et al.	2022	Mask R-CNN and Faster R-CNN	455 datasets	Panoramic radiographs	To accurately detect missing tooth regions for dental implant planning	The mean average precision was 92.14% for tooth instance segmentation and 59.09% for missing	The proposed automated method for missing tooth region detection helps in the implant planning process[15]

							tooth region detection	
7	Lyakhov et al	2023	PyTorch machine learning	1646 patients	Digital x-ray	To predict treatment outcomes for dental implants based on a range of patient-related statistical factors	Model achieved an accuracy of 94.48% for predicting the success of a single implant in a patient	Patient's various statistical factors give basis for prediction but the model is just an additional tool for diagnosis[16]
8	Kung et al.	2023	U-net, ANN, and random forest	900 datasets	Digital x-ray	Prediction of changes in tissue type and structure around different dental implant designs based on 35 days of healing period	The model achieved an accuracy of 82% in identifying changes in tissue type	Considering factors like bone properties and occlusal forces, tissue differentiation around dental implants gives clinicians a helpful hand in deciding implant performance[17]
9	Zhang et al.	2023	Deep CNN	248 patients	Periapical and Panoramic radiographs	To predict the outcome based on alveolar bone pattern around dental implants	The accuracy was 87% when combined both image types out performing models that used only periapical (78.6%) or panoramic (78.7%) images.	The model predicts implant outcomes in terms of failure with or without marginal bone loss or success—helping clinicians identify early signs for timely intervention[18]
10	Hwang et al.	2023	SinusC-Net	133 patients	CBCT	To develop an AI model that classifies approaches for surgical planning of dental implants in maxillary posterior region	The mean accuracy to classify the surgical method for sinus augmentation was 97%	Enhancing surgical planning by selecting appropriate technique for maxillary sinus augmentation is highly useful for clinician whereas more work on this needed[19]
11	Moufti et al.	2023	U-Net CNN	43 datasets	CBCT	To study the structure and outline of mandibular edentulous areas for dental implant planning	The model's accuracy which is measured by Dice Similarity Coefficient (DSC) shows overlapping between human and AI generated segmentation mentations	AI generated segmentation of edentulous areas of mandibular molars and premolars, gave better performance for unilateral cases as compared to bilateral cases due to varying jaw angulations and it can improve efficiency in implant planning by reducing manual workload and human errors[20]
12	Yang et al.	2024	Deep Learning	3045 datasets	CBCT	To predict the best position for dental	Implant Former achieved higher accuracy (AP75:	The predictions were better with 2D axial CBCT slices of

			(ImplantFormer)			implant placement	13.7%) than the other developed AI models to predict dental implant position	crown images than root images by integration of Convolutional Neural Networks (CNNs) and Transformers to accurately detect implant position[21]

Table 4: AI for the prediction of prognosis of dental implants

S. No	Author name	Year	Models	Datasets/patients taken	Radiographic technique used	Approach	Evaluation of effectiveness/accuracy	Conclusion
1	Papantonopoulos et al.	2016	KNN and SVM	72 patients	Periapical radiographs	To predict bone level around dental implants and classify bone loss patterns	In the cluster of implants susceptible to peri-implantitis, 96% of implants were affected with mean IIMBL: 5.2mm, common in lower jaw, and the other is resistant clusters with mean IIMBL: 1.6mm frequently seen in upper premolars and incisors	AI models accurately predicted individual implant mean bone levels (IIMBL) and the existence of distinct implant phenotypes were proved by network analysis[24]
2	Liu CH et al.	2018	Decision tree (DT), support vector machines, logistic regressions, and classifier ensembles (i.e., Bagging and AdaBoost)	681 patients	Digital X-ray	To predict the failure of dental implant systems showcasing various influencing factors	The bagging + decision tree model gave a prediction accuracy of 70.2%	AI can help in early detection of implant failures and it was shown that, implant system choice, its fixture width and lifestyle factors (betel nut chewing, alcohol consumption) are key to implant longevity[25]
3	Zhang et al.	2020	Support vector machine (SVM), Artificial neural network (ANN), Logistic regression (LR),	81 datasets	CBCT	To predict marginal bone loss around dental implants based on trabecular microstructure of surrounding bone	The best accuracy attained by SVM model with the sensitivity of 91.6% and AUC of 0.967	Trabecular bone microstructure is indicator of risk to bone loss and these models can effectively predict marginal bone loss around implants[26]

			and Random forest(RF)					
4	Cha et al	2021	Mask R-CNN	708 datasets	Periapical radiographs	To determine the bone loss around dental implants and classify the severity of peri-implantitis	For the detection of key anatomical landmarks, the model achieved an average precision of 0.761 for upper jaw implants and 0.786 for lower jaw implants	Measured bone around implants and classified them into four categories: ≤10% is considered normal, >10% and ≤25% is early, >25% and ≤50% is moderate and >50% is classified as severe[27]
5	Liu et al.	2022	Faster R-CNN	1670 datasets	Periapical radiographs	To detect bone loss around dental implants	The mean average precision for implant classification and detection of bone loss was 73%	The described model can be a dependable diagnostic tool, although the performance was slightly below of experienced dentists[28]
6	Chen et al.	2023	CNN (YOLOv2 and AlexNet)	456 datasets	Periapical radiographs	To detect the amount of damage around dental implants due to peri-implantitis	YOLOv2 model achieved a detection accuracy of 89.31% in locating the position of dental implant and the AlexNet assesses the degree of per-implantitis achieving an accuracy of 90.45%	This system identified the damage reaching the first implant thread resulting in early detection of peri-implantitis and and the model's performance was also compared with expert dentists[29]

Table 5: AI for dental implant system classification

S. No	Author name	Year	Models	Datasets/ patients taken	Radiographic techniques used	Approach	Evaluation of effectiveness/ accuracy	Conclusion
1	Kim et al.	2020	Deep neural networks (SqueezeNe, GoogLeNet, ResNet-18, MobileNet-v2, and ResNet-50	801 patients	Periapical radiographs	To evaluate whether deep neural networks can classify differed dental implants	All models demonstrated test accuracy exceeding 90%	More precise judgment can be done for appropriate implant design selection for patients to avoid complications[32]
2	Lee JH et al.	2020	Deep CNN (GoogLeNe, Inception v3)	10,770 datasets	Panoramic and Periapical radiographs	To identify and classifying dental implant systems	This architecture showed a performance accuracy of 97.1%	It is a transformative technology for identification and classification of implants and gives an upper hand performance as compared to

								dental professionals[33]
3	Sukegawa et al.	2020	Deep CNN	8859 datasets	Panoramic radiographs	To evaluate the accuracy in classifying differed dental implant brands	The accuracy of finely tuned VGG16 was 93.5%, for finely tuned VGG19 was 92.7%, for VGG16-transfer was 89.9%, for VGG19-transfer was 86% and for basic CNN was 86%	Among the five models used, VGG16 and VGG19 finely tuned CNNs demonstrated excellent classification performance[34]
4	Takahashi et al.	2020	Deep learning (Yolov3)	1282 datasets	Panoramic radiographs	To identify various dental implants	The mean average precision of the described model for various implants was 0.71	This system can assist in dental implant system identification but better quality images are needed for better results[35]
5	Hadj et al.	2020	CNN (GoogLeNet Inception)	1206 datasets	OPG	To identify the brand and models of dental implant	The accuracy to recognize dental implant brand was 93.8%	The model can help clinicians in routine practice to identify implants with discriminating characteristics[36]
6	Lee et al.	2021	Deep CNN (VGGNet-19, GoogL eNet Inceptionv3, and automated DCNN)	21398 datasets	Periapical and panoramic radiographs	To detect and classify fractured dental implants	The automated DCNN with periapical images gave detection accuracy of 0.984 and classification accuracy of 0.869 based on area under curve scores	This system showed high accuracy detecting and classifying fractured dental implants but a larger dataset and high resolution images are needed for better accuracy[37]

2.3. Quality appraisal

The methodological quality and bias of the study were assessed using the Critical Appraisal Skills Programme (CASP) checklist. Two CASP checklists were used separately. To appraise this review, we used CASP for systematic review 2023 (**Table 1**)[7] to validate our study and provide a qualitative assessment of the studies. The CASP checklist for clinical prediction rule (**Table 2**)[8] enabled the study design, methods to collect datasets, performance results, sources of bias, ethical considerations, and statistical design.

3. Results

Searching was performed through electronic databases to go through all the journals and then full-length articles were retrieved. The data necessary for this review was collected in two phases. Initially, articles were chosen based on the relevance of their titles and abstracts to our research topic, identifying 3486 suitable articles. After removing duplicates and articles unsuitable by automated tools, 2221 articles remained for the secondary screening phase. Implementing inclusion and exclusion criteria reduced the number of articles to 58. Additionally, 34 articles were excluded because they only contained abstracts without full text. Consequently, qualitative synthesis was conducted on 24 articles in this systematic review (**Figure 2**). A comprehensive reading of all the articles was performed considering the type of AI models utilized, their approaches in planning dental implants for patients in need, and evaluating the model's efficacy.

The CASP checklist for clinical prediction rule showed a very low risk of bias for questions 1, 9,10, and 11. Questions 3,4,5 and 8 were not applicable for the included studies. For questions 6 and 7, a low risk of bias was inferred, while question 2 was assigned a medium risk based on the credibility score criteria for the included studies (**Figure 3**).

It is also observed that most of the models are highly effective and accurate in their applications, often outperforming clinicians or giving comparable predictions. With their ability to analyze images more precisely and provide superior classification, convolutional neural networks have emerged as the most commonly used tool.

4. Discussion

Despite the relatively high survival rates observed in dental implants, reaching 95.7% at 5 years and 92.8% at 10 years, the ongoing issues of progressive marginal bone loss and peri-implantitis persist as significant potential complications.[9] Therefore, hard and soft tissue evaluation should be done precisely, considering the factors of occlusal loading after prosthetic rehabilitation. However, due to variable implant designs, bone loss, and soft tissue analysis parameters, there is a wide range of prevalence in such circumstances.

Although CBCT scans are considered the gold standard for the planning of dental implants, their effectiveness relies on the dentist's skill in interpreting images and identifying various anatomical structures. AI algorithms, however, can analyze patterns, anticipate potential complications, and suggest optimal implant designs, thereby enhancing the treatment process. Kurt et al. used a deep convolutional neural network for planning dental implants in CBCT images, segmenting the teeth and jaws, identifying the missing tooth, and creating a virtual tooth mask based on the position and alignment of the neighboring teeth.[12] Alsomali et al. developed and evaluated an AI model for object detection by first manually labelling gutta-percha markers in CBCT images and then training the model to identify these markers accurately.[14] Further, it is seen that many researchers used intraoral radiography techniques like panoramic and periapical views for implant planning and treatment outcomes because of their cost-effectiveness and less radiation exposure. Park et al. developed an effective detection algorithm to enhance treatment planning by automating tooth instance segmentation and missing tooth region detection. However, further improvements in accuracy require additional training data and advanced algorithms.[15] Lyakhov et al. attained superior prediction accuracy compared to similar neural network systems by analyzing a large array of statistical factors related to patients that impact implant survival.[16] Zhang et al. predicted a model for dental implant outcome that used both periapical and panoramic images and they achieved high accuracy for combined radiographic images as compared to only periapical and panoramic images.[18] Although many researchers have given explicit data on how AI is implemented in every aspect of treatment planning, there is always a need for advancement and more robust and reliable references (**Table 3**).

The consensus within the scientific community is that evaluating implant success solely on implant survival is insufficient, and factors such as peri-implant conditions and stability of crestal bone level should also be considered.[22] Despite the established long-term success rate of implant treatment, concerning reports have surfaced regarding a notable prevalence of soft-tissue inflammation around implants linked with bone loss around the implant site.[23] Cha et al. used the Mask R-CNN network to determine the extent of bone loss on periapical radiographs for diagnosing peri-implantitis which was quite promising but there was no statistically notable difference between the model used by him and dentists for detecting landmarks around dental implants.[27] Similarly, Liu et al. performed a pilot study to detect marginal bone loss around dental implants except he used the Faster R-CNN model of AI.[28] Another model was designed by Chen et al.[29] in which first the location of landmark on implants is detected (by using YOLOv2/YOLOv3 models), and then the degree of the image is quantified by deep image understanding. Integrating all these domains into clinical practice still needs clinical evidence with long-term studies (**Table 4**).

Identifying implant brands is essential for treating patients with failing or ailing implants, but the variety of brands complicates diagnosis and treatment. AI offers a promising solution to this challenge. Current methods rely on manual comparison with a radiographic database (whatimplantisthat.com)[30] or a questionnaire-based system by Michelinakis et al.[31], both requiring expertise and posing a risk of human error. The need for accurate dental implant system identification through radiographs is increasing and AI is precisely compelling the researchers to evaluate its accuracy. Kim et al. employed deep neural networks to distinguish between four distinct types of implants in periapical radiographs, achieving a test accuracy exceeding 90%.[32] In a pilot study by Takahashi et al., six implant systems from three manufacturers were analyzed, achieving up to 85% precision, though some were less distinguishable.[35] Lee et al. efficiently evaluated the detection and classification of fractured dental implants using periapical and panoramic views.[37]Accurate data extraction and image identification require precise models, adaptable to various architectures, datasets, and implant brands (**Table 5**).

The amalgamation of robotics and AI within dentistry is termed "dentronics",[38] enhances precision and accuracy in implant procedures. While adopting new technologies is challenging, clinicians must stay updated on advancements.

Robotic-assisted implant surgeries improve implant survival rates and patient satisfaction. The first commercially available robot that is FDA (Food and Drug Administration) approved for dental implant surgery was developed in 2017 and was named YOMI.[39] Li et al. published a clinical report detailing the utilization of an autonomous implant robot for placing two adjacent implants with immediate postoperative restoration.[40] Subsequently, numerous case reports have emerged in the literature giving intriguing research demonstrating successful implant placement by robots.[41-42]

5. Conclusion

AI tools can help clinicians by decreasing chairside time, achieving optimal patient outcomes, and ensuring accurate and precise treatment plans. It has the potential to revolutionize implant dentistry through precise diagnosis, prognosis, treatment planning, and implant system classification.

However, AI in implant dentistry is critically acclaimed nowadays for better diagnosis and clinical decision-making in search of the best results for the benefit of the patients, understanding the fundamental algorithms behind AI tools and utilizing them effectively continues to be a challenge. Ensuring a better understanding of these innovations is crucial, and further research is needed to establish their credibility and effectiveness.

6. Source of Funding

None.

7. Conflict of Interest

None.

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