RESEARCH PAPER

"Accuracy of Ai-Driven Detection of Marginal Bone Loss Around Dental Implants Through Intra-Oral Radiographic Analysis- A Systematic Review"

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Abstract

Purpose: Over the last decade, AI has witnessed considerable innovation to aid digital dentistry. AI has been evolving as a vital component in providing faster and effective healthcare as an auxiliary tool. Considering the work in implantology, research is going on regarding the application of AI for diagnosis and treatment planning of periodontal bone loss and dental implants.

Aim: To assess the accuracy and compare the usage of AI for detection of peri-implant bone loss using radiographs with that of dental clinicians.

Methods: The information was acquired by looking for articles in well-known search engines; which were released between January 2014 till December 2024, following the PICO format. Most of the included studies have reported testing precision, sensitivity and specificity and peri-implant bone loss as the outcomes of AI models. QUADAS-2 was the Risk of Bias analysis tool in the included studies.

Results: AI system performs about as well as human clinicians in detecting marginal bone loss. The level of agreement between AI and the experts is moderate to substantial with kappa scores of 0.547 for general bone loss and 0.568 for bone loss around implants.

Conclusion: The review concluded that the AI model can be utilized and can act as a promising diagnostic tool to measure the radiographic peri-implant bone loss and AI performs comparably or shows moderate agreement with that of the expert implantologists.

Keywords: Artificial intelligence, marginal bone loss, deep learning tools, dental implants, artificial neural networks

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1. Introduction

Dental implants play a crucial role in restoring the biological function in patients with edentulous conditions and have gained significant popularity since the start of the 20th century. Continuous observation and preventative care are essential for ensuring long-term stability, subsequent to the procedure of implant placement. The loss of marginal bone constitutes a critical factor that necessitates monitoring.[1] Bone loss of less than 1.5 mm within one-year post-loading is typically deemed acceptable, with an anticipated subsequent followed annual loss of 0.2 mm. Scenarios where this amount of bone loss is exceeded, a thorough examination is required, particularly in cases where gradual bone loss following osseointegration is seen. The initiation of bone resorption is often attributable to iatrogenic and localized conditions (e.g. implant-specific factors, occlusal trauma, prosthetic restorations, etc.) The phenomenon of bone loss can be categorized into both, late and additional types.[2] Through marginal bone loss monitoring, identifying the preliminary changes in clinical parameters becomes easier. Additional bone resorption along with inflammation of the connective tissue surrounding the implant (i.e. bleeding and/or suppuration), is diagnosed as peri-implantitis. This calls

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for intervention and patient education regarding the oral health.[1,3]

Evaluation of peri-implant bone levels through conventional intra-oral periapical radiographs is often challenging due to the fact that the 3D bone structure is portrayed within a 2D image. Therefore, osseous boundaries around an implant, along with the heights of buccal and lingual bone, must be delineated by skilled clinicians. Inexperienced clinicians are susceptible in making diagnosis with errors and even false diagnoses as indicated by research pertaining to the learning curve related to this field. The implant restoration procedure has gained significant popularity; however, the requisite follow-up may demand a substantial amount of clinical time and resources.[4,5]

Current best practices emphasize the use of a graduated probe for measuring soft tissue and the utilization of radiographic imaging, employing various indices and vector systems to assess hard tissues. However, the complexity of recognizing MBL on radiographs poses greater difficulty attributed to variations around crown margins (supra/subgingival), types of crowns, tooth angulation, radiographic standardization, angulation/ magnification and /or distortion. Moreover, inter-rater and intra-rater reliability reflect certain number of variations.[6,7] Furthermore, radiographic interpretations be likely to vary between observers. These issues may be addressed using automated systems, as they have the ability to read and analyse periapical intra-oral radiographs of dental implants. One plausibility to overcome the aforementioned limitation is the integration of AI to augment the likelihood of achieving standardized outcomes within the realm of periodontology. Zhang et al and Vera et al. reported good prospects for AI to be employed collectively for predicting MBL and to assist dental specialists in diagnosing and treatment planning.[6,8] For an extended duration, machine predictions have been viewed as less effective than human counterparts in object detection and instance segmentation. Nevertheless, there are limited number of comprehensive comparisons between AI technology and humans.

Over the last decade, considerable innovation has been done in artificial intelligence (AI) to aid digital dentistry. It has been evolving as a vital component in providing safe and effective healthcare as an auxiliary tool.[9-11] The aim is to generate artificial neural networks (ANNs) that can simulate human behaviour in a variety of learning processes by altering the strength of connections across layers of sigmoid functions in artificial neurons.[12,13] In implantology, there is limited literature on the application of AI for tooth numbering, diagnosis and treatment planning of periodontal bone loss, dental caries, and dental implants. But no studies have evaluated and compared the difference in accuracy of AI as compared to dental clinicians' assessment in this field. Thus, this systematic review was carried out with an aim to assess and compare, usage of AI for peri-implant bone loss using radiographs and its comparison with conventional methods of assessment like those examined by dental clinicians.

Materials& Methods:

Information sources & Eligibility criteria

This review has been performed and written as per the "Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA Statement) checklist Recommendations.[14] This review has been PROSPERO registered; with the number, CRD42024549547. The focussed research question was, Are Artificial Intelligence Algorithms accurate in detecting Marginal Bone Loss surrounding Dental Implants using Radiographs?

Eligibility criteria were based on PICO elements i.e. patient or population, intervention or indicator, comparator or control, with outcomes as described in Table 1. Inclusion criteria were, English language studies, studies that included implants with restoration and have used AI to analyse the marginal bone resorption around implants and compared it with the performance of dental clinicians. Studies conducted from the past 10 years (2014 to 2024) were included. The exclusion criteria were those articles that weren't just about AI technology but other methods for detection of bone loss. Abstracts, reviews, case reports, case series, conference proceedings and Letters to editor were excluded.

[Table 1] –PICO elements i.e. patient or population, intervention or indicator, comparator or control, with outcomes of this systematic review

Elements	Description
Population	Radiographs of the patients who have undergone dental implant placement with restorations.
Intervention	Artificial Intelligence as a method to detect and measure marginal bone loss.
Comparator	Accurate detection of marginal bone loss around dental implants by the artificial intelligence with that of the dental practitioners.
Outcomes	Accuracy, Specificity, Sensitivity.

Search Strategy, Study identification and Selection

A systematic search strategy was developed to include all available studies reporting artificial intelligence algorithms for the detection of marginal bone loss around dental implants using radiographs. The search strategy having all identified keywords, was adapted for each included information source.

All the studies in English language published from January 2014 till December 2024, globally were screened for inclusion criteria. The search was conducted on

PubMed, Scopus, Science direct, and Google Scholar etc. The reference lists were searched thoroughly from all the studies that met the inclusion criteria. Experts from the respective subjects were contacted for identifying the grey literature. Cross references for pertinent papers were verified. When the whole texts of the pertinent research were not accessible through an electronic database, a manual search in the institutional library was performed.

Every keyword and index term that were acknowledge in the search strategy were modified for every included information source. To search for data, a variety of keywords were utilized, including "dental implants radiographs", "periapical radiographs of dental implants", "artificial intelligence", "deep learning", "artificial neural networks, "Peri-implant bone loss", "Bone loss in implants", "Precision", "Sensitivity" and "Specificity"

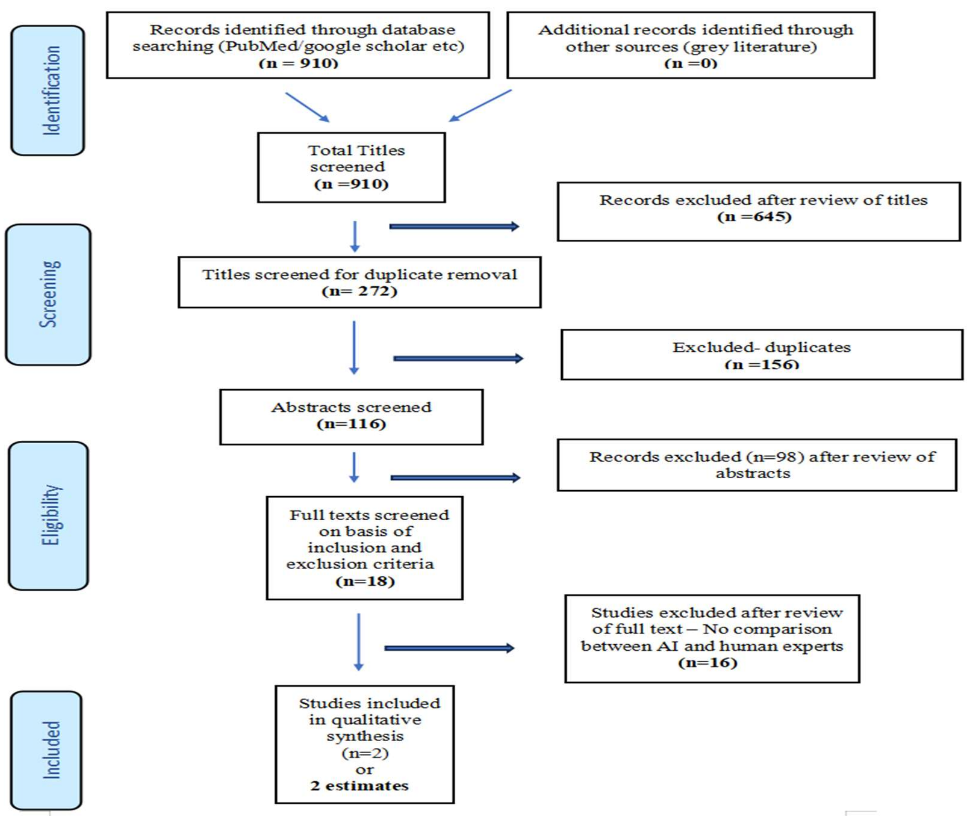
Based on the usage of Boolean operators, the strategy was prepared. The basic and advanced literature search with combination of keywords with Boolean operators was "[(artificial intelligence OR machine learning OR deep learning methods OR convolutional neural networks OR artificial neural networks)" AND "(dental implants radiographs OR periapical radiographs of dental implants)" AND "(marginal bone loss OR bone loss sites OR bone loss in implants)" AND "(Accuracy OR Precision OR Sensitivity OR Specificity)"]

Data extraction and Management

Titles along with the abstracts were screened for eligibility prior to the full text screening of eligible articles. The full-text articles were thoroughly reviewed, to determine if they met the inclusion criteria. For those instances where there was uncertainty regarding a study's eligibility, the problem was resolved through consultation/discussion with a second author. In case of disagreement, a consensus was arrived at after discussion with the third author. The study reviewers after discussion; developed a consensus while making decision regarding discrepancies in selection of studies. Duplicates were removed using Rayyan QCRI software and the data was stored in MS Excel 2017. Eighteen studies were selected for full text review after which 16 were excluded and 2 were eligible for the systematic review. The "screening process of studies is presented in the form of PRISMA flow-chart [Figure 1]

Risk of bias assessment

The included papers in the systematic review were evaluated using "QUADAS-2" (Quality Assessment and Diagnostic Accuracy technique).[15] This technique is used for assessing the quality of studies based on diagnostic testing.



[Figure. 1]: PRISMA Flow chart presenting the screening process

Results:

Two studies were included in the systematic review based on eligibility criteria. Both studies assessed and compared the precision and accuracy in the detection of marginal bone loss around dental implants between AI algorithms/models and dental clinicians. One study was published in 2021 and the other was published in 2022. Both the studies were diagnostic accuracy studies; wherein AI model was compared with that of the dental practitioner/clinician's assessment. The total data set included around 708 dental radiographs in one study and 1670 dental radiographs in another study. Table. 2 represents study characteristics for different data items like author name, year, AI algorithms, data sets, intervention and comparator, and outcomes. The quantitative results in both studies are presented in Table 3 according to the outcomes reported in both the studies.

[Table. 2]- Details of the study parameter, intervention/exposure, and comparator/control of the studies included in the systematic review.

Sr. no	Author	AI Algorithm Architecture	Network backbone	Parameter (P)/Dataset test size: Radiographs for training/ calibration (validation)	Parameter (P)/Dataset test size: Radiographs for testing	Exposure (E): Study factor	Modality	Comparator/control (C), if any	Primary and secondary outcomes: Evaluation accuracy /average accuracy	Quantitative results	Results- effective, on effective, neutral	Conclusion
1	Cha YJ et al	Modified region-based convolutional neural network (R-CNN)	Res Net-FPN	708 periapical radiographic images; training (n = 508), validation (n = 100)	test (n = 100) datasets	bone loss percentage and classifying the bone resorption severity around dental implants	dental periapical radiographs	dental clinician evaluation	average precision, average recall, and mean object key point similarity (OKS)	Mean OKS - Model - 0.8885, Dentist 0.9012, Average Precision - Model -0.627, dentist -0.684	No statistically significant difference was found between the modified R-CNN model and dental clinician for detecting landmarks around dental implants	The modified R-CNN model can be utilized to measure the radiographic peri-implant bone loss ratio to assess the severity of peri-implantitis.

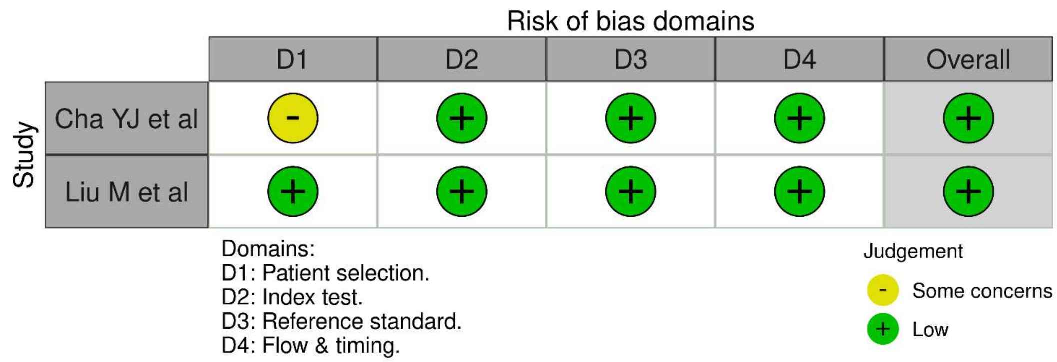
Sr. no	Author	AI Algorithm Architecture	Network backbone	Parameter (P)/Dataset test size: Radiographs for training/ calibration (validation)	Parameter (P)/Dataset test size: Radiographs for testing	Exposure (E): Study factor	Modality	Comparator/control (C), if any	Primary and secondary outcomes: Evaluation accuracy /average accuracy	Quantitative results	Results- effective, on effective, neutral	Conclusion
2	Liu M et al	Faster region-based convolutional neural network (R-CNN)	Inception Resnet v2 (Atrous version)	1670 periapical radiographic images; training (n = 1370), validation (n = 150)	test (n = 150) datasets	marginal bone loss and bone loss sites around dental implants	periapical radiographs	dental clinicians' decision	Sensitivity, Specificity, Mistake diagnostic rate, Omission diagnostic rate, Positive predictive value	Sensitivity- 67 (AI), 93 (DC1), 62 (DC2), Specificity- 87 (AI), 64 (DC1), 77 (DC2)	Evaluation metrics of AI system is equal to resident dentist. The agreement between the AI system and expert is moderate to substantial (κ = 0.547 and 0.568 for bone loss sites and bone loss implants, respectively) for detecting marginal bone loss around dental implants.	This AI system based on Faster R-CNN analysis of periapical radiographs is a highly promising auxiliary diagnostic tool for peri-implant bone loss detection.

[Table. 3] – Quantitative outcomes reported in the included studies in the systematic review

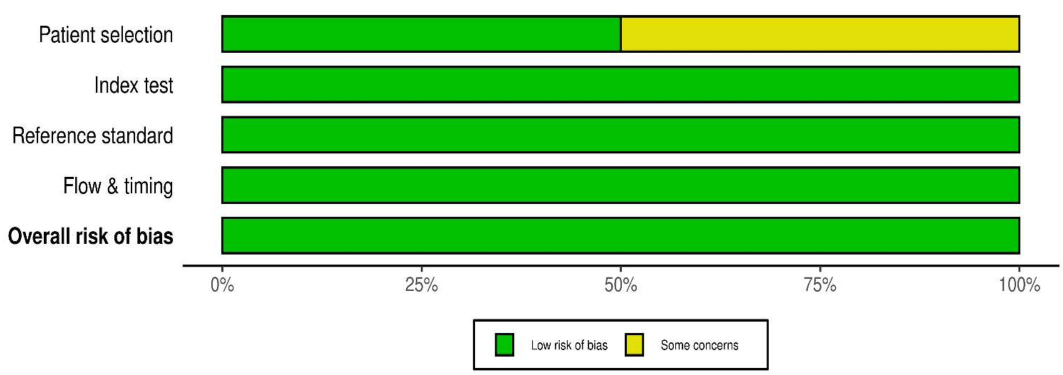
Sr. no	Included studies	Sensitivity		Specificity		Average precision		Mean OKS	
		AI model	Dentist	AI model	Dentist	AI model	Dentist	AI model	Dentist
1	Cha YJ et al	-	-	-	-	0.627	0.684	0.8885	0.9012
2	Liu M et al	67%	62%	87%	77%	-	-	-	-

Assessment of "Risk of Bias" & concerns for applicability

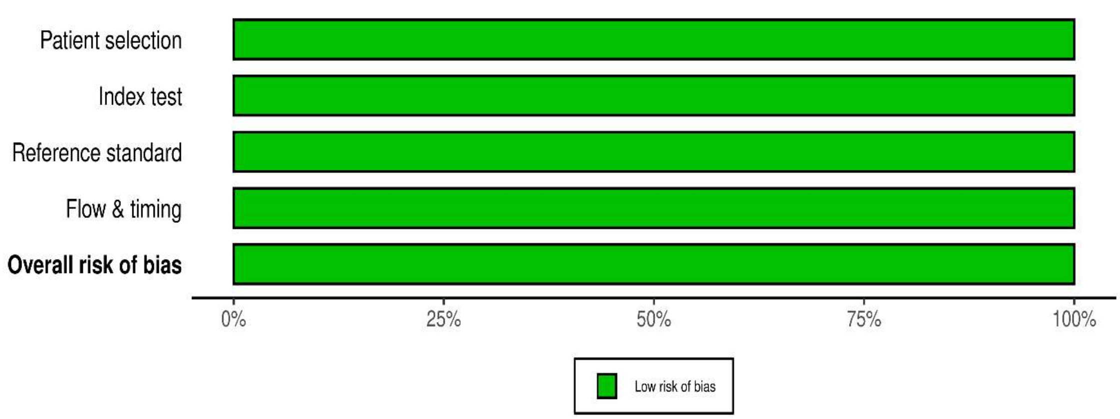
The QUADAS-2 tool21 for diagnostic testing was used to assess risk of bias. One study demonstrated low risk of bias in the patient selection (Liu M et al, 2022) and the other study showed some concerns in patient selection (Cha YJ et al, 2021). Since data feeding for AI is required to be highly standardized, and the flow and time frame are ineffective in the final output, both the aspects were regarded as low-risk categories in both studies. Both the studies compared AI with assessment by dental practitioners/clinicians. Hence, reference standards in both studies were reported as low risk. So, the overall assessment showed a low risk of bias for included studies in the systematic review.[Figure 2a and Figure 2b]. Following the QUADAS-2 assessment tool, risk of bias arm and the applicability concern arm showed similar results; wherein low risk of bias was noted in applicability of the index test (AI Model). [Figure 3]. And Table. 4 presents QUADAS-2 tool domains with descriptions for included studies.



[Figure 2 a] – Risk of Bias traffic light plot for studies included in the systematic review



[Figure 2 b] – Risk of Bias Summary plot for studies included in the systematic review



[Figure 3] –Concerns regarding applicability for studies included in the systematic review

[Table. 4] - QUADAS-2 tool[22] domains with descriptions for included studies

DOMAIN	PATIENT SELECTION	INDEX TEST	REFERENCE STANDARD	FLOW AND TIMING

Description	Describe methods of patient selection: Describe included patients (prior testing, presentation, intended use of index test and setting):	Describe the index test and how it was conducted and interpreted:	Describe the reference standard and how it was conducted and interpreted:	Describe any patients who did not receive the index test(s) and/or reference standard or who were excluded from the 2x2 table (refer to flow diagram): Describe the time interval and any interventions between index test(s) and reference standard:
Cha YJ et al	Some concerns regarding patient selection	Yes, mentioned in the study	Yes, mentioned in the study	Yes, mentioned in the study
Liu M et al	Yes, mentioned in the study	Yes, mentioned in the study	Yes, mentioned in the study	Yes, mentioned in the study
Signalling questions(yes/no/unclear)	Was a consecutive or random sample of patients enrolled?	Were the index test results interpreted without knowledge of the results of the reference standard?	Is the reference standard likely to correctly classify the target condition?	Was there an appropriate interval between index test(s) and reference standard?
	Was a case-control design avoided? Did the study avoid inappropriate exclusions?	If a threshold was used, was it pre-specified?	Were the reference standard results interpreted without knowledge of the results of the index test?	Did all patients receive a reference standard? Did all patients receive the same reference standard? Were all patients included in the analysis?
Cha YJ et al	Yes	Yes, pre-specified threshold was set-up using training datasets	Yes	Yes
Liu M et al	Yes	Yes, pre-specified threshold was set-up using training datasets	Yes	Yes
Risk of bias: High/low/unclear	Could the selection of patients have introduced bias?	Could the conduct or interpretation of the index test have introduced bias?	Could the reference standard, its conduct, or its interpretation have introduced bias?	Could the patient flow have introduced bias?
Cha YJ et al	Yes, with some concerns	Low	Low	Low
Liu M et al	Low	Low	Low	Low
Concerns regarding applicability: High/low/unclear	Are there concerns that the included patients do not match the review question?	Are there concerns that the index test, its conduct, or interpretation differ from the review question?	Are there concerns that the target condition as defined by the reference standard does not match the review question?	
Cha YJ et al	No	No	No	

Liu M et al	No	No	No	

Discussion

On the basis of diagnostic performance, cost-benefit ratio and patient outcomes, AI technologies can be clinically evaluated. Historically, machine predictions were inferior when it came to the detection of object and instance segmentation compared to humans and large-scale comparisons are insufficient between AI systems and human observers.[16-18] This systematic review included studies in which the AI detected implants with high accuracy. Detecting MBL can be difficult, requiring multiple diagnostic performance metrics to assess the effectiveness of a model. Specificity indicates the likelihood that a bounding box for marginal bone loss truly includes the affected area, whereas sensitivity reflects the likelihood that an image with the disease is accurately identified as “disease”. Different AI algorithms like machine learning, different types of neural networks are being used in various studies to assess the peri-implant bone loss.[19-21]

CNN is the most basic core model of ANNs, with image recognition and segmentation capabilities that may be used in conjunction with radiographs to identify periodontal disease. In MBL, CNNs are able to identify edges and identify patterns.[22] Deep CNN algorithms are able to extract regional patterns from intraoral radiographs and build hierarchical feature representations mainly to their numerous convolutional and hidden layers. Recent studies conducted by Bayrakdar et al and Chen et al, reported the degree of MBL around the implant with an accuracy of 91% and 90.45% respectively. Thus, through the provision of real-time treatment, training a reliable and accurate CNN model can significantly improve healthcare.[23,24] Moreover, Cha et al. and Liu M et al, reported 90% accuracy and 87 % specificity of R-CNN in MBL detection in radiographs.[25-28]

What does Cohen’s Kappa (κ) measure?

It tells us how much two raters agree, beyond what would happen by chance.

The value ranges from -1 to 1:

< 0: Less than chance agreement (poor)

0.01–0.20: Slight agreement

0.21–0.40: Fair agreement

0.41–0.60: Moderate agreement

0.61–0.80: Substantial agreement

0.81–1.00: Almost perfect agreement

The calculated Cohen's Kappa indicated moderate agreement (κ = 0.547 to 0.568) between the AI models and expert clinicians, demonstrating consistent, though not perfect, diagnostic performance.

This current systematic review is one of its kind which assess the marginal bone loss of implants using periapical radiographs. Moreover, the bone loss detected by AI algorithm is compared with the assessment of dental practitioner. The study outcomes report the accuracy of these AI techniques and thus contribute to significant literature evidence supporting the implementation of AI technology in health services. All these contribute to the strengths of this systematic review. A few limitations of this review are; there are certain inherent challenges with adopting new technology into a facility, specifically include lack of readability, hardware, code sharing, and data curation, resistance to modification inside existing infrastructures, and continuing cost-effective maintenance. Latest criticism has focused on the prevalence of implicit biases in datasets training and the repercussions of performance in AI. Another drawback is that intra-oral periapical radiography cannot portray the three-dimensional interaction in between prosthesis and surrounding bone. Only a few researches have exhibited robust accuracy of these models in detecting bone defects.

This review has provided valuable insights in the need of utilizing AI technology in assessing dental implants success rates. The included study designs were homogenous in this systematic review with similar conclusions; which reported that both the studies noted AI model as an effective tool in assessing peri-implant or marginal bone loss in comparison to conventional method of assessment by clinical practitioners. Moreover, this current review suggests that, the diagnostic performance metrics of AI is equivalent to the resident dentist and the level of agreement between AI and the expert in identifying marginal bone loss around dental implants ranges from moderate to substantial. However, further studies on these AI systems are required to evaluate the acceptability as well as the usage with accurate feasibility in different clinical settings. Furthermore, developing a user interface could improve consumer satisfaction as well as the ease of use and efficiency of system, resulting in improved work productivity and product quality.

Conclusion and Future Recommendations:

Within the limitations of this systematic review, it can be concluded that, the accuracy of AI models in recognising MBL around fixed prosthesis seems promising. An accurate diagnostic tool can be developed from the AI model; Faster R-CNN, as it is capable of detecting MBL on intra-oral periapical radiographs. Their capacity to provide precise predictions and analyse intricate information presents chances for early identification and targeted interventions. However, these models are still in the early stages of developmental phase. Prior to advocating these models be used in clinical practice, it is critical to evaluate the efficacy as well as reliability of these models given the growing trend of artificial intelligence in periodontology. This automated technique enhances efficiency and consistency while also reducing human errors. Furthermore, it is advisable to investigate the potential advantages of integrating improved imaging techniques or generating advanced algorithms capable of detecting even slight amounts of bone loss. In future, the model performance can be enhanced by even more high-quality training images.

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