Journal of Health Informatics in Developing Countries
http://www.jhidc.org/
Vol. 17 No. 1, 2023

Submitted: Nov 25th, 2022 Accepted: Jan 20th, 2023

Beyond Traditional Methods: Leveraging Artificial Intelligence to Detect Peri-Implant Marginal Bone Loss - A Systematic Review

Nora Saleh Al-Nomay[1] *, Bader Aldebasi [2], Aisha Ali Alshaya [3]

[1] Preventive Dental Science Department, College of Dentistry, King Saud Bin Abdulaziz University for Health Sciences, King Abdu laziz Medical City, Ministry of National Guard Health Affairs, Riyadh, Saudi Arabia.

[2] King Abdullah International Research Centre, King Saud bin Abdulaziz University for Health Science, Riyadh, Saudi Arabia

[3]Dental Services, Family Medicine and Primary Health Care, King Abdulaziz Medical City, Ministry of National Guard for Health Affairs, Riyadh, Saudi Arabia

Abstract

Background: Dental implants are a popular solution for replacing missing teeth, but one potential complication is marginal bone loss around the implant site. Researchers have turned to artificial intelligence models for predictive analysis to address this concern. The objective of this systematic review was to evaluate how well artificial intelligence models perform in predicting the occurrence of marginal bone loss around dental implants.

Methods: This systematic review conformed to Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020 guidelines. PubMed, Scopus, ScienceDirect, and Cochrane were searched from inception till June 7, 2023. Studies were selected based on the following predefined criteria: 1) studies investigating peri-implant bone loss through artificial intelligence models; 2) no date restriction; and 3) studies available in English language. Keywords such as "artificial intelligence", "machine learning", "neural network", "deep learning", "dental implant", "implant dentistry", "peri-implant", "marginal bone loss", and "bone loss" were used. Two review authors assessed the methodological quality using the Joanna Briggs Institute Critical Appraisal Checklist for Quasi-Experimental Studies (non-randomized experimental studies).

Results: Three relevant studies were included in this systematic review. Support vector machine, artificial neural network, logistic regression, random forest, and convolutional neural network artificial intelligence models were used. Cone-beam computed tomography and periapical radiographs were used to develop artificial intelligence models. All three research studies confirmed the effectiveness of artificial intelligence models in feasibly predicting peri-implant bone loss at par with dental physicians and clinicians. The overall risk of bias assessment of studies demonstrated a consistently low risk of bias across all included articles.

Conclusion: The artificial intelligence models have the potential to predict marginal bone loss around dental implants and, therefore, can be considered for utilization and deployment in clinical practice.

Keywords: Artificial Intelligence; Machine Learning; Implant Dentistry; Per-Implant; Marginal Bone Loss.

*Nora Saleh Al-Nomay- Preventive Dental Science Department, College of Dentistry, King Saud Bin Abdulaziz University for Health Sciences, King Abdulaziz Medical City, Ministry of National Guard Health affairs- PO Box 22490, Riyadh 11426, Saudi Arabia; E-mail: nomayn@ksau-hs.edu.sa.

1. Introduction

Dental implants play a crucial role in restoring the functional capabilities of individuals with missing teeth [1]. Ensuring long-term stability following implantation necessitates careful monitoring and maintenance [2]. An important parameter that requires monitoring is marginal bone resorption. It is generally considered acceptable to have <1.5 mm of bone loss one year after loading, followed by an annual loss of 0.2 mm afterwards [3, 4]. When bone loss surpasses these thresholds, a thorough investigation becomes necessary, even in cases where the failure occurs gradually after osseointegration [5, 6].

Experts agree that marginal bone loss is a complex condition influenced by multiple risk factors that act simultaneously [7]. During the early post-loading phase, occlusal force is transmitted from the implant to the alveolar bone, triggering bone remodelling. Additionally, several other factors, such as dental implant configuration [8], cortical bone thickness [9], susceptibility to periodontal disease [10], and smoking habits [11], can potentially impact bone remodelling and marginal bone loss.

In clinical practice, the identification of peri-implant bone levels primarily depends on imaging. Cone-beam computed tomography, panoramic radiography, and periapical radiography are commonly utilized imaging modalities in dental practice. Cone-beam computed tomography provides a three-dimensional visualization of the dental implant and its relationship with the surrounding alveolar bone, demonstrating robust accuracy in detecting peri-implant bone defects [12]. Periapical radiographs have also been used in studies to assess bone condition around implants [13]. Two-dimensional radiographic images, such as periapical radiographs, are widely favoured in clinical settings due to their cost-effectiveness and low radiation dose. However, evaluating peri-implant marginal bone levels on conventional periapical radiographs can be challenging since the two-dimensional image representation does not fully capture the three-dimensional bone shape. Skilled clinicians are required to determine the boundaries of the bone around the implant and the buccal and lingual bone heights [14]. Inexperienced clinicians may encounter diagnostic errors and false diagnoses [15]. Additionally, interpretations of radiographs often exhibit variations among different observers. To address these challenges, automated systems for reading and analyzing periapical radiographs of dental implants have emerged as a potential solution. These systems can potentially improve efficiency, consistency, and accuracy in assessing implant-related radiographs, assisting clinicians in their diagnostic processes.

Artificial intelligence utilizes statistical and optimization techniques to learn and identify intricate relationships within complex and extensive datasets. Artificial intelligence has found successful applications in various medical domains, including disease detection, diagnosis, and treatment [16, 17]. In the dental field, artificial intelligence models have been employed for predicting prognosis in dental implant cases, as evidenced by several clinical studies [18-20]. These promising findings motivate us to systematically explore whether artificial intelligence models can outperform conventional statistical methods in accurately predicting a peri-implant marginal bone loss.

The rationale for conducting this systematic review lies in the increasing significance of dental implantology and the potential of artificial intelligence to revolutionize its diagnostic capabilities. Dental implants have become a widely accepted and effective treatment option for patients with missing teeth. However, dental implants' long-term success and stability are contingent upon maintaining healthy peri-implant tissues, particularly the marginal bone surrounding the implant. Detecting peri-implant marginal bone loss is crucial in the early identification of implant complications, such as peri-implantitis, which can lead to implant failure if left untreated. Traditional methods of assessing marginal bone loss rely on radiographic imaging and clinical examinations, are subject to observer variability and may not always detect subtle changes in bone levels. Herein lies the potential role of artificial intelligence in improving the accuracy and efficiency of peri-implant marginal bone loss detection. By conducting a systematic review of existing literature on the role of artificial intelligence in detecting peri-implant marginal bone loss, this study aims to consolidate and evaluate the available evidence. The findings of this study will help identify the strengths and limitations of artificial intelligence-based approaches, as well as highlight any existing gaps or areas that require further investigation.

2. Subjects and Methods

2.1 PRISMA 2020 Statement

This systematic review confirmed the updated guidelines in the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020 Statement [21].

2.2 Eligibility Criteria

The studies were selected for systematic review based on the following predefined criteria: 1) studies investigating peri-implant bone loss through artificial intelligence models; 2) no date restriction; and 3) studies available in the English language. Editorials, opinions, perspectives, letters to the editors, correspondences, narrative reviews, systematic reviews, meta-analyses, and conference abstracts were omitted.

2.3 Population or Problem, Intervention, Comparison, Outcome (PICO)

A PICO question was created, focusing on artificial intelligence's role in detecting peri-implant bone loss. The population or problem comprises the clinical relevance of artificial intelligence models in implant dentistry for identifying peri-implant bone loss. The intervention comprised of artificial intelligence models. The comparison was not applicable. The outcome was the efficacy of artificial intelligence models in detecting peri-implant bone loss.

2.4 Search Strategy and Databases

The electronic databases PubMed, Scopus, ScienceDirect, and Cochrane were searched from inception till June 7, 2023. Following medical subject headings (MeSH) terms and keywords such as “artificial intelligence”, “machine learning”, “neural network”, “deep learning”, “dental implant”, “implant dentistry”, “peri-implant”, “marginal bone loss”, and “bone loss” were used in combination with Boolean operators (AND, OR) for precise results. The reference lists of the relevant full-text articles were also reviewed to find additional pertinent articles.

2.5 Study Selection

Two reviewers independently evaluated the retrieved articles for eligibility, and any unrelated articles were dismissed. We made sure that both reviewers were unaware of each other’s decisions regarding the inclusion and exclusion of the articles. First, titles and then abstracts of the articles were reviewed and retained for full-text assessment. During the independent full-text review by the same authors, studies were deemed appropriate if they documented evidence of using artificial intelligence models in implant dentistry to identify peri-implant bone loss. Disagreements, if any, during the title, abstract and full-text assessments of the articles were healthily debated and resolved by discussion.

2.6 Data Extraction

The selected articles underwent full-text review by two independent reviewers, and the following information was extracted in a standardized data extraction sheet: first author’s name and year of publication, country, artificial intelligence model used, source of data, dataset, and main findings.

2.7 Methodological Quality of Included Studies

The review authors assessed the methodological quality in all of the included studies by using the Joanna Briggs Institute Critical Appraisal Checklist for Quasi-Experimental Studies (non-randomized experimental studies). The Joanna Briggs Institute Critical Appraisal Checklist consists of a comprehensive set of criteria that enables systematic evaluation of the key components of such studies. By utilizing this checklist, researchers can assess the risk of bias and methodological rigor, ensuring that the findings are reliable and can be confidently incorporated into evidence-based practice. Appraisal for each question provides a subjective assessment of the risk of bias (low, unclear, or high) [22].

3. Results

3.1.Systematic Search Results

The search methods produced a total of 99 research studies from PubMed, Scopus, ScienceDirect, and Cochrane. Among these, nine duplicate studies were discovered. The remaining 90 articles underwent screening and eligibility assessment based on their titles and abstracts. Out of these, 20 articles were selected for a thorough examination of the full text. After the full-text review, 17 articles were excluded.

Two of the articles were excluded after the full-text review presented artificial intelligence models for periodontal bone loss, while one article focused on dental restoration. Additionally, one article centered around periapical lesion analysis, and another article specifically addressed preoperative radiographs using an artificial intelligence model. Twelve investigations were unrelated to artificial intelligence models (Figure 1).

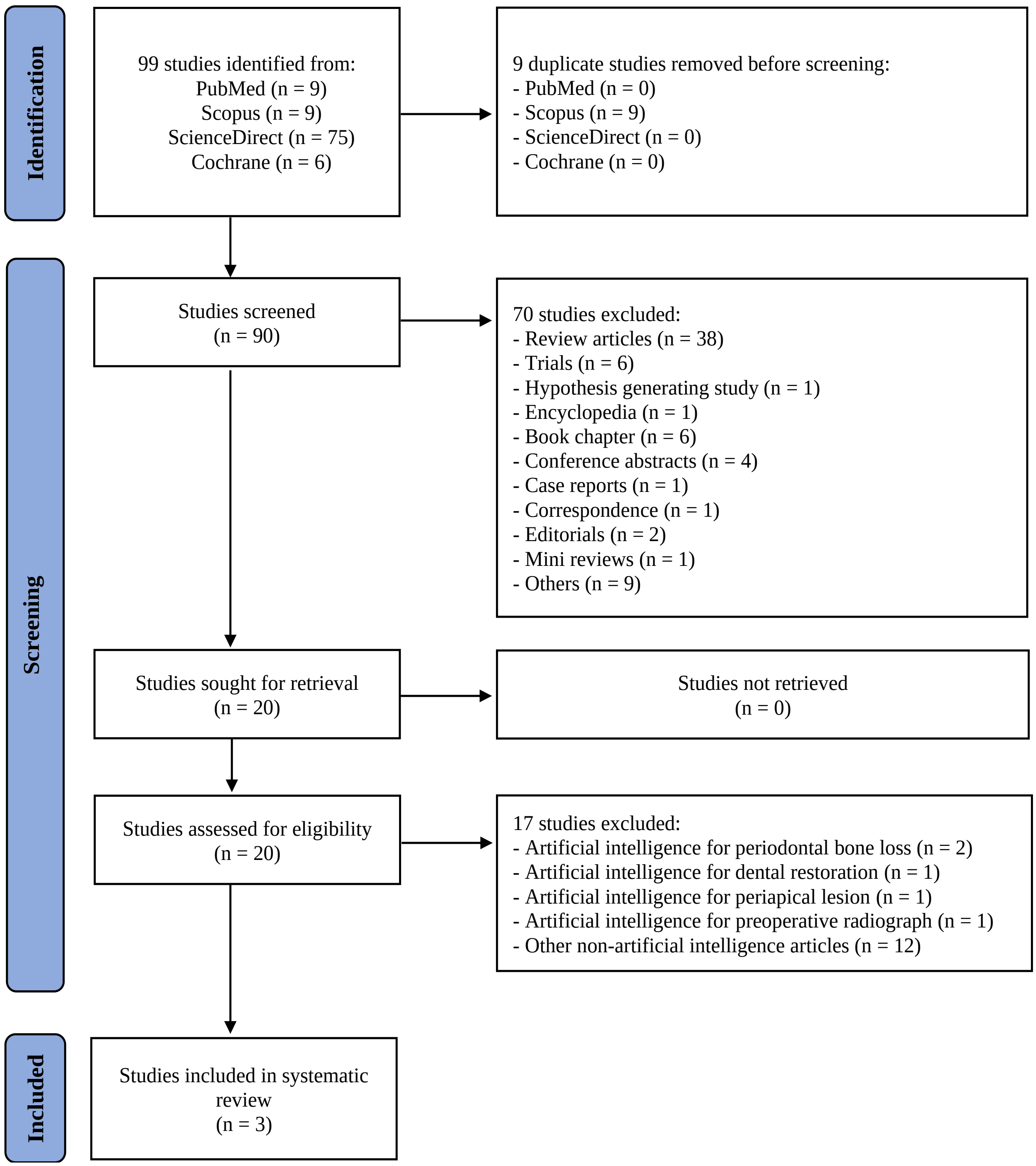

Figure 1. PRISMA Flow Diagram for Identification of Relevant Studies

3.2.Characteristics of Included Studies

Three relevant studies were included in this systematic review. Research studies were published between 2020 and 2022. Two research studies were published in China [18, 19], while one was from Korea [20]. The following artificial intelligence models were used in the research studies: support vector machine, artificial neural network, logistic regression, random forest, and convolutional neural network. Zhang et al. (2020) used cone-beam computed tomography radiographs for artificial intelligence modelling, whereas Cha et al. (2021) and Liu et al. (2022) used periapical radiographs. The primary aim of all the research studies was to develop an artificial intelligence model that can feasibly predict marginal bone loss in dental implants. The dataset, data source, and main findings of the eligible research studies are presented in Table 1.

Table (1) Characteristics of Studies Included in Systematic Review

Author and Year	Country	Artificial Intelligence Model	Radiographs	Data Source and Dataset	Main Findings
Zhang *et al*. 2020 [18]	China	Support vector machine (SVM), artificial neural network (ANN), logistic regression (LR), and random forest (RF)	Cone-beam computed tomography (CBCT) radiographs	**Data Source:** Department of Oral and Maxillofacial Surgery of Affiliated Stomatological Hospital of Nanjing Medical University between January 2016 and March 2019. **Dataset:** Cone-beam computed tomography (CBCT) radiographs of 81 patients (41 severe marginal bone loss cases and 40 normal controls) were examined.	The SVM model demonstrated the best outcome in predicting marginal bone loss (AUC= 0.967, sensitivity = 91.67%, specificity = 100.00%), followed by ANN (AUC= 0.928, sensitivity = 91.67%, specificity = 93.33%), LR (AUC= 0.906, sensitivity = 91.67%, specificity = 93.33%), RF (AUC= 0.842, sensitivity = 75.00%, specificity = 86.67%). **Conclusion:** Artificial intelligence models that utilize the morphological variation of trabecular bone have the potential to be employed collectively for predicting severe marginal bone loss.
Cha *et al*. 2021 [20]	Korea	Convolutional neural network (CNN)	Periapical radiographs	**Data Source:** Seoul National University Dental Hospital between December 2018 and June 2020. **Dataset:** For final analysis, 708 periapical images were divided into upper and lower periapical radiographs. Each subset was further categorized into training, validation, and test datasets for subsequent analysis and model development.	The mean object keypoint similarity (OKS) values of the model were 0.8748, 0.9029, and 0.8885 for upper, lower, and total test datasets, respectively. The mean OKS of a dentist for the total test dataset was 0.9012. **Conclusion:** No statistically significant distinction was observed in the detection of landmarks around dental implants between the CNN model and dental clinicians. Therefore, the CNN model can be effectively employed to measure the radiographic peri-implant bone loss

					ratio, enabling the assessment of peri-implantitis severity.
Liu *et al.* 2022 [19]	China	Convolutional neural network (CNN)	Periapical radiographs	**Data Source:** Peking University School and Hospital of Stomatology. **Dataset:** A total of 2500 periapical radiographs of bone-level implants were collected. Of which, 835 images exhibiting marginal bone loss around the implants were identified and classified as the case group. To form the control group, 835 radiographs were randomly selected from the primary dataset, specifically from those that did not display any marginal bone loss around the implants.	The evaluation metrics of the artificial intelligence model are comparable to those of a resident dentist. There is a moderate to substantial level of agreement between artificial intelligence model and the expert in detecting marginal bone loss around dental implants, with κ values of 0.547 and 0.568 for bone loss sites and bone loss implants, respectively. **Conclusion:** The application of CNN on periapical radiographs has yielded a highly promising auxiliary diagnostic tool for the identification of peri-implant bone loss.

3.3.Risk of Bias Findings

The overall risk of bias assessment of studies demonstrated a consistently low risk of bias across all included articles. Regarding Question 1, all three studies [18-20] exhibited a low risk of bias. As for Question 4, Zhang et al. (2020) [18] and Liu et al. (2022) [19], excluding Cha et al. (2021) [20], maintained a low risk of bias. All studies [18-20] were identified as having a low risk of bias for Questions 8 and 9. Lastly, Questions 2, 3, 5, 6, and 7 were deemed irrelevant for this systematic review (Figure 2)

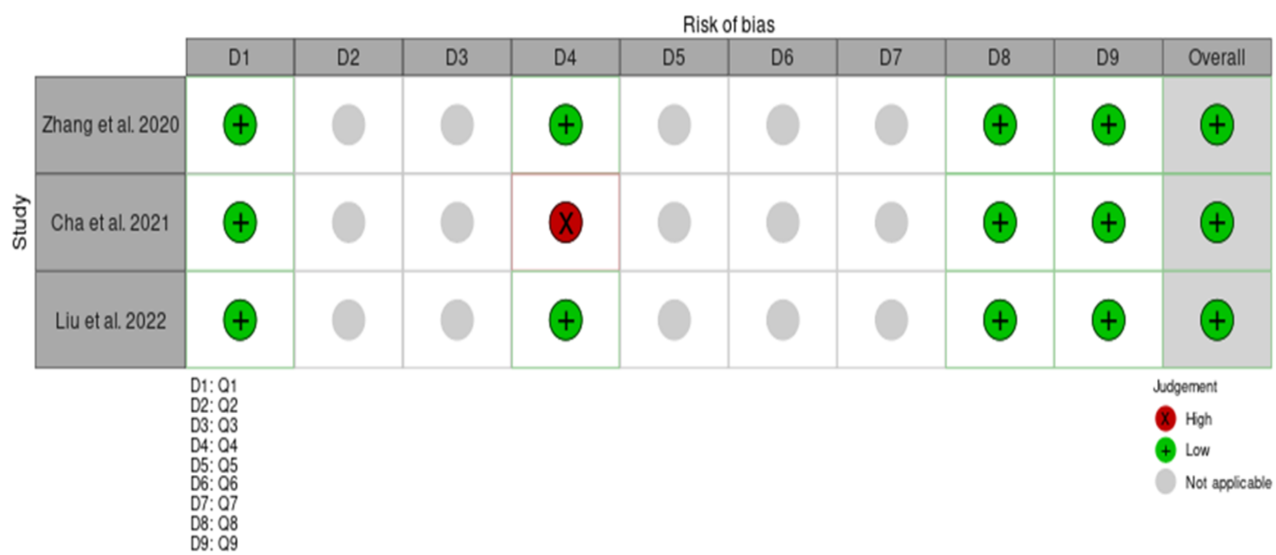

Figure 2. Risk of Bias Assessment through Joanna Briggs Institute Critical Appraisal Checklist for Quasi-Experimental Studies

4. Discussion

Artificial intelligence models offer promising opportunities for predicting marginal bone loss around dental implants due to their ability to analyze complex datasets and identify patterns that may not be easily discernible through traditional statistical methods. By incorporating various input parameters such as patient characteristics, implant features, and relevant clinical variables, artificial intelligence models can generate accurate predictions regarding the likelihood and severity of marginal bone loss [18-20]. The present systematic review aimed to evaluate the performance of artificial intelligence models in predicting peri-implant marginal bone loss in dental implant patients. The findings of this review highlight the potential of artificial intelligence models in enhancing our understanding and management of marginal bone loss complications.

The utilization of artificial intelligence models in this context may have significant clinical implications. Early detection of marginal bone loss is crucial for timely intervention and appropriate treatment planning. Artificial intelligence models can aid in identifying individuals at higher risk of developing marginal bone loss, allowing clinicians to implement preventive measures and tailored management strategies. This can ultimately improve long-term implant survival rates and enhance patient outcomes [18-20].

This systematic review included three studies published between 2020 and 2022 from China and Korea that designed artificial intelligence models to determine marginal bone loss around dental implants [18-20]. Zhang et al. (2020) explored the potential of employing machine learning algorithms that utilize trabeculae microstructure parameters to forecast the likelihood of severe marginal bone loss development. In this study, the investigators recruited 81 participants, comprising 41 individuals with severe marginal bone loss around implant and 40 normal controls. To predict the occurrence of severe marginal bone loss, four artificial intelligence models were employed: support vector machine, artificial neural network, logistic regression, and random forest. The performance of these models was evaluated using metrics of the area under the receiver operating characteristic curve (ROC) and Area Under A Curve (AUC), sensitivity, and specificity. During the initial stages of functional loading, significant increases in the structure model index and trabecular pattern factor were observed in peri-implant alveolar bone among severe marginal bone loss cases. Among the artificial intelligence models tested, the support vector machine model yielded the highest predictive accuracy for marginal bone loss with AUC of 0.967, sensitivity of 91.67%, and specificity of 100.00%. The artificial neural network model followed closely with AUC of 0.928, sensitivity of 91.67%, and specificity of 93.33%, while the logistic regression model with AUC of 0.906, sensitivity of 91.67%, and specificity of 93.33% and random forest model with AUC of 0.842, sensitivity of 75.00%, and specificity of 86.67% exhibited slightly lower performance. The study concluded artificial intelligence models that utilize morphological variations in the trabecular bone to have the potential to predict the occurrence of severe marginal bone loss around dental implants [18].

Cha et al. (2021) assessed the deep convolutional neural network to identify the marginal bone level, top, and apex of dental implants on periapical radiographs. The study aimed to develop an automated artificial intelligence model capable of determining the percentage of bone loss and classifying the severity of bone resorption. To achieve this, the authors utilized a modified region-based convolutional neural network that was trained using transfer learning with the Microsoft Common Objects in Context dataset. The dataset consisted of 708 periapical radiographic images, which were split into training (n = 508), validation (n = 100), and test (n = 100) sets. They employed random data augmentation to enhance the training dataset. To evaluate the performance, average precision, average recall, and mean object keypoint similarity was calculated, and compared the mean object keypoint similarity values of artificial intelligence model with those of a dental clinician. By detecting specific keypoints, the authors were able to measure and classify radiographic bone loss. Notably, there was no statistically significant difference between modified region-based convolutional neural network model and the dental clinician in terms of detecting bone loss landmarks around dental implants. Consequently, the authors concluded that modified region-based convolutional neural network model can indeed effectively measure the radiographic peri-implant bone loss ratio, providing a means to assess the severity of peri-implantitis [20].

Liu et al. (2022) investigated the precision of an artificial intelligence model application in identifying marginal bone loss on periapical radiographs. Specifically, a Faster region-based convolutional neural network was developed and instructed for this purpose. The study dataset comprised a total of 1670 periapical radiographic images, which were categorized into training (n = 1370), validation (n = 150), and test (n = 150) sets. Various evaluation parameters such as sensitivity, specificity, mistake diagnostic rate, omission diagnostic rate, and positive predictive value were utilized to assess the system's performance. The study also compared the artificial intelligence model with dental clinicians by employing kappa (κ) statistics. The artificial intelligence model's evaluation metrics were found to be equivalent to those of a resident dentist. The agreement between the artificial intelligence model and expert clinicians in detecting marginal bone loss around dental implants was moderate to substantial, with κ values of 0.547 and 0.568 for bone loss sites and bone loss implants, respectively. Based on the analysis of periapical radiographs using the Faster region-based convolutional neural network approach, the authors confirmed the potential of this artificial intelligence model as an adjunct diagnostic tool for detecting peri-implant bone loss [19].

However, it is important to acknowledge certain limitations and considerations associated with the use of artificial intelligence models in predicting peri-implant marginal bone loss. Firstly, the availability and quality of data used for training the artificial intelligence models can significantly impact their performance and generalizability. Therefore, efforts should be made to ensure the inclusion of diverse and representative datasets to enhance the accuracy and reliability of the predictions. Furthermore, while artificial intelligence models can provide valuable predictions, they should not replace clinical expertise and judgment. The integration of artificial intelligence models should be seen as a supportive tool rather than a substitute for clinical decision-making. It is essential for clinicians to interpret the artificial intelligence-generated predictions in conjunction with their own expertise and consider individual patient factors when formulating treatment plans.

Future research should focus on refining and validating artificial intelligence models specifically tailored for predicting peri-implant marginal bone loss. Prospective studies with larger sample sizes and longer follow-up periods would provide more robust evidence regarding the performance and effectiveness of these models. Additionally, efforts should be made to develop user-friendly interfaces and decision-support systems that facilitate the seamless integration of artificial intelligence models into clinical practice.

5. Conclusion

To summarize, artificial intelligence models show promise in identifying the marginal bone loss around dental implants. Their ability to analyze complex datasets and generate accurate predictions offers opportunities for early detection and targeted intervention. However, these models are still in the developmental phase. As the use of artificial intelligence in implant dentistry continues to expand, it is crucial to assess the effectiveness and reliability of these models before recommending their use in clinical practice.

6. Declarations

6.1 Conflict of Interest Statement

The authors have no conflict of interests to declare.

6.2 Funding Disclosure

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

7. References

1. Kanehira Y, Arai K, Kanehira T, Nagahisa K, Baba SJTJoAP. Oral health-related quality of life in patients with implant treatment. 2017;9(6):476-81.
2. Lang NP, Berglundh T, periodontology WGotSEWoPJJoc. Periimplant diseases: where are we now?–Consensus of the Seventh European Workshop on Periodontology. 2011;38:178-81.
3. Albrektsson T, Buser D, Chen ST, Cochren D, De Bruyn H, Jemt T, et al. Statements from the Estepona consensus meeting on peri-implantitis, February 2-4, 2012. 2012;14(6):781-2.
4. Papaspyridakos P, Chen C-J, Singh M, Weber H-P, Gallucci GJJodr. Success criteria in implant dentistry: a systematic review. 2012;91(3):242-8.
5. Albrektsson T, Canullo L, Cochran D, De Bruyn HJCID, Research R. "Peri-implantitis": a complication of a foreign body or a man-made "disease". Facts and fiction. 2016;18(4):840-9.
6. Dalago HR, Schuldt Filho G, Rodrigues MAP, Renvert S, Bianchini MAJCoir. Risk indicators for peri-implantitis. A cross-sectional study with 916 implants. 2017;28(2):144-50.
7. Derks J, Tomasi CJJocp. Peri-implant health and disease. A systematic review of current epidemiology. 2015;42:S158-S71.
8. Sener-Yamaner ID, Yamaner G, Sertgöz A, Çanakçi CF, Özcan MJId. Marginal bone loss around early-loaded SLA and SLActive implants: radiological follow-up evaluation up to 6.5 years. 2017;26(4):592-9.
9. Simons WF, De Smit M, Duyck J, Coucke W, Quirynen MJCoir. The proportion of cancellous bone as predictive factor for early marginal bone loss around implants in the posterior part of the mandible. 2015;26(9):1051-9.
10. Corcuera-Flores JR, Alonso-Domínguez AM, Serrera-Figallo MÁ, Torres-Lagares D, Castellanos-Cosano L, Machuca-Portillo GJJop. Relationship between osteoporosis and marginal bone loss in osseointegrated implants: A 2-year retrospective study. 2016;87(1):14-20.
11. Ali A, Al Attar A, Chrcanovic BR. Frequency of Smoking and Marginal Bone Loss around Dental Implants: A Retrospective Matched-Control Study. J Clin Med. 2023;12(4).
12. Al-Okshi A, Paulsson L, Rohlin M, Ebrahim E, Lindh CJDR. Measurability and reliability of assessments of root length and marginal bone level in cone beam CT and intraoral radiography: a study of adolescents. 2019;48(5):20180368.
13. Marc El Hage D, Nurdin N, Abi Najm PS, Bischof MM, Nedir RJP. Osteotome sinus floor elevation without grafting: a 10-year study of cone beam computerized tomography vs periapical

radiography. 2019;39:e89-e97.

14. Misch CEJDIP-E-B. An implant is not a tooth: a comparison of periodontal indices. 2014;46:18-3.

15. Cassetta M, Altieri F, Giansanti M, Bellardini M, Brandetti G, Piccoli LJIjoo, et al. Is there a learning curve in static computer-assisted implant surgery? A prospective clinical study. 2020;49(10):1335-42.

16. Kim DW, Kim H, Nam W, Kim HJ, Cha I-HJB. Machine learning to predict the occurrence of bisphosphonate-related osteonecrosis of the jaw associated with dental extraction: a preliminary report. 2018;116:207-14.

17. McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, Ashrafian H, et al. International evaluation of an AI system for breast cancer screening. 2020;577(7788):89-94.

18. Zhang H, Shan J, Zhang P, Chen X, Jiang HJSr. Trabeculae microstructure parameters serve as effective predictors for marginal bone loss of dental implant in the mandible. 2020;10(1):18437.

19. Liu M, Wang S, Chen H, Liu YJBOH. A pilot study of a deep learning approach to detect marginal bone loss around implants. 2022;22(1):11.

20. Cha JY, Yoon HI, Yeo IS, Huh KH, Han JS. Peri-Implant Bone Loss Measurement Using a Region-Based Convolutional Neural Network on Dental Periapical Radiographs. J Clin Med. 2021;10(5).

21. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Bmj. 2021;372:n71.

22. JBI. Checklist for Quasi-Experimental Studies (non-randomized experimental studies) 2017 [09-06-2023]. Available from: http://joannabriggs.org/research/critical-appraisal-tools.html.