

Diagnostic accuracy of artificial intelligence versus manual detection in marginal bone loss around fixed prosthesis; a systematic review

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Abstract

Objectives: The aim of the review is to evaluate the existing precision of artificial intelligence (AI) in detecting Marginal Bone Loss (MBL) around prosthetic crowns using 2-Dimensional radiographs. It also summarises the recent advances and future challenges associated to their clinical application.

Methodology: A literature survey of electronic databases was conducted in November 2023 to recognize the relevant articles. MeSH terms/keywords were used to search ("panoramic" OR "pantomogram" OR "orthopantomogram" OR "opg" OR "periapical") AND ("artificial intelligence" OR "deep" OR "machine" OR "automated" OR "learning") AND ("periodontal bone loss") AND ("prosthetic crown") in PubMed database, SCOPUS, COCHRANE library, EMBASE, CINAHL and Science Direct.

Results: The searches identified 49 relevant articles, of them 5 articles met the inclusion criteria were included. The outcomes measured were sensitivity, specificity and accuracy of AI models versus manual detection in panoramic and intraoral radiographs. Few studies reported no significant difference between AI and manual detection, whereas majority demonstrated the superior ability of AI in detecting MBL.

Conclusion: AI models show promising accuracy in analysing complex datasets and generate accurate predictions in the MBL around fixed prosthesis. However, these models are still in the developmental phase. Therefore, it is crucial to assess the effectiveness and reliability of these models before recommending their use in clinical practice.

Keywords: Artificial Intelligence, Alveolar Bone Loss, Reproducibility, Electronics, Prostheses, Implants, Bibliometrics, Machine learning, Prosthetic crown, Panoramic.

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Introduction

Over the last decade, considerable innovation has been done in artificial intelligence (AI) to aid digital dentistry and telemedicine.¹ It has been evolving as a vital component in providing safe and effective healthcare as an auxiliary tool.¹ 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.^{2,3} The neuronal networks algorithm acquire raw knowledge from unprocessed input data and categorize it without the need for extraction of features manually.⁴ It involves different components of AI e.g., deep learning, machine learning (ML) and neural networks.⁴ From the time of initial publications using neural networks in the early 2010s, a great upsurge in the amount of publications in dentistry asserting this tool has taken place.⁵ Several studies have been conducted for tooth numbering, diagnosis and treatment planning of periodontal bone loss, dental caries, and dental implants.^{6,7}

Within periodontology, accurate diagnosis and sequential recognition of marginal bone loss (MBL) is challenging.^{8,9} MBL is defined as apical loss of alveolar bone adjacent to a prosthetic fixed crown, in comparison with baseline readings.¹⁰ Current best practices emphasize using a graduated probe for measuring soft tissues and utilizing radiographic imaging by using different indices and vector systems to assess hard tissues.^{9,11} 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.¹² Moreover, inter-rater and intra-rater reliability reflects certain amount of variations.¹³ 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.¹⁴ Studies by Vera et al. and Zhang et al. reported good prospects for AI to be employed collectively for predicting MBL and to assist dental specialists in diagnosing and treatment

planning.^{10,15} For an extended duration, machine predictions have been viewed as less effective than human counterparts in object detection and instance segmentation. Nevertheless, comprehensive comparisons between AI and human observers are limited.

In the field of periodontology, artificial intelligence (AI) is still in its developmental phase and hasn't reached its maximum potential.¹⁶ Considering the limited amount of available literature in this domain, this systematic review aimed to evaluate the existing evidence concerning the precision of artificial intelligence in detecting Marginal Bone Loss (MBL) around prosthetic crowns using 2-Dimensional radiographs in the developed automated system versus manual detection. It also summarises the recent advances and future challenges associated to their clinical application.

Methods

Search Strategy

In November 2023, an exploration of diverse electronic databases was conducted to locate the necessary articles for a review on automated detection of periodontal bone loss around prosthetic crowns using AI. MeSH terms/keywords (All fields) using Boolean operators were used to search ("panoramic" OR "pantomogram" OR "orthopantomogram" OR "opg" OR "periapical") AND ("artificial intelligence" OR "deep" OR "machine" OR "automated" OR "learning") AND ("periodontal bone loss") OR ("dental crown") in the electronic databases. Articles published in English language which fulfilled the objectives of PICOS criteria (Population, intervention, comparison, outcomes and study design) of the study were included [Figure 2].¹⁶

Article selection criteria

The eligibility criteria for the articles required for the review was as follows:

1. Original Articles, clinical trials and randomized controlled studies.
2. Studies on characteristics of artificial intelligence in detection of periodontal bone loss including fixed prosthesis in periapical radiographs and/ or orthopantomograms.
3. Studies with same outcome measures were included.

Exclusion criteria

1. Investigative reports, literature/ systematic reviews and publication language other than English.
2. Panoramic reconstructions from CT images.
3. Algorithms of no medical relevance.

Screening and Data Collection

The primary authors (SAT and BF) conducted a comprehensive review process. The process of screening and selecting articles was segmented into two distinct stages: a preliminary screening of titles and abstracts, followed by a final screening of full text publications. Initially, articles containing the specified keywords in their title or abstract were examined, after which a full-text publication screening was conducted. Throughout this phase, articles were assessed and chosen according to predetermined inclusion and exclusion criteria. Notably, there were no disagreements among the authors during the screening process.

Results

The initial search identified 49 articles meeting the inclusion criteria through MeSH terms/keywords in

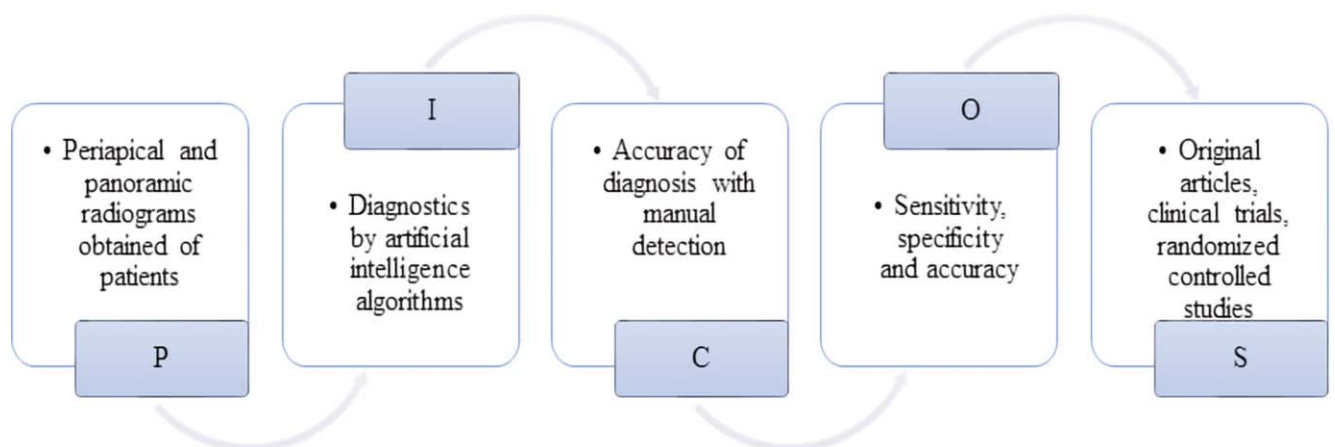


Figure-2: PICOS criteria¹⁶

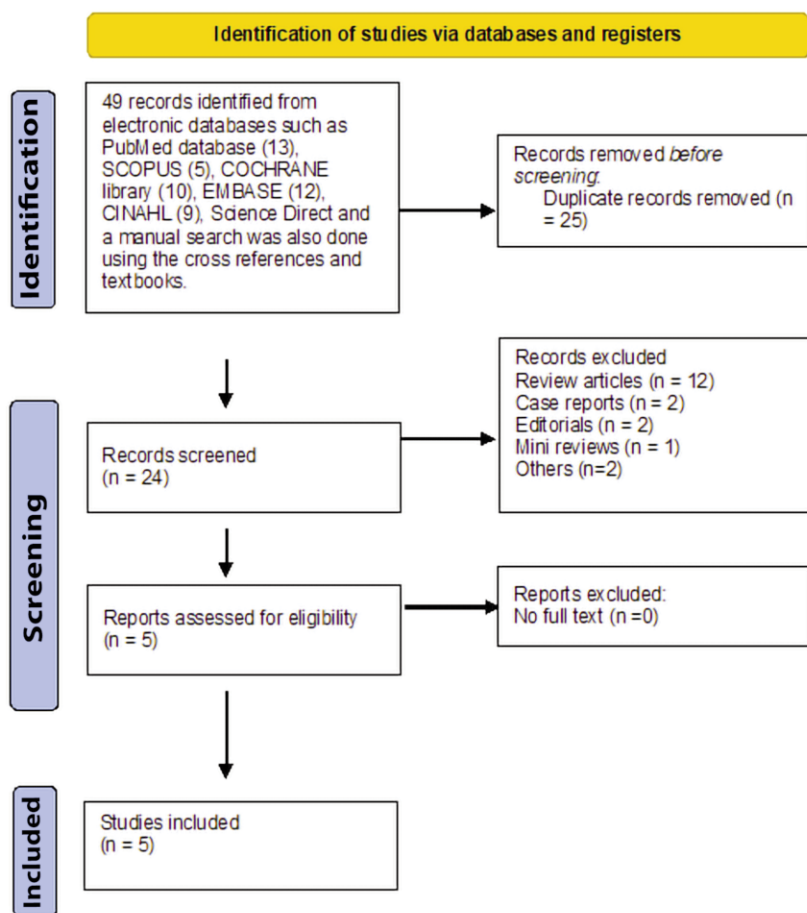


Figure-1: Prisma flow diagram¹⁷

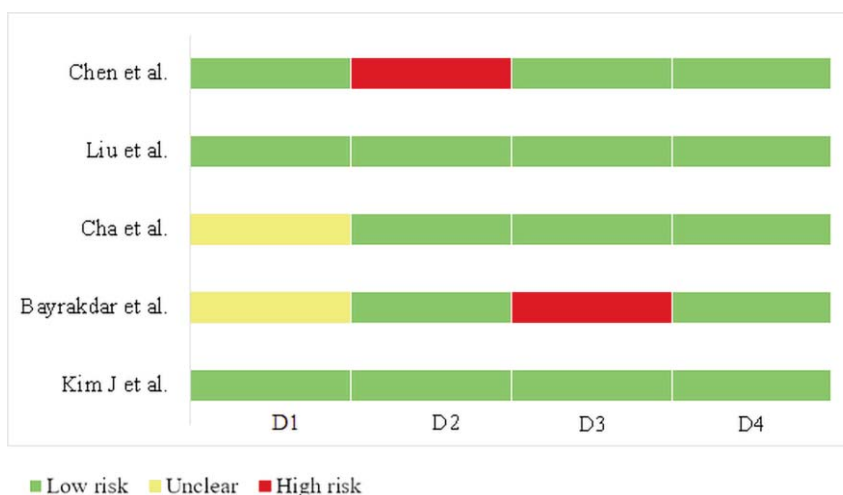


Figure-3: Risk of bias assessment using Newcastle-Ottawa score.
 D1: Representativeness of exposure cohort
 D2: Selection bias
 D3: Comparison bias
 D4: Outcome bias

various electronic databases: PubMed database (13), SCOPUS (5), COCHRANE library (10), EMBASE (12), CINAHL (9), Science Direct. Additionally, a manual search was conducted using cross-references and textbooks. The remaining articles underwent further assessment, focusing on duplication, language, relevance to the subject, and availability of full text. Out of these, 5 studies were included and summarized in the PRISMA flowchart [Figure 1].¹⁷ Subsequently, the results and outcomes from these studies were evaluated. The variables included sensitivity, specificity and accuracy of AI models were extracted. Data presented in percentages were converted to decimal form. Risk of bias assessment using Newcastle-Ottawa score were performed [Figure 3].

Discussion

Ground-breaking accuracy of AI technologies in terms of clinical diagnosis, treatment outcomes, and the cost-effectiveness has been paving its way since decades.^{18,19} Since MBL detection is frequently challenging, the AI models with several metrics were generated using a number of diagnostic performance indicators.²⁰ Sensitivity is defined as the probability that an image is accurately classified as "disease," whereas specificity is the probability that a marginal bone loss surrounding a fixed prosthesis genuinely encompasses the lesion state.^{20,21} The AI processing is an accurate representation of human reasoning; that is created using various network phases with varying degree of accuracy within the framework of computational training [Table 1] [Figure 4].

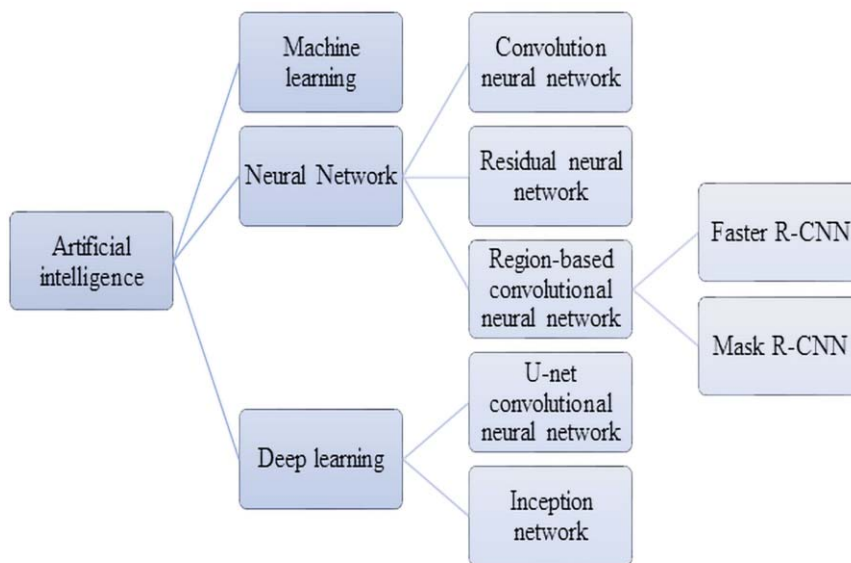
Machine learning (ML)

Rather than explicitly programming computers, ML attempt to provide data with knowledge based on repetitive observations.²² Decision tree (DT) learning is a supervised ML approach that uses repetitive categorization to develop a module that identify the target variable based on several input variables, known as recursive partitioning.²³ This model is

Table-1: Outcome metrics of AI in detecting periodontal bone loss around prosthetic crowns.

Authors	Year	Data inclusion period	Radio-graph	AI tool	AI software	Annotators/ comparison	Sensitivity	Specificity	Accuracy
Kim et al. ³⁰	2019	January 2014 to February 2016	OPG	DL/ CNN	DeNTNet	Hygienist	0.78/0.87	0.92/0.96	N/S
Bayrakdar et al. ²⁵	2020	N/S	OPG	CNN	Google Net Inception v3	Radiologist and periodontologist	-/0.94	-/0.88	0.91
Cha et al. ²⁸	2021	December 2018 and June 2020	PAs	R-CNN	ResNet	Dentist	N/S	N/S	0.90
Liu et al. ²¹	2022	N/S	PAs	R-CNN	Inception ResNet v2	Dentist	0.93/0.67	0.64/0.87	N/S
Chen et al. ²⁶	2023	N/S	PAs	CNN	YOLOv2	Dentist	N/S	N/S	0.90

N/S: Not specified, PAs: Periapical radiographs, OPG: Orthopantomograms.

**Figure-4:** Basic networks of AI.

made up of nodes, branches, and leaves, similar to a tree structure. Each node is ordered using a mathematical method known as attribute selection.²³ A study by Kim et al. reported that ML models significantly outperformed single predictors and traditional statistical approaches in alveolar bone loss around extraction socket.²² However to date, negligible work has been done MBL around fixed prosthesis through ML.

Neural networks

Convolution neural network (CNN)

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.²⁴ In MBL, CNNs are able to identify edges and identify patterns. 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.^{24,25} Recent studies 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.^{25,26} Thus, through the provision of real-time treatment, training a reliable and accurate CNN model can significantly improve healthcare.

Region-based convolutional neural networks (R-CNNs)

R-CNNs were designed for identification/ detection of object (regions of interest), in which target objects are auto-detected and annotated.²⁷ A more efficient version of the R-CNN, Faster R-CNN was later developed. Similarly, the Mask R-CNN method was developed on the basis of Faster R-CNN; that can identify targets in data set and produces superior quality segmentation outputs.²⁷

Moreover, a more rapid variant of the R-CNN, known as Quicker R-CNN, was developed. Based on Faster R-CNN, the mask R-CNN technique was developed to identify targets in images and offer superior division and segmentation.²⁷ It has proven to be an effective clinical module for assessing the degree of peri resorption -implant marginal bone on periapical radiography.²⁸ Recent studies by Cha et al. and Liu et al. reported 90% accuracy and 87 % specificity of R-CNN in MBL detection in radiographs.^{21,28}

Deep learning (DL)

More recently, DL has been the core of this endeavour, primarily because of its applications that stem from the use of ANNs that display a remarkably high degree of complexity. Hundreds or thousands of layers are assembled into specific structures known as architectures from a large number of artificial neurons (or nodes) that are connected into layers.¹ At the DL level, object detector proved to identify implant crowns and screws, playing a significant role in the initial stages of development.²⁹ This allows conveniently to identify the edges and margins of the crown and implant screws with

quantification. Work done by Kim et al. observed sensitivity and specificity to be 87% and 96% respectively.³⁰

Assessment of the MBL is typically challenging on conventional radiographs, due to the two-dimensional representation of the three-dimensional bone form.²⁴ Therefore, the buccal and lingual bone heights, as well as the boundaries of the bone around the prosthesis should clinically be evaluated by experienced clinicians.²⁵ Studies on learning curve indicated greater probability of novice clinicians to make incorrect diagnosis and errors.^{31,32} Hence, the prevalence of periodontal disease has been increasing, follow-up thereof can involve a significant amount of clinical time and effort.²⁵ Additionally, it is worthwhile to note that the automated process may be incorporated to the populations that exhibit comparable features in periapical radiographs, even if they are attained with a different devices. In this instance, it would be preferable to modify the DL procedure to relabel any fixed prosthesis that was used during training.

Limitations

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 cone-beam computed tomography cannot portray the three-dimensional interaction between a prosthesis and the surrounding alveolar bone, and only a few researches have demonstrated robust accuracy of this model in detecting bone defects.

Conclusion and Future Challenges

In summary, the accuracy of artificial intelligence models in recognising the MBL around fixed prosthesis seems promising. 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. 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.

Limitation: This review is limited by the fact that it was not registered in a systematic review registry, PROSPERO.

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