SYSTEMATIC REVIEW ARTICLE

OPEN ACCESS

Artificial Intelligence for Detecting Periodontitis: Systematic Literature Review

Desy Fidyawati[1,5,*] , Sri Lelyati C Masulili[2], Hanna Bachtiar Iskandar[3], Heru Suhartanto[4] and Yuniarti Soeroso[2]

[1]Doctoral Candidate at Faculty of Dentistry, University of Indonesia, Jakarta, Indonesia
[2]Department of Periodontology, Faculty of Dentistry, University of Indonesia, West Java, Indonesia
[3]Department of Dental Radiology, Faculty of Dentistry, University of Indonesia, West Java, Indonesia
[4]Faculty of Computer Science, University of Indonesia, West Java, Indonesia
[5]Department of Periodontology, Faculty of Dentistry, University of Prof. Dr. Moestopo(B), West Java, Indonesia

Abstract:

Background: The determination of the diagnosis of inflammatory periodontitis is generally based on clinical examination, which is then strengthened by radiographic examination. Still, the inequality of assessment of clinical conditions, along with limitations of radiographic interpretation, makes determining the diagnosis of the periodontal disease difficult. The use of artificial intelligence as a digital system approach is believed to reduce costs, time, the need for medical services, and medical errors that may occur due to human factors.

Objective: This systematic review study is to analyze the use of dental and panoramic radiographs combined with the use of artificial intelligence in establishing the diagnosis of periodontitis based on the parameters of periodontal disease severity according to the 2017 American Academy of Periodontology/European Federation of Periodontology Workshop (pocket depth, clinical attachment loss (CAL) and the pattern and level of alveolar bone damage that occurs).

Methods: Journal searches for articles published in English were carried out through the PubMed and Scopus databases in the 2011-2021 period, using the search terms periodontitis, periodontal disease, food impaction, trauma occlusion, periapical radiograph, panoramic, machine learning, artificial intelligence, and periodontal bone loss, after going through article selection, two suitable articles were obtained.

Results: Two studies fell into the analyzed category. Both list periodontal bone loss as a parameter that marks periodontitis, and the use of panoramic photos in detecting this parameter assisted by Convolutional Neural Networks as artificial intelligence.

Conclusion: The use of panoramic radiographs and Convolutional Neural Networks as artificial intelligence that serves as a tool to detect periodontal bone damage has almost the same results as experienced clinicians In order for this method to be developed in the future to help clinicians establish the diagnosis, more clinical and image data will be required.

Keywords: Periodontitis, Periodontal disease, Panoramic, Convolutional neural network, Artificial intelligence, Radiographic examination.

1. INTRODUCTION

1.1. Background Systematic Review

The development of science and innovation in recent years has resulted in many significant advances in the determination of diagnosis, treatment, and even the determination of preventive measures against periodontal disease [1]. The diagnosis of periodontal disease, which includes damage to soft and hard tissues, should be systematic and should involve clinical examination and radiographic examination [2-5]. Radiographs play an important role in the diagnosis, research, and treatment of periodontal disease, although there are sometimes limitations when periodontal abnormalities are not indicated in radiographic images [6, 7]. The best approach to the diagnosis of periodontal disease is clinical examination and radiographic examination, to establish the diagnosis of periodontal disease or to obtain other supporting evidence for determining the diagnosis [7, 8]. Several types of conventional radiographic examinations can be used to diagnose periodontal disease and even determine prognosis, including periapical, bitewing, and panoramic [2, 6]. Full-mouth periapical radiographs have been the first choice and also the gold standard for evaluating periodontal disease abnormalities [4, 7, 8]. Panoramic radiographs, which capture the entire mouth, have been widely used for their advantages over intra-oral images, such as better patient comfort and easier procedure. The selection of the use of periapical radiograph techniques for the determination of diagnosis should also pay attention to the radiation dose. The recommended recommendation for the radiation dose of one periapical photo is 0.001 mSv, and the recommended radiation dose for panoramic photos is 0.007 mSv [9, 10]. Selection of panoramic radiographs, if necessary, should be combined with periapical radiographs to reduce the amount of radiation that occurs [11]. However, there are often many things that influence consideration in the selection of appropriate radiographic techniques in determining the diagnosis of periodontal disease, especially among clinicians [12, 13].

The use of artificial intelligence in dentistry can be widely applied, depending on needs, ranging from dental emergencies to prosthetic planning. In the use of artificial intelligence, machines will learn from old experiences or data, adapt new data, and process like humans [14, 15]. As the trend of digital systems approaches in dentistry has increased in the last 10-20 years, clinicians lacking accurate diagnostic skills are driving the need for the use of technology, especially Artificial Intelligence (AI) software. This system is believed to reduce costs, time, the need for medical services, and also medical errors that may occur due to human factors [16]. Artificial intelligence intends to reproduce the cognitive processes of the human being and obtain the same result, in this case, the determination of the diagnosis of a disease with that produced by the clinician, with more accuracy and shorter time [17]. In establishing the diagnosis of periodontal disease, AI can be the link between disease indicators, immunology, and microbiology to obtain a diagnosis of periodontal disease [17].

1.2. Research Objectives

The purpose of this systematic review study is to evaluate the use of conventional periapical, bite-wing, and panoramic radiographs that have been an option in helping to establish the diagnosis of periodontal disease, combined with the use of machine learning as artificial intelligence to determine the diagnosis of periodontal disease based on severity parameters periodontal disease according to the 2017 AAP / EFP Workshop, which are pocket depth, clinical attachment loss (CAL) and the pattern and level of alveolar bone damage that occurs. This study reviewed observational research types, such as cross-sectional, cohort, and randomized controlled clinical trials (RCT study), to see the relationship between determining the diagnosis of periodontitis influenced by periodontal disease severity parameters based on periapical and panoramic conventional radiographic examinations. Study indicators are those who are diagnosed with periodontitis and have conventional radiographic supporting examinations accompanied by supporting data that show the severity of the periodontal disease.

2. MATERIALS AND METHODS

2.1. Research Protocol

This systematic review research protocol follows the rules of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses, which provides research protocol points linked to references used in systematic reviews. This research question uses the PICOS method (Population) for Patients with a diagnosis of periodontitis and aggressive periodontitis aggravated by local predisposing factors, food impaction, food retention, and occlusion trauma (Intervention). The use of machine learning and artificial intelligence in Panoramic photographs in the determination of periodontal diagnosis, (Comparison) Periapical and bitewing radiographic photographs, (Outcomes) CAL, pocket depth, and periodontal bone loss, (Study) Cohort, cross-sectional and randomized control trials.

2.2. Eligibility Criteria

2.2.1. Inclusion Criteria

In the systematic literature review, all articles focus on patients diagnosed with periodontitis with the provision of criteria adapted to the research question (PICOS), namely a study participant diagnosed with periodontitis, the presence of panoramic photos or periapical / bite-wing photos that can confirm periodontitis, which is characterized by several indicators contained in conventional radiographic photos, such as periodontal bone loss, and clinical attachment loss, the use of machine learning which also functions as Artificial Intelligence (AI) and the use of conventional radiographic photos (panoramic and periapical/bitewing) which confirm the presence of abnormalities. There are quantitative data

Table 1. Inclusion and exclusion criteria in the selection of journal articles.

-	Inclusion Criteria	Exclusion Criteria
Source	Pubmed, Scopus	Another database
Dates	Dec 18, 2011 – Dec 17 2021	Studies published before or after this period
Language	English	Other
Population	Periodontitis Periodontal disease Aggressive periodontitis Local predisposing factors Trauma occlusion Food Impaction Food retention	Other
Intervention/Exposure	Panoramic Machine learning Artificial intelligent	Other
Comparative	Dental radiography Periapical dental radiography Bite-wing	-
Outcome measure	Level of Periodontitis (parameters: PBL, CAL, Pocket depth)	Other
Studies	All	
Type of Publication	Free full text	Other and paid

related to the determining parameters of the diagnosis of periodontitis contained in panoramic photos or periapical / bite-wing photos and are observational cohort, cross-sectional, and RCT studies.

2.2.2. Exclusion Criteria

Literature review research or meta-analysis, without the intervention of the use of artificial intelligence, and there is no tentative data related to periodontal disease severity parameters that can be detected through conventional radiographic photos (Table **1**).

2.3. Literature Search

The literature search for this research includes relevant studies over the past 10 years. The database search engines used in this study were Pubmed and Scopus. The same keyword is used for searches in both databases using the Boolean terms "OR" and "AND." With the following filters: free full text, humans, English, and MEDLINE.

2.4. Selection of Studi

Two independent researchers (D.F., Y.S.) independently analyzed titles, abstracts, and full text to identify articles eligible for systematic review based on inclusion and exclusion criteria. Disagreements between researchers regarding the selection of articles were resolved by agreement.

2.5. Data Collection

Researchers (D.F) analyze and check data related to research methodology and heterogeneity of clinical parameters. Analysis of data from each article as follows: research design studies (cohort, cross-sectional, or rando-mized clinical trial), characteristics of participant studies, such as diagnosed periodontitis, local predisposing factors that affect periodontitis, the use of *artificial intelligence* in reading conventional radiographic image data and quanti-tative data (parameters used (outcome)), such as Clinical

Attachment Loss (CAL), alveolar/periodontal bone loss and pocket depth. Use sensitivity and specificity values for each existing quantitative data (outcome).

3. RESULTS

3.1. Determination of Research Design Studies and Research Characteristics

The total number of research studies that fit the inclusion criteria of this system literature review research obtained from the journal article search database (Pubmed and Scopus) is 32 journal articles *published* between 2011 and 2021 (December 18, 2011, to December 17, 2021). After passing the examination which includes the title, abstract, free full text, and language used, then only 2 journal articles meet the criteria, as shown in the PRISMA chart below [18, 19] (Fig. **1**).

The detailed characteristics of the 2 research studies that are eligible for the criteria appear in the following table, accompanied by researchers in each research study, year of publication, time of study, research design, and parameters used as quantitative data.

3.2. Results from Each Research Study

Research conducted by Kim *et al*. [20] and Krois *et al*. [21], (Tables **2** and **3**) aimed to determine the severity of periodontal disease with periodontal bone damage parameters using panoramic radiographs analyzed by machine learning, then compared with the determination of periodontal bone loss, previously marked by clinicians who are observers, whose reliability will be assessed intra- and inter-rater between observers (Table **4**) [20, 21]. To the best of our knowledge, determining periodontal bone damage on dental radiographs is often difficult due to the limitations of different clinicians for damage determi-nation periodontal bone [20-23]. Kim *et al*. [20] used a Deep Neural Transferred Network (DeNTNet), which is a development of the Convolutional Neural Network (CNN) used in the research conducted by Krois *et al*. [21]
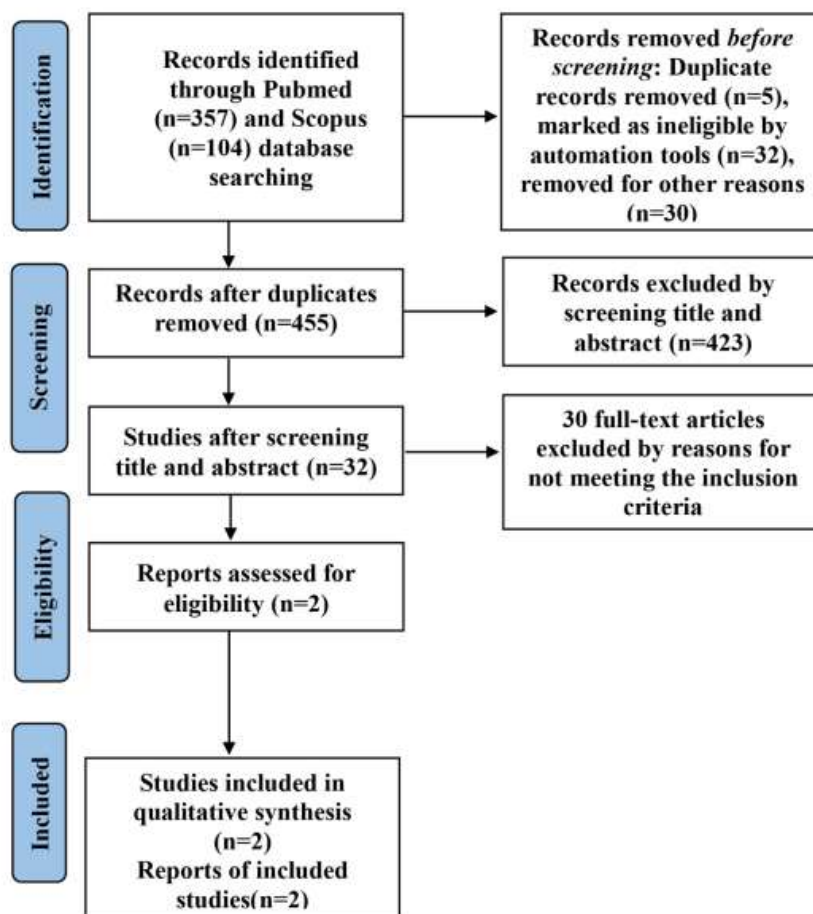
Fig. (1). PRISMA flow diagram of the workflow [18].

Table 2. Journal literature review based on research studies [20, 21].

No.	Author/Year	Study Period	Country	Method	Sampling Method	Sample Size	Parameter of Periodontal Status
1.	Jaeyoung Kim, Hong-Seok Lee, In-Seok Song, Kyu-Hwan Jung/2019 [20]	January 1, 2014- February 14, 2016	South Korea	Cross-sectional	N/A	12,179 panoramic	Periodontal bone loss
2.	Joachim Krois, Thomas Ekert, Leonie Meinhold, Tatiana Golla, Basel Kharbot, Agnes Wittemeier, Christof Dörfer, Falk Schwendicke/2019 [21]	2018	Berlin, Germany	Cross-Sectional	N/A	305 panoramic	Periodontal bone loss

Table 3. The use of artificial intelligence and sample sets and parameters used in each study [20, 21].

No.	Author	Radiographic / Aircraft Engineering	Artificial Intelligence	Sample set	Parameter of Periodontal Status
1.	Jaeyoung Kim, Hong-Seok Lee, In-Seok Song, Kyu-Hwan Jung [20]	Panoramic / Orthophos XG 3 (Sirona, Bensheim, Germany, year of construction: 2009)	Deep Neural Transferred Network (DeNTNet)	12,179 panoramics: 800 image segments; 190 for validation 11.189 training	Periodontal bone loss

(Table 5) contd.....

No.	Author	Radiographic / Aircraft Engineering	Artificial Intelligence	Sample set	Parameter of Periodontal Status
2.	Joachim Krois, Thomas Ekert, Leonie Meinhold, Tatiana Golla, Basel Kharbot, Agnes Wittemeier, Christof Dörfer,Falk Schwendicke [21]	Panoramic (HDXWILL, South Korea), Hyper-XCM (Asahi, Japan), CS 9300 (Carestream Dental, USA), Papaya (Genoray, South Korea), and PHT-30LFO (Vatech, South Korea)	Deep convolutional neural networks (DCNNs)	305 panoramic: 1750 image segments; 350 for validation; 1400 training	Periodontal bone loss

Table 4. Inter-rater observer scores in each study [20, 21].

No.	Author	Inter-rater Observer	Periodontal Bone Loss
1.	Jaeyoung Kim, Hong-Seok Lee, In-Seok Song, Kyu-Hwan Jung [20]	Kappa: (N/A) Validity; 0.98 (Automatic panoramic determination of PBL)	Yes/No
2.	Joachim Krois, Thomas Ekert, Leonie Meinhold, Tatiana Golla, Basel Kharbot, Agnes Wittemeier, Christof Dörfer,Falk Schwendicke [21]	Kappa 0.52 (moderate) Validity: PBL 20% = 0.45 PBL 25% = 0.31 PBL 30% = 0.20 (Manual determination of panoramic PBL on *cropped images*)	Yes/No (PBL in % of the root length) Percentage distance from CEJ to apex alveolar bone: distance from CEJ to the apex of the tooth root. (on single root tooth) For double root teeth, the measurement is the same as for a single root, only it is done 2 times for the mesial side and the distal side, then what is taken is the largest value between mesial/distal on the teeth.

For the determination of bone damage (Table **4**), Krois *et al*. [21] used 3 parameters, there are cemento enamel junction (CEJ) in the mesial and distal regions of the tooth, the most apical point of the apex of the tooth, and the most apical point of extension loss of the apex of the alveolar bone, then determined the percentage value of bone damage, which calculates the distance from CEJ to the top of the alveolar bone divided by the distance from CEJ to the dental apex [21], if the tooth is covered by the restoration, the most apical point of the restoration is taken as CEJ [24]. For premolar and molar, which have two or more dental roots, the largest percentage is taken in the distal or mesial region. The use of periodontal bone loss percentages instead of precise calculations, such as millimeters, helps reduce radiographic film distortion caused by the position of the patient and magnification of the panoramic plane [21]. While Kim *et al* determine bone damage, based on the presence or absence of alveolar bone damage [20]. Both studies used clinicians with sufficient practical experience as dentists, periodontists, and radiologists [20, 21].

Table **4** shows the agreement among the clinicians. There were six dentists in the study conducted by Krois *et al*. [21]; two of them specialized in operative dentistry and periodontology, and four of them were general dentists [21]. The score of Kappa (0,52 as a moderate's score) determined the intra-rater reliability of this study [25, 26]. In the study conducted by Kim *et al*. [20], the determination of bone damage began with a pre-trained model, namely the determination of ROI (region of interest) in panoramic, then the determination of ROI in the trained model to predict periodontal bone loss (PBL) on each tooth. Then, the premolars and molars are made a separate assessment on the existing trained model, and this is due to the morphology of the two types of teeth, which sometimes cannot be seen in panoramic photos, which could need the training data set twice, compared to anterior teeth (incisive and canine) which have one root,

Table 5. Diagnostic test results based on periodontal bone damage that occurred in each study [20, 21].

No.	Author	Diagnostic Test Results	Periodontal Bone Loss
1.	Jaeyoung Kim, Hong-Seok Lee, In-Seok Song, Kyu-Hwan Jung [20]	Clinician (1-5) Sensitivity/Specificity = 0.78/0.92 PPV/NPV = 0.62/0.96 Baseline Sensitivity/Specificity = 0.66/0.94 PPV/NPV = 0.65/0.94	Yes/No
2.	Joachim Krois, Thomas Ekert, Leonie Meinhold, Tatiana Golla, Basel Kharbot, Agnes Wittemeier, Christof Dörfer,Falk Schwendicke [21]	PBL 20% Sensitivity/Specificity = 0.92/0.63 PPV/NPV = 0.68/0.90 PBL 25% Sensitivity/Specificity = 0.95/0.53 PPV/NPV = 0.48/0.96 PBL 30% Sensitivity/Specificity = 0.96/0.46 PPV/NPV = 0.31/0.98	Yes/No Percentage distance from CEJ to apex alveolar bone: distance from CEJ to the apex of the tooth root. (on single root tooth) For double root teeth, the measurement is the same as for a single root, only it is done 2 times for the mesial side and the distal side, then what is taken is the largest value between mesial/distal on the teeth.

Note: PPV: positive predictive value, NPV: negative predictive value [20, 21].

Table 6. Diagnostic test results based on periodontal bone loss that occurred in the anterior and posterior segment teeth in each study.

No.	Author	Diagnostic Test Results	Periodontal Bone Loss
1.	Jaeyoung Kim, Hong-Seok Lee, In-Seok Song, Kyu-Hwan Jung [20]	Clinician (1-5) Before ROI Segmentation: Average periodontal bone damage in all teeth: 0.66 After ROI Segmentation: Average periodontal bone damage in all teeth:0.68 After ROI Segmentation+ pre-trained weight: Average periodontal bone damage in all teeth:0.70 After ROI Segmentation+ pre-trained weight + auxiliary loss: Average periodontal bone damage in all teeth:0.72 After ROI Segmentation+ pre-trained weight + auxiliary loss + ensembled network: Average periodontal bone damage in all teeth:0.75	Yes/No
2.	Joachim Krois, Thomas Ekert, Leonie Meinhold, Tatiana Golla, Basel Kharbot, Agnes Wittemeier, Christof Dörfer,Falk Schwendicke [21]	Incisive 20% Sensitivity/Specificity = 0.89/0.58 PPV/NPV = 0.68/0.84 Caninus 20% Sensitivity/Specificity = 0.91/0.67 PPV/NPV = 0.54/0.95 Premolar 20% Sensitivity/Specificity = 0.91/0.65 PPV/NPV = 0.62/0.92 Molar 20% Sensitivity/Specificity = 0.95/0.2 PPV/NPV = 0.79/0.92	Yes/No Percentage distance from CEJ to apex alveolar bone: distance from CEJ to the apex of the tooth root. (on single root teeth) For double root teeth, measurements are the same as single roots, only they are done 2 times for the mesial side and the distal side, then what is taken is the largest value between the mesial/distal on the tooth.

Note: PPV: positive predictive value, NPV: negative predictive value [21].

this is because, in research conducted by Kim *et al.*, ROI segmented for premolar and molar are performed vertical split [20]. The image data will be adjusted up to 512x512 pixels. While in research conducted by Krois *et al* [21], image data will be processed digitally, previously it will be converted to gray-scale, and then teeth on the upper jaw will be flipped in the next process. Then, the image data is adjusted to 64x64 pixels to facilitate data reading. Randomly, the data set will be divided into two data sets: a training data set and a validation data set [21]. The results of research conducted by Kim *et al*. and Krois *et al*. with diagnostic tests produced sensitivity values with a range of 0.70 to 0.90 and specificity of 0.46 up to 0.96 (Table 5) [20, 21].

The assessment of diagnostic test results based on bone damage in each segment of the dentition can be seen in Table 6 below.

Accuracy in the anterior region (incisive and canine) is lower than in the posterior region (premolars and molars). Radiographic interpretation of the anterior region is often influenced by the speed and inclination of the rotation of the panoramic plane, affecting the radiographic image of the anterior region and giving the picture that the anterior region is narrower than the posterior region [27].

4. DISCUSSION

Periodontal inflammation caused by bacterial infection can affect the condition of the gingiva and the underlying periodontal structure. It can result in periodontal bone damage, which, if not properly diagnosed, can result in tooth loss, leading to a detrimental effect on quality of life also general health [28, 29]. The use of dental and panoramic radiographs plays an important role in the early detection of periodontal bone loss. Panoramic radiographs provide better comfort, easier and faster, for patients and clinicians in treatment procedures than dental radiographs [9, 30]. For screening patients, panoramic radiographs provide less radiation than dental radiographs, as well as provide a wider field of view and get to know the patterns of damaged bones, periapical lesions, and pathological lesions in the oral cavity [16]. The use of CNNs as an artificial intelligence application in both studies is due to the ability of the CNN to extract image data automatically. It can be excellent for analyzing large clinically relevant data sets [31-33]. Image classification is the most important and basic thing in machine learning [34-36]. A different data set will have an impact on the result, and a large data number of data sets will affect the accuracy of classification, and to obtain a large data set is not something easy [37]. Algorithm CNN has important step as follow: feature extraction, classification, identification, and prediction or making a decision [38]. Processing of segmentation of panoramic radiographs is difficult cause there is no homogeneity between panoramic radiographs with one another, determined by noise level, vertebral column images, and low contrast [39, 40]. Previously, the image had to be extracted manually for further processing [41], and using

multiple layers simultaneously with the appropriate algorithm allows for more complex filters. The existence of complex filters cannot only detect more complex shapes in the image but it can improve the appearance of the model when compared with the conventional methods. In fact, in the use of CNNs, errors in the weighting of output values can be eliminated so that complex filters are expected to produce outputs according to the following desired [41, 42]. Convolutional Neural Network is formed from several layers: (1) the convolutional layer, which is based on convolutional operation, aims to extract information from data and transform it into several forms of data; (2) the pooling layer, which aims to reduce the dimension of data in the next layer, (3) Dense layer, which is the last layer that connects neurons in first layer and next layer to produce output, which can be a classification [42]. The important thing to know in terms of choosing this deep learning technique is that this method requires a lot of image data with good quality [42]. The accuracy of CNNs is improved when image data and clinical data are analyzed simultaneously. Also, the morphological assessment of periodontal bone loss (horizontal or vertical bone loss) and root morphology can predict periodontal abnormalities more accurately using algorithms [43]. The use of panoramic radiographs that provide a broad picture of the upper jaw and lower jaw has the disadvantage of low resolution in each tooth [9, 30].

CONCLUSION STRENGTHS AND LIMITATIONS OF EACH STUDY

The strength of this review is the systematic approach and teamwork (dentist, periodontist, restorative dentist) and almost all reviewed articles and examinations related to disease severity parameters periodontal is performed by dentists, periodontists, and oral surgeons and there is sufficient quantitative data so that it is possible to proceed to *meta-analysis* research. The limitations of this review are the need to use more data to produce more adequate results, as well as weak reliability among observers.

LIST OF ABBREVIATIONS

CAL   = Clinical Attachment Loss

PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PBL   = Periodontal Bone Loss

CONSENT FOR PUBLICATION

Not applicable.

STANDARDS OF REPORTING

PRISMA guidelines and methodologies were followed.

AVAIALABILITY OF DATA AND MATERIALS

All the data and supportive information are provided within the article.

FUNDING

None.

CONFLICT OF INTEREST

The authors declared no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

SUPPLEMENTARY MATERIAL

PRISMA checklist is available as supplementary material on the publisher's website along with the published article.

Supplementary material is available on the publisher's website along with the published article.

REFERENCES

[1] du Bois AH, Kardachi B, Bartold PM. Is there a role for the use of volumetric cone beam computed tomography in periodontics? Aust Dent J 2012; 57(s1) (Suppl. 1): 103-8.
http://dx.doi.org/10.1111/j.1834-7819.2011.01659.x PMID: 22376102

[2] Sairam V, Puri G. Comparison of measurements of alveolar bone levels by clinical, bitewing, and panoramic radiography. J Indian Acad Oral Med Radiol 2011; 23(4): 543-7.
http://dx.doi.org/10.5005/jp-journals-10011-1219

[3] Muhammed AH, Manson-Hing LR, Ala B. A comparison of panoramic and intraoral radiographic surveys in evaluating a dental clinic population. Oral Surg Oral Med Oral Pathol 1982; 54(1): 108-17.
http://dx.doi.org/10.1016/0030-4220(82)90425-X PMID: 6956817

[4] Chapple ILC, Wilson NHF. Manifesto for a paradigm shift: Periodontal health for a better life. Br Dent J 2014; 216(4): 159-62.
http://dx.doi.org/10.1038/sj.bdj.2014.97 PMID: 24557384

[5] Moutinho RP, Coelho L, Silva A, Lobo Pereira JA, Pinto M, Baptista IP. Validation of a dental image-analyzer tool to measure the radiographic defect angle of the intrabony defect in periodontitis patients. J Periodontal Res 2012; 47(6): 695-700.
http://dx.doi.org/10.1111/j.1600-0765.2012.01483.x PMID: 22537145

[6] Vijay G, Raghavan V. Radiology in periodontics. J Indian Acad Oral Med Radiol 2013; 25(January): 24-9.
http://dx.doi.org/10.5005/jp-journals-10011-1334

[7] Worth H. Principles and Practice of Oral Radiologic Interpretation. (1st ed.), Chicago: Year Book Medical Publishers 1963.

[8] Zaki HAM, Hoffmann KR, Hausmann E, Scannapieco FA. Is radiologic assessment of alveolar crest height useful to monitor periodontal disease activity? Dent Clin North Am 2015; 59(4): 859-72.
http://dx.doi.org/10.1016/j.cden.2015.06.009 PMID: 26427571

[9] Akkaya N, Kansu Ö, Kansu H, Çağirankaya LB, Arslan U. Comparing the accuracy of panoramic and intraoral radiography in the diagnosis of proximal caries. Dentomaxillofac Radiol 2006; 35(3): 170-4.
http://dx.doi.org/10.1259/dmfr/26750940 PMID: 16618850

[10] HirschmannP.H.Guidelines on radiology standards for primary dental care: A resumé. Royal College of Radiologists and the National Radiological Protection Board. Br Dent J 1995; 178(5): 165-7.

[11] Mol A. Imaging methods in periodontology. Periodontol 2004; 34(1): 34-48.
http://dx.doi.org/10.1046/j.0906-6713.2003.003423.x PMID: 14717854

[12] Tugnait A, Clerehugh V, Hirschmann PN. Use of the basic periodontal examination and radiographs in the assessment of periodontal diseases in general dental practice. J Dent 2004;

32(1): 17-25.
http://dx.doi.org/10.1016/S0300-5712(03)00126-X   PMID:
14659714

[13]   Leroy R, Eaton KA, Savage A. Methodological issues in epidemiological studies of periodontitis - how can it be improved? BMC Oral Health 2010; 10(1): 8.
http://dx.doi.org/10.1186/1472-6831-10-8 PMID: 20409298

[14]   Currie G. Intelligent imaging: Anatomy of machine learning and deep learning. J Nucl Med Technol 2019; 47(4): 273-81.
http://dx.doi.org/10.2967/jnmt.119.232470 PMID: 31401617

[15]   Park WJ, Park JB. History and application of artificial neural networks in dentistry. Eur J Dent 2018; 12(4): 594-601.
http://dx.doi.org/10.4103/ejd.ejd_325_18 PMID: 30369809

[16]   Machoy M, Szyszka-Sommerfeld L, Vegh A, Gedrange T, Woźniak K. The ways of using machine learning in dentistry. Adv Clin Exp Med 2020; 29(3): 375-84.
http://dx.doi.org/10.17219/acem/115083 PMID: 32207586

[17]   Shan T, Tay FR, Gu L. Application of artificial intelligence in dentistry. J Dent Res 2021; 100(3): 232-44.
http://dx.doi.org/10.1177/0022034520969115 PMID: 33118431

[18]   Liberati A, Altman DG, Tetzlaff J, *et al*. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. J Clin Epidemiol 2009; 62(10): e1-e34.
http://dx.doi.org/10.1016/j.jclinepi.2009.06.006 PMID: 19631507

[19]   Palaskar J. Cochrane systematic review protocols. J Dental Allied Sci 2015; 4(2): 63.
http://dx.doi.org/10.4103/2277-4696.171511

[20]   Kim J, Lee HS, Song IS, Jung KH. DeNTNet: Deep Neural Transfer Network for the detection of periodontal bone loss using panoramic dental radiographs. Sci Rep 2019; 9(1): 17615.
http://dx.doi.org/10.1038/s41598-019-53758-2 PMID: 31772195

[21]   Krois J, Ekert T, Meinhold L, *et al*. Deep learning for the radiographic detection of periodontal bone loss. Sci Rep 2019; 9(1): 8495.
http://dx.doi.org/10.1038/s41598-019-44839-3 PMID: 31186466

[22]   White S, Pharoah M. Oral Radiology: Principles and Interpretation. (7th ed.), St. Louis: Elsevier 2014.

[23]   Choi IGG, Cortes ARG, Arita ES, Georgetti MAP. Comparison of conventional imaging techniques and CBCT for periodontal evaluation: A systematic review. Imaging Sci Dent 2018; 48(2): 79-86.
http://dx.doi.org/10.5624/isd.2018.48.2.79 PMID: 29963478

[24]   Graetz C, Dörfer CE, Kahl M, *et al*. Retention of questionable and hopeless teeth in compliant patients treated for aggressive periodontitis. J Clin Periodontol 2011; 38(8): 707-14.
http://dx.doi.org/10.1111/j.1600-051X.2011.01743.x   PMID:
21627675

[25]   Fleiss JL. Measuring nominal scale agreement among many raters. Psychol Bull 1971; 76(5): 378-82.
http://dx.doi.org/10.1037/h0031619

[26]   Landis JR, Koch GG. The measurement of observer agreement for categorical data. Biometrics 1977; 33(1): 159-74.
http://dx.doi.org/10.2307/2529310 PMID: 843571

[27]   Walker C, Thomson D, McKenna G. Case study: Limitations of panoramic radiography in the anterior mandible. Dent Update 2009; 36(10): 620-3.
http://dx.doi.org/10.12968/denu.2009.36.10.620 PMID: 20166378

[28]   Papapanou PN, Sanz M, Buduneli N, *et al*. Periodontitis: Consensus report of workgroup 2 of the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions. J Periodontol 2018; 89(S1) (Suppl. 1): S173-82.
http://dx.doi.org/10.1002/JPER.17-0721 PMID: 29926951

[29]   Papapanou PN, Susin C. Periodontitis epidemiology: Is

periodontitis under-recognized, over-diagnosed, or both? Periodontol 2000 2017; 75(1): 45-51.
http://dx.doi.org/10.1111/prd.12200 PMID: 28758302

[30]   Persson RE, Tzannetou S, Feloutzis AG, Brägger U, Persson GR, Lang NP. Comparison between panoramic and intra-oral radiographs for the assessment of alveolar bone levels in a periodontal maintenance population. J Clin Periodontol 2003; 30(9): 833-9.
http://dx.doi.org/10.1034/j.1600-051X.2003.00379.x   PMID:
12956660

[31]   Celi LA, Cellini J, Charpignon ML, *et al*. Sources of bias in artificial intelligence that perpetuate healthcare disparities—A global review. PLOS Digital Health 2022; 1(3): e0000022.
http://dx.doi.org/10.1371/journal.pdig.0000022 PMID: 36812532

[32]   Wang Q, Li X, Xu D. An improved deep learning framework brief-net based on convolutional neural networks. ICIC Express Lett 2017; 11(8): 1323-30.

[33]   Wang Q, Li X, Shi C. Research on image classification based on HP — Net convolutional neural networks. =2017 3rd IEEE International Conference on Computer and Communications (ICCC). 13-16 December 2017, Chengdu, China, 2017.
http://dx.doi.org/10.1109/CompComm.2017.8322872

[34]   Liu J, Yu H, Yang W, Sun C. Combining active learning and semi-supervised learning based on extreme learning machine for multi-class image classification.Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). New York City: Springer International Publishing 2015; 9242: pp. : 163-75.
http://dx.doi.org/10.1007/978-3-319-23989-7_18

[35]   Qassim H, Verma A, Feinzimer D. Compressed residual-VGG16 CNN model for big data places image recognition. 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC). 08-10 January 2018, Las Vegas, NV, USA, 2018.
http://dx.doi.org/10.1109/CCWC.2018.8301729

[36]   Shang L, Yang Q, Wang J, Li S, Lei W. Detection of rail surface defects based on CNN image recognition and classification. Int Conf Adv Commun Technol 2018; 2018: 45-51.
http://dx.doi.org/10.23919/ICACT.2018.8323642

[37]   Luo C, Li X, Wang L, He J, Li D, Zhou J. How does the data set affect CNN-based image classification performance? 2018 5th International Conference on Systems and Informatics (ICSAI). 10-12 November 2018, Nanjing, China, 2018.
http://dx.doi.org/10.1109/ICSAI.2018.8599448

[38]   Zheng L, Zhao Y, Wang S, Wang J, Tian Q. Good practice in CNN feature transfer. arXiv: 160400133 2016.

[39]   Kanuri N, Abdelkarim AZ, Rathore SA. Trainable WEKA (Waikato Environment for Knowledge Analysis) segmentation Tool: Machine-learning-enabled segmentation on features of panoramic radiographs. Cureus 2022; 14(1): e21777.
http://dx.doi.org/10.7759/cureus.21777 PMID: 35251847

[40]   Silva G, Oliveira L, Pithon M. Automatic segmenting teeth in X-ray images: Trends, a novel data set, benchmarking and future perspectives. Expert Syst Appl 2018; 107: 15-31.
http://dx.doi.org/10.1016/j.eswa.2018.04.001

[41]   Harris C, Stephens M. A combined corner and edge detector. Open J Marine Sci 2016; 6(4): 147-15231.
http://dx.doi.org/10.5244/C.2.23

[42]   Goodfellow I, Bengio Y, Courville A. Deep Learning.Deep Learning. (1st ed..). Cambridge, Massachusetts: MIT Press 2016; Vol. 1.

[43]   Carrillo-Perez F, Pecho OE, Morales JC, *et al*. Applications of artificial intelligence in dentistry: A comprehensive review. J Esthet Restor Dent 2021; (June): 1-22.
http://dx.doi.org/10.1111/jerd.12844 PMID: 34842324