



Article Automated Detection of Periodontal Bone Loss Using Deep Learning and Panoramic Radiographs: A Convolutional Neural Network Approach

Jihye Ryu¹, Dong-Min Lee¹, Yun-Hoa Jung², OhJin Kwon³, SunYoung Park⁴, JaeJoon Hwang^{2,*} and Jae-Yeol Lee^{1,*}

- ¹ Department of Oral and Maxillofacial Surgery, School of Dentistry, Dental and Life Science Institute & Dental Research Institute, Pusan National University, Yangsan 50612, Republic of Korea
- ² Department of Oral and Maxillofacial Radiology, School of Dentistry, Dental and Life Science Institute & Dental Research Institute, Pusan National University, Yangsan 50612, Republic of Korea
- ³ Global R & D Data Analysis Center, Data Analysis Division, Korea Institute of Science and Technology Information, Seoul 02792, Republic of Korea; dbajin@kisti.re.kr
- ⁴ Busan, Ulsan, Gyeongnam Branch, Data Analysis Division, Korea Institute of Science and Technology Information, Busan 48059, Republic of Korea; sypark@kisti.re.kr
- * Correspondence: softdent@pusan.ac.kr (J.H.); omsljy@pusan.ac.kr (J.-Y.L.); Tel.: +82-51-831-2498 (J.H.); +82-55-360-5100 (J.-Y.L.)

Abstract: (1) Background: The accurate diagnosis of periodontal disease typically involves complex clinical and radiologic examination. However, recent studies have demonstrated the potential of deep learning in improving diagnostic accuracy and reliability through the development of computer-aided detection and diagnosis algorithms for dental problems using various radiographic sources. This study focuses on the use of panoramic radiographs, which are preferred due to their ability to assess the entire dentition with a single radiation dose. The objective is to evaluate whether panoramic radiographs are a reliable source for the detection of periodontal bone loss using deep learning, and to assess its potential for practical use on a large dataset. (2) Methods: A total of 4083 anonymized digital panoramic radiographs were collected using a Proline XC machine (Planmeca Co., Helsinki, Finland) in accordance with the research ethics protocol. These images were used to train the Faster R-CNN object detection method for detecting periodontally compromised teeth on panoramic radiographs. (3) Results: This study demonstrated a high level of consistency and reproducibility among examiners, with overall inter- and intra-examiner correlation coefficient (ICC) values of 0.94. The Area Under the Curve (AUC) for detecting periodontally compromised and healthy teeth was 0.88 each, and the overall AUC for the entire jaw, including edentulous regions, was 0.91. (4) Conclusions: The regional grouping of teeth exhibited reliable detection performance for periodontal bone loss using a large dataset, indicating the possibility of automating the diagnosis of periodontitis using panoramic radiographs.

Keywords: artificial intelligence; deep learning; diagnostic imaging; periodontitis; periodontal bone loss

1. Introduction

Chronic periodontitis is a leading cause of the loss of teeth and affects about twenty to fifty percent of the global population [1]. Detecting its progression is important to prevent and further lessen the burden of public health. The diagnosis of periodontal conditions is, however, complex and often requires both clinical and radiologic examination [2]. The diagnosis of alveolar bone loss is determined based on the clinical attachment level, and a radiologic assessment is carried out accordingly [3]. While periodontal bone loss is one of the signs of the presence of periodontal disease and the inflammatory condition of adjacent structures [3], radiographic assessment can provide sufficient information about the pattern



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). and extent of bone loss, aiding in the detection and progression of periodontal disease [4–6]. Nonetheless, similar to clinical assessment, radiographic examination is also subject to interobserver variation (such as between specialists or general practitioners) [7], leading to potential errors in diagnosis that may affect the timing of treatment initiation and the prevention of further disease-related issues in adjacent areas.

The emergence of deep learning in medical imaging has led to a growing interest in the use of convolutional neural networks in the field of radiology. This rapidly advancing area of research has captured the attention of many researchers worldwide [8]. Machine learning has been used in medical imaging for decades, and with its growing popularity, computer-aided detection and diagnosis algorithms have advanced alongside computational technologies [8]. In medical imaging, the application of deep learning has expanded beyond organ segmentation to include lesion detection, characterization, and diagnosis. The widespread use of deep learning has demonstrated its effectiveness and reliability in many aspects of medical image analysis [8,9].

The incorporation of deep learning in dental radiology has enabled prompt diagnosis and treatment planning. Recent research has concentrated on segmenting anatomical structures and detecting dental problems, including caries, periodontal disease, periapical lesions, sinusitis, cystic or tumor lesions, and anatomical anomalies [7,10–15]. As an illustration, Vasconcelos et al. compared the detection of periodontal bone loss using two imaging modalities: intraoral radiographs and cone-beam computed tomography (CBCT) scans [6]. Additionally, Lin et al. developed an automatic detection system for the horizontal bone loss of alveolar bone utilizing periapical radiographs [16]. Some studies have also used dental panoramic radiographs to evaluate periodontal bone loss [4,5]. These studies varied not only in their algorithmic methodology but also in the use of radiography.

Vasconcelos et al. found no statistically significant differences in the detection of bone loss patterns between intraoral radiographs and CBCT scans. Nevertheless, the use of panoramic radiographs is favored since they enable the assessment of the entire dentition with a single radiation dose [6,15]. Modern panoramic machines are capable of producing high-quality images that eliminate the need for additional intraoral radiographs, minimizing exposure in cases requiring a full mouth series [13]. However, the limited sample sizes used in previous studies indicate that larger training datasets may improve the performance of deep learning systems [8].

The objective of this study is to develop an automated screening program for detecting periodontal bone loss using panoramic radiographs and to evaluate its potential for practical use. The performance of deep learning in detecting periodontal bone loss automatically on panoramic radiographs will be tested using a large dataset.

The significance of this present study lies in its potential to transform the detection and diagnosis of periodontal disease. The null hypothesis (H_0) suggests that panoramic radiographs are not a reliable source for identifying periodontal bone loss through deep learning, while the alternative hypothesis (H_1) proposes the opposite. The study aims to evaluate the validity of H_1 and assess the feasibility of using deep learning for identifying periodontal bone loss. The feasibility criterion is set at an AUC between 0.8 and 0.9, indicating good performance. If the results demonstrate that deep learning is a reliable method for detecting periodontal bone loss, it has the potential to significantly alter current diagnostic practices in the management of periodontal disease.

2. Materials and Methods

2.1. Ethics Statement

This study was conducted with the approval of the Institutional Review Board (IRB) of Pusan National University Dental Hospital (IRB No.: PNUDH-2020-022).

2.2. Data Set

All patients with periodontal disease who underwent examination and treatment between January 2010 and December 2015 were identified. A dataset of 5000 panoramic

radiographs was initially collected, but 917 were excluded due to factors such as previous maxillofacial surgery, image blurring, or noise. The final dataset consisted of 4083 anonymized digital panoramic radiographs collected using a Proline XC machine (Planmeca Co., Helsinki, Finland), with a resolution of 2943×1435 pixels. The radiographic images were collected anonymously and in accordance with the research ethics protocol.

The World Health Organization's standardized Community Periodontal Index (CPI) classifies the periodontal condition into 4 groups, as shown below [17].

- 1. Edentulous: the total absence of teeth in the region; the presence of at least one tooth was used to demonstrate the region.
- 2. Normal: confined level of bone loss up to CEJ.
- 3. Moderate: periodontal bone loss extending beyond CEJ but limited up to furcation of the tooth.
- 4. Severe: periodontal bone loss extending beyond the furcation of the tooth.

To integrate the WHO CPI into dental panorama images, our study categorized moderate-to-severe periodontal bone loss as periodontitis, indicating the involvement of alveolar bone loss from the cemento-enamel junction to furcation and beyond. However, in the anterior region, we evaluated alveolar bone defects extending beyond two-thirds of the entire length of a tooth. Once periodontitis was detected in each region, we categorized its severity into two stages: moderate to severe, indicating the need for treatment.

In our dataset of 48,996 ROIs, 66.57%, 28.79%, and 4.64% of teeth were healthy, periodontally compromised, and edentulous (Table 1).

Table 1. The distribution of three regions of interest (edentulous, healthy, periodontitis).

Class	Edentulous	Normal	Periodontitis	Total
Number	2271	32,619	14,106	48,996
Ratio (%)	4.64	66.57	28.79	100

The periodontal condition found on the panoramic radiographs, as shown in Figure 1, was annotated in three groups (edentulous, healthy, periodontitis) by two dentists to obtain the ground truth. The experts were trained for two months and asked to draw a rectangular bounding box to frame each section of the molar, premolar, and anterior region (including the crown and root of teeth), reflecting three sections of the open flap treatment. To avoid the overlapping of boxes due to the varying axis of teeth, each section was grouped together.



Figure 1. The labelling procedure of periodontitis in nine regions of a dental panoramic radiograph with custom-made software.

2.3. Experiment

The faster R-CNN [18] detector was used for object detection in this study. The Faster R-CNN detector includes a region proposal network (RPN) that generates region proposals directly within the network instead of using external algorithm-like Edge Boxes. The RPN uses anchor boxes for object detection, which have different sizes and ratios compared to the ground truth. Generating region proposals within the network is faster and better tuned to the data. When the intersection over union (IoU) between the ground truth and proposed boxes exceeds a specific threshold, the boxes are recognized as objects without any class label. The RPN stage generates anchor boxes of various sizes and ratios, which are then passed on as region proposals. Each box is assigned a classification score and four coordinates indicating the object's location. Later, the selected region proposals are fed into the next phase, as in a fast R-CNN.

To reduce overfitting and compensate for the limited number of available datasets, the training data were augmented by randomly flipping each image horizontally and vertically with a probability of 0.5. Additionally, the images were randomly rotated between 0 and 60 degrees before feeding them into the deep learning model. To further enhance the model's robustness regarding periodontal structure and radiographic image color, the images were also augmented by applying random brightness and contrast ranging from 0.9 to 1.1 with respect to the image color.

The performance of the Faster R-CNN was assessed for robustness using a 5-fold cross-validation approach. For implementation, we used the Detectron2 platform (which was built by Facebook AI research) and COCO-Detection/faster_rcnn_R_101_FPN_3x.yaml, which was written in PyTorch, to train and test the deep learning object detection model on a single Nvidia RTX3080 GPU [19]. The dataset for the train and test was mapped for the COCO format. Additionally, the training data were transformed for the augmentation mentioned above. The Faster R-CNN utilized a pre-trained ResNet-101 architecture and underwent 20,000 iterations of training with a learning rate of 0.001 and optimization using stochastic gradient descent with a momentum value of 0.9 and weight decay of 0.005. A batch size of image and a batch size of ROI heads per image were set to 4 and 128, respectively. The images were resized to 1400×688 pixels. Every 400 iterations, a model was evaluated on the test dataset, and the best model which showed the highest AP50 during training was saved. The COCO Evaluator was used for measuring the model's performance.

In order to assess the effectiveness of the faster R-CNN object detection method in identifying periodontally compromised teeth on panoramic radiographs, precision, recall, and average precision (AP) were calculated by comparing the model prediction with the correct answer for each class. This process was repeated for all classes, and the final mean average precision (mAP) was obtained by averaging the AP results. The receiver operating characteristics and the Area Under the Curve (AUC) were also calculated using the Map by using the metrics function of the scikit-learn machine learning framework [20]. Additionally, any bounding box with an IoU value less than 0.5 with the ground truth was considered a false prediction. F1-score was also evaluated in this study as follows:

- Precision = TP/(TP + FP);
- Recall = TP/(TP + FN);
- F1 Score = (2 × (Recall × Precision))/(Recall + Precision);
- TP: true positive, FP: false positive, FN: false negative, TN: true negative.

3. Results

3.1. Inter- and Intra-Examiner Correlation Coefficient

One hundred panoramic radiographs were randomly chosen and independently measured by two dentists on two occasions within a 2-week interval. The overall interand intra-examiner correlation coefficient (ICC) values were 0.94, indicating a high level of consistency and reproducibility in this study.

3.2. Performance Indices and Confusion Matrix

The proposed model exhibited average performance indices (precision, recall, F1-score, Area Under the Curve) over 0.84 and 0.88 for detecting periodontally compromised and healthy teeth, respectively. The null hypothesis H_0 was rejected because the Area Under the Curve values for detecting all three classes were over 0.88 (Table 2). All cross-validation data are listed in Supplementary Table S1.

Table 2. Average peri	formance indices	of the 5-fold	cross-validation result.
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	Precision	Recall	F1-Score	AUC
whole	0.90	0.91	0.90	0.91
edentulous	0.97	0.98	0.97	0.99
healthy	0.88	0.89	0.89	0.88
periodontitis	0.86	0.84	0.85	0.88

Figure 2 shows the confusion matrix and Area Under the Curve of the first cross-validation result, which showed the highest Area Under the Curve value. Among 9804 validation Regions of Interests (ROIs), 92% were classified correctly, while 19% of periodontitis, 8% of normal, and 4% of edentulous cases were misclassified.



Figure 2. Confusion matrix (A) and AUC (B) curve of the first cross-validation result.

When excluding the Area Under the Curve values for normal and periodontitis in the anterior region, the four performance indices showed a tendency to be high in the order of edentulous, normal, and periodontitis for all regions. Additionally, the total value of the four performance indices in each region was over 0.89, and each performance index value showed a similar tendency across regions (Table 3). All cross-validation data with detailed region and class information are listed in Supplementary Table S2.

Two representative cases of the Faster R-CNN object detection method were randomly selected to demonstrate the performance of the model. The ground truth bounding box and raw image are presented in Figure 3A,C, respectively. The results obtained from the Faster R-CNN object detection deep learning method are illustrated in Figure 3B,D, along with the corresponding prediction probabilities. As shown in Figure 3B, the periodontal state of all 12 segments was correctly detected. However, in Figure 3D, the model misclassified the periodontal state of the Lt. maxillary anterior, bilateral mandibular anterior, and Lt. mandibular premolar areas.

All	Class	Precision	Recall	F1-Score	AUC
Anterior	Edentulous	0.96	0.93	0.95	0.96
	Normal	0.88	0.88	0.88	0.87
	Periodontitis	0.85	0.85	0.85	0.87
	Whole	0.90	0.89	0.89	0.90
Premolar	Edentulous	0.97	0.98	0.97	0.99
	Normal	0.89	0.91	0.90	0.88
	Periodontitis	0.85	0.83	0.84	0.87
	Whole	0.90	0.90	0.90	0.91
Molar	Edentulous	0.98	0.98	0.98	0.99
	Normal	0.88	0.89	0.88	0.89
	Periodontitis	0.87	0.86	0.87	0.88
	Whole	0.91	0.91	0.91	0.92
Total		0.90	0.90	0.90	0.91

Table 3. Average performance indices of the 5-fold cross-validation result with detailed region and class information.





Figure 3. Two representative cases of Faster-RCNN model in this study. The original panoramic radiograph with ground truth labelling is shown in (**A**,**C**), while the bounding box output from the faster R-CNN is shown in (**B**,**D**). The trained network effectively distinguishes between tooth and edentulous areas and displays the predicted probability of periodontal condition as a numerical value. In (**B**), all 12 segments were correctly detected, while in (**D**), 9 out of the 12 segments were correctly detected.

4. Discussion

Acknowledging the presence of periodontitis is a critical step in managing patients and preventing periodontal disease [21]. Staging and grading periodontitis can further guide patients to receive individually customized treatment [2,5]. The primary goal of defining staging in patients with periodontitis is to classify the severity and extent of the disease and assess its complexity [22]. Therefore, it is appropriate to recognize detectable interdental and clinical attachment loss greater than 3 mm in more than two teeth [2]. However, measuring attachment loss is only possible during a clinical examination. In this study, the assessment of periodontal disease in panoramic radiographs was carried out using the standard provided by the WHO Community Periodontal Index probe [17], as it is easy to adapt into X-ray images. Cemento-enamel junction and furcation involvement were used

as landmarks to measure alveolar bone defects. With the lack of furcation in single-rooted teeth, the compromised bone level was evaluated with respect to the entire length of the tooth. Chang et al. [5] used panoramic radiographs to classify the stages of periodontitis and the extent of the disease by calculating the percentage rate of alveolar bone loss in relation to its ratio of the intersection length of the periodontal bone level and the other cemento-enamel junction level. The stages of this study were determined according to the criteria proposed at the 2017 World Workshop 4 on the Classification of Periodontal and Peri-implant Disease and Conditions [2]. To effectively communicate and include the status of the disease, the stage or severity can aid in the management of periodontitis. Regarding the severity of periodontitis, terms such as mild, moderate, and severe may be subjective. These descriptions may not be straightforward but can be used in the clinical interpretation of one's condition as a whole. In fact, severity is frequently defined based on the measurement of clinical attachment loss as slight, moderate, and severe. Radiographic examinations are often used to categorize teeth affected by mild, moderate, or severe periodontitis in many cases [2]. Therefore, despite its subjectivity, it is adequate to inform clinicians about the general condition of periodontally compromised teeth.

Numerous studies have been conducted to investigate the accuracy of various imaging methods in dentistry, which still remain to be controversial [23–26]. Cone beam CT is necessary for assessing vertical bone height with respect to the lingual and buccal, but for general bone defect detection, no clear differences were observed between 2D and 3D images [6]. In dental radiology, a panoramic radiograph is typically used to screen patients during their initial visit to the clinic. This method provides information about the entire dentate, alveolar bone, and dentomaxillofacial anatomies of both upper and lower jaws with minimal time expense. Therefore, when a panoramic radiograph is taken, the assessment of the general condition of the periodontal bone is invaluable. The amount of alveolar bone loss and the severity of periodontitis require different therapeutic approaches [13].

Recent studies have proposed that both 2D and 3D X-rays are now being processed with technological innovations for deep learning in medical therapy [8]. Akesson et al. [26] compared the accuracy of measuring pocket depth using panoramic radiographs, intraoral radiographs, and actual probing depth. The study revealed that all images underestimated bone loss, but the difference between the measurements ranged within 1 mm. Regan and Mitchell reported their radiographic errors in 115 cases compared to gross measurement. The largest error between the actual bone height and the radiographic interpretation was 1.6 mm, indicating that the errors were within an acceptable range and justifiable [22]. Therefore, the stage interpreted based on a panoramic radiograph is representative in the clinical setting to initiate and help guide patients to receive treatment. We aimed to integrate the WHO CPI with dental panoramic images despite the challenges posed by the inherent low image sharpness and superimpositions in panoramic radiography. To achieve more reliable and reproducible results, we decided to classify moderate-to-severe periodontal bone loss as periodontitis.

The development of a deep learning algorithm for detecting periodontal disease can be complex due to the unique nature of the oral cavity and dentition [2]. Factors such as the different numbers of teeth, quadrants of jaws, and various grading systems for periodontitis can result in different approaches to developing algorithms. Furthermore, the method of detection may differ in defining the region of the affected area. While some studies focus on examining each tooth axis and periodontal bone [5], others generate anchor boxes to define the region of each tooth with respect to the adjacent alveolar bone [21].

To create an efficient and reliable diagnostic dataset, grouping the dentition is often considered. Grouping the dentition into anterior, premolar, and molar regions or dividing it into four quadrants is generally used when planning periodontal flap operations [13]. Sectioning of the dentition is also applied to overcome difficulties in taking all varying axes of the tooth and to increase efficacy in producing a dataset. Therefore, for both efficient examination and high clinical applicability, we divided the whole dentition into anterior, premolar, and molar regions.

According to this classification of regions of interest (ROIs), the best results were obtained through augmentation according to random rotation between 0 and 60 degrees. This suggests that the rotation angle of each tooth or ROI is under the range of 60 degrees from the vertical axis. Thus, this rotational parameter is suitable for building a robust model in response to augment diverse cases in a real population for the purpose of this study. In another experiment applying the image transformation of CLAHE (Contrast Limited Adaptive Histogram Equalization) to overcome the limitations of the study, we were unable to achieve better results. This may be due to the imbalance in the quality of individual or entire radiographic datasets. These innate shortcomings cannot be resolved by this study alone. To deal with higher resolution images, the use of more powerful GPUs with lots of memory might help to solve this limitation.

The study demonstrated a precision of 0.86 and recall of 0.84 in detecting periodontitis using the largest dataset comprising of 48,996 ROIs, which is consistent with the findings of Thanathornwong's study that showed an average precision of 0.81 and recall of 0.80 [21]. These results indicate that the regional grouping of teeth is a reliable approach for detecting periodontal bone loss according to the new criteria proposed at the 2017 World Workshop 4. Furthermore, the high-performance index values over 0.84 for both the edentulous and tooth areas indicate that the trained network can effectively distinguish and recognize between the tooth and alveolar bone (edentulous) areas. Additionally, the similar detection performance of the three classes regardless of the tooth's location suggests that the learned network can effectively detect periodontitis, regardless of the tooth's position. The results showed high consistency and reproducibility with an inter- and intra-examiner correlation coefficient (ICC) value of 0.94. The proposed deep learning model demonstrated high performance indices (precision, recall, F1-score, Area Under the Curve) in detecting periodontally compromised and healthy teeth. The confusion matrix and Area Under the Curve showed a high level of correct classification. Overall, the study demonstrated the potential of deep learning models in accurately detecting periodontal disease from dental radiographs, but further improvements are needed to reduce misclassifications and increase the accuracy of the model.

Incorporating panoramic radiographs into the initial screening for periodontal disease may lead to faster diagnosis. Our deep learning program can save both healthcare providers and patients time and cost during clinic visits. Further development of the algorithm into a simple cellphone application can also be considered for the interest of public health. Individuals with limited time for dental visits can take a panoramic radiograph and input it into the application to assess their periodontal disease status. This approach may also increase patients' awareness of their current status of periodontal disease since they have access to their own radiographic images. As the public's dental intelligence grows, supplementing deep learning algorithms with public access can aid in the detection of periodontitis and alveolar bone loss, providing a reliable diagnostic tool for dentistry.

The limitation of this study is related to the imaging properties of panoramic radiography, which may have an impact on the diagnostic performance for assessing periodontitis due to the innate low image sharpness and superimpositions [22]. Since periodontitis is a complex disease that requires attention to multiple aspects of bony defects, accuracy may also be enhanced by training the AI with the combined training of panoramic radiographs, cone beam CT scans, or intraoral radiographs. Future studies can improve diagnostic accuracy by incorporating these modalities of radiographic examinations. Additionally, supplementing clinically measured levels of attachment loss will enable the AI algorithm to produce more precise and valid diagnostic information.

5. Conclusions

The detection and management of periodontitis is an essential aspect of patient care, with staging and grading of the disease enabling personalized treatment plans [13]. The primary purpose of periodontitis staging is to evaluate the severity, extent, and complexity of the condition [2]. In contrast to previous studies that have utilized alternative radiographic

sources, such as cone beam CT and intraoral radiographs [5–7], our study has demonstrated that panoramic radiographs provide reliable information on the general condition of the periodontal bone. Furthermore, by categorizing the dentition into anterior, premolar, and molar regions, it was able to facilitate the creation of an efficient and reliable diagnostic dataset. Our deep learning algorithm can accurately detect alveolar bone loss, a hallmark of progressive periodontitis, from panoramic radiographs, improving diagnostic accuracy and efficiency. While other methods such as dental cone beam CTs and standard radiographs have improved their ability to detect alveolar bone loss, their cost and time-effectiveness can pose issues for routine check-ups. In contrast, panoramic radiographs capture all teeth in a single image and can be a viable option for detecting periodontal disease progression with the assistance of artificial intelligence. The regional grouping of teeth can also aid in the detection of periodontal bone loss, further improving diagnosis accuracy and efficiency. Integrating the deep learning algorithm with panoramic radiographs for periodontitis and alveolar bone loss detection can provide a reliable diagnostic tool for the dental field.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app13095261/s1.

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Informed Consent Statement: The IRB of Pusan National University Dental Hospital waived the need for individual informed consent.

Data Availability Statement: Dental panorama data cannot be disclosed due to the presence of sensitive information, such as teeth and dental restoration.

Conflicts of Interest: The authors declare no conflict of interest.

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