ORIGINAL ARTICLE

J Korean Dent Sci. 2023;16(2):156-163
https://doi.org/10.5856/JKDS.2023.16.2.156
pISSN 2005-4742 • eISSN 2713-7651

Deep Learning Based Radiographic Classification of Morphology and Severity of Peri-implantitis Bone Defects: A Preliminary Pilot Study

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Purpose: The aim of this study was to evaluate the feasibility of deep learning techniques to classify the morphology and severity of peri-implantitis bone defects based on periapical radiographs.

Materials and Methods: Based on a pre-trained and fine-tuned ResNet-50 deep learning algorithm, the morphology and severity of peri-implantitis bone defects on periapical radiographs were classified into six groups (class I/II and slight/moderate/severe). Accuracy, precision, recall, and F1 scores were calculated to measure accuracy.

Result: A total of 971 dental images were included in this study. Deep-learning-based classification achieved an accuracy of 86.0% with precision, recall, and F1 score values of 84.45%, 81.22%, and 82.80%, respectively. Class II and moderate groups had the highest F1 scores (92.23%), whereas class I and severe groups had the lowest F1 scores (69.33%).

Conclusion: The artificial intelligence-based deep learning technique is promising for classifying the morphology and severity of peri-implantitis. However, further studies are required to validate their feasibility in clinical practice.

Key Words: Artificial intelligence; Deep learning; Dental implants; Dental radiography; Peri-implantitis

Introduction

Dental implants have proven to be a highly effective treatment modality for replacing completely and partially edentulous maxillary and mandibular jaws[1]. Over the decades, significant advances

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Received for publication June 13, 2023; Returned after revision June 26, 2023; Accepted for publication June 28, 2023

have been made in the design, shape, materials and coatings of implant systems to achieve stable osseointegration and physiological functionality[2,3]. In addition, several adjunctive treatment techniques, including guided bone regeneration, sinus elevation, and alveolar ridge preservation, have been actively employed to overcome the challenges of soft and hard tissue defects surrounding the implant[4,5]. Consequently, numerous systematic reviews and meta-analyses have consistently reported success and survival rates in excess of 90% for implant treatment[6-8]. However, it is important to recognize that implant therapy is inevitably associated with various biological and mechanical complications.

Peri-implantitis (PI) is an inflammatory condition around the implant that causes swelling, redness, bleeding and pus discharge in the soft tissue and destructive bone resorption in the hard tissue[9,10]. The World Workshop on the Classification of Periodontal and Peri-implant Diseases (2017) defines PI as clinical signs of inflammation, bleeding and abscess, probing or pocket depth greater than 6 mm, and radiographic bone loss greater than 3 mm[11,12]. The prevalence and incidence of PI is highly variable in epidemiological studies, with a recent systematic review reporting a wide range of prevalence rates from 1.1% to 85.0% and 5-year incidence rates from 0.4% to 43.9%[13]. PI is affected by the severity of inflammation, duration, and surrounding tissue characteristics, and in particular, there are various non-surgical and surgical treatment methods depending on the morphology and severity of PI bone defects[14].

Convolutional neural networks based on deep learning techniques, a subset of artificial intelligence (AI), have been actively used in the field of medical image analysis for several years, and numerous studies have demonstrated their clinical efficacy[15,16]. Similarly, various AI-related studies have been conducted to determine the clinical validity of dental radiology[17]. In the field of dental implants, studies on guided surgery have proved successful toward achieving optimal positioning and identifying various types of implant systems[18-20]. This preliminary pilot study aimed to evaluate the feasibility of deep learning techniques to classify the morphology and severity of PI bone defects based on periapical radiographs.

Materials and Methods

1. Ethical Statements

The study received an IRB exemption because it did not require the collection of medical and dental records containing personal information.

2. Dataset

The dataset included in this study consisted only of dental radiological images from patients who had undergone surgical treatment for PI by a board-certified periodontist (JHL) with a diagnosis of PI. Therefore, the PI-related dataset included in this study can be considered reliable in terms of morphology and severity (Fig. 1). A total of 971 periapical radiographic images were included in this study, and the defect morphology and severity of PI were classified according to the criteria used in previous studies (Table 1)[21,22].

1) Morphology

- Class I: Infraosseous defect including buccal dehiscence and circumferential defect
- Class II: Supracrestal and/or horizontal defect

2) Severity

- Slight: 3~4 mm or 25% of the implant fixture
- Moderate: 4~5 mm or ≥25%~50% of the implant fixture
- Advanced: >6 mm or >50% of the implant fixture

The dataset was randomly and evenly divided into three groups based on the defect morphology and severity: training (n=777 [80%]), validation (n=97 [10%]), and testing (n=97 [10%]). The training dataset

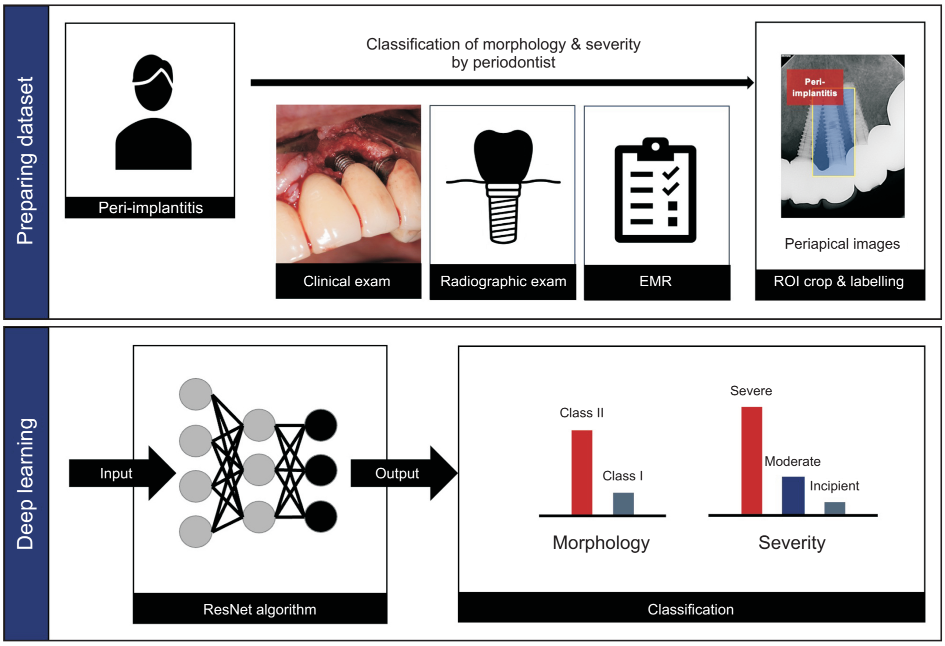

Fig. 1. Schematic representation of preparing dataset acquisition and deep learning process. EMR: electronicmedicalrecord, ROI: region of interest.

Table 1. Defect morphology and severity of peri-implantitis in the dataset included in this study

Variables	n	%
Class I		
Slight	310	31.9
Moderate	98	10.1
Severe	98	10.1
Class II		
Slight	125	12.9
Moderate	238	24.5
Severe	102	10.5

was augmented hundred times, incorporating random rotations and adjustments in hue, brightness, saturation, contrast, noise, and horizontal and vertical flips.

3. Deep Learning Algorithm

In this study, all included images were cropped and rescaled to 224×224 dimensions. A fine-tuned pre-trained ResNet-50 architecture consisting of 50 deep layers with over 25 million trainable parameters was used[23]. Algorithm modification and training were performed using MATLAB® R2023a (MathWorks, Natick, MA, USA) and Python 3.7 with the Keras framework (Python Software Foundation, Wilmington, DE, USA). To train the ResNet-50 model, Adam was used with an initial learning rate of 0.001 and momentum of 0.9. During the training process, we applied early stopping with a patience of 20 epochs to improve the validation loss and trained for a maximum of 1,000 epochs.

4. Statistical Analysis

Several metrics were calculated to measure the accuracy of the classification of defect morphology and severity of PI. These included accuracy (calculated as true positive [TP]+true negative [TN] / (TP+TN+false positive [FP]+false negative [FN])), precision (TP / (TP+FP)), recall (TP / (TP+FN)) and F1 score (2×(precision×recall) / (precision+recall)). Statistical analyses were performed using R statistical package 4.3.0 (R Foundation for Statistical Computing, Vienna, Austria).

Result

In total, 971 periapical radiographic images were included in this study. The classification accuracy was evaluated for 97 images corresponding to the test dataset, which were distributed as follows: Class

I and slight group (n=31), Class I and moderate group (n=10), Class I and severe group (n=10), Class II and slight group (n=12), Class II and moderate group (n=24), and Class II and severe group (n=10). Deep-learning-based classification achieved an accuracy of 86.0% with precision, recall, and F1 score values of 84.45%, 81.22%, and 82.80%, respectively. Among the different groups, Class II and moderate groups exhibited the highest F1 score (92.23%), with a precision of 90.64% and a recall of 93.87%. Conversely, Class I and severe groups had the lowest F1 scores (69.33%), with a precision of 74.28% and a recall of 65.00% (Table 2). Fig. 2 displays a confusion matrix with normalization, providing a summary of the multiclass classification of defect morphology and severity of PI. Classification accuracy was the highest for Class II and moderate groups (93.9%), whereas the lowest accuracy was observed for Class I and severe groups (65.0%).

Discussion

The prevalence and incidence of PI are constantly increasing, particularly owing to the increasing use of dental implants. Consequently, several epidemiological studies have been conducted to analyze microbiological profiles and risk factors and to propose different methods for the prevention and treatment of PI, including plastic or carbon-fiber curettes, ultrasonic instruments, titanium bars and brushes, air powder abrasion, lasers, photodynamic therapy, chemical methods, electrochemical disinfection, open-flap debridement, and resective and regenerative techniques with guided bone regeneration[24,25].

Table 2. Classification accuracy of defect morphology and severity of peri-implantitis based on test dataset

Variables	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Total	86.0	84.45	81.22	82.80
Class I				
Slight		88.30	92.12	90.17
Moderate		91.30	77.77	84.00
Severe		74.28	65.00	69.33
Class II				
Slight		83.16	82.35	82.75
Moderate		90.64	93.87	92.23
Severe		79.01	76.19	77.53

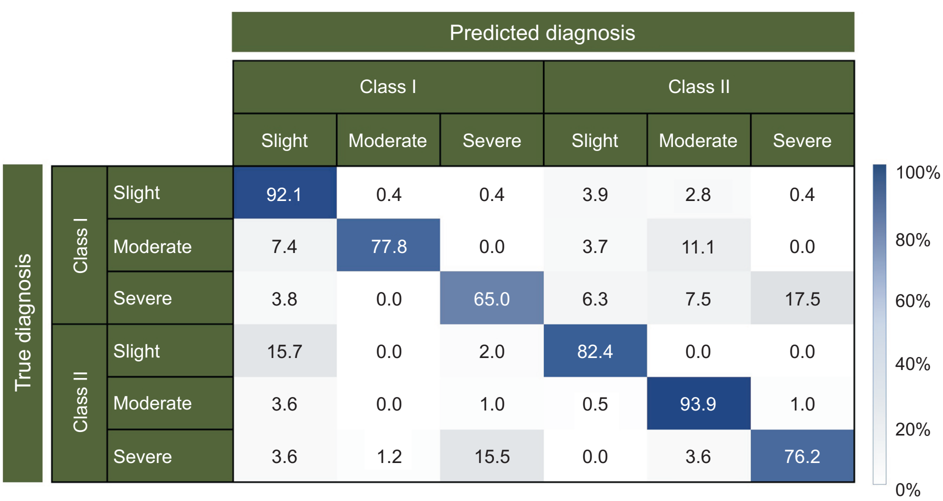

Fig. 2. Confusion matrix with normalization for multiclass classification of defect morphology and severity of peri-implantitis.

PI leads to the development of destructive bone loss in the alveolar bone surrounding implants, which is influenced by the severity and duration of inflammation as well as the volume and thickness of the surrounding soft and hard tissues[10]. A variety of non-surgical and surgical treatment options have been proposed for different types of bone loss, including horizontal, vertical, trabecular, and fracture defects, and treatment outcomes are considered to be influenced by the patient, surgeon, and environmental factors[26]. In particular, it is widely known that designing a treatment strategy based on the defect morphology and severity of PI is a critical factor affecting the success rate of PI treatment and the survival rate of implants[21,22].

The type of peri-implant bone defect can be indirectly estimated using periodontal probing and two-dimensional radiographs, including periapical and panoramic radiographs. Conversely, computed tomography (CT) provides clearer visualization of the three-dimensional bone loss pattern. However, the As Low As Reasonably Achievable (ALARA) principle makes it impractical to rely solely on cone beam CT for to diagnose PI. To effectively manage PI, it is critical to first identify and minimize the risk factors and then follow-up patients regularly with early diagnosis and maintenance protocols that include clinical and radiological evaluations[27]. Deep learning algorithms based on AI can serve as a clinical decision support tool for estimating the morphology and severity of PI. This technology is particularly beneficial for long-term management following non-surgical and surgical treatment.

In previous studies, various deep learning models such as VGG-16 and 19, GoogLeNet Inception v3 and v4, SqueezeNet, MobileNet-v2, and ResNet were commonly and widely used for dental radiological image analysis[28-30]. In this study, we adopted the ResNet-50 algorithm, and pre-trained and modified ResNet-50 architecture addresses the challenges of training deep neural networks through residual connections, leading to enhanced accuracy, transfer learning capabilities, and flexibility in model design[31]. In previous studies, the ResNet-50 algorithm successfully analyzed more than 40 different types of implant systems in more than 100,000 panoramic and periapical radiographic images, demonstrating high classification accuracy and performance of more than 80%[19,20]. Consequently, the ResNet-50 algorithm proves to be a valuable tool for classifying the morphology and severity of PI bone defects based on two-dimensional radiographic images.

This preliminary pilot study had several limitations. First, the dataset used in this study consisted of fewer than 1,000 images, which is insufficient for evaluating the feasibility of the clinical decision support tools. It is crucial to conduct further studies using much larger and more verified datasets to determine whether these tools can be used effectively in clinical practice. Second, it is important to consider the morphology of class III defects, which are combined defects, in addition to class I and II defects. However, the dataset used in this study did not include labels for class III radiographic images. This is because, as mentioned above, there are few radiographic images to classify into three classes, and the second reason is that deep learning algorithms are not yet sophisticated enough to classify the three complex types of PI defects. In future studies, as additional datasets become available and the deep learning architecture improves, it will be necessary to include a class III deep learning-based classification analysis. Third, although this study only classified the morphology and severity of PI bone defects on periapical radiographs, panoramic radiographs should also be considered. Previous studies have reported that the classification accuracy of implant systems based on panoramic radiographs is comparable to that of periapical radiographs[32,33]. Therefore, additional studies are required to compare the classification performance of morphology and severity based on both panoramic and periapical images.

Conclusion

The use of AI-based deep learning algorithms is promising for classifying the morphology and severity of PI bone defects to aid in long-term management after treatment. However, further studies are required to validate and extend the effectiveness of these tools in clinical practice.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

Acknowledgement

This study was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (No. 2019R1A2C1083978).

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