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Original research

SUCCESS OF ARTIFICIAL INTELLIGENCE SYSTEM IN DETERMINING ALVEOLAR BONE LOSS FROM DENTAL PANORAMIC RADIOGRAPHY IMAGES

ABSTRACT

Objectives: This study aims to detect alveolar bone loss from dental panoramic radiography images by using an artificial intelligence (AI) system.

Materials and Methods: A total of 2276 panoramic radiography images were evaluated. Of these, 1137 were of bone loss cases and 1139 were of periodontally healthy cases. This dataset is divided into training (n = 1856), validation (n = 210), and testing (n = 210) sets. All images were resized to 1472x718 pixels before training. A random sequence was created using the open-source Python programming language and OpenCV, NumPy, Pandas, and Matplotlib libraries. A pretrained Google Net Inception v3 convolutional neural network (CNN) was used for preprocessing, and the datasets were trained using transfer learning. The diagnostic performance was evaluated using a confusion matrix in terms of the sensitivity, specificity, precision, accuracy, and F1 score.

Results: Of 105 cases with bone loss, the CNN system detected 99 with sensitivity, specificity, precision, accuracy, and F1 score of 0.94, 0.88, 0.89, 0.91, and 0.91, respectively.

Conclusions: The CNN system successfully determines periodontal bone loss. Therefore, it can be used to facilitate diagnosis and treatment planning by oral physicians in the future.

Keywords: Panoramic radiography, artificial intelligence (AI), alveolar bone loss, periodontitis.

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INTRODUCTION

Periodontitis is a chronic inflammatory disease that affects the supporting tissues of the teeth, and it has clinical findings such as attachment loss and probing pocket depth.[1] Clinical periodontal evaluations and various radiographs are used for managing this common disease.[1-3] Radiography images enable observing the alveolar bone condition and determining any alveolar bone loss and bone resorption patterns.[2,4,5]

Various intraoral and extraoral imaging methods such as periapical, bitewing, panoramic radiographs, and cone-beam computed tomography (CBCT) are used for periodontal evaluations.[2,5] Panoramic radiographs are a very fast and easy imaging method that enable imaging the teeth and edentulous alveolar bone area by using low-dose radiation.[2,6] They also provide oral physicians with general information about the periodontal status of patients and assist them in determining the extent of alveolar bone loss.[4,6,7]

Artificial intelligence (AI) deals with machines capable of learning, problem-solving, and analysis in a manner similar to human intelligence.[8] Many studies have used convolutional neural networks (CNNs), a type of artificial neural network, for image interpretation, diagnosis, and treatment planning in dental radiology.[9-12] Dental radiographs are a diagnostic tool that can be effectively used to evaluate the condition of periodontal hard tissues and to analyze the success of periodontal treatment.[2,5] However, only a few studies have used CNN systems to determine periodontal disease[13,14] and alveolar bone loss[15-17] from radiography images.

Applying a CNN system to periodontal radiography images as a decision-support mechanism for oral physicians in diagnosis and treatment planning seems promising. The most important clinical benefit of using CNN systems in dental diagnosis and treatment planning is that it allows oral physicians to reduce diagnostic mistakes arising from strain or fatigue. The CNN system can also capture details overlooked by oral physicians in radiographic diagnoses, and its radiographic examinations can be recorded to build a database for oral physicians. In this light, the present study uses a CNN system to determine alveolar bone loss and periodontal disease/health status from dental panoramic radiography images.

MATERIALS AND METHODS

Patient selection and imaging

This study was conducted with a dataset of panoramic images obtained from the Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Eskişehir Osmangazi University. This study was approved by the Noninterventional Clinical Research Ethics Committee (decision date and number: 08.07.2019/ 2019-227), and it followed the principles of the Declaration of Helsinki.

Panoramic radiographs of patients with a large number of teeth missing (i.e., patients with less than 20 teeth), patients younger than 18 years, and patients with excessive crown-damaged teeth as well as images with artifacts or partial/severe distortion were excluded from the dataset. Further, all radiographs used in this study were taken with the same device (Planmeca Promax 2D, Planmeca, Helsinki, Finland), and only one radiograph of each patient was used. The final dataset contained 2276 panoramic images, of which 1137 were of bone loss cases and 1139 were of periodontally healthy cases, regardless of gender. All images were evaluated by an oral and maxillofacial radiologist and a periodontologist (İŞB and SKB, with at least 9 years of professional experience) for determining bone loss. The presence/absence of resorption at the bone crest was recorded in consideration of the distance between the enamel-cement junctions of the teeth and the alveolar bone crest. Radiographs showing bone resorption with a horizontal/vertical shape or bone defects were included in the bone loss group. Radiographs with no loss of bone crests or with the alveolar bone completely covering the root surfaces of the teeth (normal anatomical structure) were included in the periodontally healthy group.

Evaluation of panoramic radiography images

All images in the dataset were resized to 1472x718 pixels before training. A random sequence was created by using the open-source Python programming language and OpenCV, NumPy, Pandas, and Matplotlib libraries. The dataset is divided into training, validation, and testing sets. The training set consisted of 1856 images (927 with bone loss and 929 with good periodontal health), validation set consisted of 210 images (105 with bone loss and 105 with good periodontal health), and testing set consisted of 210 images (105 with bone loss and 105 with good periodontal health). Table 1 shows the details of these datasets.

Table 1. Details of study datasets.

Dataset	Bone destruction	Periodontally healthy	Total
Training	927	929	1856
Validation	105	105	210
Testing	105	105	210

A pretrained Google Net Inception v3 CNN network was used for preprocessing, and the datasets were trained using transfer learning. This CNN performed perfectly in the 2014 ImageNet Large Scale Visual Recognition Contest, and it initially learned ~1.28 million images consisting of 1000 object categories. This CNN consists of 22 deep layers, and it can obtain features of different scales by applying convolutional filters of different sizes in the same layer.

The training and validation datasets were used to predict and generate optimal weight factors for this CNN. In this study, all CNNs used the InceptionV3 architecture with the TensorFlow library in Python, and they were trained using 20000 steps (Figures 1 and 2) (CranioCatch, Eskisehir, Turkey).

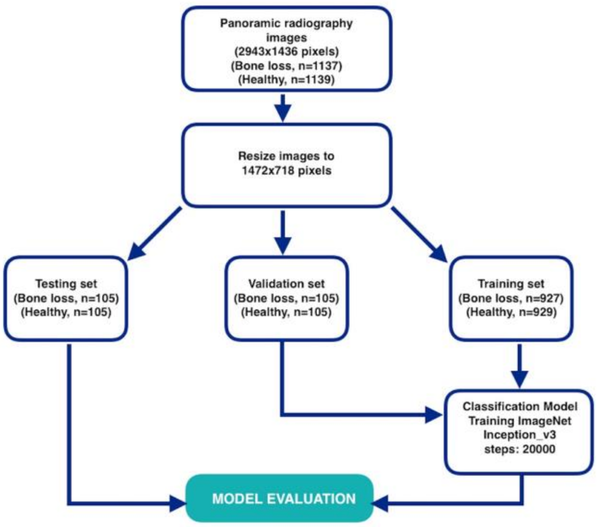

Figure 1. Evaluation of panoramic radiography data

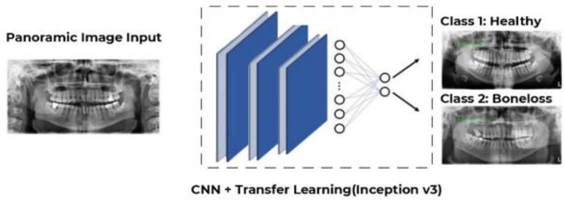

Figure 2. Evaluation of panoramic radiography data using CNN system

Statistical analyses

Statistical analyses were performed using a confusion matrix, a meaningful table that summarizes predicted and actual situations as metrics.

RESULTS

Table 2 shows the number of true positive and true negative cases determined using the CNN system. Of 105 bone loss cases, the CNN system evaluated 99 correctly and 6 incorrectly. Further, of 105 periodontally healthy cases, it evaluated 93 correctly and 12 incorrectly.

Table 2. Number of cases determined by the AI model as true positive and true negative.

	True Positive	True Negative
Predicted Positive	99	12
Predicted Negative	6	93
TOTAL	**105**	**105**

Table 3 shows the performance of the CNN system as calculated using the confusion matrix. The sensitivity, specificity, precision, accuracy, and F1 score were 0.9429, 0.8857, 0.8919, 0.9143, and 0.9167, respectively.

Table 3. AI performance calculated using the confusion matrix. TPR, true positive rate; TP, true positive; FN, false negative; SPC, specificity; TN, true negative; FP, false positive; PPV, positive predictive value; ACC, accuracy; P, positive; N, negative.

	Value	Derivations
Sensivitiy	0.9429	TPR = TP / (TP + FN)
Specificity	0.8857	SPC = TN / (FP + TN)
Precision	0.8919	PPV = TP / (TP + FP)
Accuracy	0.9143	ACC = (TP + TN) / (P + N)
F1 Score	0.9167	F1 = 2TP / (2TP + FP + FN)

DISCUSSION

Panoramic radiographs are extraoral radiographs that are commonly used in dentistry to provide a complete perspective through full mouth imaging of patients.[2,4] Studies are increasingly investigating the use of computer-aided systems for interpreting dental radiography images.[9-12,14-25] In this light, the present study used a CNN system to determine common periodontal diseases including alveolar bone loss from panoramic radiography images.

Panoramic radiographs are preferably not used alone for diagnosis; serial intraoral radiographs are used instead.[2,4] For performing periodontal diagnosis and treatment planning, it is recommended that panoramic radiographs be used with other radiographic techniques (e.g., periapical, bitewing).[2,4] Panoramic radiographs, despite their relatively low radiation dose compared to the intraoral mouth series, can give a general idea of both the teeth and the jaws of the patient, and panoramic radiography is inexpensive and easy to use compared to other extraoral imaging methods. Panoramic radiographs are one of the most preferred methods for routine evaluations in clinical dentistry.[26]

The use of AI systems for interpreting dental radiography images shows promise for diagnosis and treatment planning. When diagnosis is difficult owing to a lack of experienced oral or specialist physicians in small clinics/hospitals, AI systems could be used as a decision-support mechanism for oral physicians. Further, they could capture details overlooked by oral physicians owing to strain or fatigue. Diagnostic decisions made by oral physicians/dental students are subjective and could be wrong; AI systems will enable standardizing such decisions.[27] AI systems can also easily record the radiography images of all patients in a dental clinic/hospital with high workload in a database. Therefore, applying an AI system for analyzing periodontal diseases and other dental conditions from panoramic radiographs, which are frequently used in dentistry, could facilitate the early diagnosis, treatment planning, and archiving of information.

Studies have successfully used CNN systems for detecting sinus pathologies[16], vertical root fractures[10], mandibular canals[28], jaw tumors[22], first molar tooth root morphology[11], and teeth and tooth numbers[25] from panoramic radiographs. Other studies have used CNN systems for analyzing dental radiography images obtained by techniques such as periapical, bitewing, and CBCT.[12,24,29] However, few studies have used CNN systems for evaluating the alveolar bone status in clinical dentistry, and literature reviews have noted the importance of this issue.[13-17,30]

Aberin and Goma[13] used a CNN system for determining periodontal diseases from dental plaque microscopy images. Specifically, they used the CNN system to analyze images of periodontally healthy and unhealthy patients to match them to periodontally healthy and unhealthy conditions and achieved an accuracy of 75.5%. Similarly, Balaei *et al.*[30] used a CNN system to determine periodontal disease from intraoral images and achieved an accuracy of 66.7% for disease detection and 91.6% for pretreatment evaluation. These two studies show that CNN systems can be used successfully to determine the periodontal status.

Lee *et al.*[14] used a CNN system to determine periodontally risky teeth from 1044 periapical radiography images and classified the teeth as healthy, moderate, and severe. They calculated the accuracy separately for the mandible and maxilla and achieved a lowest and highest accuracy of 73.4% and 82.8%, respectively. They stated that their CNN system seemed promising in that it provided good predictions in the diagnosis of teeth with periodontal insufficiency. Their study could be considered more comprehensive than our study because it made clinical evaluations. In future studies, we could obtain more accurate diagnostic results by reporting clinical evaluations using a CNN system for determining the periodontal status from radiography images.

Krois *et al.*[15] reported a sensitivity, specificity, and accuracy of 0.81, 0.81, and 0.81, respectively; these results were similar to those of our study (sensitivity, specificity, precision, accuracy, and F1 score of 0.94, 0.88, 0.89, 0.91, and 0.91, respectively). However, Krois *et al.* evaluated 2001 radiography images, whereas we evaluated 2276 images. At the same time, Krois *et al.*[15] recorded and statistically compared the evaluation results of six dentists by using their CNN system; although our study achieved higher accuracy, its interpretability could be increased if it were performed with more dentists. Similarly, Kim *et al.*[16] used a CNN system to successfully evaluate periodontal bone loss from panoramic radiographs and stated that this system could reduce the image interpretation workload of dental radiologists.[16]

Chang *et al.*[17] reported high accuracy and reliability when using a CNN system for determining bone loss and periodontitis staging in line with the criteria of the "2017 World Workshop on the classification of periodontal and peri-implant diseases and conditions." By contrast, a limitation of our study was that it used only a classification model and did not perform evaluations through segmentation. Further, instead of performing disease classification, we used our CNN system only to determine the presence of bone resorption and to determine healthy and bone resorption radiographs. Therefore, our study cannot be compared with the study by Chang *et al*.

Thanathornwong and Suebnukarn[31] used a faster regional CNN system to analyze periodontal destroyed teeth from 100 panoramic radiographs. They reported that their system could be used to quickly detect periodontal destroyed teeth and to provide automatic documentation. They reported a sensitivity, specificity, precision, and F1 score of 0.84, 0.88, 0.81, and 0.81, respectively; however, they used a smaller dataset compared with our study.

CONCLUSIONS

Our study uses a CNN system to determine alveolar bone loss and periodontal disease from panoramic radiographs, and its results are comparable with those of other studies that have successfully used different CNN systems to determine the periodontal health status. Training such CNN systems with more cases will increase the accuracy rates of periodontal diagnosis. Studies investigating the use of CNN systems for the evaluation of periodontal status from intraoral photographs and intraoral and extraoral radiography images will open up new possibilities in clinical dentistry. Future studies should focus on the presence of bone loss and the staging of the disease and thereby observe the severity of the periodontal condition causing bone loss. In addition, more comprehensive studies comparing the radiographic interpretations of many oral physicians and CNN systems will increase the interpretability of the success of these systems. We believe that the promising results of our study on using a CNN system for interpreting dental radiography images will encourage further developments in this area.

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CONFLICTS OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

Dental Panoramik Radyografi Görüntülerinden Alveolar Kemik Kaybını Belirlemede Yapay Zeka Sisteminin Başarısı

ÖZ

Amaç: *Bu çalışma, yapay zeka (Artificial Intelligence) (AI) sistemi kullanarak dental panoramik radyografi görüntülerden alveoler kemik kaybını tespit etmeyi amaçlamaktadır.* ***Gereç ve Yöntem:*** *Toplam 2276 panoramik radyografik görüntüsü değerlendirildi. Bunlardan 1137'si kemik kaybı olan vakalardı, 1139'u periodontal olarak sağlıklı vakalardı. Bu veri seti eğitim (n = 1856), doğrulama (n = 210) ve test (n = 210) setlerine ayrıldı. Eğitimden önce tüm görüntüler 1472x718 piksel olarak yeniden boyutlandırıldı. Açık kaynaklı Python programlama dili ve OpenCV, NumPy, Pandas ve Matplotlib kütüphaneleri kullanılarak rastgele bir dizi oluşturuldu. Ön işleme için önceden eğitilmiş bir Google Net Inception v3 konvolüsyonel nöral ağı (CNN) kullanıldı ve veri setleri aktarım öğrenimi kullanılarak eğitildi. Tanısal performans, duyarlılık, özgüllük, kesinlik, doğruluk ve F1 skoru bir konfüzyon matris kullanılarak değerlendirildi.* ***Bulgular:*** *Kemik kaybı olan 105 olgunun 99'u CNN sistemi ile sırasıyla 0.94, 0.88, 0.89, 0.91 ve 0.91'lik duyarlılık, özgüllük, kesinlik, doğruluk ve F1 skoru ile tespit edildi.* ***Sonuç:*** *CNN sistemi periodontal kemik kayıplarını başarıyla belirlemektedir. Bu nedenle, gelecekte diş hekimleri tarafından tanı ve tedavi planlamasını kolaylaştırmak için kullanılabilir.* ***Anahtar Kelimeler:*** *Panoramik radyografi, yapay zeka, alveoler kemik kaybı, periodontit.*

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