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Research Article

Using Deep Learning Algorithms to Predict Dental Implant Brands from Panoramic Radiographs

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Abstract

Aim: The aim of this study is to predict dental implant brands from panoramic radiographs using deep learning algorithms.
Material and Method: Panoramic radiographs of patients previously undergoing dental implant procedures were retrospectively screened. Radiographs were grouped into three different implant brands, with a minimum of 250 dental implants from each brand. The obtained radiographs were divided into three groups: training, validation, and test sets, with an equal distribution of implant brands in each group. 70% of the implants were used for training, 20% for validation, and 10% for the test dataset. Trained models were tested on the previously separated test set that was not used in the deep learning model training to determine the implant brand.
Results: A total of 882 implants were evaluated in 220 panoramic radiographs. The study found that the accuracy of the implants tested in the deep learning model was 75% and the sensitivity was 78.26%. The accuracy of the model was 94.73%. The F1 score, which is a parameter frequently used in comparing artificial intelligence models with each other, was found to be 85.71%.
Conclusion: The results of this study show that implants can be identified from panoramic radiographic images using deep learning algorithms. However, to use this system routinely in clinical practice, it is necessary to create libraries by conducting studies that include many different implant systems and a large number of images.

Keywords: Deep learning, dental implant, artificial intelligence

INTRODUCTION

Dental implants began to be used in the 1980s for the treatment of missing teeth and are now frequently used worldwide for patients with tooth loss (1). Implants, which play a significant role in the treatment of dental deficiencies, are used both in fixed prosthetic restorations and as support for removable prostheses, significantly improving patients' quality of life (2,3). Today, implant treatment has become one of the classical treatment methods for both practitioners and patients (4). Although implants have been used in clinical applications successfully for years, their complications, such as peri-implantitis and peri-implant mucositis in implants and various types of complications in implant-supported prostheses have been frequently reported (5,6). It has been reported that the technical complication rate in dental implants used for more than 5 years varies between 10% and 15% (7). When implants used for 10 years are evaluated, this rate varies between 25% and 32% (8). Additional prosthetic, periodontal, or surgical treatments are needed to resolve these issues. While performing these treatments, detailed information about the previously applied implant, including the implant's brand, length, diameter, and the type of abutment used, may be required. If the patient has previously been treated at the same clinic, this information can be easily obtained from the patient's medical records. However, if the treatment was performed at another clinic and the patient cannot communicate with the previously treated clinic, obtaining this information could be difficult or impossible (9). Some patients experiencing problems

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with their implants may seek treatment at other clinics due to various reasons, such as moving to a different city or country or the closure of the clinics where they were previously treated. In these cases, dentists try to identify the implants previously applied to the patient by asking the patient or evaluating radiographs with limited data. Specifically, identifying the brand of the implant is necessary to perform additional treatments. Despite the long history of dental implant systems, there are relatively few studies and techniques available for identifying the specific systems used (10). With thousands of implant brands now available and widely applied by practitioners, determining the brand of an implant in a patient has become increasingly challenging. This highlights the need for specialized programs or systems to aid in identification (9).

Deep learning technology has been applied in various fields today, bringing significant conveniences in many areas. In deep learning technology, various methods are used in alignment with the task (11). In medicine, deep learning has been utilized in areas such as medical diagnosis, statistics, and human biology (12,13). As one of the artificial intelligence technologies, the deep learning method is suitable for tasks such as prediction, object detection, classification, and other similar tasks. In dentistry, issues such as the diagnosis of dental diseases using radiographic images, treatment predictions, classification, statistical analysis of research data, and other topics have been addressed using the deep learning method (9,14-16). Notably, there has been an increase in studies focused on disease diagnosis using deep learning, with deep learning-based object detection algorithms commonly used for this task (17,18). The capability of diagnostic systems using deep learning is currently close to or superior to that of humans (19). The use of these systems will help reduce the risk of errors by preventing dentists from overlooking various diseases and pathologies. If this system can also be applied to identify implant brands using radiographic images, it will assist both dentists and patients in resolving complications and problems related to implants. In this study, we aim to predict dental implant brands from panoramic radiographs using deep learning algorithms.

MATERIAL AND METHOD

Ethical approval for this study was obtained from the Medical Research Ethics Committee of Karamanoğlu Mehmetbey University Medical Faculty (Decision Number: 01-2024/14). The panoramic radiographs used in our study were obtained from the periodontology and oral and maxillofacial surgery departments at the Ahmet Keleşoğlu Faculty of Dentistry, Karamanoğlu Mehmetbey University, where implants had previously been applied, and control radiographs that met the criteria were available. These images were acquired using two different panoramic radiography devices, Myray 3D Ready (Cefla, Imola, Italy) and Vatech PCH-2500 (Vatech, Hwaseong, South Korea), following the manufacturer's instructions. Radiographs meeting the criteria from three different implant brands were grouped. Portions of the radiographic images containing patient information were cropped out. The inclusion criteria for the radiographs were "individuals over 18 years old," "having Medentica, Osstem, or Nucleoss brand implants placed," and "not having radiographic imaging errors." The resolution of the radiographs ranged from 2868x1504 to 2505x1515. These radiographs contained a total of 882 implants. The marking process to indicate the brand and boundaries of the implants in the radiographs was carried out using Roboflow software (Figure 1). The resolution of these radiographs is relatively high for artificial intelligence training. To accelerate the AI training process and increase success, all implants were cropped to stay within the image's long edge and then resized to a resolution of 640x640. Approximately 70% of the 220 radiographs were allocated for training, 20% for validation, and 10% for testing. The exact distribution of the radiographs and implants is provided in Table 1. No image preprocessing procedures other than resizing were applied to the radiographs. The prepared dataset was trained using the Roboflow 3.0 Instance Segmentation (Fast) AI model.

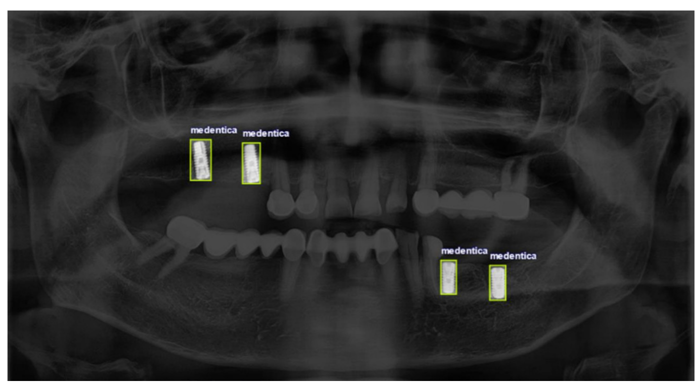

Figure 1. Labeling the implants on the radiograph as Medentica and marking the region of interest (ROI) of the implants

Table 1. Distribution of 220 radiographs and the implants in these radiographs according to brands and artificial intelligence training datasets

Implant brands	Radiographs				Implants			
	Training	Validation	Test	Total	Training	Validation	Test	Total
Medentica	51	18	7	76	192	65	26	283
Osstem	55	17	8	80	215	85	26	326
Nucleoss	48	9	7	64	214	40	19	273
Total	154	44	22	220	621	190	71	882

RESULTS

The success of the trained artificial intelligence model in identifying the implant brand was tested on the radiographs allocated for the test dataset (Figure 2). Correctly predicting the implant brand was considered a true positive (TP), incorrectly predicting the implant brand was considered a false positive (FP), and making no inference about the implant was considered a false negative (FN). Using these parameters, accuracy, sensitivity, precision, and the F1 score (the harmonic mean of precision and sensitivity) were calculated.

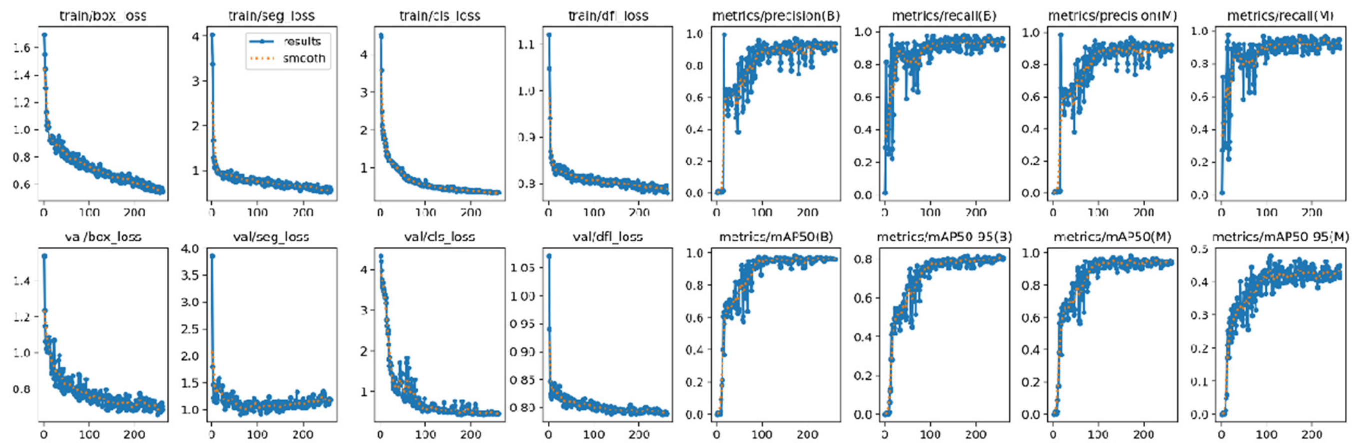

Figure 2. Metrics in the artificial intelligence training process

Of the total of 882 implants, 621 were used for training, 190 for validation, and 71 for testing. The 71 implants we tested were present on 22 radiographs. The brands of 54 of the 71 implants were correctly predicted (TP), 3 were incorrectly predicted (FP), and no implant brand was predicted for 15 (FN). Based on this data, the model's accuracy was found to be 75%, and its sensitivity was 78.26%. The precision of the model was relatively high at 94.73%. The F1 score, a parameter frequently used for comparing AI models, was 85.71%.

DISCUSSION

In recent years, with the development of artificial intelligence, deep learning technologies have begun to be used in many areas within the healthcare field (20). Specifically, deep learning-based neural networks have been successfully employed in dental applications, including cephalometric film analysis, segmentation of anatomical structures, detection and classification of various pathological formations, and detection of dental caries (21). Similarly, deep learning algorithms have been used in the field of implantology to identify the type and brand of implants since 2020 and most studies have demonstrated accuracy and reliability performance above 70% (10,20,22).

Images from periapical radiographs, panoramic radiographs, and computed tomography can be used to identify dental implants from radiographic images. It is thought that the deep learning algorithm identifies implants based on their unique features, such as shape, thread structure, and design, as well as the specific design of the implants in the apical third. The quality of training images is also important for the detailed recognition of implants in this manner (9). Most studies have used panoramic radiographic images (23). The advantage of using panoramic radiographs is that they are standardized to a certain level, independent of the patient, and the shapes of the implants in the images are also standardized. The drawback is that implants may not be visible when overlapping anatomical structures like the maxillary sinus floor, or when they are too short or overly curved, which can reduce image clarity. In such cases, this can lead to misperceptions and incorrect interpretations.

In our study, we also utilized panoramic radiograph records. In previous studies, before feeding the images into deep learning algorithms, the portions of the images containing implants were cropped in various ways. While one study cropped only the area surrounding the implant, in all other studies, rectangular or square areas encompassing the entire implant were cropped from the images (23,24). It has been reported that when the cropped area is not a standard shape, such as a square or rectangle, the quality of the dataset decreases (23). Therefore, in our study, we cropped rectangular areas that included the entire implants and fed these into the deep learning algorithms.

A review of studies utilizing deep learning algorithms to identify implant types and brands shows a reported minimum accuracy rate of 70%, demonstrating that deep learning-based AI technology has potential as a tool to assist in clinical decision-making (23). In our study, we achieved an accuracy rate of 75% when analyzing three different implant brands.

In our study, the F1 score was found to be 85.71%. The F1 score is a performance metric commonly used in deep learning, particularly for classification tasks and object detection to measure a model's accuracy. It provides a balance between precision and recall, which are two important aspects of classification performance (25).

CBCT images are frequently used in the field of dental implantology because they have less distortion and can obtain three-dimensional images with CBCT, while two-dimensional images can be displayed in panoramic radiographs (26). However, there are not many studies using deep learning and CBCT images in predicting implant brands (23). Therefore, it would be useful to conduct future studies using CBCT images along with panoramic radiographs in the detection of implant brands using deep learning.

CONCLUSION

Although studies on identifying implant brands from panoramic radiographs using deep learning algorithms are still very new and limited, both our study and previous studies have demonstrated high levels of accuracy and reliability. To increase the learning performance and to apply this system more widely in clinical practice, higher quality and more implant images and images of many different types and brands of implants will be needed in future studies.

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Ethical approval: *Commitee of Karamanoğlu Mehmetbey University Medical Faculty (Approval Number: 01-2024/14).*

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