DIAGNOSTIC CHARTING ON PANORAMIC RADIOGRAPHY USING DEEP-LEARNING ARTIFICIAL INTELLIGENCE SYSTEM

Abstract

Aims of the Study: A radiographic examination is a significant part of the clinical routine for the diagnosis, management, and follow-up of the disease. Artificial intelligence in dentistry shows that the deep learning technique high enough quality and effective to diagnose and interpret the images in the dental practice. For this purpose, it is aimed to evaluate diagnostic charting on panoramic radiography using a deep-learning AI system in this study.

Methods: 1084 anonymized dental panoramic radiographs were labeled for 10 different dental situations including crown, pontic, root-canal treated tooth, implant, implant-supported crown, impacted tooth, residual root, filling, caries, and dental calculus. AI Model (Craniocatch, Eskişehir, Turkey) based on a deep CNN method was proposed. A Faster R-CNN Inception v2 (COCO) model implemented with Tensorflow library was used for model development. The training and validation data sets were used to predict and generate optimal CNN algorithm weight factors.

Results: The proposed artificial intelligence model has promising results for detecting dental conditions in panoramic radiographs except for caries and dental calculus. The most successful F1 Scores were obtained from the implant, crown, and implant-supported crown as 0,9433, 0,9122, 0,8947, respectively.

Conclusion: Thanks to the improvement of the success rate of AI models in all areas of dentistry radiology, it is predicted that they will help physicians especially in panoramic diagnosis and treatment planning, as well as digital-based student education, especially in this pandemic period when online training is on our agenda.

Keywords: Artificial Intelligence, Craniocatch, Dentistry, Panoramic Radiography

What's Known: Panoramic radiography is a low dose and cost-effectiveness imaging modality that is used frequently in dental practice as the initial evaluation image for the screening of the teeth, jaws, and their surrounding anatomic structures. One of the important technological developments that have changed our quality of life and comfort in recent years in technological terms is artificial intelligence (AI). AI in the form of human cognition is imitated by computers. Interest in AI applications in dentistry radiology has recently increased. Many studies such as tooth numbering and tooth detection, periapical pathology detection, caries detection have been studied with artificial intelligence applications in dentistry radiology. Until now, the studies are still limited and further research is necessary to develop the AI systems.

What's New: To the best of our knowledge, there is no total charting study on panoramic radiographs, which is a routine practice in dental practice. Teaching anatomy and pathologies to AI on radiographs paves the way for a decision support mechanism for physicians. AI will have a huge impact on populations with a shortage of radiologists and screening programs. AI-enabled radiological services would be of great benefit to relieve radiologists in large hospitals.

Introduction

A radiographic examination is a significant part of the clinical routine for the diagnosis, management, and follow-up of the disease. Panoramic radiography is a low dose and cost-effectiveness imaging modality that is used frequently in dental practice as the initial evaluation image for the screening of the teeth, jaws, and their surrounding anatomic structures (1, 2). On the panoramic images, the condition of existing teeth can be evaluated, pathologies like caries in the teeth, lesions, anomaly, and fracture of the maxillofacial structures can be diagnosed, restorative and prosthetic rehabilitation of the patients can be planned easily by the dentists. However, due to this modality has unequal magnification, multiple superimpositions, and geometric distortions, sometimes it can occur misdiagnose and difficult in interpreting (1-3).

Machine learning is an umbrella term to describe a field of artificial intelligence (AI) and expresses computers learn automatically from a big data set (4). The deep learning (DL) system which is one of the AI methods has been used recently in medical fields. In this method, the computer system can be taught to automatically extract appropriate image properties to perform various tasks such as classification, image enhancement, and segmentation (1). DL systems can label as data sets automatically with convolutional neural networks (CNN) that consisting of multiple layers. These layers accumulate from training image data inputs and supply output and the learning of DL systems is repeated automatically (1, 4, 5). This system has been used for medical purposes especially for image interpretation and image-based diagnosis (1, 5, 6). In dentistry, DL has been used for lesion/cyst and caries determination, diagnosis of osteoporosis, evaluation of tooth detection and numbering, root morphology, and maxillary sinusitis. Studies on AI in dentistry shows that the DL technique high enough quality and effective to diagnose and interpret the images in the dental practice (7). Tuzoff et al. (8) investigated tooth detection and numbering on panoramic images with

the CNN system and found that this system had high sensitivity and specificity rates and results of tooth detection and numbering of the system close to the expert level. Hong-lee et al. (9) evaluated the usefulness of deep CNN algorithms for the diagnosis and detection of dental caries on periapical radiographs. They stated that by using these algorithms considerable efficiency and accuracy of diagnosis and detection of dental caries in periapical radiographs were obtained. Ariji et al. (6) examined mandibular radiolucent lesions on panoramic images with the DL technique and according to the results of their study, the DL systems had nearly 90% sensitivity to detect radiolucent lesions. Although there have been studies about AI in dentistry, the studies are still limited and further research is necessary to develop the AI systems. For this purpose, it is aimed to evaluate diagnostic charting on panoramic radiography using a deep-learning AI system in this study.

Material and Methods

Radiographic data set

Panoramic radiographs were obtained from the archive of the Department of Oral and Maxillofacial Radiology, Faculty of Dentistry of Eskisehir Osmangazi University. The radiographic datasets included 1084 anonymized dental panoramic radiographs used for different diagnostic aims from adults obtained from February 2019 to February 2020. The radiographic datasets comprise of optimizing panoramic radiographs. Panoramic radiographs with artifacts cause of patient position, motion and superposition of foreign subjects, etc. were not included in to study database. The research protocol was approved by the Non-interventional Clinical Research Ethics Committee of Eskisehir Osmangazi University (decision date and number: 06.08.2019/14) and was following the principles of the Declaration of Helsinki. The Planmeca Promax 2D (Planmeca, Helsinki, Finland) with the following parameters: 68 kVp, 16 mA, and 13 s. was used to obtain panoramic radiographs.

Image annotation

2 dento-maxillofacial radiologists (E.B. with 10 years of experience and M.B. with 6 years of experience) labeled ground truth images with agreement on all dental panoramic radiographs using Colabeler Annotation Software (MacGenius, Blaze Software, CA, USA). 1084 anonymized dental panoramic radiographs were labeled for 10 different dental situations including crown, pontic, root-canal treated tooth, implant, implant-supported crown, impacted tooth, residual root, filling, caries, and dental calculus. The rectangular boxes were used to localize these dental conditions.

Deep CNN architecture

Faster R-CNN method and Google Net Inception v2 architecture implemented with Tensorflow library were used for model development. Inception v2 was a unit that formed to decrease the confusion of the convolution network. It has three 3 × 3 convolutions unlike the traditional 5 × 5 convolutions to enhance computational speed. 3 x 3 convolution is 2.78 times cheaper than a 5 x 5. Thus, using two 3×3 layers in place of 5×5 enhances the performance of architecture. This module allows the convolution network to be wider rather than deeper. Following the principle that higher-dimensional representations are easier to handle locally within a network, the filter has been expanded. It would get ahead of the loss of information which leads on when it has been deeper. Convolution Neural Network (CNN) is a common method that works as a neural network in AI studies. CNN was improved by the Inception module decreased CNN computational time. Besides, Recurrent CNN was introduced to advanced CNN performance. Then fast R-CNN and faster R-CNN were modified from R-CNN. Region Proposal Network (RPN) was offered to reduce computational time and make a

high accuracy. Faster R-CNN announced the Region Proposal Network (RPN) in their architecture. RPN menages heavy search discriminating algorithm with the fast neural network. After the last convolution layer of CNN, RPN is placed. ROI pooling layer was raised with a proposal from RPN.

Model pipeline and training phase:

To detection of 10 different dental situations including crown, pontic, root-canal treated tooth, implant, implant-supported crown, impacted tooth, residual root, filling, caries, and dental calculus, AI Model (Craniocatch, Eskişehir, Turkey) based on a deep CNN method was proposed. A Faster R-CNN Inception v2 (COCO) model implemented with Tensorflow library was used for model development. The training and validation data sets were used to predict and generate optimal CNN algorithm weight factors. Training parameters were summarized in Table 1.

Statistical analysis

The assessment of AI model success was performed using a confusion matrix. Confusion Matrix is a table in a matrix format that summarizes the actual and predicted classifications made by a classification system. The performance of systems is often evaluated using the data in the matrix. The metrics used to evaluate the success of the model were as follows: True positive: dental condition correctly detected, False positive: dental condition incorrectly detected, False negative: dental condition was not detected. The success criteria and formulas used in our study calculated with the help of the Confusion Matrix were as follows: Sensitivity (TP / (TP + FN)), Precision (TP / (TP + FP)), and F1 Score (2TP / 2TP + FP + FN)).

Result

The proposed AI model has promising results for detecting dental conditions in panoramic radiographs except for caries and dental calculus (Figure). The most successful sensitivity values were obtained from the crown, impacted tooth, and implant as 0,9674, 0,9658, 0,9615, respectively. The most successful precision values were obtained from the implant, implant-supported crown, and pontic as 0,9259, 0,8947, 0,8783, respectively. The most successful F1 Scores were obtained from the implant, crown, and implant-supported crown as 0,9433, 0,9122, 0,8947, respectively. The value of success metrics was summarized in Table 2.

Discussion

One of the important technological developments that have changed our quality of life and comfort in recent years in technological terms is AI. AI in the form of human cognition is imitated by computers (10). Interest in AI applications in dentistry radiology has recently increased. Teaching anatomy and pathologies to AI on radiographs paves the way for a decision support mechanism for physicians. AI will have a huge impact on populations with a shortage of radiologists and screening programs. AI-enabled radiological services would be of great benefit to relieve radiologists in large hospitals (11-14).

Most of the AI applications in dentistry radiology have been made for tooth numbering and detection. Few studies are dealing with pathology and restoration detection (7, 8, 15-18).

It is seen that the success rate of AI has improved in these studies. In our study; when other articles in the literature regarding caries detection are examined, it is observed that the F1 score and sensitivity values are quite low (9, 19, 20).

In the study conducted by Lee et al. (9) in 2018 on the detection of caries, it was found that the number of training and test labels was higher than our study and that the study was conducted with periapical radiographs. It is a known fact that periapical radiographs provide images free from superpositions and distortions and are more successful than panoramic

radiographs in detecting caries (2). In this context, the discrepancy between the results can be explained. However, when evaluated in terms of dental panoramic charting, the necessity of developing models arises.

Takashi et al. (21) reported that average precision rates varied from 0.51 to 0.85 in the detection of different implant systems. In our study, only the detection of the presence of the implant was evaluated and the precision value was found to be 0.93.

Using the "Affinity propagation clustering" technique, Ngan et al. (22) and Son et al. (23) found an accuracy of 93.02% and 92.74%, respectively, to detect different dental problems. In our study, AI models were obtained with the DL method.

Aslan et al. (16) tested the determinability of the restorations in AI models and found the sensitivity values for an amalgam filling, composite filling, crown, dental implant, root canal treatment, and core as 100% 83.1% 100% 94.2% 83.2% 98.9%, respectively. Although amalgam and composite fillings were not evaluated separately in our study, the sensitivity value for determination of filling was 87%. Values for crown, implant, and root canal treatment are 97%, 96%, and 87%, respectively. Although the sensitivity values are close to this study, more training and test data were studied in our study, and more comprehensive AI models were developed and tested for dental abnormalities.

Devito et al. (20) found the success rate of the model they obtained in the detection of caries higher than the investigators in their in vitro study. They reported that their models can be used both in decision support mechanisms and in student education. Thanks to the improvement of the success rate of AI models in all areas of dentistry radiology, it is predicted that they will help physicians especially in panoramic diagnosis and treatment planning, as well as digital-based student education, especially in this pandemic period when online training is on our agenda.

Until now, many studies such as tooth numbering and tooth detection, periapical pathology detection, caries detection have been studied with AI applications in dentistry radiology (24-26). However, to the best of our knowledge, there is no total charting study on panoramic radiographs, which is a routine practice in dental practice. In this study, "10 different dental situations including crown, pontic, root-canal treated tooth, implant, implant-supported crown, impacted tooth, residual root, filling, caries, and dental calculus" were evaluated.

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Table 1. The data in the test group was not reused.

	Panoramic graph numbers for training	Label numbers for training	Panoramic graph numbers for test	Label numbers for training	Learning Rate	Epoch
Crown	231	1104	50	236	0.00001	200
Pontic	169	387	37	80	0.00001	200
Root-canal treatment	426	1159	74	162	0.0001	300
Implant	42	107	9	26	0.00001	200
Implant sup. crown	26	65	7	19	0.00001	200
Impacted tooth	336	796	52	115	0.0001	300
Residual root	86	150	12	29	0.0001	300
Filling	657	2965	118	519	0.0001	300
Caries	513	1425	91	256	0.0001	300
Dental calculus	163	518	31	107	0.0001	300

Table 2: The value of success matrix

	True-positive (TP)	False-Positive (FP)	False-Negative (FN)	Sensitivity (TP / (TP + FN))	Precision (TP / (TP + FP))	F1 Score (2TP / 2TP + FP + FN))
Crown	208	33	7	0,9674	0,8630	0,9122
Pontic	65	9	19	0,7738	0,8783	0,8227
Root-canal treatment	150	43	23	0,8670	0,7772	0,8196
Implant	25	2	1	0,9615	0,9259	0,9433
Implant sup. crown	17	2	2	0,8947	0,8947	0,8947
Impacted tooth	113	32	4	0,9658	0,7793	0,8625
Residual root	23	11	5	0,8214	0,6764	0,7419
Filling	99	14	16	0,8608	0,8761	0,8684

Caries	79	76	182	0,3026	0,5096	0,3798
Dental calculus	10	42	97	0,0934	0,1923	0,1257

Figure Legends:

Figure: The results for detecting dental conditions in panoramic radiographs with AI models a) pontic b) implant supported crown c) residual root d) filling e) root canal treatment

Disclosures

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.