Medical Principles and Practice

Original Paper

Med Princ Pract 2022;31:555–561 DOI: 10.1159/000527145 Received: January 12, 2022 Accepted: September 14, 2022 Published online: September 27, 2022

A Deep Learning Model for Idiopathic Osteosclerosis Detection on Panoramic Radiographs

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Highlights of the Study

- To the best our knowledge, there are no studies examining the performance of artificial intelligence systems in the evaluation of idiopathic osteosclerosis on panoramic radiographs.
- In the present study, sensitivity, precision, and *F*-measure values were found to be 0.88, 0.83, and 0.86, respectively.
- Deep learning-based artificial intelligence algorithms have the potential to accurately detect idiopathic osteosclerosis on panoramic radiographs.

Keywords

Artificial intelligence · Deep learning · Idiopathic osteosclerosis · Panoramic radiography · Dentistry

This study was presented as an oral presentation in the 72nd American Academy of Oral and Maxillofacial Radiology (AAOMR) Annual Session, December 13–15, 2021, and Abstracts were published in Oral Surg Oral Med Oral Pathol Oral Radiol [2022;134:77].

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Abstract

Objective: The purpose of the study was to create an artificial intelligence (AI) system for detecting idiopathic osteosclerosis (IO) on panoramic radiographs for automatic, routine, and simple evaluations. **Subject and Methods:** In this study, a deep learning method was carried out with panoramic radiographs obtained from healthy patients. A total of 493 anonymized panoramic radiographs were used to develop the AI system (CranioCatch, Eskisehir, Turkey) for the detection of IOs. The panoramic radiographs were acquired from the radiology archives of the Department of Oral and

Correspondence to: Selin Yesiltepe, dt_selin@yahoo.com Maxillofacial Radiology, Faculty of Dentistry, Eskisehir Osmangazi University. GoogLeNet Inception v2 model implemented with TensorFlow library was used for the detection of IOs. Confusion matrix was used to predict model achievements. **Results:** Fifty IOs were detected accurately by the AI model from the 52 test images which had 57 IOs. The sensitivity, precision, and F-measure values were 0.88, 0.83, and 0.86, respectively. **Conclusion:** Deep learning-based AI algorithm has the potential to detect IOs accurately on panoramic radiographs. AI systems may reduce the workload of dentists in terms of diagnostic efforts.

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Introduction

Idiopathic osteosclerosis (IO) is defined as non-expanding radiopaque changes in the trabecular bone which are of various shapes and sizes. Although its etiology is unknown, it may be a result of internal stress and insufficient blood flow to form bone masses in the jaws. This lesion can affect both the maxilla and mandible, but it is frequently observed in the mandibular premolar-molar region. This benign lesion is mostly asymptomatic and is generally discovered incidentally on panoramic radiographs taken for routine examination [1].

Panoramic imaging is a specialized tomographic technique used to create a flat representation of the curved surfaces of the jaws. It provides the opportunity to view the entire maxilla, mandible, temporomandibular joints, and related structures in a single film. However, interpretation of panoramic radiographic images can sometimes be difficult, especially for inexperienced observers, resulting in overlooked critical diseases [2]. Therefore, in the last two decades, due to the increased availability of digital medical data, increased computing power, and advancement in artificial intelligence (AI), diagnosis with computer-aided detection/diagnosis systems has been developed and applied to a variety of medical problems [3, 4].

Since 2010, convolutional neural networks (CNNs), the latest core model of artificial neural networks and deep learning in computer vision, have developed rapidly [5, 6]. This approach has been used successfully in medical applications. This rapidly growing new field of research has yielded impressive results in terms of diagnosis and prediction of radiological and pathological analysis [7, 8]. Also, in the field of oral and maxillofacial diagnostic imaging, studies on the application of CNNs in dentistry have shown promising results, but it is still a developing area of research [9, 10]. In this study, we aimed to examine the performance of AI systems in evaluating IO on panoramic radiographs.

Methodology

Study Design

In this retrospective study, we developed automatic IO detection models (CranioCatch, Eskisehir, Turkey) in dental panoramic radiographs using a pretrained GoogLeNet Inception v2 Faster R-CNN architecture implemented with TensorFlow library. The Eskisehir Osmangazi University Non-Interventional Clinical Research Ethics Committee (decision date and number: August 6, 2019/14) approved the study protocol. The principles of the Helsinki Declaration were followed in this study.



Fig. 1. Deep learning architecture.

Med Princ Pract 2022;31:555–561 DOI: 10.1159/000527145 Yesiltepe/Bayrakdar/Orhan/Çelik/Bilgir/ Aslan/Odabaş/Costa/Jagtap

Radiographic Data Source

Panoramic radiographs taken on patients over the age of 18 years, regardless of gender differences, were included in the study. Panoramic radiographs were obtained from the radiology archive of the Department of Oral and Maxillofacial Radiology, Eskisehir Osmangazi University School of Dentistry. The dataset included 493 anonymized dental panoramic radiographs with IO from March 2018 to March 2019. Panoramic radiographs with artifacts, trauma, jaw pathologies like cyst and tumor, etc., were excluded from study group. Panoramic radiographs were acquired on the Planmeca ProMax 2D (Planmeca, Helsinki, Finland) with following parameters: 68 kVp, 16 mA, and 13 s.



Fig. 2. Steps in the development of IO detection model.



Fig. 3. IO detection on panoramic radiographs using the AI model (CranioCatch, Eskisehir, Turkey).

Table 1. Predictive performance measurement of IO detection using the AI model (CranioCatch, Eskisehir, Turkey) in test dataset

	ТΡ	FP	FN	Sensitivity	Precision	F1 score
IO detection	50	10	7	0.88	0.83	0.86

Ground Truth Annotation

Three oral and maxillofacial radiologists (S.Y., I.S.B., E.B.) with at least 10 years of experience labeled each tooth on the dental panoramic radiographs using CranioCatch Labeling Tool (Eskisehir, Turkey) and agreed on each label. Polygonal boxes tool was used to annotate all IO on dental panoramic radiographs.

Development of Detection Model

Preprocessing Steps

493 anonymized panoramic radiographs were used to develop AI algorithm. In the first preprocessing step, panoramic radiographs were divided into 4 equal parts including mandible left, mandible right, maxilla left, maxilla right for shrinkage to the region of interest. All images were resized to 512×256 . Images with no IO label were removed. The dataset was divided into training group 454 (467 labels), validation group 50 (50 labels), and test group 52 (57 labels).

Deep CNN Architecture

GoogLeNet Inception v2 architecture implemented with TensorFlow library was used for model creation. Inception v2 was developed to decrease the confusion of the convolution network. It has three 3×3 convolutions unlike the traditional 5×5 convolutions to enhance computational speed. 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 [11] (Fig. 1).

Training

The open-source programming language Python (version 3.6.1; Python Software Foundation, Wilmington, DE, USA) was used to develop AI algorithm. TensorFlow library was used for producing AI model with GoogLeNet Inception v2 network. The training method was applied using computer equipment of Eskisehir Osmangazi University Faculty of Dentistry Dental-AI Laboratory including Dell PowerEdge T640 GPU Calculation Server NVIDIA Tesla with V100 16G Passive GPU (Dell Inc., Texas, USA). The IO detection model with GoogLeNet Inception v2 network implemented with TensorFlow library was trained with 200,000 epochs (Fig. 2).

Evaluation of Performance of the Model

Model performance was evaluated using the confusion matrix. The metrics used to assess the performance of the IO detection model were as follows.

True positive (TP): the number of accurately detected IO.

False positive (FP): the number of detected IO even though there was no IO.

False negative (FN): the number of IO that was not detected. The performance metrics of the model were determined ac-

- cording to the formulas using number of TP, FP, and FN below. Sensitivity (Recall, True positive Rate [TPR]): TP/(TP + FN) Precision (Positive Predictive Value [PPV]): TP/(TP + FP)
 - F1 Score: 2TP/(2TP + FP + FN)

Results

The created AI models (CranioCatch, Eskisehir, Turkey) based on the deep CNN method has promising results for IO detection on panoramic radiographs. In the 52 test images, there were 57 IOs; 50 IOs were detected by AI model, accurately (Fig. 3). Seven IOs were not detected. The sensitivity, precision, and *F*-measure values were 0.88, 0.83, and 0.86, respectively (Table 1).

Discussion

Osteosclerosis is a general term to describe areas of increased bone formation and is usually detected incidentally on radiographs. The radiopacity of IO may be similar to other pathologies of the jaw such as condensing osteitis, retained root fragments, hypercementosis, cementoblastoma, impacted teeth, focal cemento-osseous dysplasia, and rarely, complex odontomas. Accurate diagnosis is based on bone morphology. There is no enlargement or absence of radiolucent halo or lack of signs. Panoramic radiography is still used clinically as one of the main imaging examinations. IO usually does not require any treatment other than diagnosis. In general, lesions likely persist for years, and surgical intervention is not recommended. Periodic follow-up of the lesions is necessary to ensure that the clinical diagnosis is correct [12]. With this, IOs may undergo changes in the young population and have the potential to expand over time. Sclerotic lesions may enlarge or stabilize. Also, IO may cause root resorption, nerve compression, dental impaction, dental displacement, and difficulties in orthodontic movement. It was reported that the dense bone island lesion detected in the adolescent patient may increase in size and density, potentially causing other problems such as increased inclination of adjacent teeth, and the presence of the lesion may complicate any future orthodontic treatment [13]. Marques-Silva et al. [14] claimed that IO may cause changes in tooth position or problems during orthodontic treatment, and they reported a case of tooth resorption caused by IO-induced ectopic eruption course. Mainville et al. [15] reported that external root resorption is present in 10-12% of cases of IO which often involves permanent mandibular first molars.

In the literature, there are studies examining the frequency and distribution of IO of the jaws [1, 16, 17]. However, to the best of our knowledge, there are no studies examining the performance of AI systems in the evaluation of IO on panoramic radiographs. The current study aimed to examine the performance of AI systems in evaluating IO on panoramic radiographs.

The use of AI systems for radiographic image interpretation in the healthcare field has ushered in a new era in diagnosis and treatment planning. Diagnostic decisions made by dentists can be sometimes subjective and sometimes wrong. The purpose of radiological AI systems is to create automatic, routine, simple evaluations so that radiologists can read images faster and save time for more complex cases [18]. AI systems allow archive systems where the radiological images of all patients can be regularly reported and stored without the need for extra workload and time. In order to standardize the interpretation of images and provide equal service in diagnostic accuracy, anonymous datasets can be made available and thus helpful in situations where radiological expertise is limited. For this reason, analysis made with AI on panoramic radiographs can facilitate early diagnosis, treatment planning, and archiving of information.

AI has rapidly improved the interpretation of medical and dental images [19] through the application of deep learning models and CNNs [20]. Deep CNN architecture appears to be the most widely used deep learning approach. This is due to the efficient self-learning algorithms and high computational power that provide superior detection, classification, and quantization performance based on image data [21]. In the literature, there are studies about detecting vertical root fractures [22], first molar tooth root morphology [23], periapical pathosis [24], mandibular canal detection [25], tooth and tooth numbering [26] using the CNN system.

Murata et al. [27] showed that deep learning systems can diagnose sinusitis on panoramic radiography at a rate similar to that of radiologists, and their performance is superior to the skills of dentists. In this study, diagnostic performance of the deep learning system for maxillary sinusitis on panoramic radiographs was high, with an accuracy of 87.5%, sensitivity of 86.7%, specificity of 88.3%, and the area under the curve of 0.875. Lee et al. [28] performed dental segmentation on panoramic radiographs and reported that they achieved high success rate in AI performance. This method obtained an F1 score of 0.875 (precision: 0.858, recall: 0.893) and a mean intersection over union of 0.877. Ekert et al. [29] investigated the ability of deep CNNs to detect apical lesions on panoramic radiographs. According to the methodology applied in their study, a moderately deep CNN trained on a limited amount of image data showed satisfactory discriminating ability to detect apical lesions in panoramic radiographs. Krois et al. [30] evaluated the success of CNN systems in determining periodontal bone destruction with 1,780 panoramic images, reported that the result was similar to that of dentists and that AI systems could reduce the physician's efforts to make periodontal diagnoses. In this study, mean classification accuracy of the CNN was found to be 0.81. Mean sensitivity and specificity were 0.81 and 0.81. The mean accuracy of the dentists was 0.76. In the present study, sensitivity, precision, and F-measure values were 0.88, 0.83, and 0.86, respectively. Thus, we suggest that AI models based on the deep CNN method have promising results for the detection of IO on panoramic radiographs. This study is one of a series of studies aimed at using deep learning AI to automate diagnoses in panoramic radiography.

This study has a few limitations. The radiologic dataset included only IO as radiopaque lesions; future studies should eliminate this limitation and expand the use of the network and include other hypersclerotic lesions in the dataset like osteitis, odontomas, etc., to propose a network that is of true clinical value. Besides, panoramic images taken from different radiologic equipment with different radiologic parameters should be used for the development of AI models in order to have reliable algorithms for clinical practice. Moreover, differential diagnosis or follow-up of IO was not done in the present study. Further studies can be done with AI regarding the differential diagnosis or follow-up of IO and large datasets.

Conclusion

Deep learning-based AI algorithm has the potential to detect IOs accurately on panoramic radiographs. AI systems may reduce the workload of dentists in terms of diagnostic efforts in the future.

Statement of Ethics

All procedures performed in studies involving human participants were in accordance with the ethical standards of the Institutional and/or National Research Committee and in alignment with

References

- 1 Sisman Y, Ertas ET, Ertas H, Sekerci AE. The frequency and distribution of idiopathic osteosclerosis of the jaw. Eur J Dent. 2011;5(4): 409–14.
- 2 Nardi C, Calistri L, Grazzini G, Desideri I, Lorini C, Occhipinti M, et al. Is panoramic radiography an accurate imaging technique for the detection of endodontically treated asymptomatic apical periodontitis? J Endod. 2018;44(10):1500–8.
- 3 Ohashi Y, Ariji Y, Katsumata A, Fujita H, Nakayama M, Fukuda M, et al. Utilization of computer-aided detection system in diagnosing unilateral maxillary sinusitis on panoramic radiographs. Dentomaxillofac Radiol. 2016; 45(3):20150419.
- 4 Maia PRL, Medeiros AMC, Pereira HSG, Lima KC, Oliveira PT. Presence and associated factors of carotid artery calcification detected by digital panoramic radiography in patients with chronic kidney disease under-

going hemodialysis. Oral Surg Oral Med Oral Pathol Oral Radiol. 2018;126(2):198–204.

- 5 Song Q, Zhao L, Luo X, Dou X. Using deep learning for classification of lung nodules on computed tomography images. J Healthc Eng. 2017:8314740–7.
- 6 Sklan JES, Plassard AJ, Fabbri D, Landman BA. Toward content-based image retrieval with deep convolutional neural networks. Proc SPIE Int Soc Opt Eng. 2015:94172C.
- 7 Rezaei M, Yang H, Meinel C. Deep Neural Network with l2-norm unit for brain lesions detection. International Conference on Neural Information Processing; 2017. p. 798–807.
- 8 Liu J, Wang D, Lu L, Wei Z, Kim L, Turkbey EB, et al. Detection and diagnosis of colitis on computed tomography using deep convolutional neural networks. Med Phys. 2017; 44(9):4630–42.
- 9 Arık SÖ, Ibragimov B, Xing L. Fully automated quantitative cephalometry using convolu-

the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Additional informed consent was obtained from all participants included in the study.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest.

Funding Sources

This work was supported by Eskisehir Osmangazi University Scientific Research Projects Coordination Unit under grant number 202045E06.

Author Contributions

Ibrahim Sevki Bayrakdar and Kaan Orhan: literature search and design of the work; Elif Bilgir and Selin Yesiltepe: acquisition of data and writing of the manuscript; Alper Odabaş, Özer Çelik, and Ahmet Faruk Aslan: analysis and interpretation of data; and Andre Luiz Ferreira and Rohan Jagtap: drafting of manuscript and revisions.

Data Availability Statement

All data generated or analyzed during this study are included in this article. Further inquiries can be directed to the corresponding author.

tional neural networks. J Med Imag. 2017; 4(1):014501.

- 10 Miki Y, Muramatsu C, Hayashi T, Zhou X, Hara T, Katsumata A, et al. Classification of teeth in cone-beam CT using deep convolutional neural network. Comput Biol Med. 2017;80:24–9.
- 11 Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2016. p. 2818–26.
- 12 Bsoul SA, Alborz S, Terezhalmy GT, Moore WS. Idiopathic osteosclerosis (enostosis, dense bone silands, focal periapical osteopetrosis). Quintessence Int. 2004;35(7): 590–1.
- 13 Nakano K, Ogawa T, Sobue S, Ooshima T. Dense bone island: clinical features and possible complications. Int J Paediatr Dent. 2002; 12(6):433–7.

- 14 Marques Silva L, Guimaraes ALS, Dilascio MLC, Castro WH, Gomez RS. A rare complication of idiopathic osteosclerosis. Med Oral Patol Oral Cir Bucal. 2007;12(3):E233–4.
- 15 Mainville GN, Lalumière C, Turgeon D, Kauzman A. Asymptomatic, nonexpansile radiopacity of the jaw associated with external root resorption: a diagnostic dilemma. Gen Dent. 2016;64(1):32–5.
- 16 Moshfeghi M, Azimi F, Anvari M. Radiologic assessment and frequency of idiopathic osteosclerosis of jawbones: an interpopulation comparison. Acta Radiol. 2014;55(10):1239– 44.
- 17 Naser AZ, Roshanzamir N. Prevalence of idiopathic osteosclerosis in an Iranian population. Indian J Dent Res. 2016;27(5):544–6.
- 18 Ozden FO, Ozgonenel O, Ozden B, Aydogdu A. Diagnosis of periodontal diseases using different classification algorithms: a preliminary study. Niger J Clin Pract. 2015;18(3): 416–21.
- 19 He K, Zhang X, Ren S, Sun J. Delving deep into rectifiers: surpassing human-level performance on ImageNet classification. Proc IEEE Int Conf Comput Vis. 2015:1026–34.
- 20 Lakhani P, Sundaram B. Deep learning at chest radiography: automated classification

of pulmonary tuberculosis by using convolutional neural networks. Radiology. 2017; 284(2):574–82.

- 21 Soffer S, Ben-Cohen A, Shimon O, Amitai MM, Greenspan H, Klang E. Convolutional neural networks for radiologic images: a radiologist's guide. Radiology. 2019;290(3):590–606.
- 22 Fukuda M, Inamoto K, Shibata N, Ariji Y, Yanashita Y, Kutsuna S, et al. Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol. 2019;36(4):337–43.
- 23 Hiraiwa T, Ariji Y, Fukuda M, Kise Y, Nakata K, Katsumata A, et al. A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography. Dentomaxillofac Radiol. 2019;48(3):20180218.
- 24 Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J. 2020;53(5):680–9.
- 25 Fukuda M, Ariji Y, Kise Y, Nozawa M, Kuwada C, Funakoshi T, et al. Comparison of 3 deep learning neural networks for classifying the relationship between the mandibular third molar and the mandibular canal on pan-

oramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol. 2020;130(3):336–43.

- 26 Tuzoff DV, Tuzova LN, Bornstein MM, Krasnov AS, Kharchenko MA, Nikolenko SI, et al. Tooth detection and numbering in panoramic radiographs using convolutional neural networks. Dentomaxillofac Radiol. 2019; 48(4):20180051.
- 27 Murata M, Ariji Y, Ohashi Y, Kawai T, Fukuda M, Funakoshi T, et al. Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. Oral Radiol. 2018; 35(3):301–7.
- 28 Lee JH, Han SS, Kim YH, Lee C, Kim I. Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol. 2020; 129(6):635–42.
- 29 Ekert T, Krois J, Meinhold L, Elhennawy K, Emara R, Golla T, et al. Deep learning for the radiographic detection of apical lesions. J Endod. 2019;45(7):917–22.e5.
- 30 Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, et al. Deep learning for the radiographic detection of periodontal bone loss. Sci Rep. 2019;9:8495–6.