Oral Radiology
https://doi.org/10.1007/s11282-022-00634-x

ORIGINAL ARTICLE

Deep learning for preliminary profiling of panoramic images

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Received: 11 January 2022 / Accepted: 27 May 2022

Abstract

Objective This study explored the feasibility of using deep learning for profiling of panoramic radiographs.

Study design Panoramic radiographs of 1000 patients were used. Patients were categorized using seven dental or physical characteristics: age, gender, mixed or permanent dentition, number of presenting teeth, impacted wisdom tooth status, implant status, and prosthetic treatment status. A Neural Network Console (Sony Network Communications Inc., Tokyo, Japan) deep learning system and the VGG-Net deep convolutional neural network were used for classification.

Results Dentition and prosthetic treatment status exhibited classification accuracies of 93.5% and 90.5%, respectively. Tooth number and implant status both exhibited 89.5% classification accuracy; impacted wisdom tooth status exhibited 69.0% classification accuracy. Age and gender exhibited classification accuracies of 56.0% and 75.5%, respectively.

Conclusion Our proposed preliminary profiling method may be useful for preliminary interpretation of panoramic images and preprocessing before the application of additional artificial intelligence techniques.

Keywords Deep learning · Preliminary profiling · Panoramic image · Artificial intelligence (AI) · Dental radiology · Oral health

Abbreviation

AI Artificial intelligence

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Introduction

Among various artificial intelligence (AI) technologies, deep learning has demonstrated robust image detection performance. Therefore, deep learning-assisted detection/diagnosis is receiving considerable attention [1, 2].

In the field of dentistry, panoramic radiography is regarded as the ideal modality to rapidly screen patient dentition. AI software may thus be useful for scanning panoramic images and generating accurate dental diagnoses. Several AI software systems have been proposed to determine dental status using panoramic, periapical, and dental cone-beam CT images [3–9].

In previous studies regarding the deep-learning analysis for the panoramic radiograph, the tooth region detection was first performed. Famous convolutional neural networks such as DetectNet and GoogLeNet was used to perform so-called bounding-box type region detection [10, 11]. These systems have demonstrated robust diagnostic performance to detect and/or evaluate various dental conditions. Then classification of each tooth by the type of tooth (tooth number) and/or the dental treatment status was performed using the ResNet, AlexNet, VGG-Net, and etc. [12, 13]. However, forementioned deep learning approach has not yet achieved

Published online: 27 June 2022

accurate identification of each tooth [6]. It may be due to the huge morphological variety of panoramic radiography. The appearance of the panoramic radiograph changes greatly depending on the person's subject’s generation and the condition of the maxillofacial region. This makes to be difficult for AI to perform accurate image region detection and classification. Therefore, it may be reasonable to classify the entire panoramic image before extracting the tooth region to perform region detection.

Regarding the clinical aspect, a preliminary interpretation and classification system for panoramic radiograph will be useful for dentists to perform assessment of patient's dental status. This system would allow patient profiling from panoramic images. For example, it could distinguish between healthy dentition and dentition that contains multiple prostheses and/or missing teeth. Additionally, it could distinguish between permanent dentition and mixed dentition. The system might enable dentists to provide concise explanations for patients regarding the need for dental treatment.

This study was performed to explore the usefulness of deep learning image classification for preliminary interpretation and classification of panoramic images.

Materials and methods

An image database containing panoramic radiographs of 1000 patients was established with approval from the Asahi University School of Dentistry ethics committee (approval no. 31040). And this study was conducted according to the principles expressed in the Declaration of Helsinki. Panoramic radiography examinations were performed in Asahi University dental hospital using a panoramic radiography machine (Veraview-epocs, Morita Inc., Kyoto, Japan) and a photostimulable storage phosphor digital radiograph system (Prima T2, Fuji Film Co., Kanagawa, Japan). Panoramic images were stored in DICOM format (3,000 × 1,500 pixels). The database consisted of 445 male patients and 555 female patients with various dental diseases; patients were excluded if they had extensive cysts, tumors, and/or fractures.

Patients were categorized using the dental and physical characteristics described in Table 1. Physical characteristics comprised gender and age groups. Dental characteristics comprised mixed and permanent stages of dentition, as well as the following statuses: impacted wisdom tooth, implant, and prosthetic. Patients were also stratified according to the number of presenting teeth (≤ 19 and ≥ 20). Figure 1 shows examples of patient panoramic images and possible classification categories.

We used a Neural Network Console ver. 1.5.0 for Windows (Sony Network Communications Inc., Tokyo, Japan) deep learning system, along with the VGG-Net deep convolutional neural network. Figure 2 shows the VGG-Net architecture used in this study. We trained networks to perform classification using the above six categories. We randomly assigned images at a 7:1:2 ratio into training, validation, and test datasets. The training process was performed for 30 epochs, using a batch size of 50 and a convolutional neural network of 19 layers. We trained the AI to recognize the entire area of a panoramic image as single region of interest.

Table 1 Panoramic radiograph classification categories

Classification category		Group	Number of patients
Physical characteristics	Gender	Male	445
		Female	555
	Age (years)	≤ 15	184
		16–29	189
		30–49	220
		50–69	272
		≥ 70	135
Dental characteristics	Dentition	Mixed	158
		Permanent	842
	Impacted wisdom tooth status	Present	505
		Absent	495
	Number of presenting teeth	≤ 19	113
		≥ 20	887
	Implant status	Present	142
		Absent	858
	Prosthetic treatment status	Present	752
		Absent	248

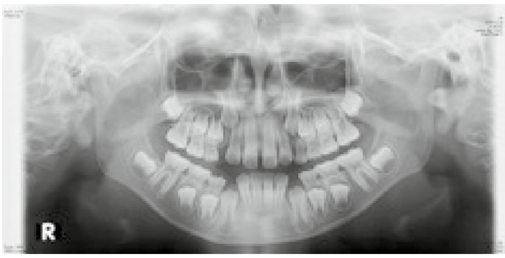
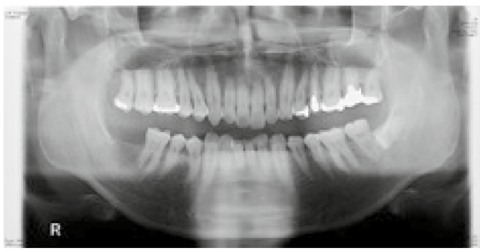
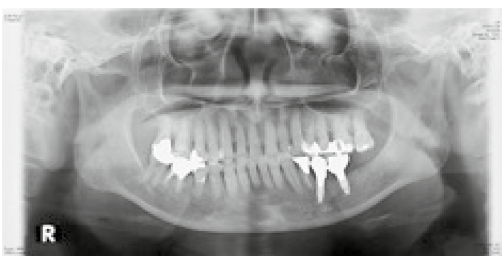
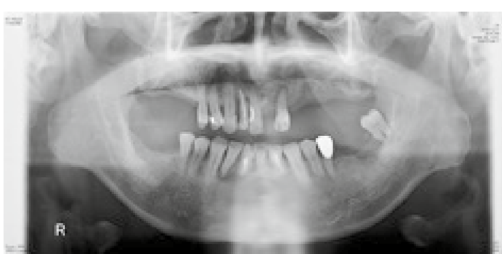
Panoramic image	Assigned classification group
	• Gender: Female • Age: <15 • Dentition: Mixed • Number of presenting teeth: 20< • Dental treatment: No prosthetic
	• Gender: Male • Age: 30-49 • Dentition: Impacted wisdom tooth • Number of presenting teeth: 20< • Dental treatment: Prosthetics
	• Gender: Female • Age:50-69 • Dentition: Permanent • Number of presenting teeth: 20< • Dental treatment: Implant
	• Gender: Male • Age:50-69 • Dentition: Permanent • Number of presenting teeth: 19< • Dental treatment: Prosthetics

Fig. 1 Panoramic images and applicable classification categories. Preliminary dental profiles of patients could be extracted from the test images

Therefore, each panoramic image was resized to a resolution of 474×234 pixels (36 pixels per inch).

Results

Figure 3 shows the learning curves of the seven classification categories. The shapes of the learning curves indicated that smooth progression with respect to classifying permanent or mixed dentition, prosthetic treatment status, number of teeth (≥ 20 or ≤ 19), and implant status. The values of the corresponding cost (loss) functions, as well as the rates of validation and training error, nearly reached zero during the learning period. In contrast, gender and impacted wisdom tooth status showed slightly higher cost values and error rates. The age group (five categories) demonstrated a higher error value during the learning period, compared with the other characteristics.

Dentition and prosthetic treatment status exhibited classification accuracies of 93.5% and 90.5%, respectively. Tooth number and implant status both exhibited 89.5% classification accuracy; impacted wisdom tooth status exhibited 69.0% classification accuracy. Age and gender exhibited classification accuracies of 56.0% and 75.5%, respectively.

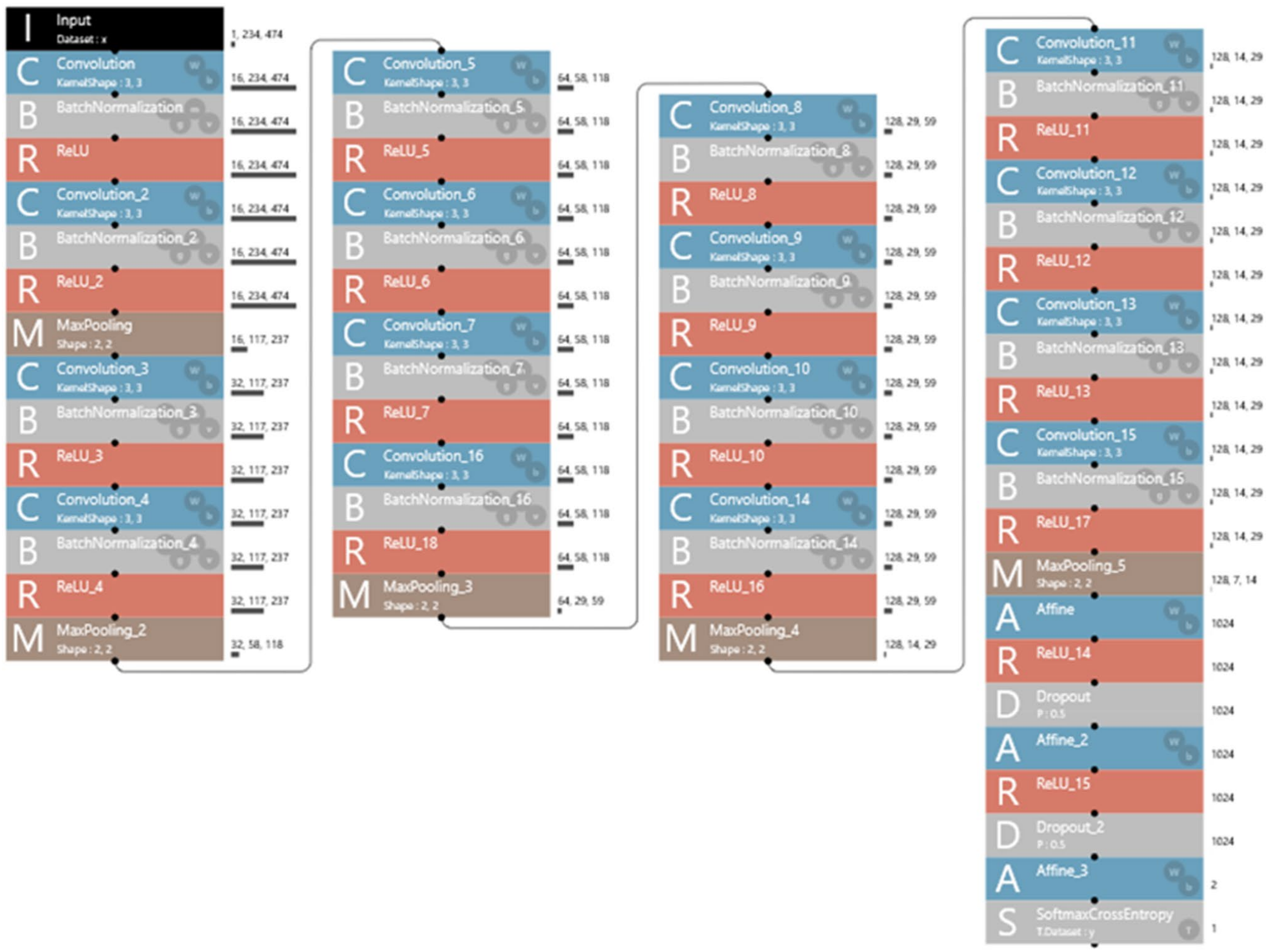


Fig. 2 VGG-Net architecture used in this study

Table 2 shows the accuracy, sensitivity, and specificity values for all characteristics.

Discussion

Panoramic radiography is the most frequently used imaging modality in dental practice. Many dental offices currently use a digital panoramic radiography system and millions of panoramic images are acquired annually. The regions in such images include the teeth and jaws, as well as the facial and cervical regions. It is thus reasonable for panoramic radiographs to be used in the development of an automatic diagnostic system [14]. Several deep-learning AI techniques have been proposed for detection of cystic lesions in the jaw [15, 16], impacted teeth [17, 18], fractures [19], and maxillary sinusitis [20, 21]. Additionally, software that perform tooth detection and numbering in panoramic radiographs have been implemented in dental practice [3–6]. Automation of X-ray image diagnoses will improve diagnostic accuracy and reduce burdens on dentists.

Most of the existing techniques require region detection and/or image segmentation to define the appropriate area of interest before precise detection/diagnosis can be performed. However, it is difficult for AI systems to accurately perform both segmentation and detection in panoramic radiograph. For example, although existing tooth detection and numbering techniques have demonstrated accuracy of > 95% per tooth, this accuracy decreases if the area of interest focuses on the entire dentition in a patient's mouth. The accuracy may be improved if a panoramic image can be preliminarily classified to several groups, prior to implementation in training a specific segmentation and detection AI network. Therefore, our proposed preliminary profiling method may be useful for preprocessing before application of the segmentation and/or region detection technique. In addition, the AI profiling we propose may be useful for post-mortem personal identification in the event of a natural disaster. [22]

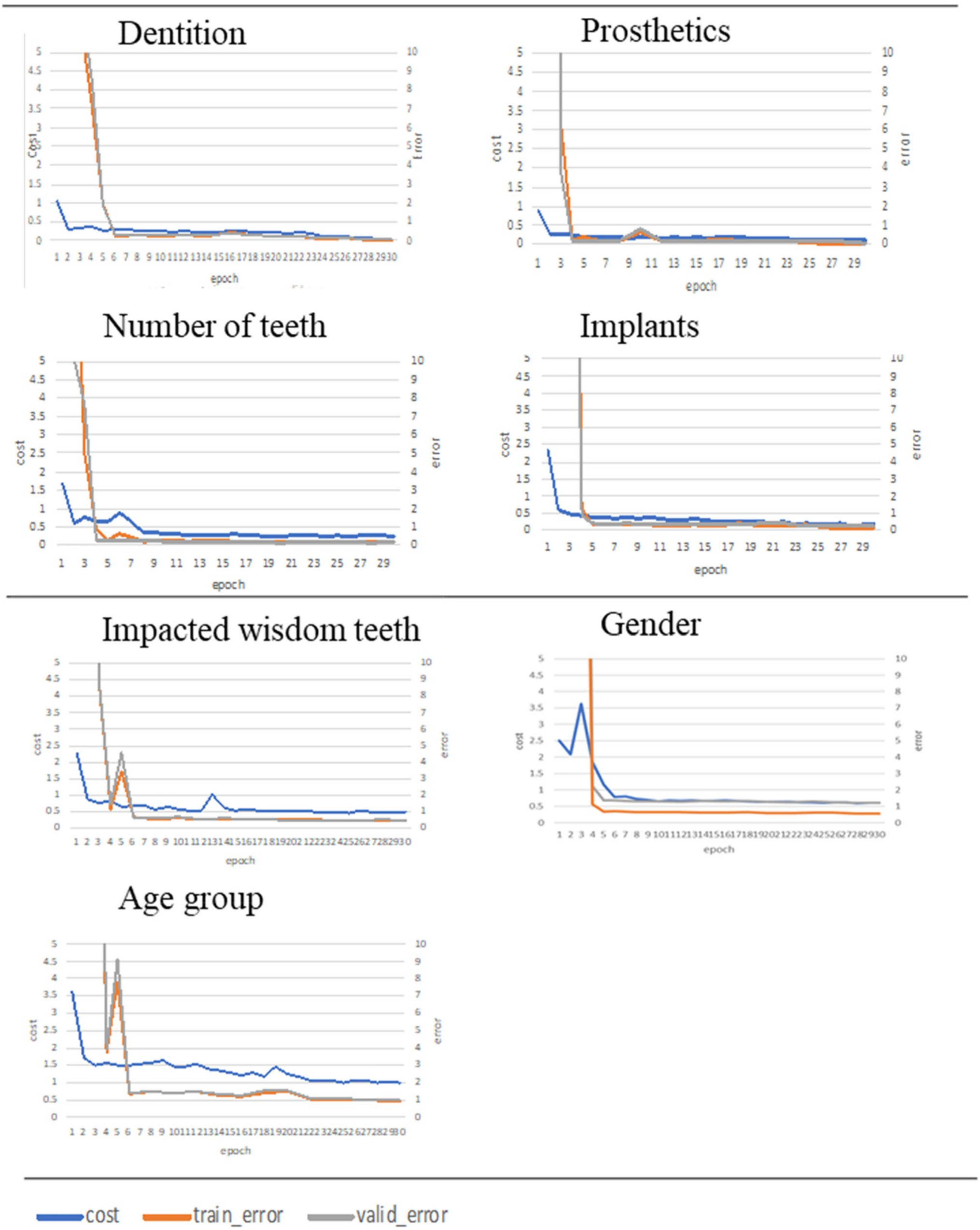


Fig. 3 Learning curves of seven classification categories. In the four categories in the upper row, errors and costs converge to nearly zero as training progresses. In the three categories in the middle and lower rows, no distinct error or cost convergences were observed

Table 2 Deep learning classification results

Classification category		Accuracy (%)	Sensitivity (%)	Specificity (%)
Physical characteristics	Gender	75.5	76.9	76.5
	Age	56.0	50.2	54.9
Dental characteristics	Dentition	93.5	78.3	96.5
	Number of presenting teeth	89.5	56.2	82.4
	Impacted wisdom tooth status	69.0	69.0	74.7
	Implant status	89.5	89.7	79.0
	Prosthetic treatment status	90.5	91.2	83.9

Our results revealed that only some physical and dental characteristics (i.e., categories) were suitable for AI classification. Four categories exhibited high classification performance: mixed or permanent dentition, number of presenting teeth, implant status, and prosthetic treatment status. Notably, these categories constitute distinctive features that can be clearly identified by the human eye. Implants and dental prostheses materials exhibit visibly greater image contrast, compared with other hard tissue. However, impacted wisdom tooth status did not exhibit high classification accuracy, presumably because impacted wisdom teeth do not demonstrate visibly greater image contrast compared with surrounding hard tissue structures. Gender exhibited higher classification accuracy than expected, possibly because of gender differences in jaw bone size. However, patient age group could not be clearly identified, even by experienced radiologists. Previous studies have reported that it is difficult for deep learning algorithms to accurately detect low contrast anatomical structures [23]. We suspect that classification of panoramic images into the categories of children, young adults, and older adults may be better than classification according to specific age groups. We plan to further investigate possible revisions of existing classification criteria. Additionally, AI diagnostic performance could be improved by training with greater numbers of panoramic images, acquired using an array of panoramic imaging systems to ensure AI exposure to differences among imaging systems.

In this study, we used the VGG-Net deep convolutional neural network. Although various deep learning networks (e.g., LeNet, AlexNet, ResNet, and VGG-Net) have been used to classify images, we previously demonstrated similar classification performance among these networks [24]. In this study, we used the Neural Network Console interactive rapid-prototyping tool, which has been validated in the construction and implementation of several deep learning networks [25]. This deep learning tool enabled the application of an advanced AI network without complex coding requirements. Moreover, the Neural Network Console system contains an automatic adjustment function that supports network architecture.

We plan to use our panoramic image profiling system for automatic definition and evaluation of specific dental diseases (e.g., dental caries, periodontitis, and periapical lesions). Additionally, the system might be appropriate for application in forensic dentistry: [26] the identification of deceased individuals after traumatic death via comparison with panoramic images of dental profiles previously obtained in regional dental clinics.

In conclusion, this study investigated the use of deep learning for preliminary profiling of panoramic images. Using the VGG-Net deep convolutional neural network, high classification accuracies were achieved in terms of distinguishing between mixed or permanent dentition, stratifying according to the number of presenting teeth, and determining the implant and prosthetic treatment statuses.

Acknowledgements We thank Ryan Chastain-Gross, Ph.D., from Edanz (https://jp.edanz.com/ac) for editing a draft of this manuscript.

Funding This work was supported by JSPS KAKENHI Grant Number JP19K10347.

Declarations

Conflict of interest None to declare.

Ethical approval Asahi University School of Dentistry ethics committee (approval no. 31040).

Informed consent Informed consent was obtained from the patient for publication of accompanying images.

References

1. Fujita H. AI-based computer-aided diagnosis (AI-CAD): the latest review to read first. Radiol Phys Technol. 2020;13:6–19.
2. Hung K, Montalvao C, Tanaka R, Kawai T, Bornstein MM. The use and performance of artificial intelligence applications in dental and maxillofacial radiology: a systematic review. Dentomaxillofac Radiol. 2020;49:20190107.
3. Tuzoff DV, Tuzova LN, Bornstein MM, et al. Tooth detection and numbering in panoramic radiographs using convolutional neural networks. Dentomaxillofac Radiol. 2019;48:20180051.
4. Kılıc MC, Bayrakdar IS, Çelik Ö, et al. Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs. Dentomaxillofac Radiol. 2021;50:20200172.

5. Bilgir E, Bayrakdar İŞ, Çelik Ö, et al. An artificial intelligence approach to automatic tooth detection and numbering in panoramic radiographs. BMC Med Imaging. 2021;21:124.
6. Muramatsu C, Morishita T, Takahashi R, et al. Tooth detection and classification on panoramic radiographs for automatic dental chart filing: improved classification by multi-sized input data. Oral Radiol. 2021;37:13–9.
7. Chen H, Zhang K, Lyu P, et al. A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. Sci Rep. 2019;9:3840.
8. Mori M, Ariji Y, Fukuda M, et al. Performance of deep learning technology for evaluation of positioning quality in periapical radiography of the maxillary canine. Oral Radiol. 2021. https://doi.org/10.1007/s11282-021-00538-2.
9. Miki Y, Muramatsu C, Hayashi T, et al. Classification of teeth in cone-beam CT using deep convolutional neural network. Comput Biol Med. 2017;80:24–9.
10. DetectNet: Deep Neural Network for Object Detection in DIGITS. https://devblogs.nvidia.com/detectnet-deep-neural-network-object-detection-digits/. Accessed 26 Apr 2022
11. Szegedy C, Liu W, Jai Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. IEEE Conf Comput Vis Pat Recog CVPR. 2015. https://doi.org/10.48550/arXiv.1409.4842.
12. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2016. pp. 770–8. https://doi.org/10.1109/CVPR.2016.90.
13. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. ICLR. 2015. https://doi.org/10.48550/arXiv.1409.1556.
14. Katsumata A, Fujita H. Progress of computer-aided detection/diagnosis (CAD) in dentistry. Jpn Dent Sci Rev. 2014;50:63–8.
15. Ariji Y, Yanashita Y, Kutsuna S, et al. Automatic detection and classification of radiolucent lesions in the mandible on panoramic radiographs using a deep learning object detection technique. Oral Surg Oral Med Oral Pathol Oral Radiol. 2019;128:424–30.
16. Watanabe H, Ariji Y, Fukuda M, et al. Deep learning object detection of maxillary cyst-like lesions on panoramic radiographs: preliminary study. Oral Radiol. 2021;37:487–93.
17. Kuwada C, Ariji Y, Fukuda M, et al. Deep learning systems for detecting and classifying the presence of impacted supernumerary teeth in the maxillary incisor region on panoramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol. 2020;130:464–9.
18. Orhan K, Bilgir E, Bayrakdar IS, Ezhov M, Gusarev M, Shumilov E. Evaluation of artificial intelligence for detecting impacted third molars on cone-beam computed tomography scans. J Stomatol Oral Maxillofac Surg. 2020. https://doi.org/10.1016/j.jormas.2020.12.006.
19. Fukuda M, Inamoto K, Shibata N, et al. Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol. 2020;36:337–43.
20. Mori M, Ariji Y, Katsumata A, et al. A deep transfer learning approach for the detection and diagnosis of maxillary sinusitis on panoramic radiographs. Odontology. 2021;109:941–8.
21. Kuwana R, Ariji Y, Fukuda M, et al. Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs. Dentomaxillofac Radiol. 2021;50:20200171.
22. Alalharith DM, Alharthi HM, Alghamdi WM, Alsenbel YM, Aslam N, Khan IU, Shahin SY, Dianišková S, Alhareky MS, Barouch KK. A Deep learning-based approach for the detection of early signs of gingivitis in orthodontic patients using faster region-based convolutional neural networks. Int J Environ Res Public Health. 2020;17(22):8447.
23. Hiraiwa T, Ariji Y, Fukuda M, et al. A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography. Dentomaxillofac Radiol. 2019;48:20180218.
24. Fukuda M, Ariji Y, Kise Y, et al. Comparison of 3 deep learning neural networks for classifying the relationship between the mandibular third molar and the mandibular canal on panoramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol. 2020;130:336–43.
25. Aoyama Y, Maruko I, Kawano T, et al. Diagnosis of central serous chorioretinopathy by deep learning analysis of en face images of choroidal vasculature: a pilot study. PLoS ONE. 2021;16:e0244469.
26. Ortiz AG, Soares GH, da Rosa GC, Biazevic MGH, Michel-Crosato E. A pilot study of an automated personal identification process: applying machine learning to panoramic radiographs. Imaging Sci Dent. 2021;51:187–93.