

# A deep learning approach to permanent tooth germ detection on pediatric panoramic radiographs

Emine Kaya<sup>1,\*</sup>, Huseyin Gurkan Gunec<sup>2</sup>, Kader Cesur Aydin<sup>3</sup>, Elif Seyda Urkmez<sup>4</sup>,  
Recep Duranay<sup>5</sup>, Hasan Fehmi Ates<sup>6</sup>

<sup>1</sup>Department of Pediatric Dentistry, Faculty of Dentistry, Istanbul Okan University, Istanbul, Turkey

<sup>2</sup>Department of Endodontics, Faculty of Dentistry, Atlas University, Istanbul, Turkey

<sup>3</sup>Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Istanbul Medipol University, Istanbul, Turkey

<sup>4</sup>Basaksehir Inci ADSM, Istanbul, Turkey

<sup>5</sup>Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Atlas University, Istanbul, Turkey

<sup>6</sup>Department of Computer Engineering, School of Engineering and Natural Sciences, Istanbul Medipol University, Istanbul, Turkey

## ABSTRACT

**Purpose:** The aim of this study was to assess the performance of a deep learning system for permanent tooth germ detection on pediatric panoramic radiographs.

**Materials and Methods:** In total, 4518 anonymized panoramic radiographs of children between 5 and 13 years of age were collected. YOLOv4, a convolutional neural network (CNN)-based object detection model, was used to automatically detect permanent tooth germs. Panoramic images of children processed in LabelImg were trained and tested in the YOLOv4 algorithm. True-positive, false-positive, and false-negative rates were calculated. A confusion matrix was used to evaluate the performance of the model.

**Results:** The YOLOv4 model, which detected permanent tooth germs on pediatric panoramic radiographs, provided an average precision value of 94.16% and an F1 value of 0.90, indicating a high level of significance. The average YOLOv4 inference time was 90 ms.

**Conclusion:** The detection of permanent tooth germs on pediatric panoramic X-rays using a deep learning-based approach may facilitate the early diagnosis of tooth deficiency or supernumerary teeth and help dental practitioners find more accurate treatment options while saving time and effort. (*Imaging Sci Dent* 2022; 52: 275-81)

**KEY WORDS:** Tooth Germ; Radiograph, Panoramic; Pediatric Dentistry

## Introduction

An accurate diagnosis can be characterized as the first and the most crucial step for performing successful dental treatments. Panoramic radiography has been a valuable tool that is widely used by dental practitioners to make correct diagnoses.<sup>1</sup> Panoramic radiography makes it possible to visualize the entire maxillofacial region on a single image with minimal patient discomfort, fast and easy application,

and a limited radiation dose.<sup>2</sup> With these advantages, panoramic radiography does not adversely affect patient cooperation, which is particularly essential in pediatric dentistry.<sup>3</sup> However, interpreting the detected conditions and lesions may be challenging because of superimpositions caused by the complexity of the 3-dimensional anatomic structures on the panoramic image.<sup>4</sup> Computer-aided diagnosis systems have been developed to prevent clinicians from overlooking dental diseases and to increase the accuracy of radiological diagnoses.<sup>5</sup> In recent years, computer-aided detection or diagnosis systems created by conventional methods have been replaced by artificial intelligence (AI)-based systems aiming to enhance radiological diagnoses.<sup>6</sup>

Deep learning is an AI-based approach employed in

Received March 10, 2022; Revised May 19, 2022; Accepted June 1, 2022

Published online July 5, 2022

\*Correspondence to : Prof. Emine Kaya

Department of Pediatric Dentistry, Faculty of Dentistry, Istanbul Okan University,  
34959 Akfırat-Tuzla, Istanbul, Turkey

Tel) 90-5545017015, E-mail) eminetaass@gmail.com

Copyright © 2022 by Korean Academy of Oral and Maxillofacial Radiology

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<http://creativecommons.org/licenses/by-nc/3.0>) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

Imaging Science in Dentistry · pISSN 2233-7822 eISSN 2233-7830

several clinical fields to make automated decisions. Convolutional neural networks (CNNs), a particular class of deep learning models, have gained tremendous attention in medical imaging.<sup>7</sup> CNNs have the ability to “learn” how to make a diagnosis based on a sufficient amount of provided data, such as images, by mimicking the neurons of the human brain.<sup>8</sup> Training a CNN from scratch, using off-the-shelf pre-trained CNN models, and performing unsupervised CNN pre-training with supervised fine-tuning are major techniques that have been employed for medical image classification.<sup>9</sup> After validation of a trained CNN model with an independent dataset, performance metrics can be obtained.

CNNs have recently been applied in dental radiology for automatic segmentation of teeth,<sup>10,11</sup> detection of caries,<sup>12,13</sup> apical lesions,<sup>14</sup> and periodontal bone loss.<sup>15</sup> Tuzoff et al.<sup>16</sup> employed the Faster R-CNN architecture for teeth detection and numbering on 1,352 adult panoramic radiographs and reported that the performance level of the CNN-based system was close to the level of radiologists. Although these studies indicated promising outcomes, this research area is not fully developed yet.<sup>16</sup> The aforementioned studies all used CNN architectures to detect dental diseases or teeth on adults’ panoramic radiographs. However, there have been limited studies on employing AI-based systems for detecting dental diseases on panoramic radiographs of pediatric patients.<sup>17-19</sup>

Generally, CNN-based models are expected to contribute to making the correct diagnosis, thereby reducing the dentists’ workload and efforts.<sup>14</sup> Particularly in pediatric dentistry, faster and more effective diagnoses help patients cooperate better with their dental practitioners and increase the success rate of dental treatment.<sup>20</sup> The diagnosis of permanent tooth deficiency or excess directly affects the treatment choice. The early detection of such conditions allows

less invasive restorative procedures and surgical removal of lesions, such as cysts and tumors, at early stages without damaging the surrounding healthy tissues.<sup>21</sup> For this purpose, this study aimed to apply a CNN architecture for pediatric panoramic radiographs to help dental practitioners make effective diagnoses. To the best of the authors’ knowledge, this is the first study using a CNN model to detect permanent tooth germs on pediatric panoramic radiographs.

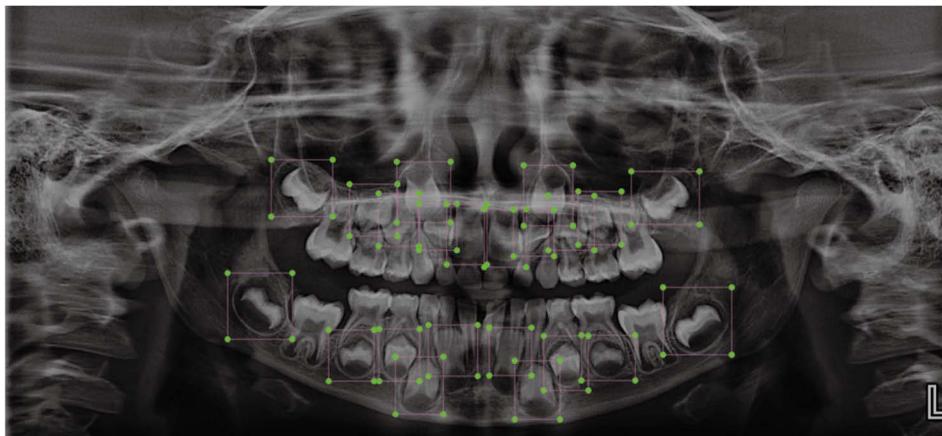
## Materials and Methods

### Image data set

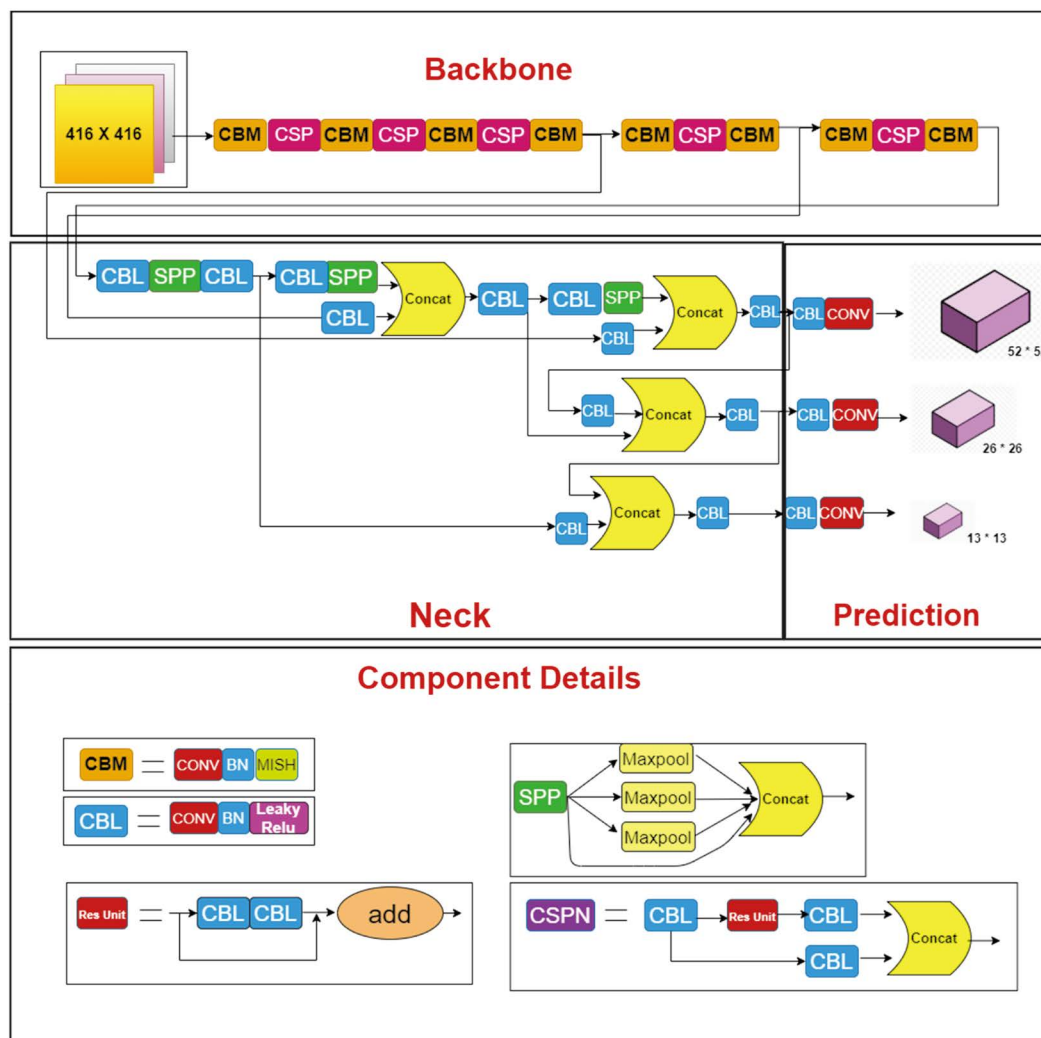
Approval for this study was obtained from the institutional ethical committee (13.01.2021/131). In total, 4,518 panoramic radiographs of pediatric patients aged 5-13 were collected from Istanbul Okan University, Faculty of Dentistry for this study. No additional information, such as age or sex, was revealed since the radiographs were collected anonymously. The Planmeca Promax 2D Panoramic system (Planmeca, Helsinki, Finland) at 68 kVp, 14 mA, and 12 s was used to obtain all the panoramic radiographs. Each permanent tooth germ in the maxillae and the mandible was manually annotated by labeling the bounding box in the LabelImg<sup>22</sup> program. The locations of permanent tooth germs were carried out by drawing a bounding box, and all permanent tooth germs were labeled (Fig. 1). The test data consisted of 10% of the panoramic radiographs. Among 4,518 radiographs, there were 50,096 permanent tooth germs in the dataset, and they were used as the ground truth data for training and testing.

### CNN modeling and YOLOv4

CNNs, a type of multi-layer perceptron, are designed to cover the entire image with cells in the visual center. Subregions are divided into simple cells and complex cells.



**Fig. 1.** Permanent tooth germs on a training image are labeled using the LabelImg<sup>22</sup> program.



**Fig. 2.** Network architecture of YOLOv4.<sup>37</sup> CSPDarknet53 is used as the backbone network for YOLOv4. While convolution-batch normalization-MISH (CBM) layers are used in the backbone, convolution-batch normalization-leaky ReLU (CBL) layers are used in the neck of the architecture.

Simple cells are arranged according to the similar features of the edges, and complex cells are arranged according to the whole image with wide sensors.<sup>23</sup> The signals of neurons in the stimulation area are calculated by mathematical convolution operations. A CNN consists of 1 or more convolutional layers, a subsampling layer, and 1 or more fully connected layers, such as a standard multilayer neural network. CNN algorithms are applied in many areas such as audio and video processing.<sup>24</sup>

As in many biomedical fields, a CNN model was applied in this study. One of the most important reasons for using a CNN model was to create a model with the best results in image processing. The YOLOv4 model used in this study is a state-of-the-art model for object detection in images. YOLOv4 achieves very fast inference for the detection

of permanent tooth germ from radiographs. YOLOv4 is designed to detect objects in real time. YOLOv4 is accepted as a model that provides some of the most accurate results, with an optimal trade-off between speed and object detection performance.<sup>25</sup> The network architecture of YOLOv4 was shown in Figure 2. CSPDarknet53 was used as the backbone network for YOLOv4.<sup>26</sup>

The model was developed and trained using the PyTorch deep learning framework in Python. Data sets of radiology images were randomly divided into training and test sets. Out of 4,518 panoramic images, 3,395 images were used for training and the remaining 523 images were used for testing. The images were resized as  $608 \times 608$  pixels for model training, which was carried out on a server with Nvidia RTX2080 Ti (11 GB RAM) (Nvidia Corp, Santa Clara, CA,

USA) graphics card, and 192 GB RAM. The model was trained for 100 epochs. During the training process, the Adam optimizer was used with a learning rate of 0.001. The batch size was given as 32, and the subdivision value was 4.

### Statistical analysis

The detection accuracy of the YOLOv4 model was evaluated based on the true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) rates. A correctly detected permanent tooth germ was defined as TP, a wrong detection as FP, a missing detection as FN, and a correct detection other than a permanent tooth germ as TN. The indices used for object detection assessment include precision, recall, the F1-score, and average precision (AP). Precision was calculated by the ratio of correct positive results in the predicted samples to all positive results.

$$Precision = \frac{TP}{TP + FP}$$

Recall was calculated as the ratio of predicted correct positive results to all results that should be positive.

$$Recall = \frac{TP}{TP + FN}$$

The F1-score was calculated by taking the harmonic mean of precision and recall.

$$F1 - Score = 2 \times \frac{P \times R}{P + R}$$

AP was computed as the area under the precision-recall curve.

$$AP = \int_0^1 P(R) dR$$

SPSS version 25.0 (IBM Corp, Armonk, NY, USA) statistical program and Python 3 (Python Software Foundation, Wilmington, DE, USA) in Jupyter (NumFOCUS Foundation, Austin, TX, USA) were used to perform the statistical analysis. While performing permanent tooth germ detection in YOLOv4, the statistical analysis of confidence values was carried out with true values coded as “1” and false values coded as “0”.

## Results

The trained model was tested with 523 panoramic radiographs that contained a total of 5,898 permanent tooth germ

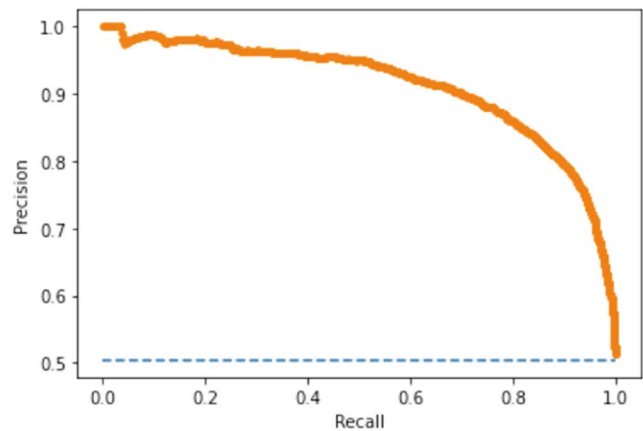
ground truth labels. The YOLOv4 model provided 6,043 detections, out of which 5,364 were TP detections and 679 were FP detections. The total number of FN detections was 534.

In the descriptive statistics, out of 6,043 detections, the minimum confidence score was calculated as 0.250 and the maximum confidence score was 0.999; the mean was  $0.877 \pm 0.196$ . With 5,364 TP detections and 679 FP detections, the t-test showed statistical significance at  $P < 0.05$ .

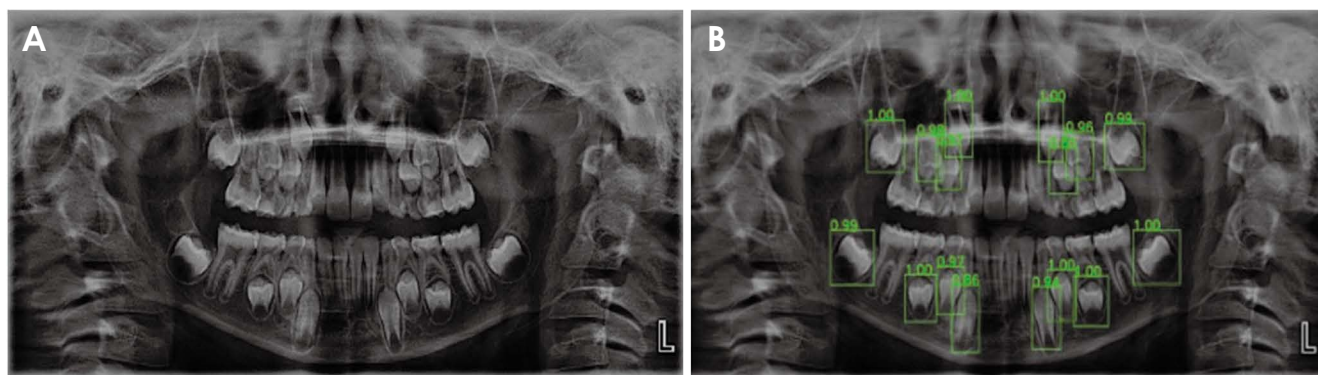
To evaluate the model’s success, a confusion matrix was used together with the following procedures and metrics: using 5,364 TP detections, 679 FP detections, and 534 FN detections in the above formulas, the precision, recall, and F1-score were computed to be 0.89, 0.91, and 0.90 respectively. Using the area under the precision-recall curve, the AP value was calculated as 94.16%. The AP, precision, and recall values indicated the success of the model for permanent tooth germ detection. It is significant when the F1-score yields a value above  $P = 0.5$ . Since  $P > 0.5$  in this study, the F1-score was a strong indicator of the success and significance of this study (Fig. 3).

Figure 4 provides sample permanent tooth germ detections from a test set image, together with the ground truth labels. All permanent tooth germs were correctly detected in this image, and the confidence scores of detection were very high.

The YOLOv4 inference time was 90 ms on average. Hence, the model can process about 11 images per second. Together with a 94.16% AP value and close-to-real-time inference speed, the YOLOv4 model has proven that very accurate results can be obtained at very fast speeds, when compared to other CNN-based object detection models.



**Fig. 3.** Precision and recall curve. The area under this curve gives the average precision value.



**Fig. 4.** Visual results from the test set. A. Original pediatric panoramic radiograph. B. Permanent tooth germ detection using YOLOv4 (prediction scores are provided on top of each detection. The model predicts the ground truth annotations and bounding boxes with high accuracy).

Moreover, the high precision and high recall values all indicate that the model presented in this study was statistically powerful.

### Discussion

Primary teeth and the permanent successors are interdependent components of the dental arch that closely interact with each other.<sup>27</sup> Diagnosing developmentally absent or supernumerary permanent teeth is very crucial for determining the most appropriate dental procedure in pediatric dentistry. The choice of whether to perform endodontic and restorative rehabilitation for the involved tooth depends on the presence or absence of a permanent tooth germ.<sup>21</sup> The development of a system that helps dental practitioners detect permanent tooth germs may enable more accurate diagnoses by reducing their workflow and human-induced errors. In this regard, the present study aimed to use an AI-based system to detect permanent tooth germs on panoramic radiographs.

The development of deep learning and neural methods accelerated the integration of AI into the field of medicine. In recent years, the use of deep learning methods in dentistry has gained attention, as in the medical field. Many studies have investigated deep learning methods for automated tooth segmentation and dental disease diagnosis on panoramic radiographs from adults.<sup>10,11,16</sup> However, only 1 study has used a deep learning-based AI model for the automated tooth segmentation of pediatric panoramic dental radiographs.<sup>28</sup> This is the first study to investigate the use of a CNN architecture to detect permanent tooth germs on pediatric panoramic images.

The benefits and limitations of the automatically detect-

ing deep CNN algorithm YOLOv4 were experienced in the detection of permanent tooth germs on panoramic images in this research. YOLOv4 is a real-time detection system with some outstanding features, such as classifying targeted objects in a single forward pass.<sup>29</sup> Moreover, YOLOv4 treats detection as a regression problem that does not need a complicated pipeline or semantic segmentation. YOLOv4 also learns the regions of interest and their background together and performs simple inference in a new image during the test process for predicting detections.<sup>30</sup>

The most important reason for choosing YOLO instead of other CNN models was that the algorithm is fast enough to detect objects at once and can run in real time. In addition, the most important feature that distinguishes YOLO from other algorithms is that it can accurately perform real-time object detection with its overall high mean AP.<sup>29</sup> Yang et al.<sup>30</sup> evaluated the performance of YOLO to detect and classify odontogenic cysts and tumors on 1,603 panoramic radiographs and revealed that YOLO provided at least similar diagnostic performance as experienced dentists on detection of maxillofacial lesions. Since this study evaluated a different dental issue and used panoramic images of adults, it is not possible to compare the findings directly.

Kuwada et al.<sup>6</sup> reported that deep learning systems have potential for detecting maxillary impacted supernumerary teeth on panoramic radiographs, but for the mixed dentition, it would be more difficult because of the presence of unerupted permanent teeth. It was believed that learning the permanent tooth germs may be an important step toward solving this problem. Furthermore, applying a CNN to detect permanent tooth germs on panoramic radiographs may help diagnose impacted supernumerary teeth more accurately. The diagnostic performance of the deep-learn-

ing system for maxillary sinus lesions on panoramic radiographs was found to be sufficiently high.<sup>31-33</sup> Similarly, a deep learning application provided high accuracy in the detection of impacted third molars and their relationship with anatomical structures.<sup>34,35</sup>

Ahn et al.<sup>18</sup> investigated the performance of a deep learning model to detect mesiodens on primary or mixed dentition panoramic radiographs and suggested that this method may help clinicians with insufficient clinical experience make more accurate and faster diagnoses. Ha et al.<sup>19</sup> proposed a model based on YOLOv3 to detect mesiodens on panoramic radiographs of primary, mixed and permanent dentition groups. They compared the model performance between original panoramic radiographs and contrast-limited histogram equalization (CLAHE) and found that the accuracy and specificity of the original images was higher than that of the CLAHE images. This study reported that their model was successful for clinical practice to detect mesiodens on panoramic radiographs of all dentition types. However, no study has evaluated the performance of deep learning systems for detecting permanent tooth germs on panoramic radiographs. Therefore, it is not possible to make a direct comparison with the present study.

Although the number of studies on detecting dental diseases or tooth numbering with AI-supported systems on panoramic images of adult patients is rapidly increasing,<sup>6,13-15,31-34</sup> few studies have investigated AI-based systems with pediatric panoramic images.<sup>17-19,28</sup> This may be explained by the positioning artifacts that occur due to the superposition of anatomical structures and teeth on panoramic images of children. Since visualizing both jaws in children with severe maxilla-mandible discordance and positioning children correctly during imaging are often difficult, panoramic images do not provide detailed information.<sup>36</sup> Caliskan et al.<sup>17</sup> used CNN algorithms to detect and classify submerged molars on 74 panoramic images of 5- to 12-year-old children and reported that the system was extremely accurate. It may not be possible to make a full comparison since they investigated a different task and used a different algorithm.

Further research may be required to detect which germ is absent by using tooth numbering algorithms, thereby improving the performance of YOLO. The detection of missing tooth germ may help dental practitioners determine accurate treatment approaches. The number of annotated dental tissues or diseases can be increased as well. More advanced dental imaging methods may be used to enhance the results of YOLO.

In conclusion, deep learning systems are an encouraging

approach and may have a crucial effect in terms of shortening the diagnosis time and effort in dental practice. Particularly for pediatric patients, shortening the time for diagnosis increases the cooperation of children and enables dental practitioners to perform more successful treatments. Thanks to YOLO's fast real-time results, images were processed in less time than expected, and highly accurate results were obtained. To the best of the authors' knowledge, this is the first study that used a CNN algorithm for detecting permanent tooth germ on pediatric panoramic images.

**Conflicts of Interest:** None

## References

1. Choi JW. Assessment of panoramic radiography as a national oral examination tool: review of the literature. *Imaging Sci Dent* 2011; 41: 1-6.
2. Farman A, Farman, TT. Extraoral and panoramic systems. *Dent Clin North Am* 2000; 44: 257-72.
3. Marsillac Mde W, Andrade MR, Fonseca Rde O, Marcal SL, Santos VL. Dental anomalies in panoramic radiographs of pediatric patients. *Gen Dent* 2013; 61: e29-33.
4. Yoshida K, Fukuda M, Gotoh K, Ariji E. Depression of the maxillary sinus anterior wall and its influence on panoramic radiography appearance. *Dentomaxillofac Radiol* 2017; 46: 20170126.
5. Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. *Comput Med Imaging Graph* 2007; 31: 198-211.
6. Kuwada C, Ariji Y, Fukuda M, Kise Y, Fujita H, Katsumata A, 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.
7. Li Z, Zhang X, Müller H, Zhang S. Large-scale retrieval for medical image analytics: a comprehensive review. *Med Image Anal* 2018; 43: 66-84.
8. Schwendicke F, Golla T, Dreher M, Krois J. Convolutional neural networks for dental image diagnostics: a scoping review. *J Dent* 2019; 91: 103226.
9. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, et al. Deep convolutional neural networks for computer-aided detection: cnn architectures, dataset characteristics and transfer learning. *IEEE Trans Med Imaging* 2016; 35: 1285-98.
10. 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: 635-42.
11. Mahdi FP, Motoki K, Kobashi S. Optimization technique combined with deep learning method for teeth recognition in dental panoramic radiographs. *Sci Rep* 2020; 10: 19261.
12. Devito KL, de Souza Barbosa F, Felipe Filho WN. An artificial multilayer perceptron neural network for diagnosis of proximal dental caries. *Oral Surg Oral Med Oral Pathol Oral Radiol*

- Endod 2008; 106: 879-84.
13. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. *J Dent* 2018; 77: 106-11.
  14. 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: 917-22.e5.
  15. 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.
  16. 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: 20180051.
  17. Caliskan S, Tuloglu N, Celik O, Ozdemir C, Kizilaslan S, Bayrak S. A pilot study of a deep learning approach to submerged primary tooth classification and detection. *Int J Comput Dent* 2021; 24: 1-9.
  18. Ahn Y, Hwang JJ, Jung YH, Jeong T, Shin J. Automated mesiodens classification system using deep learning on panoramic radiographs of children. *Diagnostics (Basel)* 2021; 11: 1477.
  19. Ha EG, Jeon KJ, Kim YH, Kim JY, Han SS. Automatic detection of mesiodens on panoramic radiographs using artificial intelligence. *Sci Rep* 2021; 11: 23061.
  20. Law CS, Blain S. Approaching the pediatric dental patient: a review of nonpharmacologic behavior management strategies. *J Calif Dent Assoc* 2003; 31: 703-13.
  21. Rallan M, Rallan NS, Goswami M, Rawat K. Surgical management of multiple supernumerary teeth and an impacted maxillary permanent central incisor. *BMJ Case Rep* 2013; 2013: bcr2013009995.
  22. Tzatalin D. *LabelImg* [Internet]. San Francisco: Gifthumb; 2015 [cited 2022 Apr 13]. Available from: <https://github.com/tzatalin/labelImg>.
  23. Nielsen KB, Lautrup ML, Andersen JK, Savarimuthu TR, Grauslund J. Deep learning-based algorithms in screening of diabetic retinopathy: a systematic review of diagnostic performance. *Ophthalmol Retina* 2019; 3: 294-304.
  24. Chartrand G, Cheng PM, Vorontsov E, Drozdal M, Turcotte S, Pal CJ, et al. Deep learning: a primer for radiologists. *Radiographics* 2017; 37: 2113-31.
  25. García Rubio V, Rodrigo Ferrán JA, Menéndez García JM, Sánchez Almodóvar N, Lalueza Mayordomo JM, Álvarez F. Automatic change detection system over unmanned aerial vehicle video sequences based on convolutional neural networks. *Sensors (Basel)* 2019; 19: 4484.
  26. Bochkovskiy A, Wang CY, Liao HY. YOLOv4: optimal speed and accuracy of object detection. *arXiv [Internet]*: 2020 Apr [cited 2022 Apr 13]. Available from: <https://arxiv.org/abs/2004.10934>.
  27. Cordeiro MM, Rocha MJ. The effects of periradicular inflammation and infection on a primary tooth and permanent successor. *J Clin Pediatr Dent* 2005; 29: 193-200.
  28. Kılıc MC, Bayrakdar IS, Çelik Ö, Bilgir E, Orhan K, Aydın OB, et al. Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs. *Dentomaxillofac Radiol* 2021; 50: 20200172.
  29. Redmon JDS, Girshick R, Farhadi A. You only look once: unified, real-time object detection. *arXiv [Internet]*: 2015 Jun [cited 2022 Apr 13]. Available from: <https://arxiv.org/abs/1506.02640>.
  30. Yang H, Jo E, Kim HJ, Cha IH, Jung YS, Nam W, et al. Deep learning for automated detection of cyst and tumors of the jaw in panoramic radiographs. *J Clin Med* 2020; 9: 1839.
  31. Kim Y, Lee KJ, Sunwoo L, Choi D, Nam CM, Cho J, et al. Deep learning in diagnosis of maxillary sinusitis using conventional radiography. *Invest Radiol* 2019; 54: 7-15.
  32. Kuwana R, Arijji Y, Fukuda M, Kise Y, Nozawa M, Kuwada C, 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.
  33. Murata M, Arijji 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* 2019; 35: 301-7.
  34. 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* 2021; 122: 333-7.
  35. Vinayahalingam S, Xi T, Berge S, Maal T, de Jong G. Automated detection of third molars and mandibular nerve by deep learning. *Sci Rep* 2019; 9: 9007.
  36. White SC, Pharoah MJ. *Oral Radiology: principles and interpretation*. 7th ed. St. Louis: Elsevier; 2014. p. 41-63.
  37. Ali S, Siddique A, Ateş HF, Güntürk BK. Improved YOLOv4 for aerial object detection. 2021 29th Signal Processing and Communications Applications Conference (SIU); 2021 Jun 9-11; Istanbul, Turkey. IEEE; 2021. p. 1-4.