ORIGINAL ARTICLE

An enhanced deep learning model for detection and classification of dental caries in panoramic radiographs

Dilara Ozdemir · Caner Ozcan · Ahmet Karaoglu · Adem Pekince · Yasin Yasa · Buse Yaren Kazangirler · Elif Meseci

Received: 14 March 2025 / Accepted: 12 November 2025 / Published online: 14 January 2026

Abstract
Early diagnosis of dental caries has become increasingly important in recent years. It reduces irreversible tooth loss, treatment costs and treatment time. However, since the examination of dental caries is carried out visually by experts on radiographic images, the analysis process is quite exhausting for the experts. In addition, visual analysis may miss early-stage caries due to the workload in the clinical environment. In this study, an automatic caries diagnosis system is proposed to support the expert and to reduce the clinical workload by using panoramic images. The proposed DenseNet121-C model, based on deep learning models, generates results with its configured classifier for caries detection. The dataset prepared for the study includes 14498 tooth images automatically cropped from panoramic images. The proposed model achieved the highest performance on the test set with 93.17% accuracy, 89.43% precision, 85.84% recall, and 87.49% F1-score. Considering the high results of the current study, dentists can spend more time on treatment during dental examinations, thanks to the model's ability to distinguish between caries and non-caries teeth. The results obtained were compared with the Mask R-CNN results. In addition, the performance of the deep learning architectures was investigated on an unbalanced dataset.

Keywords Dental caries diagnosis · Deep learning · Medical images · Transfer learning

1 Introduction

Dental caries is one of the most prevalent oral health problems worldwide, caused by the demineralization of tooth tissues due to bacterial activity and food residues in the mouth [1]. Recent studies estimate that 2.3 billion people worldwide are affected by dental caries [2, 3]. Despite its prevalence, dental caries is preventable and treatable when detected at early stages [4]. In clinical practice, visual examination is often insufficient for identifying caries located in deep anatomical regions of the tooth [5]. In such situations, X-ray radiography is used to show the anatomical structure of objects in depth with the beam [6].

Radiography is highly preferred in dental examinations because it can display the internal structure of objects using different beam techniques. Many types of radiographs include the appearance of different anatomical

Dilara Ozdemir, Caner Ozcan, Ahmet Karaoglu, Adem Pekince, Yasin Yasa, Buse Yaren Kazangirler, Elif Meseci have contributed equally to this work.

 https://doi.org/10.1007/s00521-025-11730-4

 https://doi.org/10.1007/s00521-025-11730-4

structures of the teeth, such as bitewing, panoramic, and periapical [7]. Although bitewing is the most widely used dental radiography in diagnosing caries, it has many disadvantages for the patient [8]. Bitewing imaging is more uncomfortable and difficult than panoramic imaging for both the patient and the technician [9]. In addition, the radiation rate in panoramic imaging is low, so the patient is exposed to less radiation during the exposure. This situation is more advantageous for the health of certain patients, such as people with disabilities, children, and older adults [10]. Consequently, although panoramic radiography is not the primary method for caries detection, it is frequently used in clinical settings due to its lower radiation exposure, cost, and ability to capture a comprehensive view of the oral cavity. However, its lower image quality and anatomical overlaps pose diagnostic challenges.

Panoramic radiographs provide a wide view of the jawbone, vertically from the sinus to the jaw and horizontally [11]. While panoramic images can show many anatomical structures, such as the oral cavity, bone structure, and all the teeth in the mouth, they cannot show the detailed structure of each tooth. In addition, due to the low quality of panoramic images, the individual examination of each tooth is more complex than with other imaging techniques [12]. As a solution to this situation, many image processing techniques and deep learning algorithms can be used to enhance the images. However, studies on panoramic images are limited to providing time management and support to dental caries analysis experts. On the other hand, since there are still many technological issues in diagnosing and treating dental caries, studies that can be applied in the clinical environment are needed [4].

Over the years, many important and diverse studies have contributed to the detection and classification of caries. Cantu et al. [13] performed caries detection on bitewing radiographs using U-Net [14] and EfficientNet-B5 [15]. The architecture was built by integrating EfficientNet-B5 into U-Net by removing the last fully connected (FC) layers. The model weights were also initialized using model weights generated by training this model on panoramic radiographs. Bayrakdar et al. [16], Lee et al. [17], and Kumari et al. [18], successfully used the U-Net and ResneXt-RNN architectures to perform segmentation in dental caries, respectively. Bayrakdar et al. also used the VGG-16 architecture [19] to detect dental caries. They used multiple cross-validation convolutions to avoid performance degradation caused by dataset selection bias between the test set and real data. Bayraktar et al. [20] used the YOLO architecture to detect dental caries on a dataset of 1,000 digital bitewing radiographs, demonstrating the applicability of object detection models in dental diagnostics.

Khan et al. [21] and Lian et al. [22] classified dental caries, alveolar bone recession, and interradicular radiolucency using U-Net and DenseNet [23] architectures by identifying caries stages on periapical and panoramic images. Zhu et al. [24] proposed CariesNet, which performed caries detection in panoramic images using PraNet [25], U-Net, DeepLabv3 [26], and Res-U-Net [27] models. Chen et al. [28] achieved an accuracy rate of 95.44% in digital periapical radiography using CNNs and Efficient Net. Jiang et al. [29] used the RDFNet architecture to classify mild, moderate, and deep caries in digital images. RDFNet has also been compared with Mask R-CNN [30], Faster R-CNN [31], and the versions of the YOLO [32] architecture. Huang et al. [33] conducted a study using OCT and micro-CT images consisting of 748 samples, where they evaluated the performance of several deep learning models, including AlexNet, VGG-16, ResNet-152, Xception, and ResNeXt-101, for dental caries detection. Mao et al. [34] used the AlexNet architecture to a dataset of 278 bitewing radiographs to detect dental caries. Ayhan et al. [35] utilized YOLOv7 on digital bitewing radiographs, where their proposed algorithm assessed which teeth had caries by comparing the detected lesions with the corresponding numbered teeth.

Although many studies investigate the applicability of deep learning in caries detection, a significant portion of these studies are based on high-quality, detailed labeled radiographs that do not accurately represent clinical conditions. In clinical settings, panoramic radiography is used more frequently than other types of radiography despite its lower resolution and diagnostic complexity, as it offers lower radiation exposure, cost, and a broader anatomical view. However, the reduced image clarity in panoramic radiographs and anatomical overlaps create challenges for detection. Therefore, a clear research gap exists in developing robust, high-performance deep learning models that work effectively on panoramic radiographs.

To address this gap, this study presents a deep learning-based dental caries detection system developed specifically for panoramic radiographs, aiming to meet the diagnostic needs of real-world clinical environments. By doing so, the system is designed to enhance diagnostic accuracy under real-world conditions, reduce patient risk, and support dental practitioners in early-stage intervention. The unique contributions of this study are as follows:

- The dataset used in this study reflects the real-world distribution of dental caries observed in clinical practice. A custom caries classifier based on deep learning was implemented and performed well.
- Unlike previous studies that developed detection algorithms using high-quality dental radiographs for clearer caries detection, this study selected panoramic radiography due to its lower radiation exposure and reduced risk to human health.
- In addition, the effect of balanced and unbalanced dental caries datasets generated with different class distributions on the performance of deep learning classifiers was investigated for the first time in dentistry.
- The study also investigates the effect of the annotation scale on model performance by training Mask R-CNN on two expert-labeled datasets: one with full panoramic images and another with individually cropped teeth. The model's ability to detect small caries labels was critically analyzed.

1.1 Data preparation and annotation

Panoramic images from the xxxxx's archive were utilized in the dataset for the study. The images were obtained using the I-Max Touch Owandy Radiology device under standard imaging protocols. These protocols include positioning the patient so the Frankfort horizontal plane is parallel to the ground, ensuring that the teeth are in centric occlusion, and using automatic exposure control to optimize radiation dose and image quality. Imaging parameters were set according to the manufacturer's recommendations to ensure repeatability and consistency across the dataset. The panoramic images used in the study are often preferred in the literature because they are easier to obtain than other types of radiographs. While taking bitewings, the patient may be exposed to higher radiation levels due to repeated imaging caused by technician-related errors. Radiographic images are difficult to obtain and exposure to high levels of radiation during repeated scanning is harmful to the health of certain patients, such as old adults, children, and people with disabilities. For this reason, panoramic X-rays, which are more comfortable and expose patients to less radiation, were preferred in the study regarding patient health and the imaging process. Another factor in selecting panoramic radiographs is that bitewing radiographs can only detect caries in the molars and premolars, whereas panoramic radiographs can detect caries in the mouth.

In the data labeling and annotation step, radiographic images were annotated and made meaningful by experts. The experts annotated the supercategory of dental objects as polygonal for each tooth during the labeling process. Caries on dental objects differ in shape, structure and size from other teeth in the mouth. Therefore, it was concluded that it is more difficult to classify caries with smaller dimensions in panoramic images that provide a wider view of the mouth than other dental problems. Each tooth was cropped according to its bounding box, as shown in Fig. 1, to overcome this problem and access relevant details of the tooth. According to the expert labels, the cropped images used to train the data for the classification stage were automatically classified as caries or non-caries. The dataset that forms the basis of the study consists of 2303 caries and 12195 non-caries images. Panoramic radiographs of patients aged between 18 and 55 were included in the dataset. We also created the dataset according to the natural distribution, considering the caries and non-caries rates encountered in clinical settings. Thus, our classification model can be adapted to real-life applications. The cropped images were also divided into caries and non-caries categories at different rates to investigate the effect of balanced and unbalanced datasets on classification.

 https://doi.org/10.1007/s00521-025-11730-4

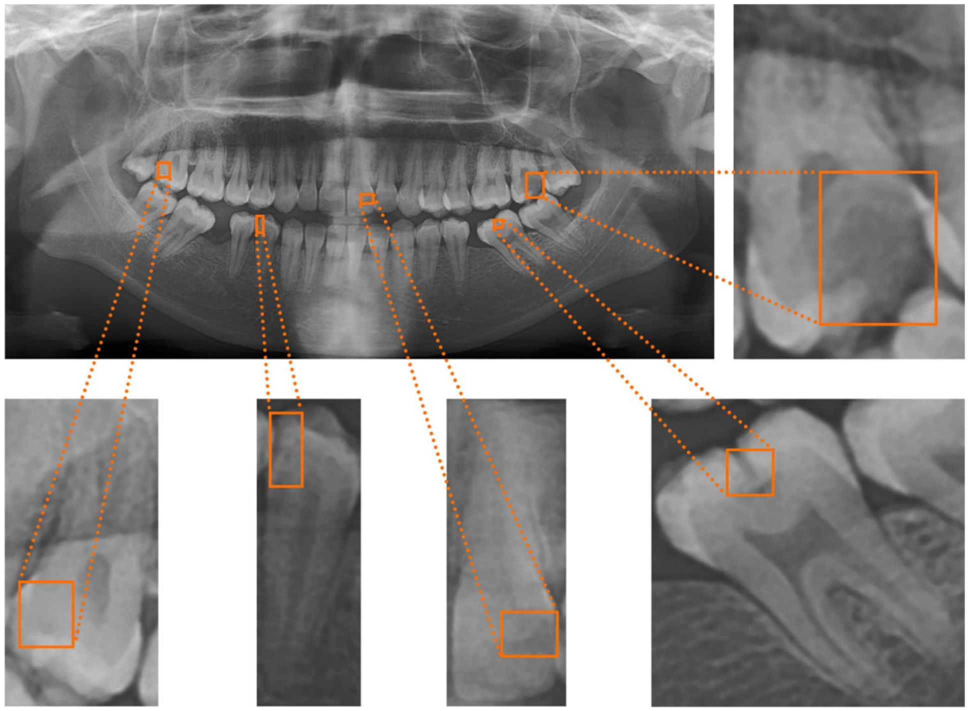

Fig. 1 Dental caries labeled by experts on panoramic images and zoomed-in examples of the dataset generated by cropped tooth images according to the bounding boxes of these labels for each tooth

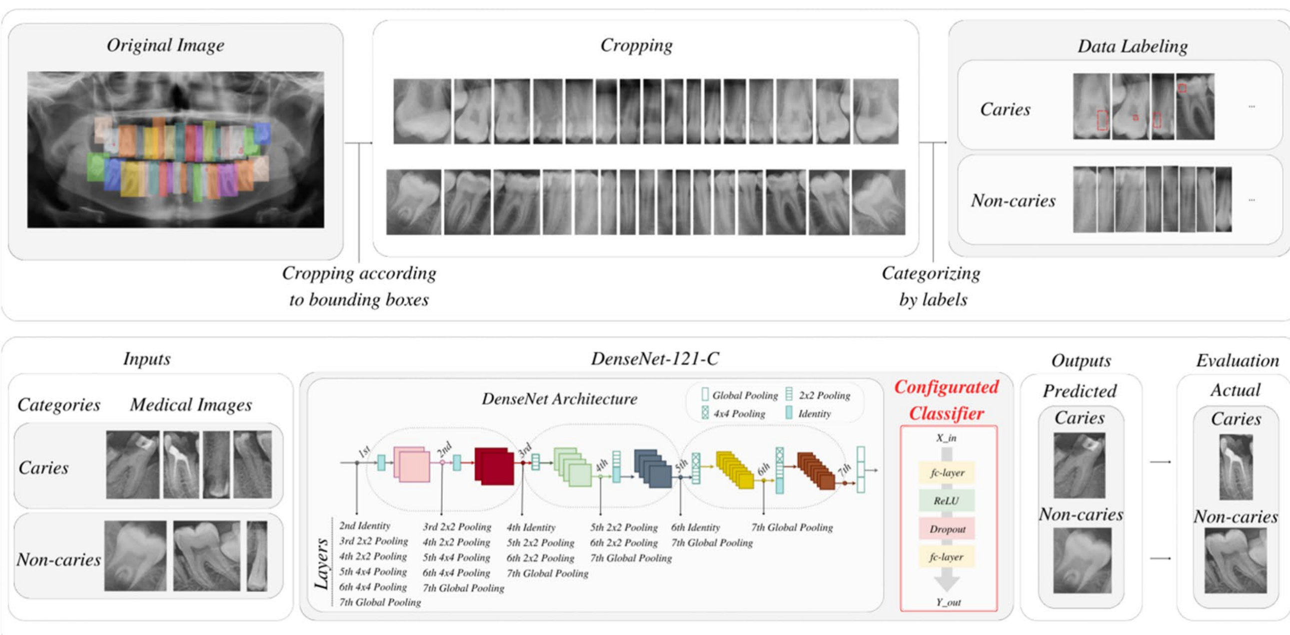

Fig. 2 The proposed configured deep densely network architecture for caries classification. The block named "Configured Classifier" belongs to the modified structure for performance increase

2 Material and methods

Panoramic images annotated by experts are automatically cropped according to the bounding box of each tooth annotation and divided into two classes, caries and non-caries, as shown in Fig. 2. The automatically cropped images and their class information are passed as input to the proposed DenseNet-121-Configured

(DenseNet-121-C) architecture. DenseNet, the base model of the proposed architecture, is based on the idea of increasing learning performance with deeper layers. More efficient training is provided by connecting each layer with the deeper layers of DenseNet. The outputs produced by each layer are transferred to the other layers as inputs in this deep learning architecture. The feature maps produced in each layer in DenseNet are concatenated in Dense Blocks, which include batch normalization [36], ReLu [37], and a convolution layer, instead of being combined with summation as in other deep learning architectures.

The “k” parameter controls the growth rate of the feature maps combined in dense blocks. This parameter controls what information is transferred from one layer to the other. The feature maps combined in the Dense Block module can become inconsistent as they grow in size. After each Dense Block, a convolution and pooling operation is performed, which provides downsampling; thus, feature maps transferred between layers can be used by other layers, and the disappearing gradient problem can be eliminated. Meanwhile, the number of parameters in the mesh is significantly reduced, and the sharing of features between layers is increased with this combining process. Although the feature map in each layer contains as much information as the growth rate, there may be an increase in the number of inputs that other layers receive. To prevent the growth of inputs, a 1 × 1 convolution operation can be used as a bottleneck layer before the convolutions. In this way, the efficiency of the layers increases, and high performance is achieved in terms of speed during training.

In this study, a configuration is applied to the output classifier of the DenseNet architecture. Features that were downsampled with the global average pooling function in the DenseNet model were sent to the FC layer. After learning the optimal weight and bias values for the outputs, the overfitting problem was prevented by providing randomness with a ReLU activation and dropout process. In addition, the outputs were compressed, and an improvement was made to the classical method. The model outputs are obtained after reprocessing the new inputs in an FC layer. Thus, a deeper classifier is obtained compared to the classifier of the classical DenseNet architecture.

In the equation below, j and k represent matrix indices. A dot product operation is performed between the weight matrix denoted as w and the inputs (x_{in}). This dot product is subjected to activation with the function denoted by f. w_0 represents the bias value. As a result of all these operations, the FC layer output defined by y_{jk} is calculated as follows:

$$y_{jk}(x_{in}) = f\left(\sum_{c=1}^{n} w_{jk} x_{in_c} + w_{j0}\right) \tag{1}$$

The output of the FC layer is multiplied in the corresponding layer with the vector $r^{(l)}$ with respect to the 2-point distribution, by element-wise product as follows:

$$\tilde{y}^{(l)} = r^{(l)} * y_{jk}^{(l)} \tag{2}$$

To create the inputs of the next layer, denoted by z, the fully connected layer output created in layer l is multiplied by the weights of the next layer $(l+1)$ and the bias value is added to this multiplication as given:

$$z^{(l+1)} = w^{(l+1)} \tilde{y}^{(l)} + w_0^{(l+1)} \tag{3}$$

The ReLU activation function limits the activation of certain neurons in the neural network and increases the learning ability of the network. The layer output vector denoted as $z^{(l+1)}$ is transferred to the ReLU activation function and calculated as follows:

$$y^{(l+1)} = ReLU\left(z^{(l+1)}\right) \tag{4}$$

Downsampling is obtained as a result of thinned outputs using the distribution vector. Finally, model outputs referred as y_{out} are generated as:

$$y_{out}\left(y^{(l+1)}\right) = f\left(\sum_{c=1}^{n} w_{jk} {y^{(l+1)}}_c + w_{j0}\right) \tag{5}$$

 https://doi.org/10.1007/s00521-025-11730-4

The output evaluation step was performed by comparing the images annotated by the experts and the output images with class information generated by the classification model.

3 Experimental results

The training was performed with pre-trained deep convolutional neural networks on cropped panoramic tooth images. The pre-trained network models selected the same parameters and images for the classification task. Tooth images with different dimensions were obtained by cropping the panoramic images based on the bounding box of each tooth. These images are fixed to input sizes compatible with each pre-trained network. Accuracy, precision, recall, and F1-score metrics were used as performance evaluation metrics [38]. The high accuracy of the DenseNet-121-C model addresses the research question of whether deep convolutional networks can reliably detect dental caries in panoramic images, confirming its potential clinical utility.

In addition to contributing to the literature with the DenseNet-121-C architecture used in the study, test results of other state-of-the-art networks are also given for classifying caries and non-caries teeth in experimental studies. Models such as GoogleNet [39], ShuffleNet [40], ResNet [41], MobileNet [42], VGGNet, and DenseNet, which are commonly used in the literature, are trained for experimental results, and their results are given in Table 1. Compared to Zhu et al. [24], who reported an accuracy rate of 93.61% on a smaller dataset, our model achieved a similar accuracy rate on a larger dataset with a natural class distribution. Similarly, while studies by Cantu et al. [13] and Lian et al. [22] emphasized the effect of balanced datasets, our results highlight the clinical importance of preserving natural imbalance. This demonstrates that our customized architecture and data preprocessing process deliver strong and consistent performance, despite using a larger and more diverse dataset. Panoramic images were automatically cropped with a previously trained deep-learning model [43] and transferred to the network in the evaluation step. The performance of the proposed model and different deep neural network models created was compared on cropped panoramic images. As shown in the table, most classifiers achieved high performance with an accuracy of 90% and above. The DenseNet-121-C model provided the best performance, achieving approximately 93.17%, 89.43%, 85.84%, and 87.49% for accuracy, precision, recall, and F1-score metrics, respectively. The high performance of the proposed model indicates that the majority of positive detections correspond to actual cavities. This is crucial for preventing unnecessary interventions in a real clinical workflow.

This section compares the results of the dataset with natural class distribution and those of datasets with different rates to investigate the unbalanced dataset. Many studies use balanced datasets for classification problems [13, 22]. However, it is still questionable whether the classes should be according to the natural distribution or balanced in health data. Datasets with different class ratios were prepared from cropped images to investigate this issue. The training was done with the models in the experimental results section and the proposed model. The test results of the training using data with different distributions are shown in Fig. 3. Figure 3 illustrates the superior performance of the proposed model under natural class distributions, emphasizing the importance of maintaining clinical relevance in dataset composition.

Table 1 Classification performance of pre-trained deep neural networks

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
GoogleNet	91.4828	84.0415	83.7380	83.8886
ShuffleNet	89.2414	79.6745	80.0951	79.8822
ResNet-50	91.1724	85.8311	78.5730	81.5560
MobileNet	91.4483	84.3871	82.6502	83.4811
VGG-19	91.2759	86.6688	78.4083	81.7151
DenseNet-169	90.9310	83.9388	83.3234	83.6261
DenseNet-121	91.7241	84.4486	84.3260	84.0853
DenseNet-121-C	93.1724	89.4359	85.8456	87.4953

This table pertains to the performance results of a dataset that created with natural distribution rate of dental caries that can be encountered in the clinical environment

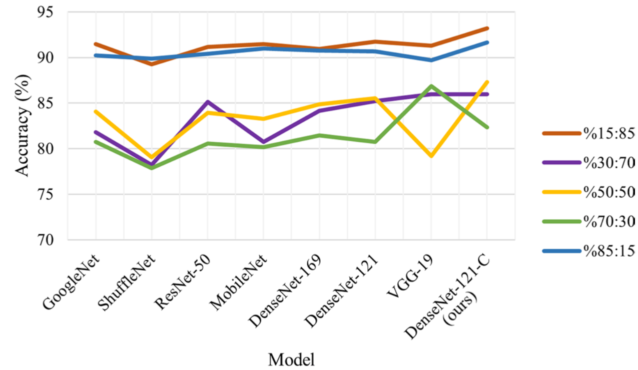

Fig. 3 The accuracy values given by each deep neural network pre-trained on datasets with different class distributions

Table 2 Classification performance of pre-trained deep neural networks on datasets with different class distributions

Distribution (%)	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
15:85	Ours	93.1724	89.4359	85.8455	87.4953
30:70	Ours	85.9459	84.7083	80.8248	82.3684
50:50	Ours	87.2973	87.3388	87.2969	87.3584
70:30	VGG-19	86.8468	84.8688	85.0160	85.1703
85:15	Ours	91.6462	82.6312	79.4985	80.9457

The highest results were obtained with our proposed model on the dataset with a class distribution of 15% caries and 85% non-caries, which is the central part of the study, as shown in Table 2. In addition, our proposed model performed the highest on other datasets except the fully balanced dataset. It is concluded that the caries data with natural class distribution in the clinical setting is the dataset that contributes the most to the study, considering the results. This table belongs to the performance results of the datasets created with different rates of class distribution.

Considering that caries problems are not evenly distributed in the mouth, i.e., caries are not found in all 32 teeth in the mouth, the caries rate in uncut panoramic images is low compared to the general tooth rate. In addition to the low number of caries objects, the size of the caries label on the 3000 × 1500 panoramic images used for model training occupies about 50 pixels. Therefore, Mask R-CNN architecture cannot provide high performance in detecting caries labels with small pixel sizes compared to other dental problems with larger pixel sizes in large images [29].

Each tooth in the panoramic images was cropped according to its bounding boxes to evaluate this issue. The results of the Mask R-CNN architecture trained on the dataset generated from the cropped images were compared with the results of the Mask R-CNN training performed on all the panoramic images that were not cropped. As a result of the testing process with panoramic dental images to which the cropping process was not applied, 45.44%, 49.27%, and 47.28% success were obtained for precision, recall, and F1-score, respectively. On the other hand, the results obtained with cropped tooth images were 57.20%, 69.15%, and 62.61%, respectively.

The experimental results show that Mask R-CNN achieves a precision value of 45.44% on a full panoramic image. In contrast, a smaller panoramic image shows a precision of 57.20% when a training and testing step is performed using the dataset where each tooth is cropped by category. Training results using uncropped panoramic dental images show that recognizing objects with small pixel sizes in large images is challenging. Training results using uncropped panoramic dental images show that object recognition with small pixel sizes in large images is challenging. Thanks to large feature maps on smaller images for the same classifier, semantic feature extraction becomes efficient and increases the performance of the network. As a result, it is concluded that Mask R-CNN is successful in detecting and segmenting objects with large feature maps but not in detecting objects with small feature maps. These experimental results demonstrate that the proposed method can support experts by improving the performance of caries detection and potentially allowing for earlier interventions. At the same time, the findings emphasize the importance of external validity and clinical studies to confirm their applicability in real-world settings.

4 Conclusions

Many state-of-the-art networks are included in the study, and the results of the classification algorithms are given by testing these networks on cropped and uncropped panoramic images. The algorithm that gives the best results in the given task has been developed, configured for improvement, and proposed. The DenseNet architecture has high performance with deepened layers connecting each layer and has been provided a much higher performance by adding a configured classifier. Accordingly, a successful method for extracting and classifying the features of the teeth and providing high accuracy is proposed.

As part of the study, it was also tested on datasets with different distribution rates using state-of-the-art networks, including the model proposed to study the problem of data imbalance, which is often discussed in deep learning studies in the literature. As a result of the experimental studies, the best performance in all tested networks was obtained with the dataset comprising 15% caries and 85% non-caries images with natural distribution prepared for the study. Thus, considering the balance between classes for classifying dental caries in panoramic images, it has been demonstrated that the error rate is reduced and high accuracy is achieved by using data with natural distribution. In addition, this study contributes to the literature by using panoramic images, having a large amount of data, and obtaining high accuracy. Future studies should focus on validating the model with external datasets and conducting additional work to bridge the gap between experimental results and clinical practice.

Author contributions Caner Ozcan conceived and designed the analysis, supervised the project. Ahmet Karaoglu contributed data or analysis tools, developed the theoretical framework. Yasin Yasa and Adem Pekince collected the data, contributed data or analysis tools. Dilara Ozdemir, Buse Yaren Kazangirler and Elif Meseci performed the analytic calculations, carried out the model design and implementation. All authors reviewed and wrote the main manuscript text.

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). This study was funded by the Scientific and Technological Research Council of Turkey (TUBITAK) as part of the Denti-Assist project numbered 2200272 and the Karabuk University Scientific Research Projects (KBUBAP) Unit with project number of KBUBAP-23-YL-066.

Data availability Data used in this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest No potential competing of interest was reported by the author(s).

Ethical approval Ethical approval for this study was obtained from the Karabuk University NonInterventional Clinical Research Ethics Committee. (Reference number: 2021/451).

References

1. Majanga V, Viriri S (2022) A survey of dental caries segmentation and detection techniques. Sci World J 1:8415705. https://doi.org/10.1155/2022/8415705
2. Organization WH et al (2022) Prevention and treatment of dental caries with mercury-free products and minimal intervention: who oral health briefing note series
3. Collaborators GOD, Bernabe E, Marcenes W, Hernandez C, Bailey J, Abreu L, Alipour V, Amini S, Arabloo J, Arefi Z (2020) Global, regional, and national levels and trends in burden of oral conditions from 1990 to 2017: a systematic analysis for the global burden of disease 2017 study. J Dent Res 99(4):362–373. https://doi.org/10.1177/0022034520908533
4. Cheng L, Zhang L, Yue L, Ling J, Fan M, Yang D, Huang Z, Niu Y, Liu J, Zhao J (2022) Expert consensus on dental caries management. Int J Oral Sci 14(1):1–8. https://doi.org/10.1038/s41368-022-00167-3
5. Fejerskov O, Nyvad B, Kidd E (2015) Dental caries: the disease and its clinical management. Wiley, New York
6. Banumathi A, Vijayakumari B, Geetha A, Shanmugavadivu N, Raju S (2007) Performance analysis of various techniques applied in human identification using dental x-rays. J Med Syst 31(3):210–218. https://doi.org/10.1007/s10916-007-9057-0
7. Tekin BY, Ozcan C, Pekince A, Yasa Y (2022) An enhanced tooth segmentation and numbering according to FDI notation in bitewing radiographs. Comput Biol Med 146(105547):10
8. Qu X, Li G, Zhang Z, Ma X (2011) Detection accuracy of in vitro approximal caries by cone beam computed tomography images. Eur J Radiol 79(2):24–27. https://doi.org/10.1016/j.ejrad.2009.05.063
9. Menaker NH, Yepes JF, Vinson LA, Jones JE, Downey T, Tang Q, Maupomé G (2022) Prescription of bite-wing and panoramic radiographs in pediatric dental patients: an assessment of current trends and provider compliance. J Am Dent Assoc 153(1):23–30. https://doi.org/10.1016/j.adaj.2021.07.001
10. Akkaya N, Kansu O, Kansu H, Cagirankaya L, Arslan U (2006) Comparing the accuracy of panoramic and intraoral radiography in the diagnosis of proximal caries. Dentomaxillofac Radiol 35(3):170–174. https://doi.org/10.1259/dmfr/26750940
11. Jaiswal P, Bhirud S (2023) An intelligent deep network for dental medical image processing system. Biomed Signal Process Control 84(104708):10
12. Naam J, Harlan J, Madenda S, Wibowo EP (2016) The algorithm of image edge detection on panoramic dental x-ray using multiple morphological gradient (mmg) method. Int J Adv Sci Eng Inf Technol 6(6):1012–1018. https://doi.org/10.18517/ijaseit6.6.1480
13. Cantu AG, Gehrung S, Krois J, Chaurasia A, Rossi JG, Gaudin R, Elhennawy K, Schwendicke F (2020) Detecting caries lesions of different radiographic extension on bitewings using deep learning. J Dent 100(103425):10. https://doi.org/10.1016/j.jdent.2020.103425
14. Ronneberger O, Fischer P, Brox T (2015) U-net: Convolutional networks for biomedical image segmentation. In: International conference on medical image computing and computer-assisted intervention. Springer, pp 234–241. https://doi.org/10.48550/arXiv.1505.04597
15. Tan M, Le Q (2019) Efficientnet: rethinking model scaling for convolutional neural networks. In: International conference on machine learning. PMLR. pp 6105–6114. https://doi.org/10.48550/arXiv.1905.11946
16. Bayrakdar IS, Orhan K, Akarsu S, Çelik Ö, Atasoy S, Pekince A, Yasa Y, Bilgir E, Sağlam H, Aslan AF et al (2021) Deep-learning approach for caries detection and segmentation on dental bitewing radiographs. Oral Radiol 38(4):1–12. https://doi.org/10.1007/s11282-021-00577-9
17. Lee S, Oh S-I, Jo J, Kang S, Shin Y, Park J-W (2021) Deep learning for early dental caries detection in bitewing radiographs. Sci Rep 11(1):1–8. https://doi.org/10.1038/s41598-021-96368-7
18. Kumari AR, Rao SN, Reddy PR (2022) Design of hybrid dental caries segmentation and caries detection with meta-heuristic-based ResneXt-RNN. Biomed Signal Process Control 78(103961):10
19. Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, https://doi.org/10.48550/arXiv.1409.1556
20. Bayraktar Y, Ayan E (2022) Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. Clin Oral Invest 26(1):623–632
21. Khan HA, Haider MA, Ansari HA, Ishaq H, Kiyani A, Sohail K, Muhammad M, Khurram SA (2021) Automated feature detection in dental periapical radiographs by using deep learning. Oral Surg Oral Med Oral Pathol Oral Radiol 131(6):711–720. https://doi.org/10.1016/j.oooo.2020.08.024
22. Lian L, Zhu T, Zhu F, Zhu H (2021) Deep learning for caries detection and classification. Diagnostics 11(9):1672. https://doi.org/10.3390/diagnostics11091672
23. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ (2017) Densely connected convolutional networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 4700–4708. https://doi.org/10.48550/arXiv.1608.06993

24. Zhu H, Cao Z, Lian L, Ye G, Gao H, Wu J (2022) Cariesnet: a deep learning approach for segmentation of multi-stage caries lesion from oral panoramic x-ray image. Neural Comput. Appl. 35(22):1–9. https://doi.org/10.1007/s00521-021-06684-2
25. Fan DP, Ji GP, Zhou T, Chen G, Fu H, Shen J, Shao L (2020) Pranet: parallel reverse attention network for polyp segmentation. In: International conference on medical image computing and computer-assisted intervention. Springer, pp 263–273. https://doi.org/10.48550/arXiv.2006.11392
26. Chen L-C, Papandreou G, Schroff F, Adam H (2017) Rethinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:1706.05587, https://doi.org/10.48550/arXiv:1706.05587
27. Diakogiannis FI, Waldner F, Caccetta P, Wu C (2020) Resunet-a: a deep learning framework for semantic segmentation of remotely sensed data. ISPRS J Photogramm Remote Sens 162(94–114):10
28. Chen IDS, Yang C-M, Chen M-J, Chen M-C, Weng R-M, Yeh C-H (2023) Deep learning-based recognition of periodontitis and dental caries in dental x-ray images. Bioengineering 10(8):911
29. Jiang H, Zhang P, Che C, Jin B (2021) Rdfnet: a fast caries detection method incorporating transformer mechanism. Comput Math Methods Med 1:9773917. https://doi.org/10.1155/2021/9773917
30. He K, Gkioxari G, Dollár P, Girshick R (2017) Mask R-CNN. In: Proceedings of the IEEE international conference on computer vision, pp 2961–2969 . https://doi.org/10.48550/arXiv.1703.06870
31. Ren S, He K, Girshick R, Sun J (2015) Faster R-CNN: towards real-time object detection with region proposal networks. In: Advances in neural information processing systems, vol 28. https://doi.org/10.48550/arXiv.1506.01497
32. Redmon J, Divvala S, Girshick R, Farhadi A (2016) You only look once: unified, real-time object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 779–788 . https://doi.org/10.48550/arXiv.1506.02640
33. Huang YP, Lee SY (2021) Deep learning for caries detection using optical coherence tomography. medRxiv
34. Mao Y-C, Chen T-Y, Chou H-S, Lin S-Y, Liu S-Y, Chen Y-A, Liu Y-L, Chen C-A, Huang Y-C, Chen S-L (2021) Caries and restoration detection using bitewing film based on transfer learning with CNNs. Sensors 21(13):4613
35. Ayhan B, Ayan E, Bayraktar Y (2024) A novel deep learning-based perspective for tooth numbering and caries detection. Clin Oral Invest 28(3):178
36. Ioffe S, Szegedy C (2015) Batch normalization: accelerating deep network training by reducing internal covariate shift. In: International conference on machine learning. PMLR, pp 448–456. https://doi.org/10.48550/arXiv.1502.03167
37. Glorot X, Bordes A, Bengio Y (2011) Deep sparse rectifier neural networks. In: Proceedings of the 14th international conference on artificial intelligence and statistics, JMLR workshop and conference proceedings, pp 315–323
38. Blagec K, Dorffner G, Moradi M, Samwald M (2020) A critical analysis of metrics used for measuring progress in artificial intelligence. https://doi.org/10.48550/arXiv.2008.02577
39. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A (2015) Going deeper with convolutions. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 1–9 . https://doi.org/10.48550/arXiv.1409.4842
40. Zhang X, Zhou X, Lin M, Sun J (2018) Shufflenet: an extremely efficient convolutional neural network for mobile devices. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 6848–6856. https://doi.org/10.48550/arXiv.1707.01083
41. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 770–778. https://doi.org/10.48550/arXiv.1512.03385
42. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M, Adam H (2017) Mobilenets: efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861, https://doi.org/10.48550/arXiv.1704.04861
43. Karaoglu A, Ozcan C, Pekince A, Yasa Y (2023) Numbering teeth in panoramic images: a novel method based on deep learning and heuristic algorithm. Eng Sci Technol Int J 37(101316):10. https://doi.org/10.1016/j.jestch.2022.101316

Authors and Affiliations

Dilara Ozdemir[1] · Caner Ozcan[2] · Ahmet Karaoglu[3] · Adem Pekince[4] · Yasin Yasa[5] · Buse Yaren Kazangirler[1] · Elif Meseci[6]

✉ Caner Ozcan
canerozcan@karabuk.edu.tr

Dilara Ozdemir
ozdemirdilara@outlook.com.tr

Ahmet Karaoglu
akaraoglu@sinop.edu.tr

Adem Pekince
adempekince@karabuk.edu.tr

Yasin Yasa
yasinyasa@odu.edu.tr

Buse Yaren Kazangirler
buseyarentekin@outlook.com

Elif Meseci
elif.meseci@beun.edu.tr

[1] Institute of Graduate Programs, Department of Computer Engineering, Karabuk University, Karabuk, Turkey

[2] Department of Software Engineering, Karabuk University, Karabuk, Turkey

[3] Department of Computer Engineering, Sinop University, Sinop, Turkey

[4] Department of Oral and Maxillofacial Radiology, Karabuk University, Karabuk, Turkey

[5] Department of Oral and Maxillofacial Radiology, Ordu University, Ordu, Turkey

[6] Department of Computer Engineering, Zonguldak Bulent Ecevit University, Zonguldak, Turkey