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Numbering teeth in panoramic images: A novel method based on deep learning and heuristic algorithm

Ahmet Karaoglu [a], Caner Ozcan [b,*], Adem Pekince [c], Yasin Yasa [d]

[a] Department of Computer Technologies, Sinop University, Sinop, Turkey
[b] Department of Software Engineering, Karabuk University, Karabuk, Turkey
[c] Department of Oral and Maxillofacial Radiology, Karabuk University, Karabuk, Turkey
[d] Department of Oral and Maxillofacial Radiology, Ordu University, Ordu, Turkey

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ABSTRACT

Dental problems are one of the most common health problems for people. To detect and analyze these problems, dentists often use panoramic radiographs that show the entire mouth and have low radiation exposure and exposure time. Analyzing these radiographs is a lengthy and tedious process. Recent studies have ensured dental radiologists can perform the analyses faster with various artificial intelligence supports. In this study, the numbering performance of Mask R-CNN and our heuristic algorithm-based method was verified on panoramic dental radiographs according to the Federation Dentaire Internationale (FDI) system. Ground-truth labelling of images required for training the deep learning algorithm was performed by two dental radiologists using the web-based labelling software DentiAssist created by the first author. The dataset was created from 2702 anonymized panoramic radiographs. The dataset is divided into 1747, 484, and 471 images, which serve as training, validation, and test sets. The dataset was validated using the k-fold cross-validation method (k = 5). A three-step heuristic algorithm was developed to improve the Mask R-CNN segmentation and numbering results. As far as we know, our study is the first in the literature to use a heuristic method in addition to traditional deep learning algorithms in detection, segmentation and numbering studies in panoramic radiography. The experimental results show that the mAp (@IOU = 0.5), precision, recall and f1 scores are 92.49%, 96.08%, 95.65% and 95.87%, respectively. The results of the learning-based algorithm were improved by more than 4%. In our research, we discovered that heuristic algorithms could improve the accuracy of deep learning-based algorithms. Our research will significantly reduce dental radiologists' workload, speed up diagnostic processes, and improve the accuracy of deep learning systems.

1. Introduction

Dentistry is a profession that keeps up with the advancements in radiological visual imaging. These advancements have made radiographic imaging increasingly crucial in diagnosing and treating patients. [1]. Panoramic radiographs are commonly used in oral radiology because of the low radiation dose, quick application time, minimal patient load, and ability to see both the upper and lower jaws in one image [2].

Rapid technological improvement in fundamental diagnostic tools has recently been driven by digitizing dental data, computer-aided imaging techniques, virtual treatment planning, and simulations [3]. Artificial intelligence applications in dentistry are increasing daily as it assists practitioners in providing high-quality patient care while simplifying complex processes by delivering predictable results [4]. With the studies, the analysis of radiological images taken for diagnosis and treatment can be done quickly. Dental radiologists mostly analyze the obtained radiographic images. However, the wide variation in pathology, the interpretation of many images in a limited time, the need for rapid treatment planning, and lack of time, experience, or concentration have made it necessary for dental radiologists to use computer-aided decision systems [5].

Deep learning systems, which have made significant progress in recent years, can automatically extract image attributes using the

* Corresponding author.
E-mail addresses: akaraoglu@sinop.edu.tr (A. Karaoglu), canerozcan@karabuk.edu.tr (C. Ozcan), adempekince@karabuk.edu.tr (A. Pekince), yasinyasa@odu.edu.tr (Y. Yasa).

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original pixels of the image as input. These new algorithms considerably minimize the effort of specialists and allow them to extract hard-to-detect characteristics in images rapidly and effectively. The ability to obtain information in real-time by analyzing panoramic images using deep learning methods and communicating it to the patient strengthens the patient's confidence in the dental diagnosis [6].

Convolutional Neural Networks (CNNs) and their derivatives are deep learning algorithms that use large datasets. With these algorithms, studies are carried out intensively using radiographic images and mainly divided into three main groups. These can be separate studies in the form of segmentation [7–14], classification [15–21], detection and numbering [22–33],detection, segmentation, and numbering [34–36] or they can be integrated studies that include each other.

In the literature, Amer and Aqel [7] have successfully detected wisdom teeth from panoramic images. However, since this is a classification study on only wisdom teeth in panoramic images, it offers limited analysis possibilities. In addition, after the classification process, numbering is not provided. Silva et al. [8] stated that the results could be higher with a dataset containing more images in their study, where they performed segmentation in various image types. Tuzoff et al. [22] proposed a system for detecting teeth in panoramic radiographs with the Faster R-CNN [37] architecture and numbering them using VGG-16. Their method has a high computational cost as it uses different deep learning algorithms at different steps. Chen et al. [23] proposed a structure based on the Faster R-CNN architecture to detect and numbering teeth in dental periapical films. To improve the results of Faster R-CNN, they proposed an intuitive technique called three post-processing techniques. Since the method they used works for periapical films, it is obvious that it is not suitable for all teeth. Kim et al. [24] detected a periodontal bone loss in panoramic dental radiographs and determined only the tooth numbers corresponding to the lesion, not the teeth in the whole image. Kim et al. [25] have presented a new technique combining regional convolutional neural network (R-CNN), Single Shot Multibox Detector (SSD) and heuristic methods to number teeth in a panoramic radiography image. Although the proposed method with this technique contributed to the results of the basic algorithm, several performance metrics remained low. Mahdi et al. [35] proposed an automated method of tooth detection in which they further improved their results using the faster R-CNN technique, using a candidate optimization technique that evaluates both the positional relationship and the confidence score of the candidates. With the proposed optimization technique, they could further improve the model results. Kaya et al. [38] used the YOLO V4 model for automatic tooth detection and numbering in pediatric panoramic radiographs. Their proposed model achieved 92.22% results in the mAP performance metric. Chandrashekar et al. [36] have proposed a new method by combining teeth segmentation with the numbering model (Mask R-CNN + Faster R-CNN). The method they proposed reached 98.44% mAP in tooth numbering.

Since the number of images in the dataset causes the performance metrics to remain low and the model does not perform adequately, more than one model is used to detect and number the teeth, which increases the computational cost. Most studies perform the numbering operations on a subset of the teeth. Kim et al. [24] in their study using 303 images and using heuristic algorithms, sensitivity achieved a value of 84.2%. Tuzoff et. al. [22] obtained a Sensitivity value of 98.9% in their study using 1574 images and using heuristic algorithms. This shows the positive contribution of a large number of images to the model accuracy.

When the literature is examined, it is seen that detection and numbering are carried out in general. Silva et al. [34] on the other hand, while identifying and numbering the teeth in their studies, also performed the segmentation of the teeth. Segmentation is important because the margins of the teeth separate the background, and each tooth is more prominently displayed. In our study, we propose a heuristic method in addition to conventional deep learning algorithms for the first time in the literature, as a difference from the methods of detection, segmentation, and numbering studies.

The proposed method aims to improve results in the literature and obtain high accuracy with a heuristic algorithm by taking the outputs of the traditional deep learning algorithm. Also, this study proposes a new method that will reduce the workload of dentists and help with diagnosis. The first step is the automatic detection, segmentation, and numbering of the teeth in the panoramic images with the deep learning algorithm according to the FDI numbering system. The second step is correcting the even-numbered teeth in the basic model results to make odd numbering with the heuristic algorithm. The third step is the correction of incorrectly numbered teeth in a way to make correct numbering. Most of the methods in the literature work only by applying a selected deep learning architecture on datasets.

The main contribution of our work can be summarized as follows:

- The study is the first to use the Mask R-CNN [39] deep learning and heuristic algorithm for detecting, segmentation, and numbering all teeth in panoramic radiography.
- The panoramic images used are new, and the number is higher than those used in most studies in the literature.
- There are images with various conditions such as missing teeth, implants, root canal treatment and caries.

2. Materials and methods

2.1. Dataset

The study was approved by Karabuk University Non-Interventional Clinical Research Ethics Committee with reference number 2021/451, and the images used were randomly selected from the archive of Karabuk Training and Research Hospital Oral and Dental Health Center and anonymized.

The dataset was created from 2702 panoramic radiographs. Two dental radiologists labelled these images with a web-based labelling software (DentiAssist, Karabuk, Turkey) [40] that we prepared to determine the boundaries of the teeth, and were numbered as 32 classes in total according to the FDI numbering system shown in 1a.

To test the accuracy of the model, it is not useful to use the images that the model used during the training process. To increase model's reliability, it is best to use a completely new dataset that the model has never seen before [41]. For this reason, the test dataset of the model was created with 471 images, independent of the train set. 1b shows an example of a panoramic radiographic image from the dataset, numbered and labeled by two dental radiologists.

The dataset's 2231 images were selected randomly as a training dataset for the model's training. The training dataset was validated using k-fold cross-validation (k = 5), 1784 train images and 447 validation images in each fold. The distribution of tooth class labels in the train and validation dataset is shown in 2.

2.2. The Model

3 shows the pipeline model for tooth numbering with the Mask R-CNN and heuristic algorithm. The Mask R-CNN model is a CNN-based method that detects, classifies and masks objects in an image. It was developed by constructing a Faster R-CNN [37]. The

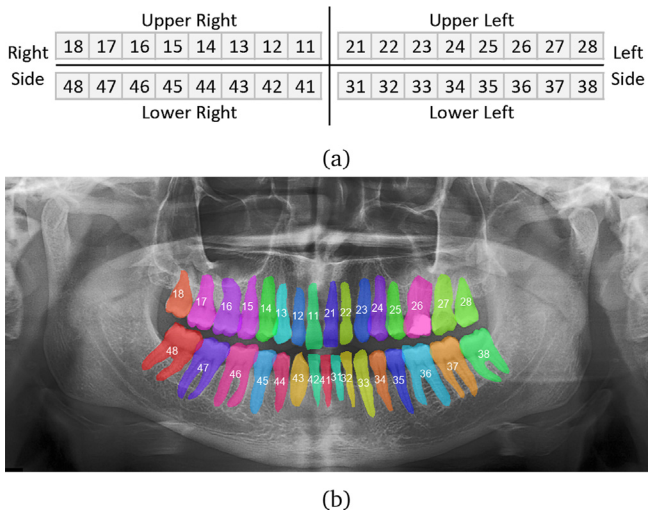


Fig. 1. (a) FDI numbering system, and (b) example of tooth labelling and numbering made by dental radiologists.

Mask R-CNN model's most notable feature is that it performs instance segmentation, the procedure for detecting and identifying each object of interest in an image. To accomplish the instance segmentation task, Mask R-CNN is a feature extractor that uses a member of convolutional neural networks. The ResNet-101 [42] network, which extracts the image features, is preferred as a backbone network. The first part of a Mask R-CNN, called the Region Proposal Network (RPN), proposes Regions of Interest (ROI) that can be objects in the image. The second part generates the binary mask for each proposed ROI in parallel with the classification and bounding box estimates [39].

Dental items found in panoramic dental radiography were passed through a two-step RPN mesh, as shown in 3. In the residual backbone network, the features of the dental images are localized and transferred to the pooling layer. Non-Maximum Suppression (NMS) was checked in overlapping boxes. The model's connection-based method divides regions containing objects into segments with a specified threshold value. For the CNN, the maximum values in the pooling layer are chosen.

As a result of the model, bounding boxes and masks are constructed per region of the corresponding region in the images. As shown in 3, the segmentation masks of the respective classes are the objects to be defined.

$$L = L_{\mathrm{cls}} + L_{\mathrm{bbox}} + L_{\mathrm{mask}} \tag{1}$$

L_{cls} and, L_{box} in Eq. (1) are the same as in the Faster R-CNN method, and, L_{mask} refers to the segmentation masks, which are expressed as i Eq. (2).

$$L_{mask} = -\frac{1}{m^2} \sum_{1 \leqslant j \leqslant m} [y_{ij} log \hat{y}_{ij}^k + 1 - y_{ij}) log(1 - \hat{y}_{ij}^k)] \tag{2}$$

k represents the total number of classes. For each class and RoI, a mask of size mxm was constructed. The output size is set at kxm^2. $\hat{y}_{ij}^k$ is the estimated value for the k class in Eq. (2), and y_{ij} is the (i,j) tag of a point in the created mask.

Mask R-CNN output is in the form of masks of panoramic image teeth. These result masks are transmitted into a heuristic algorithm that we developed to improve the model's accuracy by removing multiple number assignments and numbering errors for the same tooth.

2.3. Proposed heuristic algorithm based post-processing

A three-step heuristic is presented to improve the prediction results of the model. The structure of the proposed heuristic algorithm is shown in 4. The model can predict more than one FDI number for a tooth when the teeth are very similar. The first step of our heuristic method focused on this problem. To detect more than one numbered tooth with our method, the predicted teeth were first sorted by their prediction result. As a result of the sorting, the teeth with more than one numbering were identified by checking the numbers. Then, whether the predictions with more than one numbering overlapped with other predictions was checked. This check was performed by checking the masks of the predicted numbers for overlaps. As a result, overlapped numbers were detected, and the mask, prediction score and class information of the one with the lowest prediction score were deleted.

Then, a solution to misleading numbering errors was developed. According to the FDI tooth numbering system, the teeth in the mouth have a certain order. To check whether the order of the predicted teeth is suitable according to this system, the coordinates of the predicted tooth masks are ordered in ascending according to the x-axis. Then, starting with the first tooth, the FDI numbers of the teeth were compared with those of the neighbouring teeth. As a result of this comparison, the tooth that confused the sequence was identified, and this tooth was assigned the required FDI number.

2.4. Model Training

The model was trained on a PC with an i9 10980XE processor and an NVIDIA Quadro RTX 5000 graphics card in experimental studies. The data set images used were set to 1024x1024 to make the Mask R-CNN model compatible with data of different sizes. Transfer learning is used because the residual network, the backbone network utilized while training the neural network, is a pre-trained model. A pre-trained dataset is used to assign weights to the neural network. The model was trained 400 epochs with

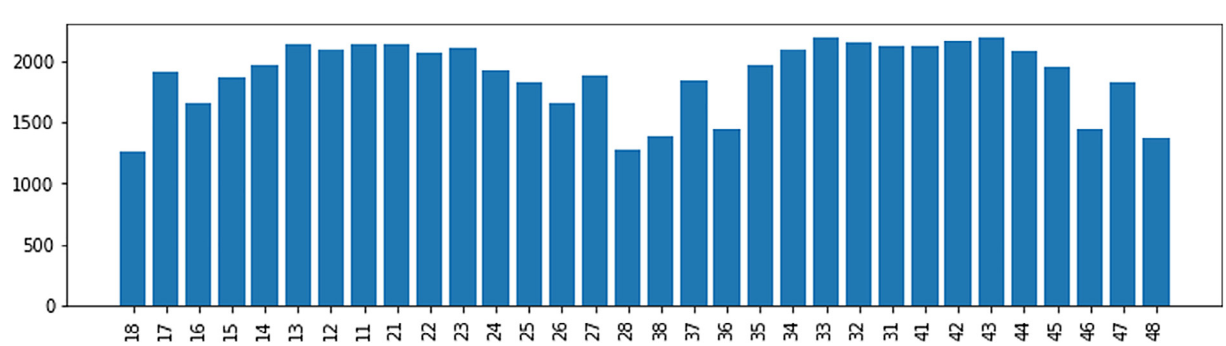


Fig. 2. Distribution of teeth in images in the dataset according to the FDI numbering standard.

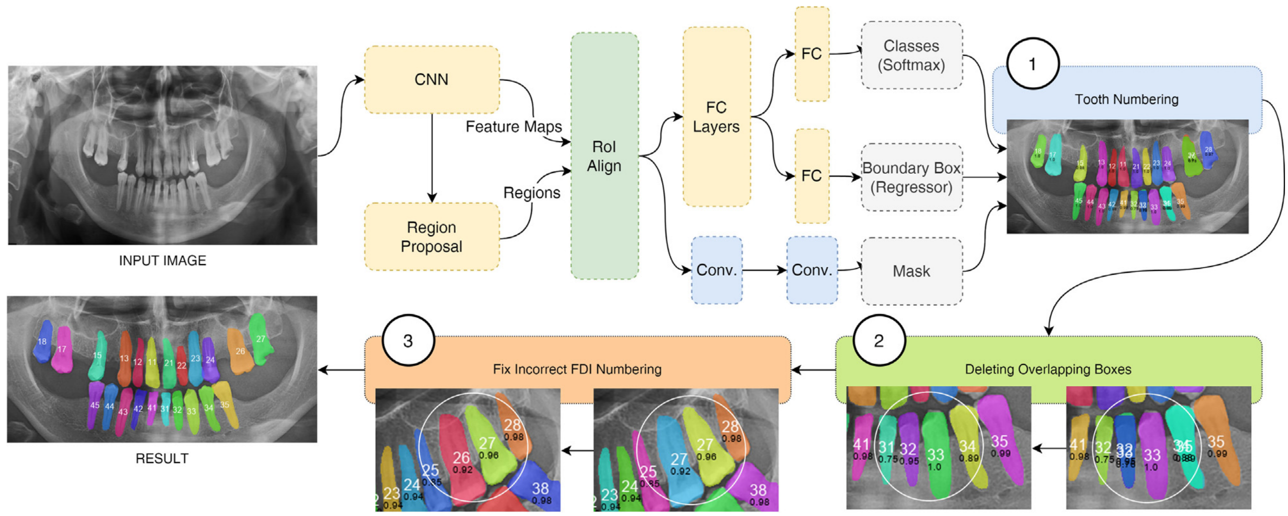


Fig. 3. System architecture and pipeline: the system consists of three modules; tooth numbering, deleting overlapping boxes and fixing incorrect numbering.

batch size 1, learning rate of 0.001, and steps per epoch of 100. Python programming language, Keras library, and Tensorflow backend are used to create the model and heuristic method.

2.5. Statistical analysis

Mean average precision (mAP) is a metric primarily used to evaluate object detection models. The metrics confusion matrix, intersection over union (IOU), recall, and precision is used when calculating mAP. *mAP* is expressed mathematically as in (3).

$$mAP = \frac{1}{2}\sum_{i=1}^{N} AP_i \quad (3)$$

The confusion matrix is used to evaluate the model's performance as a useful table that shows the predicted and actual values. The success of the deep learning model was evaluated with precision (5), recall (6), and f1-score (7) metrics by calculating true positive (TP), false positive (FP) and false negative (FN) prediction numbers. TP refers to the number of predictions in which the model correctly identified the tooth and numbered it correctly, FP refers to the number of predictions where the model correctly identified the tooth and numbered it incorrectly, and FN, in which the model incorrectly predicted the tooth and numbering.

Regarding the tooth detection task, the IOU score between the binary mask image and the Mask R-CNN output was calculated for each panoramic image examined. Predictions with an IOU score of 0.5 and above are accepted. The IoU score between the binary mask *I*, Mask R-CNN output *F* is expressed mathematically as in (4).

$$IoU_{I,F} = \frac{I \bigcap B(F)}{I \bigcap B(F)} \quad (4)$$

Precision indicates how many of the predicted teeth are an accurate estimate. Mathematically, it is expressed as in (5).

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Recall indicates how many of the teeth we should have guessed were predicted correctly. Mathematically, it is expressed as in (6).

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

F1-score value indicates us the harmonic mean of precision and sensitivity (recall) values. Mathematically, it is expressed as in (7).

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (7)$$

3. Results

After the training, we evaluated the training according to the validation loss values for each cross-validation model. 1 shows us the best epoch, precision, recall, and f1-score values according to each model's lowest validation loss value. The 368th epoch in the 5-fold, as shown in the table, had the lowest validation loss value. We evaluated our test dataset with the model file formed at the end of this epoch. After this evaluation, we developed the deep learning algorithm's results with the proposed heuristic model. The results of the basic model and the heuristic algorithm we pioneered are shown in 2. When 2 is examined, it is noticeable that the heuristic algorithm we recommend yields about 4% better results than the baseline algorithm in all metrics.

3 shows the performance results of all tooth classes. The confusion matrix allows us to see and analyze the model results clearly and understandably. 5 shows the confusion matrix of the results of our proposed heuristic algorithm on the test dataset. To display the results more clearly, the teeth in the lower and upper jaws are divided into two matrices.

4. Discussion

The performance of the tooth numbering method of the basic deep learning model is improved using a heuristic method proposed in this study. Our study gives better results than tooth numbering studies using segmentation algorithms such as PANet.

When the studies of numbering teeth in panoramic images in 4 are examined, it is seen that CNN-based algorithms are used in the proposed methods. As a result of the fact that panoramic radiographs have many advantages over other imaging methods for dental radiologists, they are highly preferred for diagnosis and treatment in clinical studies, and accordingly, the number of images available has led to the use of panoramic images to a large extent in these studies. The results showed that using a heuristic method after performing a Mask R-CNN-based tooth detection task resulted in as accurate performance in detecting and numbering permanent teeth as that of a dentist. When the results of our study are compared with the results of previous studies in 4, it is evident

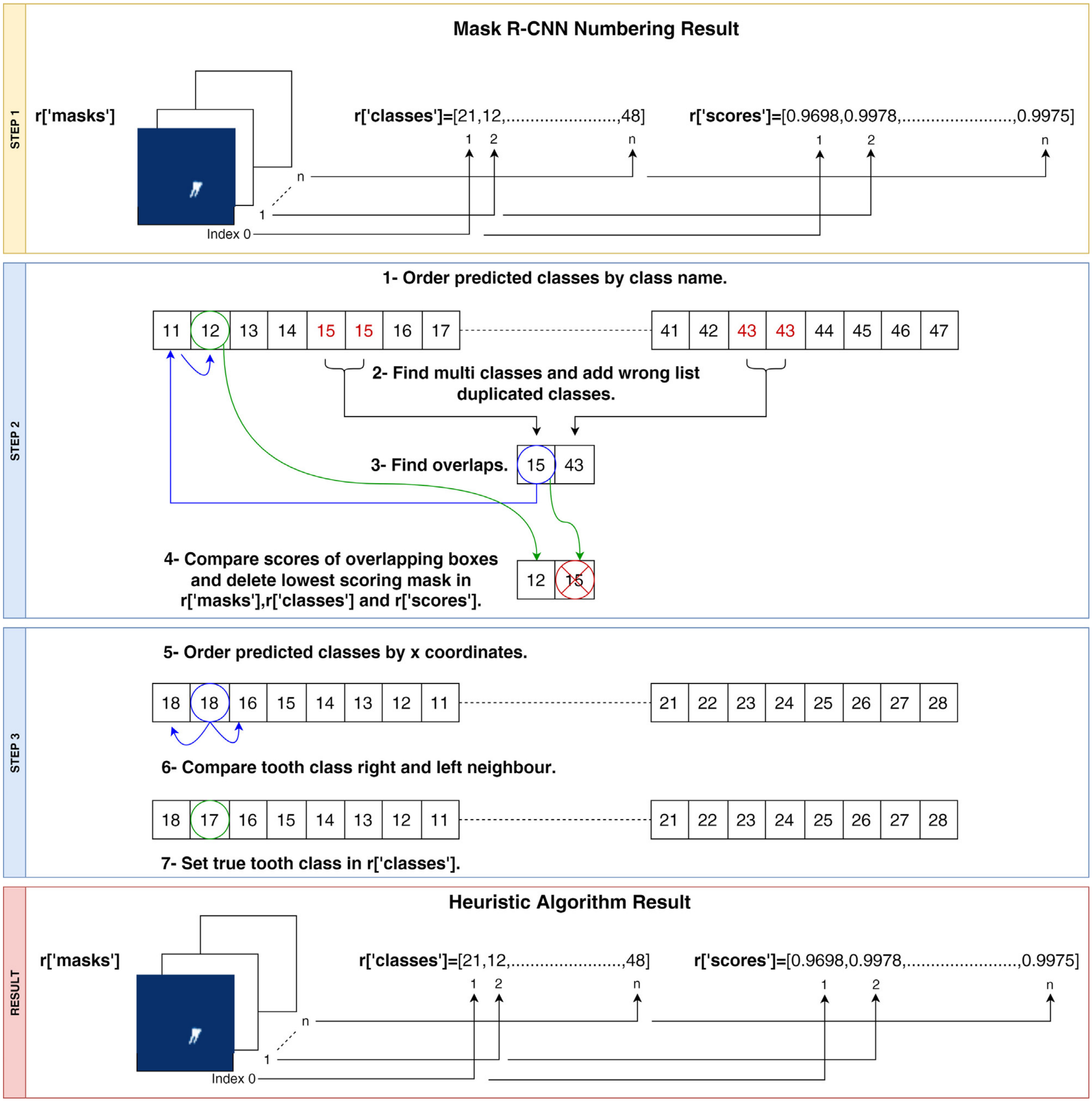


Fig. 4. Proposed heuristic algorithm.

Table 1
Evaluation of data with K-Fold Cross Validation (K = 5) result table.

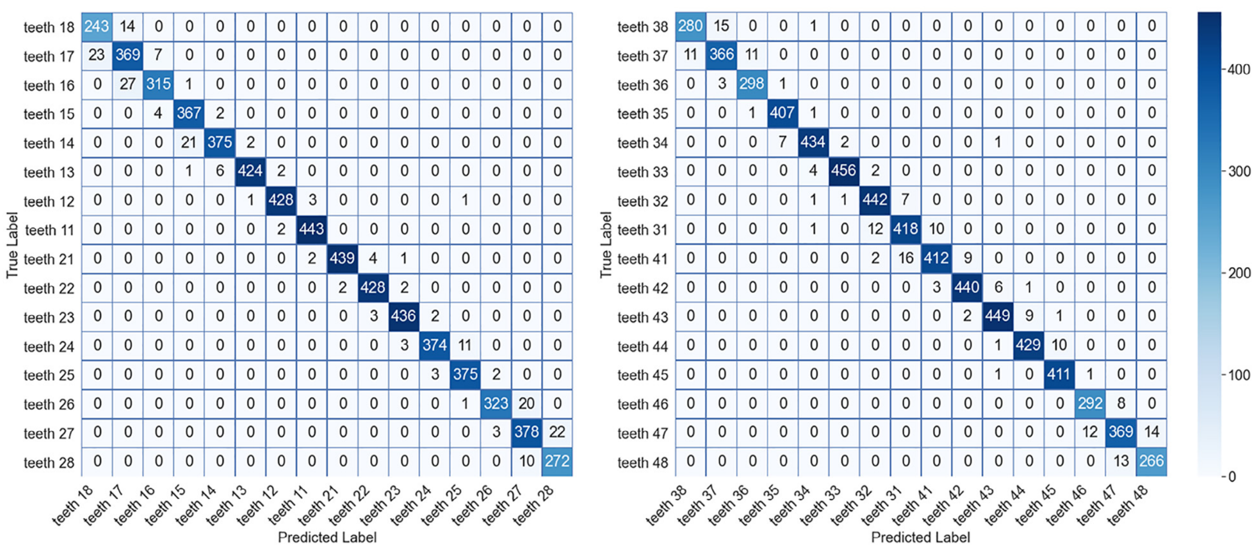
Fold Number	Best Epoch	Validation Loss	Precision	Recall	F1-score
1	309	0.5356	0.9263	0.9178	0.9220
2	398	0.5125	0.9258	0.9203	0.9230
3	389	0.5201	0.9517	0.9540	0.9528
4	392	0.5255	0.9328	0.9286	0.9307
5	368	0.5032	0.9298	0.9293	0.9295
Average		0.5194	0,9333	0,9300	0,9316

Table 2
Comparison between the proposed method and conventional algorithm.

Architecture	mAP(@IOU = 0.5)	Precision	Recall	F1-score
Conventional Algorithm (Mask R-CNN)	0.89	0.9221	0.9194	0.9207
Proposed Method (Mask R-CNN + Heuristic algorithm)	0.93	0.9608	0.9565	0.9587

Table 3
Tp, Fp, Fn, precision, recall, and F1-score value for each tooth category.

Tooth Number	Tp	Fp	Fn	Precision	Recall	F1-score	Tooth Number	Tp	Fp	Fn	Precision	Recall	F1-score
T18	243	29	24	0,89	0,91	0,90	**T38**	280	13	16	0,96	0,95	0,95
T17	369	42	31	0,90	0,92	0,91	**T37**	366	21	23	0,95	0,94	0,94
T16	315	14	33	0,96	0,91	0,93	**T36**	298	17	10	0,95	0,97	0,96
T15	367	25	15	0,94	0,96	0,95	**T35**	407	11	2	0,97	1,00	0,98
T14	375	11	34	0,97	0,92	0,94	**T34**	434	9	13	0,98	0,97	0,98
T13	424	4	16	0,99	0,96	0,98	**T33**	456	4	8	0,99	0,98	0,99
T12	428	8	9	0,98	0,98	0,98	**T32**	442	20	14	0,96	0,97	0,96
T11	443	8	4	0,98	0,99	0,99	**T31**	418	24	34	0,95	0,92	0,94
T21	439	5	7	0,99	0,98	0,99	**T41**	412	16	37	0,96	0,92	0,94
T22	428	8	7	0,98	0,98	0,98	**T42**	440	12	19	0,97	0,96	0,97
T23	436	7	9	0,98	0,98	0,98	**T43**	449	11	15	0,98	0,97	0,97
T24	374	12	26	0,97	0,94	0,95	**T44**	429	12	12	0,97	0,97	0,97
T25	375	17	12	0,96	0,97	0,96	**T45**	411	15	4	0,96	0,99	0,98
T26	323	10	26	0,97	0,93	0,95	**T46**	292	17	10	0,94	0,97	0,96
T27	378	31	27	0,92	0,93	0,93	**T47**	369	23	27	0,94	0,93	0,94
T28	272	23	13	0,92	0,95	0,94	**T48**	266	16	15	0,94	0,95	0,94



(a) (b)

Fig. 5. (a) Upper teeth, and (b) lower teeth confusion matrix of the proposed method (Mask R-CNN + Heuristic algorithm).

Table 4
Current studies on permanent tooth numbering in panoramic images.

References	Year	Dataset	Architecture	Segmentation	Evaluation
Tuzoff [22]	2019	1574	Faster R-CNN + VGG-16 + Heuristic algorithm		Sensivity 98.9%, Specifity %99.9%
Kim [24]	2019	12179	DeNTNet		F1-score 75%
Kim [25]	2020	303	R-CNN + Heuristic algorithm		Sensivity 84.2%, Specivity 75.5%, Accuracy 84.5%
Silva [34]	2020	762	PANet	✓	mAP 74%
Mahdi [35]	2020	1000	Faster R-CNN + Optimization technique		mAP 98.1%, F1-score 98.2%
Bilgir [27]	2021	2482	Faster R-CNN		Sensivity 95.6%, Precision 96.5%, F-measure 96.1%
Lin [30]	2021	895	ResNet		Accuracy 95.6%
Privado [31]	2021	1217	Mask R-CNN		Accuracy 93.8%
Estai [26]	2021	1182	U-Net + R-CNN + VGG-16		Precision 98%, Recall 98 %, F1 Score 98%
Kaya [33]	2022	4545	YOLO V4		mAP 92.22%
Chandrashekar [36]	2022	1500	Mask R-CNN + Faster R-CNN	✓	mAP 97.30%, Accuracy 98.77%, F1-score 98.83%
Our work	**2022**	**2702**	**Mask R-CNN + Heuristic algorithm**	✓	**mAP 92.49%, Precision 96.08%, Recall 95.65%, F1-score 95.87%**

that the proposed method outperforms Mask R-CNN and the heuristic algorithm in numbering.

Silva et al. [34] used PANet to achieve the best results in their segmentation and tooth numbering study with different models. PANet reached 74.0% mAP in numbering. Our study, in which we used Mak R-CNN and heuristic algorithm, reached 92.49% mAP in numbering.

Chandrashekar et al. [36] combine Mask R-CNN and Faster R-CNN models. This method causes a high computational cost. This cost will increase the processing time. In our study, the processes were made lighter and faster using a heuristic approach with the primary model.

Kaya et al. [33] used pediatric panoramic radiographs in their detection and numbering studies. Teeth 18, 28, 28 and 48 in FDI notation are not found on pediatric panoramic radiographs. Since our study was performed with adult panoramic radiographs, detection, segmentation and numbering of all permanent teeth can be performed.

Our study performed high results in mAP value. But there are studies in the literature that performed better in terms of precision, recall and F1 score. The reason for this situation is the performing segmentation in our study. When other studies are examined, it is seen that the numbering task is performed without segmentation. Segmentation is more difficult than others because all teeth are separated from the background during the segmentation process. It gives more exact results as it makes the teeth appear more evident, starting from the edges. This method is more useful for users.

Although Tuzof et al. [22] achieved high results in tooth numbering in their studies, the fact that the system they proposed uses more than one deep learning model and heuristic algorithm has increased the cost of computation. In addition, it does not perform tooth segmentation.

Kim et al. [25] used R-CNN and heuristic algorithms in their study. This study produced very low accuracy results. The reason for this is the use of the training dataset with an insufficient number of images.

Although the success of the proposed methods in tooth detection and numbering studies increases depending on the number of labelled images in the dataset in the studies, it is seen that there are studies with low accuracy due to the choice of deep learning algorithms used. For example, when one of the most up-to-date studies with Mask R-CNN, Prados-Privado et al. [31] used Mask R-CNN as a deep learning algorithm, and the number of images in the dataset is at the same as our study, it is seen that the accuracy value of the model is at the level of 94%. Considering that the dataset and deep learning algorithm in the study are the same as our study, it is seen that our study achieved much higher performance than the studies using Mask R-CNN.

Our proposed method gives high mAP results. When the images in 6, where we give examples of the prediction outputs of the model, are examined, it is seen that although the heuristic algorithm and the ground truth labelling made by the experts in the images without missing teeth are fully compatible, a partial correction has been made in the incorrect tooth numbering, especially in the images with a high number of missing teeth. Our study is at a level that will form the basis for the numbering of teeth, especially in panoramic images with missing teeth.

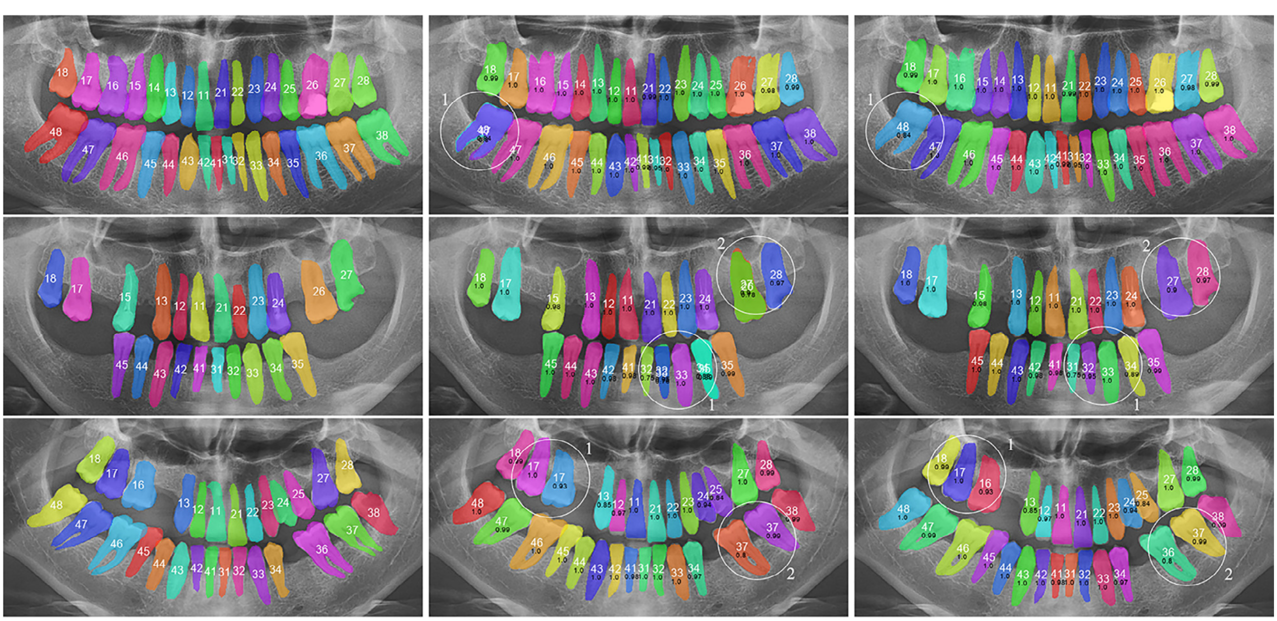
5. Conclusion

In panoramic images, the proposed deep learning and heuristic algorithm-based detection system demonstrated great accuracy in tooth numbering. The contribution of the heuristic algorithm in achieving high accuracy is very effective. Despite the high accuracy obtained, there are also incorrect numbering in the model and heuristic algorithm results. In future studies, the heuristic algorithm needs to be further developed to bring the accuracy to a higher level and to obtain numbering results that are fully consistent with the ground truth. In addition, results like these could help dental radiologists accept, develop, and use artificial intelligence.

By saving time for dental radiologists and reducing manual scheduling, the use of deep learning in daily practice, clinical practice, treatment processes, and dental education will have a direct impact on workflow efficiency in dental offices, research and university/college education laboratories, and clinical services. However, further studies are needed to translate the deep learning system into clinical practice.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



(a) (b) (c)

Fig. 6. (a) Ground-truth, (b) Mask R-CNN model results, and (c) heuristic results samples of the proposed method.

References

[1] F.G. Zanjani, A. Pourtaherian, S. Zinger, D.A. Moin, F. Claessen, T. Cherici, S. Parinussa, P.H. de With, Mask-mcnet: Tooth instance segmentation in 3d point clouds of intra-oral scans, Neurocomputing 453 (2021) 286–298, https://doi.org/10.1016/j.neucom.2020.06.145.

[2] D. Hallikainen, History of panoramic radiography, Acta Radiologica 37 (1996) 441–445. https://www.tandfonline.com/doi/abs/10.3109/02841859609177678.

[3] B. Vandenberghe, The digital patient - imaging science in dentistry, Journal of Dentistry 74 (2018) S21–S26, https://doi.org/10.1016/j.jdent.2018.04.019.

[4] Y.-W. Chen, K. Stanley, W. Att, Artificial intelligence in dentistry: current applications and future perspectives, Quintessence Int 51 (3) (2020) 248–257.

[5] D. Shen, G. Wu, H.I. Suk, Deep learning in medical image analysis, Annual Review of Biomedical Engineering 19 (2017) 221–248, https://doi.org/10.1146/annurev-bioeng-071516-044442.

[6] T. Yeshua, Y. Mandelbaum, R. Abdalla-Aslan, C. Nadler, L. Cohen, L. Zemour, D. Kabla, O. Gleisner, I. Leichter, Automatic detection and classification of dental restorations in panoramic radiographs, Issues in Informing Science and Information Technology 16 (2019) 221–234. https://doi.org/10.28945/4306.

[7] Y.Y. Amer, M.J. Aqel, An efficient segmentation algorithm for panoramic dental images, Procedia Computer Science 65 (2015) 718–725, https://doi.org/10.1016/j.procs.2015.09.016.

[8] G. Silva, L. Oliveira, M. Pithon, Automatic segmenting teeth in x-ray images: Trends, a novel data set, benchmarking and future perspectives, Expert Systems with Applications 107 (2018) 15–31, https://doi.org/10.1016/j.eswa.2018.04.001.

[9] A. Wirtz, S.G. Mirashi, S. Wesarg, Automatic teeth segmentation in panoramic x-ray images using a coupled shape model in combination with a neural network, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 11073 LNCS (2018) 712–719, doi: 10.1007/978-3-030-00937-3_81.

[10] G. Jader, J. Fontineli, M. Ruiz, K. Abdalla, M. Pithon, L. Oliveira, Deep instance segmentation of teeth in panoramic x-ray images, 2019, pp. 400–407, https://doi.org/10.1109/SIBGRAPI.2018.00058.

[11] T.L. Koch, M. Perslev, C. Igel, S.S. Brandt, Accurate segmentation of dental panoramic radiographs with u-nets, in: Proceedings - International Symposium on Biomedical Imaging, Vol. 2019-April, 2019, pp. 15–19, doi: 10.1109/ISBI.2019.8759563.

[12] M.P. Muresan, A.R. Barbura, S. Nedevschi, Teeth detection and dental problem classification in panoramic x-ray images using deep learning and image processing techniques, Proceedings - 2020 IEEE 16th International Conference on Intelligent Computer Communication and Processing, ICCP 2020 (2020) 457–463https://doi.org/10.1109/ICCP51029.2020.9266244.

[13] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You only look once: Unified, real-time object detection, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 779–788.

[14] J.H. Lee, S.S. Han, Y.H. Kim, C. Lee, I. Kim, Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs, Oral Surgery, Oral Medicine, Oral Pathology and Oral, Radiology 129 (2020) 635–642, https://doi.org/10.1016/j.oooo.2019.11.007.

[15] E. Shelhamer, J. Long, T. Darrell, Fully convolutional networks for semantic segmentation, IEEE Transactions on Pattern Analysis and Machine Intelligence 39 (2014) 640–651.

[16] A.B. Oktay, Tooth detection with convolutional neural networks, 2017 Medical Technologies National Conference, TIPTEKNO 2017 2017-January (2017) 1–4, doi: 10.1109/TIPTEKNO.2017.8238075.

[17] E. Shaheen, A. Leite, K.A. Alqahtani, A. Smolders, A.V. Gerven, H. Willems, R. Jacobs, A novel deep learning system for multi-class tooth segmentation and classification on cone beam computed tomography. a validation study, Journal of Dentistry 115 (2021) 103865, doi: 10.1016/j.jdent.2021.103865.

[18] M. Chung, J. Lee, S. Park, M. Lee, C.E. Lee, J. Lee, Y.G. Shin, Individual tooth detection and identification from dental panoramic x-ray images via point-wise localization and distance regularization, Artificial Intelligence in Medicine 111 (2021), https://doi.org/10.1016/j.artmed.2020.101996 101996.

[19] A.F. Leite, A.V. Gerven, H. Willems, T. Beznik, P. Lahoud, H. Gaêta-Araujo, M. Vranckx, R. Jacobs, Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs, Clinical oral investigations 25 (4) (2021) 2257–2267, https://doi.org/10.1007/s00784-020-03544-6.

[20] S. Vinayahalingam, R. Goey, S. Kempers, J. Schoep, T. Cherici, D.A. Moin, M. Hanisch, Automated chart filing on panoramic radiographs using deep learning, Journal of Dentistry 115 (2021), https://doi.org/10.1016/j.jdent.2021.103864 103864.

[21] C. Muramatsu, T. Morishita, R. Takahashi, T. Hayashi, W. Nishiyama, Y. Ariji, X. Zhou, T. Hara, A. Katsumata, E. Ariji, H. Fujita, Tooth detection and classification on panoramic radiographs for automatic dental chart filing: improved classification by multi-sized input data, Oral Radiology 37 (2021) 13–19, https://doi.org/10.1007/s11282-019-00418-w.

[22] D.V. Tuzoff, L.N. Tuzova, M.M. Bornstein, A.S. Krasnov, M.A. Kharchenko, S.I. Nikolenko, M.M. Sveshnikov, G.B. Bednenko, Tooth detection and numbering in panoramic radiographs using convolutional neural networks, Dentomaxillofacial Radiology 48 (4) (2019) 20180051, https://doi.org/10.1259/dmfr.20180051.

[23] H. Chen, K. Zhang, P. Lyu, H. Li, L. Zhang, J. Wu, C.H. Lee, A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films, Scientific Reports 9 (2019) 1–11, https://doi.org/10.1038/s41598-019-40414-y.

[24] J. Kim, H.S. Lee, I.S. Song, K.H. Jung, Dentnet: Deep neural transfer network for the detection of periodontal bone loss using panoramic dental radiographs, Scientific Reports 2019 9:1 9 (2019) 1–9, doi: 10.1038/s41598-019-53758-2.

[25] C. Kim, D. Kim, H.G. Jeong, S.J. Yoon, S. Youm, Automatic tooth detection and numbering using a combination of a cnn and heuristic algorithm, Applied Sciences 2020, Vol. 10, Page 5624 10 (2020) 5624, doi: 10.3390/app10165624.

[26] M. Estai, M. Tennant, D. Gebauer, A. Brostek, J. Vignarajan, M. Mehdizadeh, S. Saha, Deep learning for automated detection and numbering of permanent teeth on panoramic images 50 (2021), https://doi.org/10.1259/dmfr.20210296. 50.

[27] E. Bilgir, I.S. Bayrakdar, O. Celik, K. Orhan, F. Akkoca, H. Saglam, A. OdabaS, A.F. Aslan, C. Ozcetin, M. Killi, I. Rozylo-Kalinowska, An artificial intelligence approach to automatic tooth detection and numbering in panoramic radiographs, BMC Medical Imaging 21 (1) (2021) 1–9, https://doi.org/10.1186/s12880-021-00656-7.

[28] C. Gorurgoz, K. Orhan, I.S. Bayrakdar, O. Celik, E. Bilgir, A. Odabas, A.F. Aslan, R. Jagtap, Performance of a convolutional neural network algorithm for tooth detection and numbering on periapical radiographs, https://doi.org/10.1259/dmfr.20210246 50 (2021) 20210246, https://doi.org/10.1259/dmfr.20210246.

[29] M.C. Kilic, I.S. Bayrakdar, O. Celik, E. Bilgir, K. Orhan, O.B. Aydin, F.A. Kaplan, H. Saglam, A. Odabas, A.F. Aslan, A.B. Yilmaz, Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs, Dentomaxillofacial Radiology 50 (2021) 20200172, https://doi.org/10.1259/dmfr.20200172.

[30] S.-Y. Lin, H.-Y. Chang, Tooth numbering and condition recognition on dental panoramic radiograph images using cnns, IEEE Access 9 (2021) 166008–166026, https://doi.org/10.1109/ACCESS.2021.3136026.

[31] M. Prados-Privado, J.G. Villalón, A.B. Torres, C.H. Martínez-Martcínez, C. Ivorra, A convolutional neural network for automatic tooth numbering in panoramic images, BioMed Research International 2021 (2021) 1–7, https://doi.org/10.1155/2021/3625386.

[32] B.Y. Tekin, C. Ozcan, A. Pekince, Y. Yasa, An enhanced tooth segmentation and numbering according to fdi notation in bitewing radiographs, Computers in Biology and Medicine (2022). https://doi.org/10.1016/j.compbiomed.2022.105547 105547.

[33] E. Kaya, H.G. Gunec, S.S. Gokyay, S. Kutal, S. Gulum, H.F. Ates, Proposing a cnn method for primary and permanent tooth detection and enumeration on pediatric dental radiographs, Journal of Clinical Pediatric Dentistry 46 (4) (2022) 293–298. https://doi.org/10.22514/1053-4625-46.4.6.

[34] B. Silva, L. Pinheiro, L. Oliveira, M. Pithon, A study on tooth segmentation and numbering using end-to-end deep neural networks, Proceedings - 2020 33rd SIBGRAPI Conference on Graphics, Patterns and Images, SIBGRAPI 2020 (2020) 164–171https://doi.org/10.1109/SIBGRAPI51738.2020.00030.

[35] F.P. Mahdi, K. Motoki, S. Kobashi, Optimization technique combined with deep learning method for teeth recognition in dental panoramic radiographs, Scientific Reports 2020 10:1 10 (2020) 1–12, doi: 10.1038/s41598-020-75887-9.

[36] G. Chandrashekar, S. AlQarni, E.E. Bumann, Y. Lee, Collaborative deep learning model for tooth segmentation and identification using panoramic radiographs, Computers in Biology and Medicine 148 (2022), https://doi.org/10.1016/j.compbiomed.2022.105829 105829.

[37] S. Ren, K. He, R. Girshick, J. Sun, Faster r-cnn: Towards real-time object detection with region proposal networks, IEEE Transactions on Pattern Analysis and Machine Intelligence 39 (2017) 1137–1149. https://proceedings.neurips.cc/paper/2015/file/14bfa6bb14875e45bba028a21ed38046-Paper.pdf.

[38] N. Akkaya, Ö. Kansu, H. Kansu, L.B. Çagirankaya, U. Arslan, Comparing the accuracy of panoramic and intraoral radiography in the diagnosis of proximal caries, Dentomaxillofacial Radiology 35 (2006) 170–174, https://doi.org/10.1259/dmfr/26750940.

[39] K. He, G. Gkioxari, P. Dollár, R. Girshick, Mask r-cnn, IEEE Transactions on Pattern Analysis and Machine Intelligence 42 (2020) 386–397. https://openaccess.thecvf.com/content_ICCV_2017/papers/He_Mask_R-CNN_ICCV_2017_paper.pdf.

[40] A. Karaoglu, C. Ozcan, A. Pekince, Y. Yasa, B.Y. Tekin, D. Ozdemir, Automatic dental segmentation module supported by artificial intelligence for dentistry students education, Artificial Intelligence Theory and Applications 1 (2021) 180–190.

[41] F. Schwendicke, T. Singh, J.-H. Lee, R. Gaudin, A. Chaurasia, T. Wiegand, S. Uribe, J. Krois, on behalf of the IADR e-oral health network, the ITU WHO focus group AI for Health, Artificial intelligence in dental research: Checklist for authors, reviewers, readers, Journal of dentistry 107 (2021), https://doi.org/10.1016/j.jdent.2021.103610 103610.

[42] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.