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Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs

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Objectives. To evaluate a fully deep learning mask region-based convolutional neural network (R-CNN) method for automated tooth segmentation using individual annotation of panoramic radiographs.

Study Design. In total, 846 images with tooth annotations from 30 panoramic radiographs were used for training, and 20 panoramic images as the validation and test sets. An oral radiologist manually performed individual tooth annotation on the panoramic radiographs to generate the ground truth of each tooth structure. We used the augmentation technique to reduce overfitting and obtained 1024 training samples from 846 original data points. A fully deep learning method using the mask R-CNN model was implemented through a fine-tuning process to detect and localize the tooth structures. For performance evaluation, the F1 score, mean intersection over union (IoU), and visual analysis were utilized.

Results. The proposed method produced an F1 score of 0.875 (precision: 0.858, recall: 0.893) and a mean IoU of 0.877. A visual evaluation of the segmentation method showed a close resemblance to the ground truth.

Conclusions. The method achieved high performance for automation of tooth segmentation on dental panoramic images. The proposed method might be applied in the first step of diagnosis automation and in forensic identification, which involves similar segmentation tasks. (Oral Surg Oral Med Oral Pathol Oral Radiol 2020;129:635−642)

Dental panoramic radiography is widely used as a radiologic tool for the diagnosis of oral and maxillofacial diseases because of its cost-effectiveness and relatively low dose.[1] In panoramic radiography, which is a variation of tomography, the X-ray tube rotates around the subject. As a result, overlapping of anatomic structures, unsharp edges, and noise are unavoidable.[2-4] Thus, the automated diagnosis of dental panoramic radiographs could assist practicing clinicians by improving the efficiency of their daily workflow.

The accurate detection and localization of specific anatomic structures on medical images is referred to as *segmentation*, which is essential for automated diagnostic systems.[5] Manual segmentation involving annotation of anatomic structures by experts on radiologic images is needed to establish the ground truth for training artificial intelligence algorithms for the purpose of diagnosis automation.[6] In the dental field, dental caries, periodontal disease, and periapical lesions are found in and around teeth. Odontogenic cysts and tumors are often located near teeth in the jaws because they arise from odontogenic cells. Tooth segmentation provides a very important basis for the automatic diagnosis of tooth-related diseases on dental radiologic images, but manual annotation is a labor-intensive and time-consuming process.[6,7] Therefore, automation of tooth segmentation is the first (and most challenging) step in the development of automated interpretable diagnostic methodologies for dental images. Furthermore, automated tooth segmentation is meaningful for dental forensic science because tooth anatomy has been used to identify dental records in criminal investigations.[8-10]

Many researchers have investigated the possibility of automated segmentation of important anatomic structures on radiologic images by using mathematical methods.[9,11-14] Region-based methods,[11,14] threshold-based methods,[9,12,13,15] clustering methods,[16,17] the boundary method,[18-20] and the watershed method[21] have all been vigorously discussed. However, accurate segmentation is challenging to achieve because of the small differences in pixel intensity between bone and tooth structures on panoramic radiographs.[22] A particular obstacle is that panoramic radiographs show overlapping skeletal structures, including teeth, the maxillary sinus,

Statement of Clinical Relevance

The fully deep learning method using a fine-tuned mask region-based convolutional neural network algorithm and individually annotated training data sets showed high performance in automation of tooth segmentation on dental panoramic images, the first step in diagnosis automation.

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the nasal area, and surrounding bone, leading to complicated changes in gray levels.[2-4]

Machine learning[16,17] and deep learning algorithms have been introduced recently.[6,23-25] These artificial intelligence methods have shown better performance compared with previous mathematical approaches for automated tooth segmentation. In particular, since 2012, deep convolutional neural networks (CNNs) have been used for segmentation of anatomic structures, and CNNs have shown the potential to perform similarly to humans.[26]

CNNs have performed well in object or lesion detection[27,28] and segmentation.[29,30] In particular, mask region-based CNNs (R-CNNs) offer a powerful framework for predicting segmentation masks on each region of interest.[31] They perform object detection, segmentation, and classification.[31] Thus, some researchers have applied mask R-CNNs to detect and localize tumors as a result of the advantages of automatic image segmentation.[32]

In dental radiology, only 2 studies have explored the capability of CNNs to expand automated tooth detection and entire outline segmentation.[6,24] Silva et al.[6] first tried a mask R-CNN technique for automated tooth segmentation on panoramic radiography. However, they used only a single annotation, including all teeth in a panoramic image as the ground truth; therefore, the results did not detect the exact tooth structure. In contrast, Wirtz et al.[24] obtained the ground truth by manually annotating individual tooth forms on 10 panoramic images, and their results showed better performance than that found in the study by Silva et al. However, Wirtz et al.[24] added a modeling process to the mask R-CNN to improve its accuracy; that is, it was not a fully deep learning method.

In this study, we applied a fully deep learning CNN algorithm without modeling adaptation by using manual annotation for each tooth. The objective of this investigation was to propose a more refined, fully deep learning method that uses a mask R-CNN for automated tooth segmentation of dental panoramic images. We hypothesized that a fine-tuned, fully deep mask R-CNN model using individual tooth annotations could achieve good performance for automated tooth segmentation of teeth on dental panoramic radiographs.

MATERIALS AND METHODS

Data preparation

In total, 30 panoramic radiographs of adult patients with permanent dentition (age 20−65 years) were randomly collected from the picture archiving and communication system of Yonsei University Dental Hospital from January to June 2018 to serve as the training data set. In addition, 20 other panoramic images were randomly selected, of which 10 were used for validation and 10 for testing. Dental caries, the periapical region, periodontal disease, various types of restorations (intracoronal, crowns, and bridges), orthodontic brackets and wires, and the third molars were included in the data set.

All panoramic radiographs were exposed by using a PaX-i Plus (Vatech Co., Ltd., Hwaseong-si, Korea) at the Department of Oral and Maxillofacial Radiology. The exposure conditions were set at 73 kVp and 7 mA and an exposure time of 10.1 seconds, according to the manufacturer's instructions.

This study was approved by the Institutional Review Board of Yonsei Dental Hospital after review (IRB No. 2-2018-0027), and all data were anonymized.

Preparation of tooth annotation images used as the ground truth

The panoramic radiographs were obtained with dimensions of 2988 × 1369 pixels. Annotation of each tooth in the maxillae and the mandibles was manually performed by an oral and maxillofacial radiologist with 5 years of experience (Figure 1). Images with tooth annotation were generated according to the number of teeth on one panoramic radiograph; therefore, a total of 846 annotation images were produced from the 30 panoramic radiographs in the training data set and used as the ground truth data for training.

Data augmentation for expanding the training data set

Data augmentation uses only the information in the training data to increase the amount of training data, and the main techniques fall into the broad category of data warping, in which additional samples are created by transformations in the data space.[33] We used the augmentation technique to reduce overfitting, which occurs when the model learns both signal and noise, adversely affecting performance accuracy. We obtained 1024 training samples from the 846 original data points.

The following augmentations were performed:

- Rotation by -30° or $+30^\circ$
- Sheared affine transformation by -16° or $+16^\circ$
- Flipping along the vertical or horizontal axes
- Gaussian blur by sigma (0.0, 3.0)

Fully deep learning method using a fine-tuned mask R-CNN

We used a mask R-CNN, which is a framework developed by He et al.[31] The mask R-CNN model is a multitasking algorithm based on a CNN with the ability to detect, classify, and mask objects in an image. The key feature of the mask R-CNN model is the instance segmentation framework, which is the approach to detecting and delineating each individual object of interest in an image.[34]

A mask R-CNN has a 2-stage procedure. In the first stage, referred to as the *region proposal network*, candidate regions of interest (ROIs) are proposed. In the

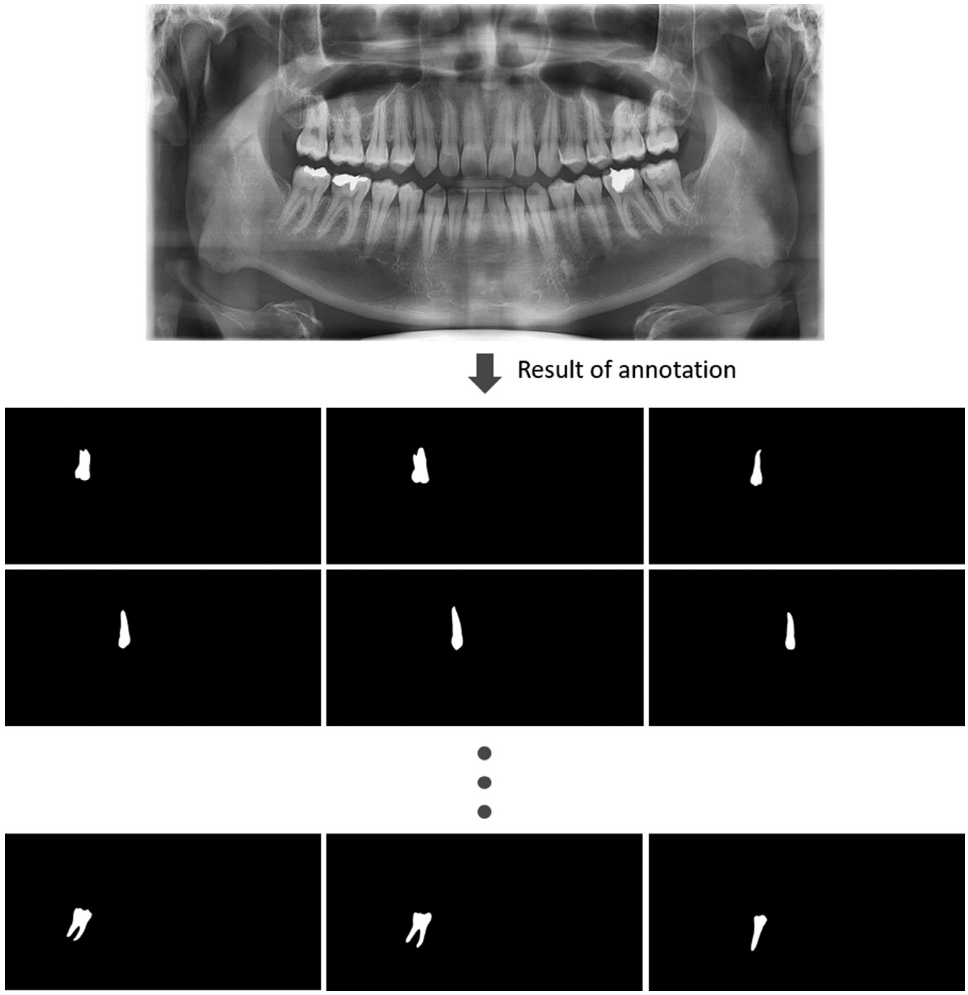

Fig. 1. The process of tooth annotation. Each panoramic radiograph was used to generate several independently annotated tooth images depending on the number of teeth.

second stage, the mask R-CNN contains a binary mask for each ROI, parallel to the classification and bounding box predictions. To enhance the accuracy of the segmentation mask, a layer called *RoIAlign* was used to extract the spatial structure of the mask in a pixel-to-pixel manner. The details of the mask R-CNN model are described in the original article.[31] An outline of the model is shown in Figure 2.

The backbone of the mask R-CNN model is the ResNet-101 network,[23] a popular CNN architecture. The initial training model used pre-trained weights with 5000 images from the "common objects in context" (COCO) data set.[35] The hyperparameters were fine-tuned based on the performance on the 10 panoramic radiographs in the validation data set during model training. For the learning process, we used a learning rate of 0.001, a stochastic gradient descent for optimization, a momentum of 0.9, and a weight decay of 0.0001. Additionally, we stopped the convergence after 170 epochs and used 1024 images for each epoch.

Performance evaluation

The following criteria were used to evaluate the performance of the proposed method on the 10 panoramic radiographs in the testing data set:

1. *F1 score:* The F1 score is a segmentation evaluation metric that can effectively interpret the extent of overlapping pixels between the ground truth and the prediction result, in the form of a balance between precision and recall. The preliminary calculations of precision and recall measurements are shown in Table I. The precision, recall, and F1 score are computed as follows:

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$$

$$\text{F1score} = 2 * (\text{precision} * \text{recall})/(\text{precision} + \text{recall})$$

where *TP* refers to true positives, *FP* refers to false positives, and *FN* refers to false negatives.

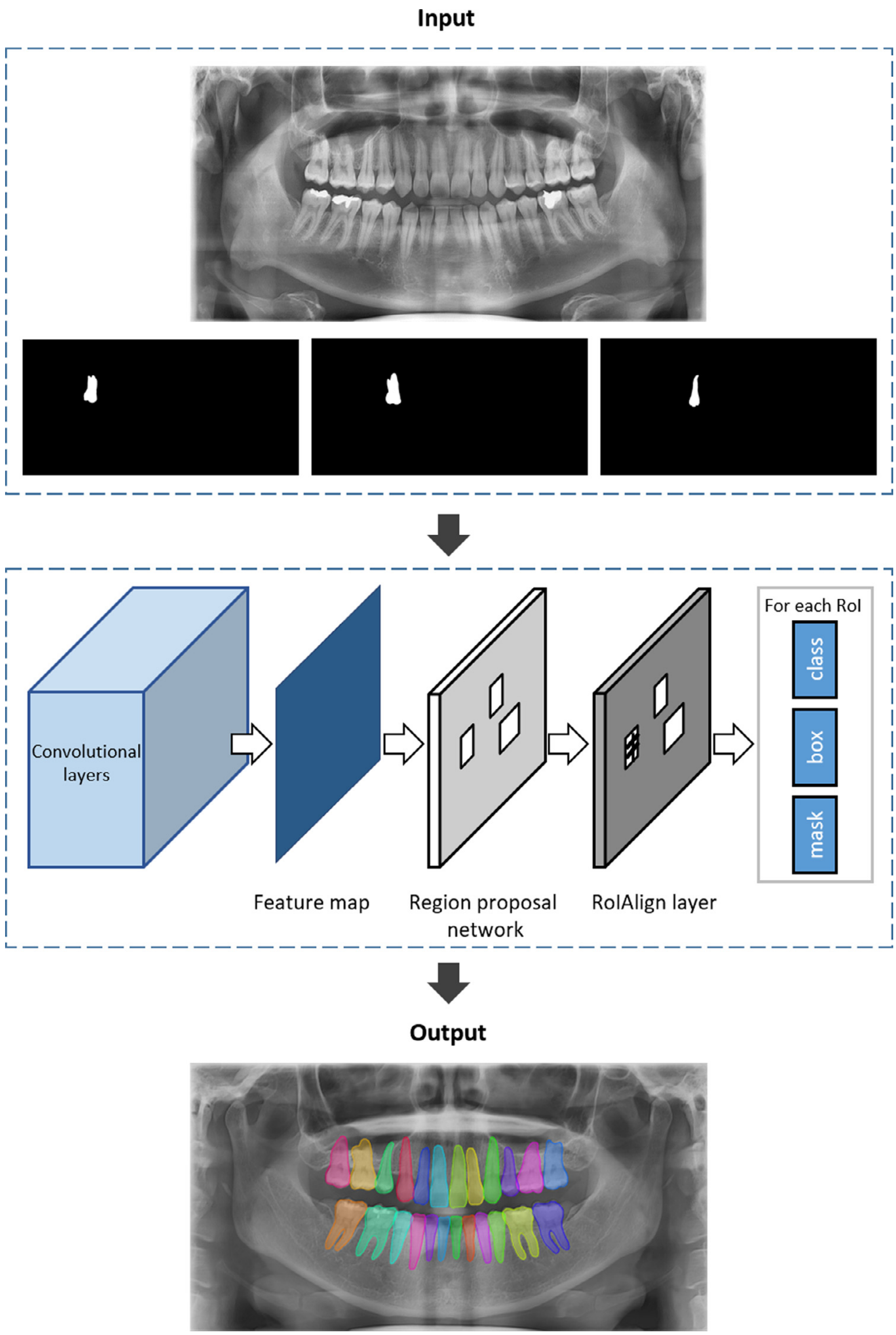

Fig. 2. Architecture for our proposed method based on a mask region-based convolutional neural network (R-CNN) framework.

2. *Mean intersection over union:* The mean intersection over union (IoU) is a standard evaluation method applied in Pascal VOC2012,[36] which uses true positives, false positives, and false negatives. The IoU metric demonstrates the overlapping region between the result of the proposed method and the ground truth area in tooth segmentation. The following equation is used to calculate the IoU:

$$\mathrm{IoU} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP} + \mathrm{FN})$$

The F1 score and mean IoU assess the performance of tooth segmentation from 0 to 1, with a number close to 1

Table I. Description of the preliminary calculations used to evaluate the segmentation method

Index	Description
TP (true positive)	Regions with overlap between the ground truth and predicted results
FP (false positive)	Nonoverlapped regions in the predicted results
FN (false negative)	Nonoverlapped regions in the ground truth

indicating high performance. The overall performance of segmentation predictions was measured by averaging the F1 score and mean IoU into a single value.

3. *Visual analysis:* The segmentation outputs were visually analyzed and verified in comparison with the ground truth. To visualize the results, the tooth segmentation results and ground truth were shown in red (proposed method) and green (ground truth) lines, respectively.

RESULTS

Table II shows the performance of the proposed method and those proposed by Silva et al.[6] and Wirtz et al.[24] for tooth segmentation on panoramic radiographs. The proposed method showed better performance than those developed by Silva et al.[6] and Wirtz et al.[24] In particular, the performance for incisors and canines was better than for other tooth types, with a mean IoU of 0.900 for the incisors and 0.889 for the canines (Table III).

A visual evaluation was conducted by using illustrated mask boundaries on the segmentation results and the ground truth. The tooth segmentation results and the ground truth are shown using red lines (proposed method) and green lines (ground truth). As shown in Figure 3, the proposed method achieved excellent results compared to the ground truth. Figure 4 shows the inference results for the proposed model using the panoramic radiographs to create visual segmentation results.

Table II. Comparison of performance for tooth segmentation

Method	Precision	Recall	F1 score	Mean IoU
Silva et al.[6]	0.837	0.762	0.794	–
Wirtz et al.[24]	0.790	0.827	0.803	–
Proposed method	0.858	0.893	0.875	0.879

IoU, intersection over union.

Table III. Segmentation accuracy by tooth type

Tooth type	Mean IoU
Maxillary and mandibular incisors	0.900
Maxillary and mandibular canines	0.889
Maxillary and mandibular premolars	0.873
Maxillary and mandibular molars	0.859

IoU, intersection over union.

DISCUSSION

Automated segmentation of the tooth structure in dental radiology is required as the first step for developing automatic diagnostic support.[24] However, it is a challenging task. At the Institute of Electrical and Electronics Engineers (IEEE) International Symposium on Biomedical Imaging 2015, a Bitewing Radiography Caries Detection Challenge was held. Only 2 of the 9 registered teams, each using a U-shaped deep convolutional network or a random forest machine learning system, reported successful test results. They reported that the segmentation of tooth structures on dental radiographs was difficult to make into a learning task, which is why the results showed high variation for caries detection.[37]

Most automatic diagnostic studies in dental radiology have focused on intraoral radiography.[9,38-42] A few studies have explored automatic diagnosis based on panoramic radiography.[6,24,43] Silva et al.[6] introduced the mask R-CNN technique for automated tooth segmentation on panoramic radiography. A single annotated image that included all teeth in one panoramic image was used as the training data set; however, the tooth structure was incorrectly detected and localized without the root shape. Even by a visual inspection of the results, only the locations of teeth were found and the shapes of teeth were not precisely segmented.

Wirtz et al.[24] presented an automatic system with a modified U net on 10 dental panoramic radiographs for tooth segmentation. In contrast to Silva et al., they obtained the ground truth by manually annotating individual teeth, and they showed better performance than Silva et al. The authors suggested that segmentation quality should be assessed by comparing the generated results to manually created ground-truth segmentation of individual teeth.[6] They used a coupled shape model as *a priori* knowledge of the shape and spatial configuration of individual teeth to handle the poor image quality of dental panoramic images; that is, their approach was not a fully deep learning method.

In this study, we used a manual approach in which annotated images were created for each tooth, similar to Wirtz et al.[24] However, we applied a fully deep algorithm using mask R-CNN without modifications or adaptations. Our results showed better performance compared with the

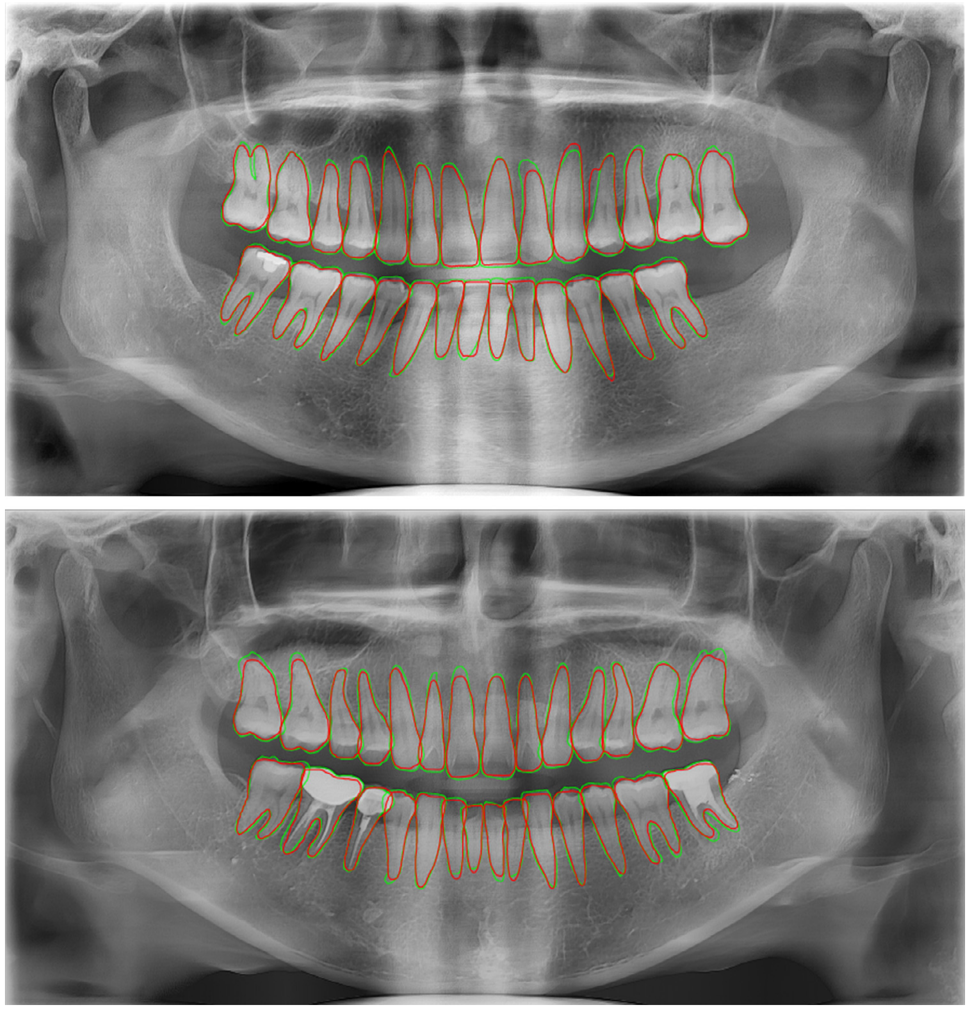

Fig. 3. Examples of visual evaluation. Mask boundaries illustrate the segmentation results for the proposed method *(in red)* and ground truth *(in green)*.

results reported in previous studies. The reasons for this are that the high-quality ground truth and fine-tuning algorithm contributed to the high performance of the mask R-CNN on panoramic radiography, and the augmentation technique reduced overfitting in image segmentation.[44]

On panoramic images, the root of the tooth in bone has an unclear boundary, unlike the crown of the tooth, which is distinct from the background.[45] Therefore, the segmentation of multirooted teeth is more difficult than that of single-rooted teeth. Additionally, the multiple roots of maxillary molars overlap with the maxillary sinus, which may make it difficult to automate segmentation. Nevertheless, our prediction results of tooth segmentation produced almost identical results to the ground truth. In our study, visual assessment of the furcation area of mandibular and maxillary molars with more than 2 roots showed high accuracy. Overall, our method demonstrated excellent results in images of teeth with a crown prosthesis and restorations.

In this study, the fully deep, fine-tuned, mask R-CNN model performed well in automated tooth segmentation on panoramic images. Our proposed CNN-based method can be extended to other tasks, including forensics, which would benefit from an automated identification system based on dental panoramic images.

CONCLUSIONS

In this study, a fully deep learning method using a fine-tuned mask R-CNN algorithm and individually annotated data sets achieved high performance for automated tooth segmentation on dental panoramic images. The proposed method has the potential to be applied in the first step of automating interpretable diagnostic systems and in forensic identification, which involves similar segmentation tasks.

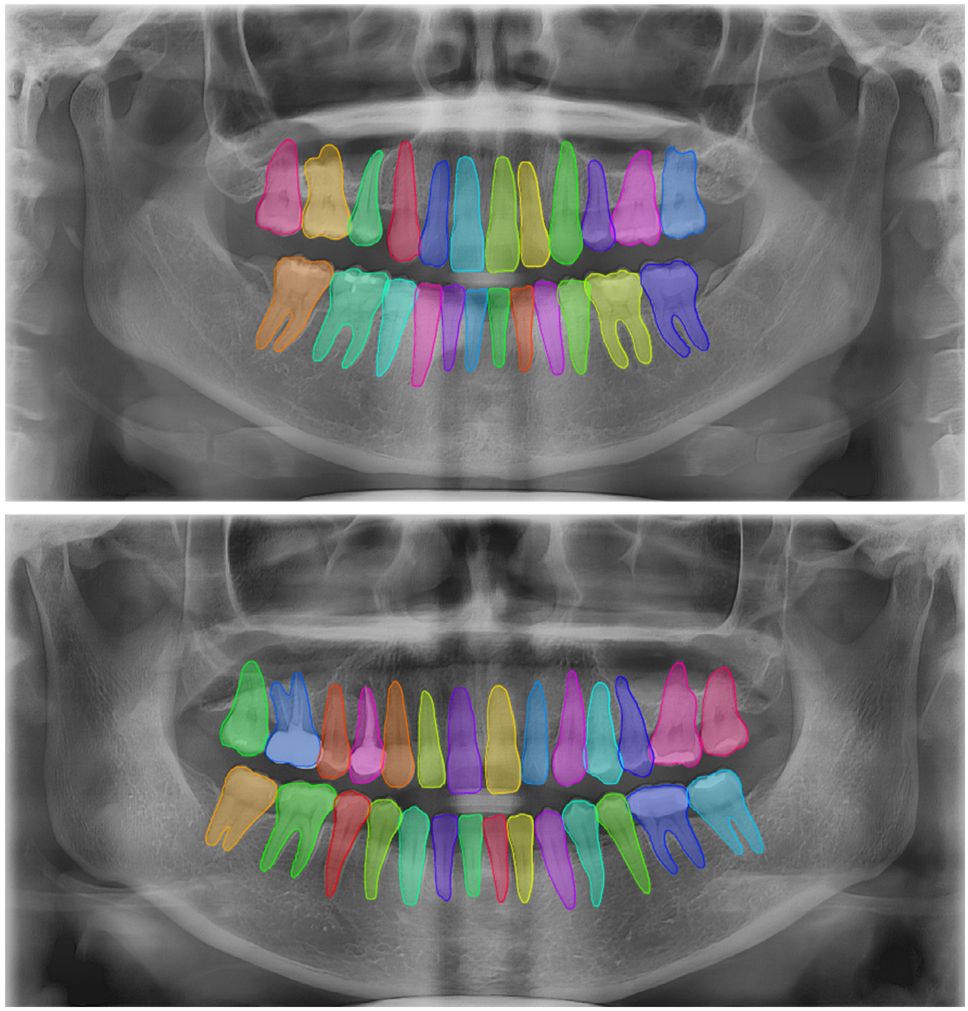

Fig. 4. Examples of inference results based on the proposed method.

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