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RESEARCH ARTICLE

Deep-learning for predicting C-shaped canals in mandibular second molars on panoramic radiographs

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Objective: The aim of this study was to evaluate the use of a convolutional neural network (CNN) system for predicting C-shaped canals in mandibular second molars on panoramic radiographs.
Methods: Panoramic and cone beam CT (CBCT) images obtained from June 2018 to May 2020 were screened and 1020 patients were selected. Our dataset of 2040 sound mandibular second molars comprised 887 C-shaped canals and 1153 non-C-shaped canals. To confirm the presence of a C-shaped canal, CBCT images were analyzed by a radiologist and set as the gold standard. A CNN-based deep-learning model for predicting C-shaped canals was built using Xception. The training and test sets were set to 80 to 20%, respectively. Diagnostic performance was evaluated using accuracy, sensitivity, specificity, and precision. Receiver-operating characteristics (ROC) curves were drawn, and the area under the curve (AUC) values were calculated. Further, gradient-weighted class activation maps (Grad-CAM) were generated to localize the anatomy that contributed to the predictions.
Results: The accuracy, sensitivity, specificity, and precision of the CNN model were 95.1, 92.7, 97.0, and 95.9%, respectively. Grad-CAM analysis showed that the CNN model mainly identified root canal shapes converging into the apex to predict the C-shaped canals, while the root furcation was predominantly used for predicting the non-C-shaped canals.
Conclusions: The deep-learning system had significant accuracy in predicting C-shaped canals of mandibular second molars on panoramic radiographs.
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Keywords: Deep learning; Convolutional neural network; C-shaped canal; Diagnostic imaging; Panoramic radiograph

Introduction

In clinical practice, we obtain information about the teeth that need treatment through radiographs. With respect to root canal treatment, the difficulty of treatment can be predicted by evaluating the shape of the tooth and the number of root canals, their curvature, and length through preoperative radiographs. The mandibular second molar has the most variations in root canal morphology in the mandible and shows a high prevalence of C-shaped root canals.[1] C-shaped canals pose difficulties in canal enlargement, irrigation, and obturation; therefore, the failure rate of root canal treatment is high in teeth with such canals.[2]

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The classification and anatomical variations of C-shaped canals in the mandibular second molar have been reported in several studies. These studies used sectioning methods,[2] radiography,[3–5] micro-CT,[6] and cone beam CT (CBCT) imaging techniques.[7] Fan et al[5] performed radiological classification of C-shaped canals in extracted teeth. However, diagnosis of C-shaped canals using two-dimensional imaging methods is challenging because of image superimposition. Some C-shaped canals are difficult to identify because of the thickness of bone trabeculae.[8] There are studies on predicting C-shaped canals on radiographs using panoramic images[3] and periapical radiographs.[4] However, the characteristics of the mandibular second molars on radiographs have not been well established.

In the field of dentistry, studies using deep learning and convolutional neural network (CNN) are being conducted in various topics: apical lesion,[9] dental caries,[10] location of the inferior alveolar nerve,[11] detection of maxillary sinusitis[12] or osteoporosis,[13] orthodontic diagnosis,[14] and morphological classification of teeth.[15] In the past, studies involving artificial intelligence (AI) for classification using deep learning focused only on the correct answer, and not on the characteristics that were used for drawing the conclusion. However, as explainable AI attracts attention, it is also possible to know the characteristics on which the classification is based.[16] Visualization of deep learning models is an important technique for spatially analyzing the localization of deep learning predictions with respect to the input image.

The purpose of this study was to determine whether it is possible to distinguish C-shaped root canals of mandibular second molars from panoramic images using deep learning.

Methods and materials

Subjects

The study consisted of 1020 patients (523 males and 497 females) who had undergone panoramic and CBCT imaging for diagnostic purposes and treatment planning between June 2018 and May 2020 at Wonkwang University Daejeon Dental Hospital (Daejeon, South Korea). Patients aged 18–60 years, having both mandibular second molars, were included. The mean age of the patients was 28.8 years. Fully developed and untreated teeth (no root fillings, posts, or crown restorations) were included in the study. Teeth with deep caries, root resorption, and open apices were excluded. Data collection was approved by the Institutional Review Board of Wonkwang University Daejeon Dental Hospital (No. W2007/003-001).

Panoramic images acquired using PCH-2500® (Vatech, Hwaseong, Korea) and ProMax® (Planmeca, Helsinki, Finland) were downloaded in the Bitmap form (.BMP) from the image database of our hospital. All images were evaluated by a single oral and maxillofacial radiologist using two CX50N monitors (WIDE Co., Hwaseong, Korea) in a dimly lit room, and images corresponding to the inclusion criteria were selected. The evaluation of the canals in the axial view of the CBCT identified 887 C-shaped canals and 1153 non-C-shaped canals. C-shaped canals were classified using the method of Fan et al.[17] These results were used as the gold standard.

Image data set & pre-processing

The radiologist labeled arbitrarily sized rectangular regions of interest that fully contained the crown and roots of the right and left mandibular second molars. A total of 2040 manually cropped image segments obtained from 1020 patients were included in this study. The dataset was randomly divided into a training set (n = 1632; 80%) and a test set (n = 408; 20%). Of the 887 C-shaped canals, 710 images were included in the training set and 117 images in the test set. For non-C-shaped canals, the training and test sets consisted of 922 images and 231 images, respectively.

Images cropped to various sizes were converted to images of the same size of 400 × 400 pixels. In order to maintain the shape and resolution of the second molars in the cropped images, the images were not resized. Instead, the edges were filled using zero-padding to compensate for the insufficient pixels in size 400 × 400. In order to compensate for insufficient data and increase generalization performance, data augmentation of training images was performed using image processing techniques such as rotation, changes in brightness, horizontal and vertical shifts, and horizontal flips. All transformations for data augmentation were applied randomly for each iteration.

Architecture of the deep convolutional neural network

The Xception architecture was used as the base model for identifying the C-shaped root canal by applying transfer learning. It is a deep learning model that improves performance by separating the convolution filter that searches for spatial area information from the convolution filter that considers the relationship between channels.[18] In order to connect the feature extractor and the fully connected layer in charge of classification, a global average pooling layer was placed in the middle. Global average pooling converts 2D features extracted by the feature extractor into 1D vectors. Finally, the feature vector was classified as a C-shaped canal or non-C-shaped canal through a fully connected layer (Figure 1).

The model was trained with an Adam optimizer for 100 epochs, with an initial learning rate of 0.001 and a batch size of 20. The learning rate decreased by 0.1 per 20 epochs from the initial value.

Evaluating the CNN model & visualization method

We evaluated the performance of the trained deep-learning model using an independent testing set that was not used during model development. To evaluate

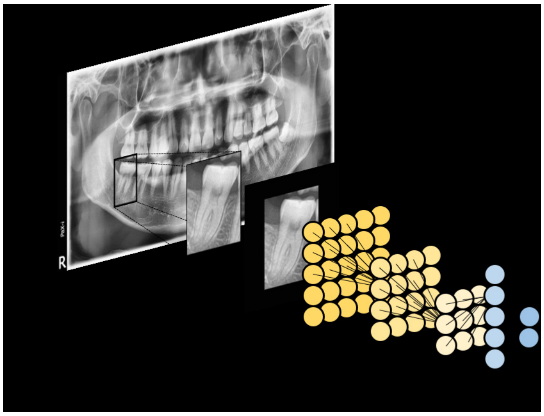

Figure 1 Schematic diagram of deep-learning system to predict C-shaped canals. The input is images zero-padded after being cropped from panoramic images. The pre-trained network for feature extraction is a structure in which depth-wise separable convolutions are repeatedly stacked with residual connections. The rest of the structures connected with feature extraction consist of a global average pooling and a fully connected layer to distinguish between C-shaped and non-C-shaped canals.

diagnostic classification, we calculated accuracy, sensitivity, specificity, and precision, which are common parameters in object detection and classification. A receiver-operating characteristic (ROC) curve was drawn, and the area under the curve (AUC) was determined.

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}}$$

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{precision} = \frac{\text{TP}}{\text{FP} + \text{TP}}$$

TP, true positive; FP, false positive; FN, false negative; TN, true negative.

Further, gradient-weighted class activation mapping (Grad-CAM) was used to analyze the main factors that influenced the prediction of the results. Grad-CAM is a method of calculating the importance of each node of the convolution layer using gradient information.[19]

Comparison with diagnostic performance of specialists

To compare the diagnostic performance of the deep-learning system with the diagnosis made by a specialist, one radiologist (experience >6 years) and one endodontist (experience >6 years) predicted C-shaped canals from panoramic images. After 3 months of data collection, 200 panoramic images were randomly selected from the dataset, and a total of 400 mandibular second molars were evaluated. The specialists evaluated the images after training on several panoramic images. The accuracy, sensitivity, specificity, precision, and AUC were calculated and compared with those of the CNN model. All statistical analyses were performed using MedCalc® Statistical Software v.19.5.3 (MedCalc Software Ltd, Ostend, Belgium). p values < 0.05 were considered statistically significant.

Table 1 Comparison of diagnostic performance between the CNN model and specialists

	Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*	*Precision (%)*	*AUC*
CNN model	95.1	92.7	97.0	95.9	0.982
Radiologist	87.3	92.5	82.0	83.7	0.872
Endodontist	88.5	91.5	85.5	86.3	0.885
p value					
CNN model *vs* Radiologist	0.0001[a]	0.9411	<0.0001[a]	0.0001[a]	<0.0001[a]
CNN model *vs* Endodontist	0.0006[a]	0.6675	<0.0001[a]	0.0014[a]	<0.0001[a]

[a]indicates significant differences ($p < 0.05$).

Results

The accuracy, sensitivity, specificity, and precision of the CNN model were 95.1, 92.7, 97.0, and 95.9%, respectively (Table 1). The comparisons of diagnostic performance between the CNN model and specialists are also shown in Table 1. The AUCs were 0.982, 0.872, and 0.885 for the CNN model, radiologist, and endodontist, respectively (Figure 2). The AUC for the CNN model was significantly higher than that for the dentists ($p < 0.0001$).

Figure 3 shows images of C-shaped canals and non-C-shaped canals predicted using the CNN model, visualized using Grad-CAM. In correctly predicted C-shaped canals (Figure 3a), the region showing the convergence of the canals to the apex was extracted as the main image feature used for the classification. In correctly predicted

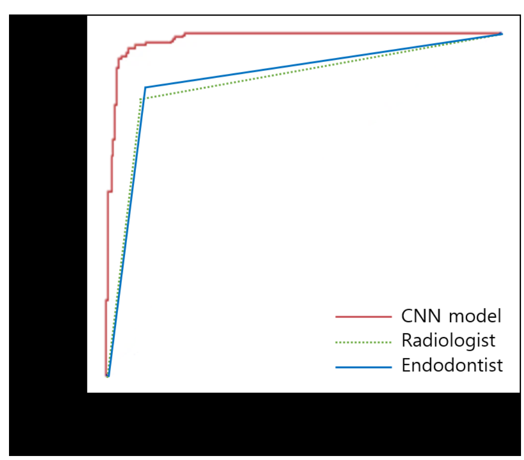

Figure 2 Receiver operating characteristic (ROC) curves for the CNN model and the specialists. The area under the curve (AUC) values were 0.982, 0.872, and 0.885 for the CNN model, radiologist, and endodontist, respectively.

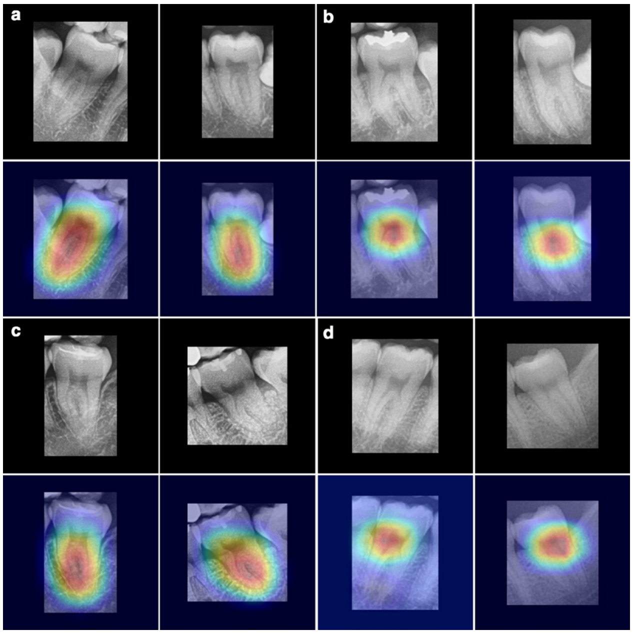

Figure 3 Representative examples of heat map images generated by using the Grad-CAM method for, a. True positive, b. True negative, c. False positive, and d. False negative. Original images (top) and overlapped on the original image (bottom). The red color highlights the activation region associated with the predicted class.

non-C-shaped canals (Figure 3b), the root furcation was extracted as the main image feature used for the classification. In case of misclassification, when a non-C-shaped canal was classified as C-shaped, visualization features similar to true positive were shown (Figure 3c). When a C-shaped canal was classified as non-C-shaped, it was done in the pulp chamber area, which is similar to a true-negative result (Figure 3d).

Discussion

In this study, deep-learning based on CNNs was used to predict C-shaped canals by analyzing panoramic images. Research in this field of dentistry mainly focusses on image analysis using deep neural models based on CNNs.[15] CNN models have showed excellent performance in various image analyses, including classification, detection, and segmentation. Studies using CNN in dentistry are being conducted for detection and classification of teeth,[20] detection of oral structures including pathologies,[21] segmentation of teeth or mandibular canal,[22] detection of carious lesions,[10] detection of osteoporosis[13] or sinusitis,[12] detection of cephalometric landmarks,[14] classification of facial features,[23] detection of periodontal bone loss,[24] and classification of root canal fillings[25] and root morphology.[26] Early studies simply assessed the accuracy of the CNN model, and the number of datasets was small. Recent studies have presented results with outcome metrics such as accuracy, sensitivity, specificity, positive-predictive value (PPV), negative-predictive value (NPV), AUC, or F1-score, and the number of datasets is much larger. In addition, some studies compared the performance of CNN models and dentists, while others compared the performance of several CNN models. In the studies that compared CNN models to dentists, the CNN model showed at least similar or better performance. In this study, accuracy, sensitivity, specificity, precision, and AUC were calculated to compare the diagnostic performance of the CNN model with the diagnosis made by dental specialists. The CNN model showed better performance than the specialists in predicting C-shaped canals.

In the field of endodontics, studies on the detection of apical lesions[9,27] and VRF[28] have been published. However, these studies had limitations in setting a clinical reference standard. Although a number of observers have set reference standards by consensus, these clinical reference standards are not error-free, and care must be taken when interpreting the results.[29] In this study, the C-shaped canal was identified in the axial view of the CBCT image, and this was used as the gold standard. In order to determine whether it was a C-shaped canal, serial CBCT images were evaluated by rolling from the pulp chamber to the apex in the axial direction. The C-shaped canal is one that has all of the following three features: fused roots, a longitudinal groove on the lingual or buccal surface of the root, and at least one cross-section of the canal belonging to the C1, C2, or C3 configuration.[17]

The C-shaped canal morphology is of clinical importance because it has a poor prognosis in terms of shaping, cleaning, and obturation.[2] Therefore, predicting the C-shaped canal through radiographs before root canal therapy is helpful in the treatment process. However, Lambrianidis et al[4] stated that only a small percentage of C-shaped canals in mandibular second molars were recognized on preoperative radiographs. Further, Cooke and Cox[30] stated that it is not possible to diagnose C-shaped canals on preoperative radiographs because the fin is so thin that they appear as two separate roots on radiographs. However, some studies have shown that C-shaped canals in mandibular molars have common characteristics such as radicular fusion or proximity, large distal canal or a narrow mesial canal, and a blurred image of a third canal in between.[5,31] On periapical radiographs, C-shaped canals are more likely to be recognized during working length determination or canal filling. If an instrument or filling material apparently penetrates the root canal, it can be predicted that it is a C-shaped canal.[4] Clinical diagnosis is possible by confirming the shape of the pulpal chamber floor via the access cavity. The combination of clinical examination under a microscope and radiographs is the most effective method to diagnose C-shaped canals.[32]

Previous studies using CNNs were only focused on classifying certain individuals with correct answers. The reason for drawing the conclusion and the validity of the process could not be logically explained, and this was a black box. However, in recent years, explainable AI has been developed to understand the AI system's decision-making and make predictions more reliable. Grad-CAM, which was used in this study, makes the CNN-based model more transparent through visual explanations.[19] Tamse and Kaffe[33] reported that 9% of 1049 mandibular second molars had a conical form. However, they did not evaluate the relationship between the conical form of the root and the existence of a C-shaped canal. In this study, the converging canals were extracted as the main image feature of the mandibular second molars with C-shaped canals by Grad-CAM. However, the CNN model identified the non-C-shaped canals by looking at the root furcation. In a study comparing panoramic images with the corresponding CBCT images of the mandibular second molars, two separate roots, either divergent or parallel, were most common in molars with non-C-shaped canals.[3]

In the existing machine-learning-based image analysis, features suitable for each application are manually extracted from the image and then processed with a shallow network. On the other hand, CNN was implemented as an end-to-end method that self-extracts features at a layer consisting of convolution operations. That is, the feature extraction and processing are integrated and are performed together. In general, the deeper the structure of the network, the better we can solve complex problems and achieve better performance, but lack of data can lead to overfitting. Therefore, in this study, transfer learning was performed to develop a model with excellent generalization performance using a small amount of panoramic data. Transfer learning is a method applied to a target field using a deep learning model learned in a field with a relatively large amount of data.[34] In this study, only the feature extractor was used in the deep learning model trained using ImageNet, and the weights of the learned feature extractor were used as the initial values for the target model and retrained together with the weights of the classifier.

This study has several limitations. First, in this experimental data set, the prevalence of the C-shaped canal of mandibular second molars was 43.5%, which was similar to previously reported high prevalence in Koreans.[35,36] Therefore, it provided an undue advantage for training AI. Second, we assessed manually cropped image segments from panoramic radiographs. Using segmentation algorithms first and then applying CNNs for predicting C-shaped canals on image segments may be a further, worthwhile, technical direction. Third, a more detailed and accurate visualization analysis is needed. Further research will be needed with larger datasets and more detailed class activation maps to establish the radiological characteristics of the C-shaped canals.

Panoramic radiography is a common diagnostic image modality that is used in treatment planning and to decide the prognosis. There is a limit to clinical application only with the results of this study. However, if we combine the results of numbering teeth in a panoramic image,[20] for example, for detecting dental caries or periodontal bone loss,[24] detecting apical lesions,[9] and detecting osteoporosis,[13] maxillary sinusitis[12] or cysts and tumors,[21] it will be possible to create a fully automated diagnostic imaging system. At the same time, it is important to remember that the opinions presented by AI are reference information for the operator, and the final decision must be made by the dentist. Therefore, as AI progresses, clinicians must become more specialized in this field and develop the ability to understand AI technology and interpret the results subjectively.

Conclusion

In conclusion, the deep-learning model has shown promise as a tool to predict C-shaped canals in mandibular second molars on panoramic radiographs and assist clinicians with dental image interpretation.

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