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Comparison between 2 Models in Detection of Second Mesio-Buccal Canal of Maxillary First Molars on CBCT Images using Deep Learning

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KEYWORDS
artificial intelligence; CNN ; deep learning; second mesiobuccal canal; MB2 canal; endodontics ; cone beam computed tomography; CBCT.

ABSTRACT:

Aim: The aim of the present study was to compare two newly developed CNN models to accurately classify MB root canals in maxillary molars to determine presence or absence of MB2 canal on CBCT compared to radiographic assessment performed by expert radiologists.

Methodology: CBCT scans of 41 patients were imported to 3d slicer software to crop the scans with two different methods: the first one is through cropping the MB root only and the second method was through cropping the whole Maxillary molar tooth with its 3 roots (Mesiobuccal – Distobuccal -Palatal). The annotated data was divided into two groups: 80% for training and validation and 20 % for testing. The data was used to develop 2 classification models based on CNN. Confusion matrix and receiver-operating characteristic (ROC) analysis were used in the statistical evaluation of the results of the classification model.

Results: The results of testing the first model (using the images of the cropped Maxillary1st molar with its 3 roots (MB – DB and Palatal) : F1-score, accuracy, recall and precision values were found to be 0.86, 0.89, 1.0 and 0.75, testing loss was 0.97 and the AUC value was found to be 0.83. While the testing results of using the images of the cropped mesiobuccal root only of Maxillary1st molar : F1-score, accuracy, recall and precision values were found to be 0.93, 0.87, 1.0 and 0.87, testing loss was 0.40 and the AUC value was found to be 0.57.

Conclusion: The performance of training CNN model using images of cropped MB root only or cropped the whole Maxillary molar roots are both effective in detection of MB2 in maxillary first molar , however, using the latter images showed slightly better performance.

Main Text

Introduction:

A multitude of studies and discussions have centered on the presence of a second canal in the mesiobuccal (MB) root of maxillary molars, as it is widely posited that one of the primary causes of endodontic failure in maxillary first molars is the challenge of identifying and managing these second mesiobuccal (MB2) canals [1]. Literature indicates that whereas MB2 canals in maxillary first molars are identified in over 70% of in vitro investigations, they are clinically observed in fewer than 40% of patients [2]. Cone beam computed tomography (CBCT) is an innovative tool in endodontics, offering

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numerous benefits such as three-dimensional (3D) imaging of root canal systems with less radiation exposure, enhanced resolution, and the absence of superimposition [3]. Researchers have assessed the efficacy of CBCT in finding MB2 canals, and it has been proposed as a dependable technique for their detection[1]

In clinically pertinent scenarios, such as minor lesions on root-filled teeth, the accuracy of CBCT is significantly diminished (sensitivity 0.63, specificity 0.69) [2]. Furthermore, clinician-dependent interpretation of CBCT images continues to exhibit limited inter- and intra-observer agreement. Computer-aided detection and diagnosis (CAD) has been extensively utilized in biomedical image analysis beyond the field of dentistry [4].

Technological advances in Oral and Maxillofacial Radiology have extended beyond imaging modalities and hardware. The quality and depth of radiology's contribution to patient care and population health, as well as radiologists' work flow, are expected to undergo a marvelous revolution in the next ten years with the applications of artificial intelligence (AI) [5].

CAD systems are computer software that aid in the detection and diagnosis of diseases by offering an impartial "second opinion" to the image interpreter, with the objective of enhancing accuracy and decreasing analysis time [6]. Due to the swift advancement of Deep Learning (DL) algorithms in image-centric applications, CAD systems may now be trained using DL to enhance their capabilities, hence providing superior assistance to doctors using artificial intelligence (AI) [7].

Despite a number of recent studies have demonstrated the feasibility of identifying canals using AI **[8-10],** only two studies have focused on maxillary molar MB root canal detection, and both of those studies have looked at the morphology and quantity of canals.**[11]**; **[12]**. The aim of the present study was to compare two newly developed CNN models to accurately classify MB root canals in maxillary molars to determine presence or absence of MB2 canal on CBCT compared to radiographic assessment performed by expert radiologists.

Methodology:

Study design

Our research is a retrospective study in which data collection occurred prior to the execution of index tests and the reference standard. This study compare the accuracy of two newly developed deep learning model (DLM) for the automatic detection of the MB2 canal in maxillary first molars by comparing their performance with that of experienced radiologists, who provide the ground truth, and then comparing them with each other. The results are presented in terms of accuracy, sensitivity (Recall), positive predictive value (Precision), and receiver operating characteristic curve, thus categorizing it as a diagnostic accuracy study.

This study was conducted under the consent of the Research Ethics Committee of the Faculty of Dentistry, Cairo University, on January 5, 2022, and adheres to the Declaration of Helsinki (2013).

Sample Size Calculation

A power analysis was carried out to guarantee that there was enough data to support a two-sided statistical test of the null hypothesis, which states that the DL model's accuracy is comparable to the radiologist's perspective. Drawing on a previous study's findings, we use a 95% confidence interval and a specificity value of 88.0% for the DL group, while the ground truth is 100% specific [13].

Sample size calculation was approved by the Medical Biostatistics Unit, Faculty of Dentistry, Cairo University on 24/7/2021.

Radiographic dataset

A CBCT database maintained by the Oral and Maxillofacial Radiology department at Cairo University's Faculty of Dentistry in Cairo, Egypt, was mined for the CBCT scans utilized in this investigation. For the patients who were considered, the scans were an integral aspect of the diagnostic and therapeutic processes.

Scans of the erupted first molar in the upper jaw with full root development; the voxel size should not be more than 0.1 mm were included. Nevertheless, we did not include first molars from the maxilla that had any abnormalities in their development, resorption of the root canals (external or internal), calcification of the root canals, prior root canal treatment, restorations, or root caries. We also did not include CBCT pictures that had artifacts, high scatter, or poor quality that prevented an accurate evaluation, images with a field of view (FOV) smaller than a single arch, or voxel sizes larger than 0.1.

The imaging technique was standardized and used for all scans. The following parameters were used: exposure time 12 seconds, voxel size 0.75-0.1 mm, field of view 5x5 - 5x8 - 8x8 cm, and Planmeca Promax 3D MID CBCT Machine. The study comprised 41 maxillary molars, 20 of which had MB2 canals and 17 of which did not.

Patient declaration of consent:

Patient declaration of consent was obtained in a Helsinki declaration consent form in their native language (Arabic).

Radiographic Annotation (Ground truth)

CBCT scans were imported into the 3D Slicer software program (open-source free software version 5.2.2, Harvard University, USA) for data annotation.

The detection of the radiologist-dependent MB2 canal was conducted on axial cuts over the whole length of the root and subsequently identified as either present or absent, with confirmation and consensus from two Oral and Maxillofacial Radiologists (OMFR) with (8 and 15 years of experience). This classification functions as the **ground truth (Fig.1).**

The scans were cropped with two different methods: the first one is through cropping the MB root only and the second method was through cropping the whole Maxillary molar tooth with its 3 roots (MB-DB-Palatal).

Then, cropped scans were saved in NiTi Format from shared with the AI team in 2 separate folders.

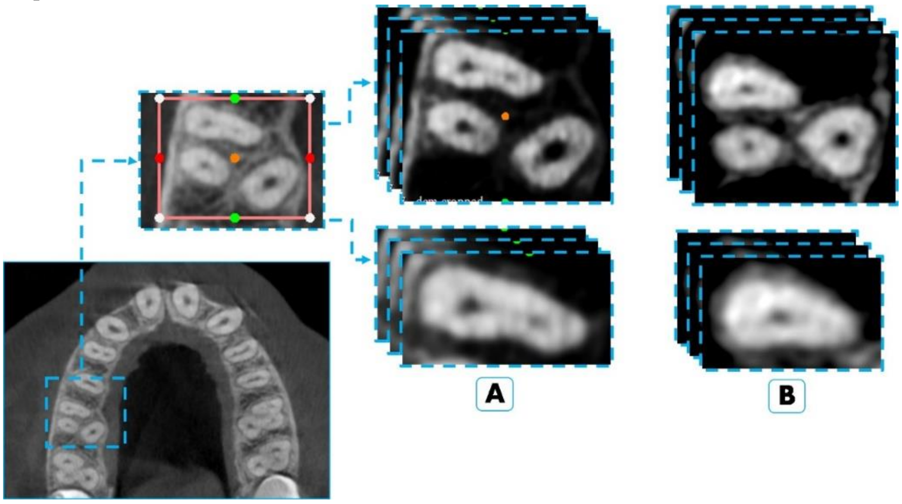

Fig.1– Illustration of the set of axial images used for training the model in the classification process a. With MB2 B. Without Mb2 with 2 different cropping methods.

Development of the AI models

The classification and segmentation algorithms were developed in the Python environment (v3.9.19; Python Software Foundation, Wilmington, DE, USA) using the TensorFlow library. Mathematical processing in the model's training was performed with a Lenovo Legion y540, intel i7-9750H, 16GB DDR4 RAM, GTX 1660 ti 6GB (Lenovo Group Limited China) at the Faculty of Computer Science MSA University, Cairo, Egypt.

A total of 37 anonymized CBCT volumes were used for training of the first model using the set of images of the cropped MB root only , while the second model was trained on total of 41CBCT scans of the cropped images of the whole Maxillary first molars . The dataset was separated into training and validation (80%) and testing (20%) groups randomly. Our study approached the process of detection of MB2 canal using CNN based model for classification trained on our data.

Convolutional Neural Networks (CNNs) automatically learn spatial hierarchies of features through convolutional layers, making them very successful at processing picture data. This is why CNNs were used as the basis for the classification model. Contrary to more conventional ML models that depend on human feature extraction, convolutional neural networks (CNNs) can natively extract intricate patterns like edges, textures, and

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forms from unprocessed images. Because of this, picture categorization jobs are a good fit for them. To improve computing efficiency and minimize overfitting, pooling layers reduce dimensionality; convolutional layers use filters to scan the input images and find important characteristics at different levels of abstraction. Additionally, convolutional neural networks (CNNs) are resilient when it comes to identifying distorted or diversified images since they are invariant to transformations such as scaling, shifting, and rotation. Convolutional neural networks (CNNs) are ideal for developing robust, scalable picture classification models due to their good feature extraction automation capabilities and their capacity to generalize across big datasets.

CNN Model architecture:

After scanning the CBCT scans into consecutive pngs, the first model sampled each scan into 19 channels while the second model sampled each scan into 29 channels to gather the most important volumetric data slices, focusing on diagnostic information. The sampling approach was developed to simplify 3D Nii images while keeping enough depth for the model to discern features across slices. Through the selected number of channels, the model balanced computational efficiency with spatial information from the original data. CNN processed the images as a sequence of connected 2D slices that represented the 3D structure using these channels as input layers. Resizing the photos standardized their dimensions and improved batch processing and training computing performance. This ensured consistent input data size while preserving essential image attributes needed for accurate classification and uniform CNN model input dimensions. This downsizing step reduces computing effort while preserving classification-critical characteristics. The model learned spatial correlations across layers using these channels, improving its capacity to spot subtle patterns. To ensure model generalization on unseen data, the data was separated into training, validation, and test sets after preprocessing **(Fig.2-3).**

The first classification model underwent training for 5982 epochs with learning rate of 0.000008 ,the patch size was 8 and the optimizer used was Adam with a total of 6264513 extracted parameter, while the second model underwent training for 67 epochs with learning rate of 0.00001 ,the patch size was 8 and the optimizer used was Adam with a total of 2,005,125 parameter extracted. After that , the customized deep-learning model was tested on an independent test dataset, and the best model was recorded **(Fig.4-5).**

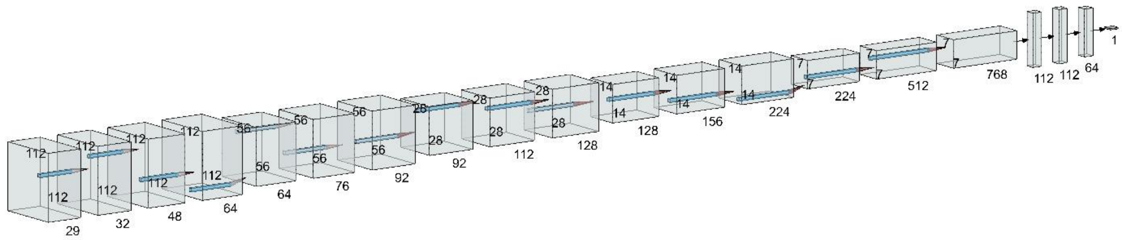

Fig.2– pipeline for the first CNN model architecture used for MB2 detection using cropped images of Maxillary 1st molar with its 3 roots.

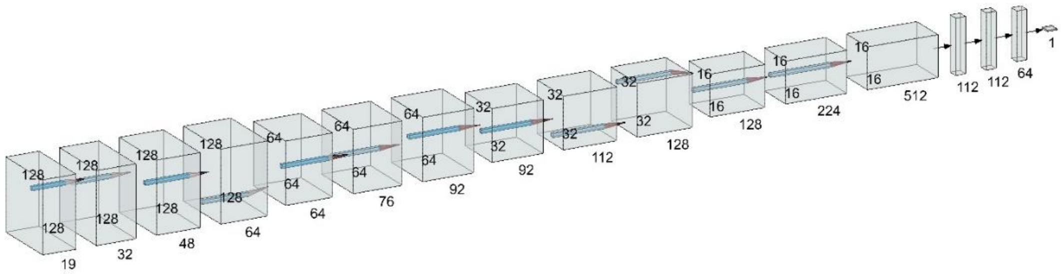

Fig.3– pipeline for the second CNN model architecture used for MB2 detection using cropped images of MB root only.

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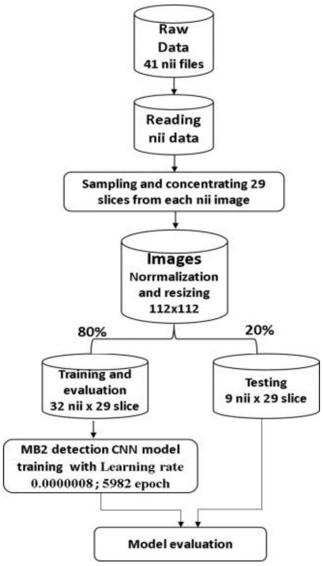

Figure.4– Diagram of the first CNN model development steps.

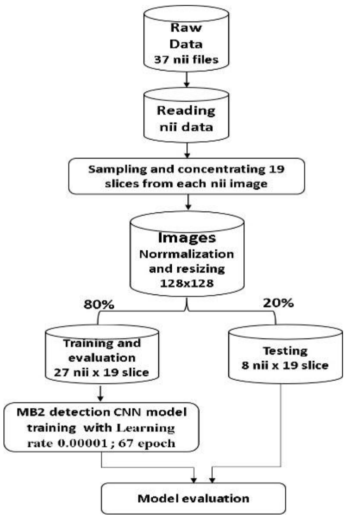

Figure.5– Diagram of the second CNN model development steps.

Evaluation metrics:

The accuracy of the deep learning models (DLM) versus the Ground truth (GT) was evaluated by a dichotomized outcome of "presence of MB2" and "absence of MB2" per MB root of DLM was compared with GT, where the GT was determined and agreed by 2 maxillofacial radiologist with 8 and 15 year-experience.

The results of the test group were put into a confusion matrix of true positive (TP), false positive (FP) and false negative (FN) parameters, where (TP) is the accurate prediction of the image with MB2, (FP) the incorrect prediction of the image with the MB2 and (FP): Incorrect prediction of the image without MB2, (TN) :) is the correct prediction of the image without MB2.

Based on this confusion matrix, precision, recall (sensitivity) and F1 score were calculated and graded according to the ranking for diagnostic tests by Leonardi Dutra et al **[14]** with scores .80% considered excellent outcomes, between 70% and 80% good, between 60% and 69% fair, and ,60% as poor. Roots with 1 canal used as control group. The definitions of the evaluation metrics are described in details in a previous study**[12].**

Accuracy evaluates the overall correctness of the model's predictions, whereas precision and recall focus on the quality of positive and negative predictions, respectively. The F1 Score provides a suitable balance between precision and recall, making it a more equitable metric for evaluating classification algorithms. The area under the curve (AUC) of the receiver operating characteristic (ROC) curve was also computed.

Results:

The simple classifier model successfully predicted the presence of Mb2 using the 2 sizes of images with slightly different accuracy where the first model showed a higher performance than the second model represented by the following:

1.The results of testing the first model (using the images of the cropped Maxillary1st molar with its 3 roots (MB – DB and Palatal) : F1-score, accuracy, recall and precision values were found to be 0.86, 0.89, 1.0 and 0.75, testing loss was 0.97 and the AUC value was found to be 0.83 (**Table 1**).

While the training results : F1-score, accuracy, recall and precision values were found to be 0.92, 0.91 , 0.85 and 1 , training loss was 0.19 and the AUC value was found to be 1.

. **Figure. 6 (a-b)** presents the study results along with confusion matrix. **Figure. 7 (a-b)** presents the Receiver-operating characteristic (ROC) curve of this group.

Table 1:Results of the first classification model.

C	Training	Testing
F1 score	0.92	0.86
Accuracy	0.91	0.89

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Precision	**1.0**	0.75
Recall	**0.85**	1.0
Loss	0.19	0.97
AUC	1	0.83

2. The testing results of using the images of the cropped mesiobuccal root only of Maxillary1st molar : F1-score, accuracy, recall and precision values were found to be 0.93, 0.87, 1.0 and 0.87, testing loss was 0.40 and the AUC value was found to be 0.57.

While the training results: The F1-score, accuracy, recall and precision values were found to be 0.76, 0.76, 0.78 and 0.73, training loss was 0.52 and the AUC value was found to be 0.8 **(Table 2**) .

Figure. 6 (c-d) presents the study results along with confusion matrix. **Figure. 7(c-d)** presents the Receiver-operating characteristic (ROC) curve of this group.

Table 2:Results of the second classification model.

c	Training	Testing
F1 score	0.76	0.93
Accuracy	0.76	0.87
Precision	**0.73**	0.87
Recall	**0.78**	1.0
Loss	0.52	0.4
AUC	0.8	0.57

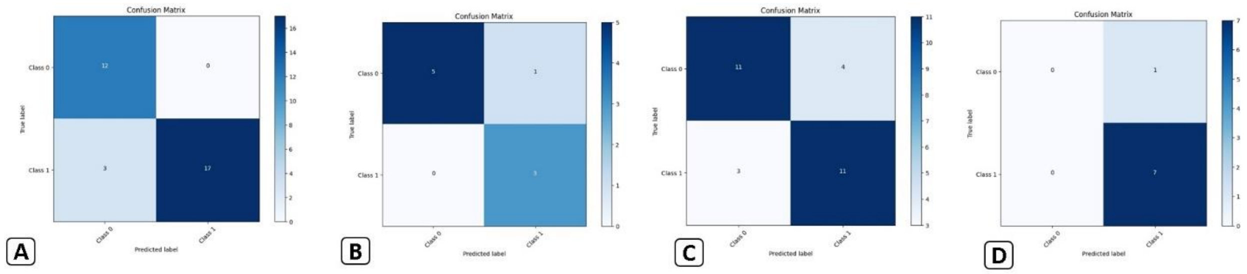

Figure 6 :Confusion matrix. A. For training B. For testing using the images of the cropped Maxillary1st molar with its 3 roots . c. for training D. For testing using the images of the cropped mesiobuccal root only .

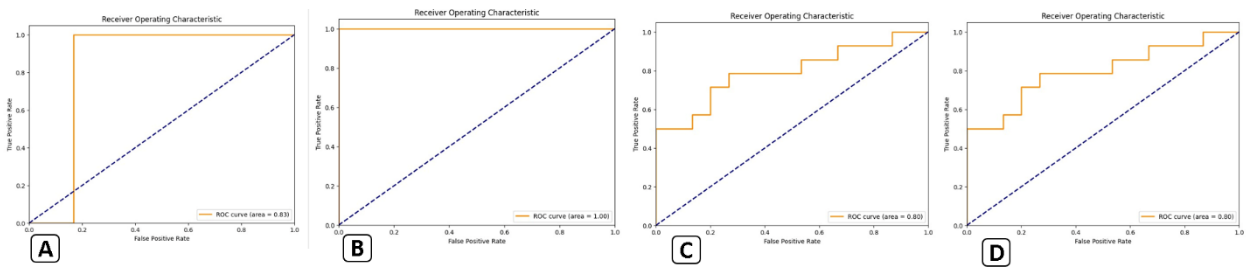

Figure 7 :Receiver-operating characteristic (ROC) curve. A. For training B. For testing using the images of the cropped Maxillary1st molar with its 3 roots . c. for training D. For testing using the images of the cropped mesiobuccal root only.

Discussion:

Using our modified CNN model, the MB2 canal was identified from axial slices of CBCT images of maxillary molar teeth in this study. Few studies have used AI algorithms to identify MB2 canals, despite the abundance of research on CBCT imaging for root canal system anatomical abnormalities [15]. Research by **Albitar et al.** [11] examined the steps involved in validating and preparing data for MB2 detection using algorithms based on artificial intelligence. Although CBCT images were utilized in their study, the sole objective was to identify

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MB2 in maxillary molars that had undergone endodontic treatment. Nevertheless, CBCT images were used to segment MB2 canals in maxillary molar teeth that had not had endodontic treatment in the present investigation.

In order to identify MB2 canals in CBCT images of maxillary molars, **Duman et al.** employed a pretrained deep learning model named (YOLO 5). This model is built on a CNN architecture. But in our research, we trained, verified, and tested a U-NET-based model that our AI team had developed [12].

The findings of this study indicate the following outcomes: initially, the deep learning algorithm exhibited steadily increasing performance in terms of accuracy in identifying MB2 canals, increasing from 87% using the cropped images of MB root only of maxillary 1st molars to 89% using the cropped images of maxillary 1st molars with its three roots in the testing phase

The dimensions of the cropped input image in the CNN models employed in this study significantly influence the model's performance. The multi-scale feature in the head area facilitates the rapid and effortless detection of targets of varying sizes. The MB2 canal's projection on the axial section image exhibits a restricted area, and the algorithm tailored to our dataset yielded excellent outcomes in our investigation.

Research on artificial intelligence in endodontics has become more popular in the last several years. With sensitivity(0.93), specifcity (0.88), positive predictive (0.87), and negative predictive (0.93), Setzer et al. [13] achieved excellent lesion detection accuracy using a deep-learning segmentation based on U-Net architecture on CBCT images containing 61 lesioned and non-lesional roots. In contrast, Orhan et al. assessed the model's accuracy in lesion localization prediction using CBCT images and a U-Net-like architecture for periapical lesion detection. They also employed binary voxel-based intersection and prediction metrics on the base true mask combination (IoU). This DL model has a 92.8% reliability rate, meaning it identified 142 out of 153 periapical lesions [16]. Zheng et al. [17] presented a new model that combines Dense U-Net—an improved version of the U-Net architecture—with oral-anatomical information for lesion diagnosis in another work that used AI algorithms on CBCT images.

In addition, AI studies have been conducted to determine root canal length, which is one of the factors affecting the success of endodontic treatment. Shagiri et al. [18] used artificial neural networks (ANN) for apical foramen fixation in fifty straight single-rooted teeth inserted into the alveolar bone of the cadaveric skull using periapical radiographs and reported a high performance in determining anatomical narrowing. In addition, vertical root fractures, which are of great importance and difficult to diagnose by clinicians, have been detected using CNNs on panoramic radiographs [19] and using probabilistic neural network (PNN) in intact or endodontically treated teeth in CBCT and panoramic radiographs [20].

Furthermore, there are published research that employ DL algorithms to detect different root canal morphological changes in mandibular molars. It was asserted by Jeon et al. [21] that C-canal second molars on panoramic radiographs could be located using the DL algorithm Xception. This CNN model outperforms radiologist (0.872) and endodontist (0.885) models in terms of area under the curve (AUC), thanks to its ability to distinguish between domain-focused and relationship-based convolution filters.

3D imaging with CBCT provides a more precise assessment of the root and canal designs and a more comprehensive inspection than 2D radiography. Using CBCT images, Sherwood et al. [10] trained a DL system using U-Net, residual U-Net, and Xception U-Net architectures to identify C-shaped canals in mandibular second molars. They found that after segmenting the C-shaped canals in their investigation, Xception U-Net and residual U-Net outperformed U-Net. In a separate investigation, 760 mandibular first molars from 400 patients were analyzed using panoramic radiographs and the AlexNet and GoogleNet algorithms to differentiate between single and multiple roots in the distal roots [22]. These two CNN architectures outperformed the radiologist with over 20 years of expertise in terms of diagnosis accuracy.

Some limitations exist in the present investigation. The effect of root canal filling artifacts on model performance is unclear. used in teeth that have undergone endodontic treatment but have had the MB2 canal omitted. On the other hand, further research utilizing DL techniques to

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identify MB2 and other additional canals in maxillary molar teeth is expected to build upon this discovery.

According to the results of the present study, we can conclude that the performance of training CNN model using cropped MB root only or Cropped the whole Maxillary molar roots are both effective in detection of MB2 in maxillary first molar , however, using the latter images showed slightly better performance.

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