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Original Article

Evaluation of artificial intelligence for detecting impacted third molars on cone-beam computed tomography scans

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ABSTRACT

Purpose: The aim of this study was to evaluate the diagnostic performance of artificial intelligence (AI) application evaluating of the impacted third molar teeth in Cone-beam Computed Tomography (CBCT) images.
Material and methods: In total, 130 third molar teeth (65 patients) were included in this retrospective study. Impaction detection, Impacted tooth numbers, root/canal numbers of teeth, relationship with adjacent anatomical structures (inferior alveolar canal and maxillary sinus) were compared between the human observer and AI application. Recorded parameters agreement between the human observer and AI application based on the deep-CNN system was evaluated using the Kappa analysis.
Results: In total, 112 teeth (86.2%) were detected as impacted by AI. The number of roots was correctly determined in 99 teeth (78.6%) and the number of canals in 82 teeth (68.1%). There was a good agreement in the determination of the inferior alveolar canal in relation to the mandibular impacted third molars (kappa: 0.762) as well as the number of roots detection (kappa: 0.620). Similarly, there was an excellent agreement in relation to maxillary impacted third molar and the maxillary sinus (kappa: 0.860). For the maxillary molar canal number detection, a moderate agreement was found between the human observer and AI examinations (kappa: 0.424).
Conclusions: Artificial Intelligence (AI) application showed high accuracy values in the detection of impacted third molar teeth and their relationship to anatomical structures.

1. Introduction

Tooth impaction is a common pathological dental condition that develops due to diverse etiological factors such as systemic, local, and genetic. Its prevalence ranges from 0.8 % to 3.6 % in the general population and the prevalence of third molar impaction ranges from 16.7% to 68.6% [1–3]. However, the most common impaction reason is the lack of space on the arc and obstacles in the eruption path of the tooth. Impacted teeth can cause dental infections such as pericoronitis, periodontitis, orofacial pain, TMJ disorders, pathological fractures, cysts, and neoplasms. It can also damage adjacent teeth. For all these reasons, tooth extraction may require. Before performing dental surgical procedures, the root canal numbers of these teeth and their relationships with neighboring anatomical structures should be evaluated. The most common radiographic methods in the diagnosis of tooth impaction are periapical or panoramic radiographs. However, due to the superimpositions, it is not possible to evaluate the root canal number, shape, the relationship of the teeth in the upper jaw with the maxillary sinus, and the inferior alveolar canal in the lower jaw. For this reason, CBCT is accepted as the gold standard in the radiographic evaluation of impacted third molars [1,4–6]. In addition to this, with the idea of reducing the errors in subjective evaluations related to the person, artificial intelligence applications have started in dental radiology. Recently, significant developments in technologies related to artificial intelligence have taken place in many areas. In the medical field, there are studies and applications that it is effective in determination of the diagnosis and prognosis, automatic prediction of pathology, and

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diseases, especially by recording information about the anamnesis and symptoms [7,8].

Artificial intelligence (AI) is defined as the ability of a machine to perform complex tasks imitating cognitive functions of humans such as problem-solving, object and word recognition, and decision making [8]. Machine learning is defined as an AI area where computers automatically learn from the accumulation of data. It refers to the learned situation when it improves performance in future tasks after observations are made on the data. Machine learning algorithms develop with increased exposure to data; they do not just rely on rules, but they develop with experience, they learn to give specific answers by evaluating large amounts of data. Deep learning is a subset of machine learning and forms the basis of most AI tools for image interpretation. Deep learning structures referred to as convolutional neural networks (CNNs), which can extract many features from abstracted layers of filters, are mainly used for processing large and complex images and has multiple layers of backpropagation algorithms (Fig. 1).

These layers accumulate data from the inputs, and the AI system provides step-by-step output after learning new features from the data [8–12]. In short, machine learning is one of the main subfields of artificial intelligence that enables a computer model to learn and predict patterns by recognizing them. It is trained by doing a lot of case analysis just like a radiologist. The AI model develops thanks to increased training on new and larger datasets [8,13,14].

There are many studies in the medical field about diagnostic AI applications such as detection of lymph nodes, polyps, aneurysms, benign malignant tumors, bone age detection, orthognathic surgery [15–19].

Studies in the field of oral and maxillofacial radiology are relatively new, and most have been carried out on panoramic radiographs [8,9,13,20–23]. However, considering the importance of the three-dimensional configuration of impacted teeth and their relationship with anatomical structures, it is necessary to perform these evaluations on three-dimensional images.

In a recent systematic review by Kang et al. [24] stated that radiographic findings, such as depth of impaction, proximity of the tooth to the mandibular canal, surgical technique, intra-operative nerve exposure, and surgeon's experience were high risk factors of inferior alveolar nerve deficit after surgical removal of impacted third molar teeth.

Hence, the aim of this study was to evaluate the performance of an artificial intelligence application according to CBCT, which is used as the gold standard in determining the impacted third molar teeth, determining the tooth structure (root-canal number), and the relationship of these teeth with neighboring anatomical structures.

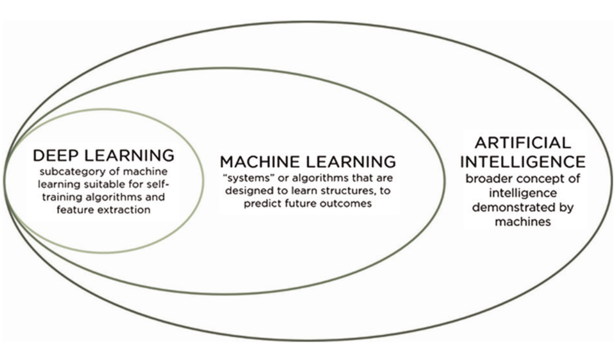

Fig. 1. The schematic drawing of artificial intelligence and its concepts.

2. Material and methods

In this retrospective study, CBCT data of 130 impacted third molar teeth from 65 patients, which were performed for various dentomaxillofacial reasons in our clinic were included. The research protocol was approved by the Non-interventional Clinical Research Ethical Committee of Eskisehir Osmangazi University (decision date and number: 28.05.2019/48) and was performed under the principles of the Declaration of Helsinki.

2.1. Imaging

The same CBCT scanner (Promax 3D Mid; Planmeca, Helsinki, Finland) was used for all patients, who were in a standing position during imaging. Diagnostic settings were as follows: 94 kVp, 14 mA, 360° rotation, 27 s. The scanner offers multiple fields of view (FOVs) allowing the dentist to select the optimum scan on a case-by-case basis.

2.2. Evaluation

Manual examination of the images was done by a single dentomaxillofacial radiologist (E.B.) using the CBCT software system (Romexis Version 4.3.0). Impacted tooth numbers, root/canal numbers of teeth, relationship with adjacent anatomical structures (inferior alveolar canal and maxillary sinus) were recorded. After this step, files were randomly uploaded to the deep convolutional neural network (Diagnocat, Inc.). The detection of parameters related to impacted teeth by the manual and artificial intelligence (AI) methods were compared.

2.3. Model pipeline

A third molar study prepared by Diagnocat includes a panoramic reformat of a specified jaw and three slice sections with different slice orientation: vestibulo-oral, axial, and mesiodistal. Slice sections that are accompanied by tomographic images highlight the corresponding slices by cursor interaction. Diagnocat's approach to numbering and segment of the teeth and the mandibular canal is based on a deep convolutional neural network using a U-net-like architecture.

A set of different models of fully convolutional nature prepare teeth, jaws, and mandibular canal segmentations that are further used to build a panoramic ribbon of both a study image and a combined segmentation mask. All slices in a study are extracted from a region of interest (RoI) of a panoramic image ribbon with a 1.5 mm step for vestibulo-oral and axial slices and variable step for mesiodistal slices in a range that covers a whole tooth in the corresponding direction. ROI for different slice sections is extracted using specific context in different directions from different combinations of mask ribbon segmentations. ROI context for the vestibulo-oral section is calculated with an indent of 3 mm for mandible case and 6 mm for maxilla case in all directions from a combined segmentation mask of molar and jaw. RoI context for axial slices is calculated using vestibulo-oral RoI from the previous section, with 15 mm indent from the molar center in mesiodistal direction, and as a range of extracted axial slices in the axial direction. ROI context for the mesiodistal section is calculated using corresponding ROIs from previous sections and with 9 mm indent from a combined segmentation mask of molar and mandibular canal for mandible case and a molar in maxilla case.

The study uses panoramic reformats of a corresponding ROI as topogram images of vestibulo-oral and axial sections and an axial maximum intensity projection of a panoramic ribbon as a topogram image of the mesiodistal section. The mandibular canal

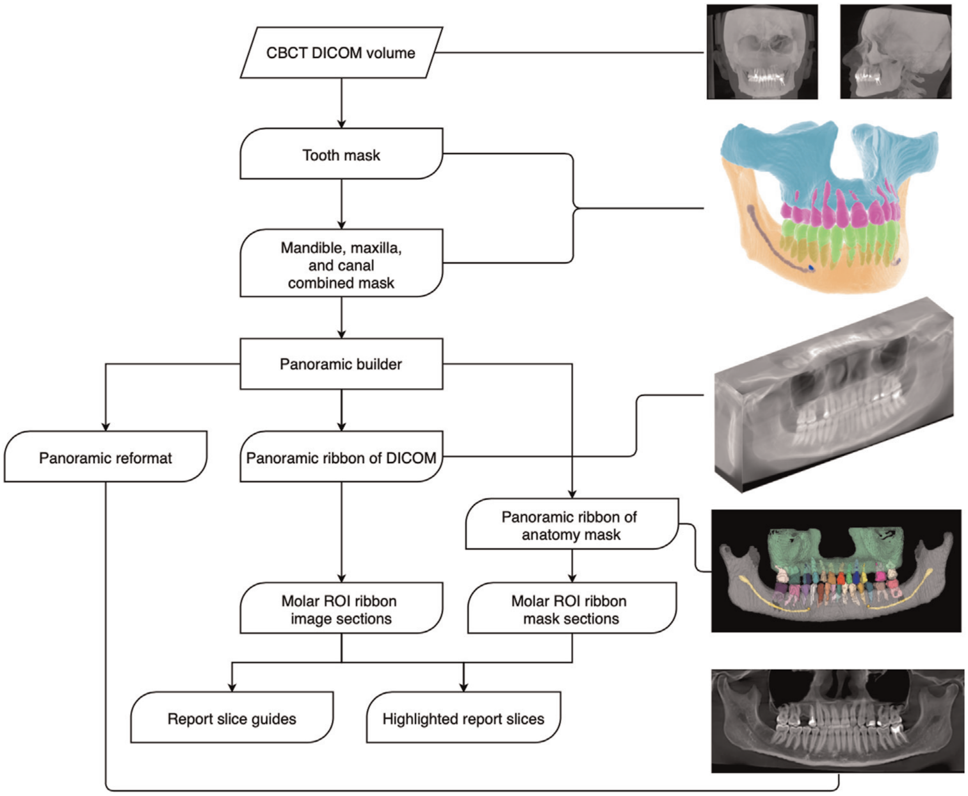

Fig. 2. AI Model pipeline is schematically shown.

area is highlighted with white color at all topogram images and slices where it intersects with a section ROI (Fig. 2 and 3).

2.4. Statistical analyses

Statistical analyses were performed on SPSS 21.0 Package Data Program (SPSS 21.0 Software Package Program, Inc., Chicago, IL, USA). Recorded parameters agreement between the manual method and deep CNN system was evaluated using the Kappa analysis.

3. Results

A total of 130 impacted third molar teeth, 42 maxillary, and 88 mandibular were evaluated in this study. The AI detected and numbered almost all teeth numbered except only four impacted teeth. In detail, 85 mandibular, 41 maxillary-impacted third molars were correctly numbered by the AI (96.9% in total). The program identified three of these four teeth as neighboring teeth and one of them as missing teeth. In total, 112 teeth were detected

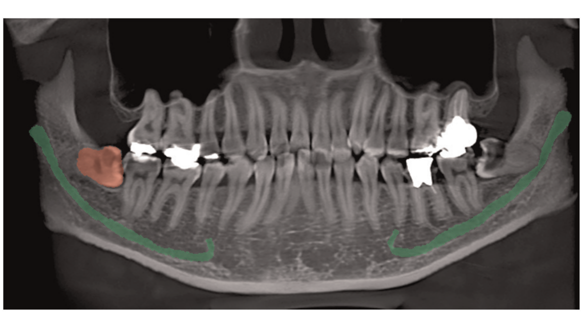

Fig. 3. The third molar and mandibular canal relations are schematically shown at panoramic reconstruction.

as impacted (86.2%) by AI. 10 of the 18 teeth that were not identified as impacted which were vertically positioned. The number of roots was correctly determined in 99 teeth (78.6%) and the number of canals in 82 teeth (68.1%). When comparing the manually and the AI examinations; there was a good agreement in the determination of the inferior alveolar canal in relation to the mandibular impacted third molars (kappa: 0.762) as well as the number of roots detection (kappa: 0.620). Similarly, there was an excellent agreement in relation to maxillary impacted third molar and the maxillary sinus (kappa: 0.860; For the maxillary molar canal number detection, a moderate agreement was found between manual and AI examinations (kappa: 0.424) (Table 1–3).

4. Discussion

Recent studies show that artificial intelligence applications developed through machine learning and deep learning, are promising for dentomaxillofacial radiology. The studies in the field of dental radiology focus on object detection, tooth detection, and teeth numbering [9–11,20,21,25,26]. Lee et al. [21] performed dental segmentation on panoramic radiographs and reported that they achieved high performance. They emphasized that these

Table 1
Impacted tooth and number detection frequencies of AI.

Accuracy	Impacted third molar	
	Impacted tooth detection	Tooth number detection
Right	86.2 % (n = 112)	96.9 % (n = 126)
False	13.8 % (n = 18)	3.1 % (n = 4)
Total	100 % (n = 130)	100 % (n = 130)

Table 2
Data of teeth whose tooth number is correctly detected in AI.

	Impacted third molar						
	Mandible				Maxilla		
	Canal detection	Canal relation detection	Root number detection	Canal number detection	Sinus relation detection	Root number detection	Canal number detection
Right	92.9% (n = 79)	85.9% (n = 73)	83.5% (n = 71)	64.7% (n = 55)	92.7% (n = 38)	68.3% (n = 28)	65.9% (n = 27)
False	7.1% (n = 6)	14.1% (n = 12)	16.5% (n = 14)	35.3% (n = 30)	7.3% (n = 3)	31.7% (n = 13)	34.1% (n = 14)
Total	100% (n = 85)	100% (n = 85)	100% (n = 85)	100% (n = 85)	100% (n = 41)	100% (n = 41)	100% (n = 41)

Table 3
The table shows the agreement between manual detection and detection by the system.

Relation	Impacted Third Molar		
	κ	p	n
Inferior Alveolar Canal/ Lower Impacted Molar	0.762	P<0.001	85
Maxillary Sinus/ Upper Impacted Molar	0.860	P<0.001	41
Root Number Accuracy	0.620	P<0.001	126
Canal Number Accuracy	0.424	P<0.001	126

*Landis and Koch (1977) that stated the agreement was: $\kappa < 0.2$, very low; κ 0.21–0.40, low; κ 0.41–0.60, moderate; κ 0.61–0.80, good; and κ 0.81–1.00, excellent.

results are also important for forensic identification [21]. Zhang et al. [27] have also announced that they have achieved significant improvements in the identification of teeth, thanks to the method they developed with deep learning. In their study, they performed teeth detection and classification on periapical radiographs and reported that they achieved high precision (95.8%) and recall (96.1%) values [27]. Tuzoff et al. [23] also reported that they found high precision for teeth detection and numbering on panoramic radiographs [23]. In these studies, a deep CNN based machine learning method has been generally used. However, Chen et al. [9] used the faster R-CNN method in their studies and they reported that the system obtained close results with the junior dentist in teeth numbering and detection [9], and obtained a relatively lower precision value than other studies in the literature. Based on these study results, it may be possible to conclude that deep CNN is more successful in teeth detection.

Most of the studies on teeth detection were performed on 2-D radiographs [9,20,23]. However, few studies are evaluating the effectiveness of artificial intelligence in teeth detection accuracy in 3-D radiographs [26]. Miki et al. [26] categorized the teeth on CBCT in 7 groups in their study. They have reported that they achieved high accuracy for the classification performance of teeth [26]. In this study, we examined the accuracy of teeth numbering of a program using a deep CNN based machine learning method on CBCT. In our study, only 4 of the 130 impacted teeth were numbered incorrectly. In line with the literature, the system had high accuracy.

Previous studies indicated that artificial intelligence was effective for the detection of dental caries and apical lesions [28–30]. Valizadeh et al. [28] reported that the artificial intelligence models they used did not achieve sufficient accuracy in determining enamel caries, but high accuracy in dentine caries [28]. Besides; Lee et al. [31] reported that dental caries could be detected in periapical radiographs with deep learning-based CNN applications [31].

Fourcarde and Khonsari stated that [32] CNNs are not replacement solutions for medical doctors, but will contribute to optimize routine tasks and thus have a potential positive impact on our practice. Specialties with a strong visual component such as radiology and pathology will be deeply transformed.

There are limited studies regarding the impacted teeth, the anatomical structure of these teeth, and their relationship with adjacent vital structures. In a recent study, the detection of the extra distal root in mandibular first molar teeth was evaluated in panoramic radiographs, but the gold standard. It was found that the deep learning system has high accuracy (86.9%) [33]. Jaskari et al. [34] also evaluated a deep learning system for automatic localization of the mandibular canals by applying a fully convolutional neural network segmentation on clinically diverse dataset of cone beam CT volumes. They stated that their deep learning model localizes mandibular canals of the voxel-level annotated set, highly accurate. The mean curve distance and average symmetric surface distance was 0.56 mm and 0.45 mm, respectively. Kwak et al. [35] generated an automatic mandibular canal detection using a deep convolutional neural network. The experiments were conducted with models based on 2D SegNet, 2D and 3D U- for a dental segmentation automation tool. The 2D U-Net in their study with adjacent images demonstrates higher global accuracy of 0.82 than other U-Net variants. The 2D SegNet showed the second highest global accuracy of 0.96, and the 3D U-Net showed the best global accuracy of 0.99. Our results are similar with these studies which we found a high accuracy for detecting the tooth number and mandibular canal segmentations with deep CNN system using U-net architecture.

5. Conclusion

In conclusion, the CNN method used in this study showed high accuracy values in the detection of impacted third molar teeth and their relationship to anatomical structures. Further algorithm and machine learning methods can be used for improving the detection of dentomaxillofacial anatomy and pathologies, especially for third molar detection.

Informed consent

Additional informed consent was obtained from all individual participants included in the study.

Authors' contributions

Each author is expected to have made substantial contributions to the conception. KO, ISB design of the work; ISB and EB interpretation of data and writing manuscript; EB the measurement and evaluation of images; ME, MG and ES developed artificial intelligence model, KO have drafted the work or substantively revised it.

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Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Conflict of interest

The authors declare that they have no conflict of interest.

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