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Evaluation of the Mandibular Canal by CBCT with a Deep Learning Approach

SUMMARY

Background/Aim: *The mandibular canal including the inferior alveolar nerve (IAN) is important in the extraction of the mandibular third molar tooth, which is one of the most frequently performed dentoalveolar surgical procedures in the mandible, and IAN paralysis is the biggest complication during this procedure. Today, deep learning, a subset of artificial intelligence, is in rapid development and has achieved significant success in the field of dentistry. Employing deep learning algorithms on CBCT images, a rare but invaluable resource, for precise mandibular canal identification heralds a significant leap forward in the success of mandibular third molar extractions, marking a promising evolution in dental practices.* ***Material and Methods****: The CBCT images of 300 patients were obtained. Labeling the mandibular canal was done and the data sets were divided into two parts: training (n=270) and test data (n=30) sets. Using the nnU-Netv2 architecture, training and validation data sets were applied to estimate and generate appropriate algorithm weight factors. The success of the model was checked with the test data set, and the obtained DICE score gave information about the success of the model.* ***Results****: DICE score indicates the overlap between labeled and predicted regions, expresses how effective the overlap area is in an entire combination. In our study, the DICE score found to accurately predict the mandibular canal was 0.768 and showed outstanding success.* ***Conclusions****: Segmentation and detection of the mandibular canal on CBCT images allows new approaches applied in dentistry and help practitioners with the diagnostic preoperative and postoperative process.*

Key Words: Deep Learning, Artificial Intelligence, Mandibular Canal, CBCT

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Introduction

The mandibular canal is a tube-shaped structure within the bone of the mandible and is an anatomical structure located in the corpus region. It starts from the mandibular foramen, close to the lingual surface of the mandible, and ends at the mental foramen. The vascular nerve package running inside the mandibular canal is the inferior alveolar nerve. The location of the mandibular canal is also very important due to the surgical procedures performed[1].

The position of the mandibular canal is very important during the extraction of the mandibular third molar teeth (MM3), which is one of the most frequently performed dentoalveolar surgical procedures in the lower jaw. Inferior alveolar nerve paralysis is the biggest complication during this procedure. This may result in temporary or permanent damage. Nerve damage can result in paresthesia, dysesthesia and hypoesthesia of the lower lip, lower teeth, gums[1,2].

Highly impacted MM3 may cause multiple complications in surgical procedures of third molars. Inferior alveolar nerve (IAN) injury is one of the most important and frequent complications resulting in hypoesthesia and numbness in the lower lip and chin. The incidence of IAS injury is 1-7%, while permanent damage is less common and is found to be 0.01-2% [3].

While the tooth roots are in contact with the IAN, the continuity of the bone cortex around the IAN may not be observed. Therefore, it is necessary to predict the contact relationship between MM3s and IAN by radiographic examination before tooth extraction, which contributes to the preoperative prediction of surgical difficulty and the possibility of complications. Thus, a more minimally invasive imaging strategy can be developed[4].

To examine the relationship between the MM3 and IAN panoramic radiographs are most commonly used for radiographic examination, and since they can provide adequate dental images with a short scanning time and low radiation dose, they can help dentists about the positions of the mandibular canal borders with MM3. Based on panoramic radiographs, the incidence of complications may increase with some radiographic changes in the root and canal. These changes stated by are defined as deterioration of the image quality of the root in two-dimensional radiography, thinning, bending, and the radiolucent appearance of the root of MM3 superposed with the canal[5].

In the examination of the relationship between the MM3 and IAN, Cone Beam Computed Tomography (CBCT) images are preferred over panoramic radiographs due to their superior accuracy and detail. Unlike panoramic radiographs, which often suffer from superimposition, geometric distortion, and limited dimensional perspectives, CBCT provides three-dimensional, high-resolution images that clearly delineate the spatial relationships and anatomical details[4,5]. This is crucial for accurately locating the mandibular canal and assessing its proximity or potential entanglement with the roots of the third molar. Such precision is essential for planning surgical procedures, predicting complications such as nerve damage, and ultimately ensuring safer and more effective patient outcomes. Additionally, CBCT's ability to offer cross-sectional views allows clinicians to make more informed decisions and adopt precise surgical approaches, significantly reducing the risk of postoperative complications and enhancing the overall treatment efficacy[6-8].

Jung YH *et al*. evaluated the relationships of MM3s with the canal in both panoramic radiographs and CBCT images in their study. They suggested that data such as a more radiolucent appearance at the canal borders in panoramic radiographs and interruption of the canal borders are indicators of the relationship of MM3 with its roots, but CBCT images are needed to clearly examine the exact location of the canal and its relationship with the roots, especially in cases where the canal roots are buccally positioned[9].

Today, deep learning, a subset of artificial intelligence, is in rapid development and has achieved significant success in the medical field. Deep learning models and supervised learning of convolutional neural networks have been evaluated in studies that equal or exceed the level of expert physicians in many medical imaging fields. In these studies, detection, classification and segmentation of anatomical structures, dental caries, periapical lesions, periodontal defects, cystic lesions and tumors, maxillary sinusitis and cephalometric analyzes and analysis of anatomical points were performed. Although these applications are still in their infancy, promising results have been reported[10, 11].

Recently, deep learning algorithms have been used in studies based on convolutional neural network models for detection and segmentation of the third mandibular molar and mandibular canal relationship with panoramic radiographs and CBCT, developmental staging, and angle measurements of the third mandibular molar on panoramic radiographs[12].

The aim of this study is to evaluate the mandibular canal with cone beam computed tomography using a deep learning approach.

Material and Methods

This study's dataset comprises images from 300 patients who visited the Department of Oral and Maxillofacial Radiology at Marmara University Faculty of Dentistry and had CBCT images taken following necessary indications. CBCT images were acquired using the Planmeca Promax 3D Mid (Planmeca Oy, Helsinki, Finland, 2012) with the settings of 90kV, 10mA, and 36s, and a FOV of 16x9cm. The images have an isotropic voxel size of $0.4mm^3$ and a slice thickness of 0.4mm.

Image Evaluation

The study used CBCT images from 300 patients, stored as DICOM files. These DICOM files were converted to JPEG format axial section images. Annotations on the radiographs were performed using the CranioCatch labeling software (CranioCatch, Eskişehir, Turkey), which allows for polygonal type free drawing. Different CBCT images of the 300 patients were annotated. These datasets were divided into training (n=270) and test (n=30) sets. A deep learning approach, the nnU-Net architecture, was used to develop an artificial intelligence model. Labeling was performed on axial sections for the mandibular canal. Training and validation datasets were used to estimate and generate optimal artificial intelligence algorithm weight factors. The model's success was verified with the test dataset. The success of the developed AI model was determined by formulating true positive/negative and false positive/negative values. These values provide information on the model's accuracy, sensitivity, precision, and DICE-score.

Deep Learning Architecture: U-Net

U-net is a convolutional neural network specifically designed for the efficient segmentation of biomedical images, featuring a distinctive encoder-decoder structure. In this architecture, the encoder reduces the image dimensions while increasing the feature depth to capture contextual information, which is then expanded in the decoder to construct a detailed segmentation map. Critical to U-net is the skip connections that link the encoder and decoder, enhancing the network's ability to capture fine details necessary for high accuracy in medical tasks. Each stage in the encoder consists of two 3x3 convolutions followed by a ReLU activation and a 2x2 max pooling operation. The decoder inversely increases spatial dimensions through up-convolutions and concatenations with corresponding encoder outputs, ending with a 1x1 convolution that classifies each pixel. U-net is particularly advantageous in dentistry for segmenting dental radiographs, identifying tissues, and detecting pathologies like caries or periodontal diseases due to its precision in handling complex images. Expanding on U-net; nnU-net adapts its configuration dynamically to optimize itself for different biomedical segmentation tasks without requiring manual tuning. It automatically adjusts its network structure, preprocessing, and training strategy based on specific dataset characteristics. This includes choosing among its three versions—2D, 3D full resolution, and 3D cascaded—based on the input data. In dentistry, nnU-net facilitates intricate tasks such as detailed segmentation in volumetric scans like CBCT, accommodating varying slice thicknesses and modalities with minimal user intervention. The adaptability and automation of nnU-net make it a robust tool for dental applications, where it enhances diagnostic accuracy and efficiency by tailoring its approach to the nuanced requirements of dental imagery.

Confusion matrix and performance criteria

Confusion matrix is a performance evaluation tool used to measure the accuracy of algorithms, and it is needed to establish success parameters. Four values need to be known to create the matrix.

- True Positive (TP): The situation where the object actually exists and the prediction perceives the object.
- True Negative (TN): The situation where the object does not actually exist and the prediction does not detect an object.
- False Positive (FP): The situation where the object does not actually exist but the prediction perceives an object.
- False Negative (FN): It is the situation where the object actually exists but the prediction does not detect the object.

The performance parameters of the algorithm were calculated using the results obtained using the confusion matrix. These are Accuracy, Sensitivity, Precision and DICE score[13, 14].

Accuracy

Accuracy is a method to measure the success of an algorithm. It is calculated by the ratio of the sum of true positive and true negative values to the total values[15].

Sensitivity/Recall

Sensitivity or Recall, indicates how accurately the algorithm predicts cases that should be positive. It is calculated by the ratio of true positive values to the sum of true positive and false negative values[15].

Precision

Precision measures how many of the algorithm's positive predictions are actually positive. It is calculated by the ratio of true positive values to the sum of true positive and false positive values[15].

DICE Score

The Dice score is a statistical measure used to gauge the similarity between two sets. It is often used in image segmentation tasks to compare the overlap between a predicted segmentation and the ground truth segmentation. The score ranges from 0 to 1, where 1 indicates perfect overlap and 0 indicates no overlap.[15].

Results

Using CBCT images, a deep learning model was able to identify the mandibular canal with sufficient sensitivity, accuracy, and precision. The particular metrics that we found in the study clarify how well the model recognizes and defines the mandibular canal, which is essential for preventing problems like paralysis of the IAN during dental procedures.The model achieved an impressive accuracy rate of 99%, indicating that it could correctly identify and segment the mandibular canal in nearly all instances.

The high level of accuracy means that the model is dependable and may be used with confidence in clinical settings for preoperative planning and risk assessment. Sensitivity, which measures the true positive rate or the proportion of actual positives correctly identified by the model, was recorded at 75%. This indicates that while the model is quite adept at detecting the presence of the canal when it is indeed present, there is still room for improvement in capturing all relevant cases. The precision of the model was observed at 78%. This metric highlights the model's ability to provide true positive identifications as a proportion of all positive identifications it makes, underscoring its utility in ensuring that interventions are necessary and appropriately targeted.

The Dice score, which measures the overlap between predicted and actual labels, was calculated to be 0.76. This metric underscores the model's robustness in accurately identifying the mandibular canal. The relatively high Dice score reflects a strong agreement between the predicted segmentation and the ground truth, confirming the model's effectiveness in this complex task.

Figure 1. Image of the mandibular canal (blue) used for training (left) and prediction of the deep learning algorithm (right). The findings suggest that the integration of CBCT images and advanced deep learning algorithms could significantly enhance the accuracy of identifying the mandibular canal, which is pivotal for successful dental surgery.

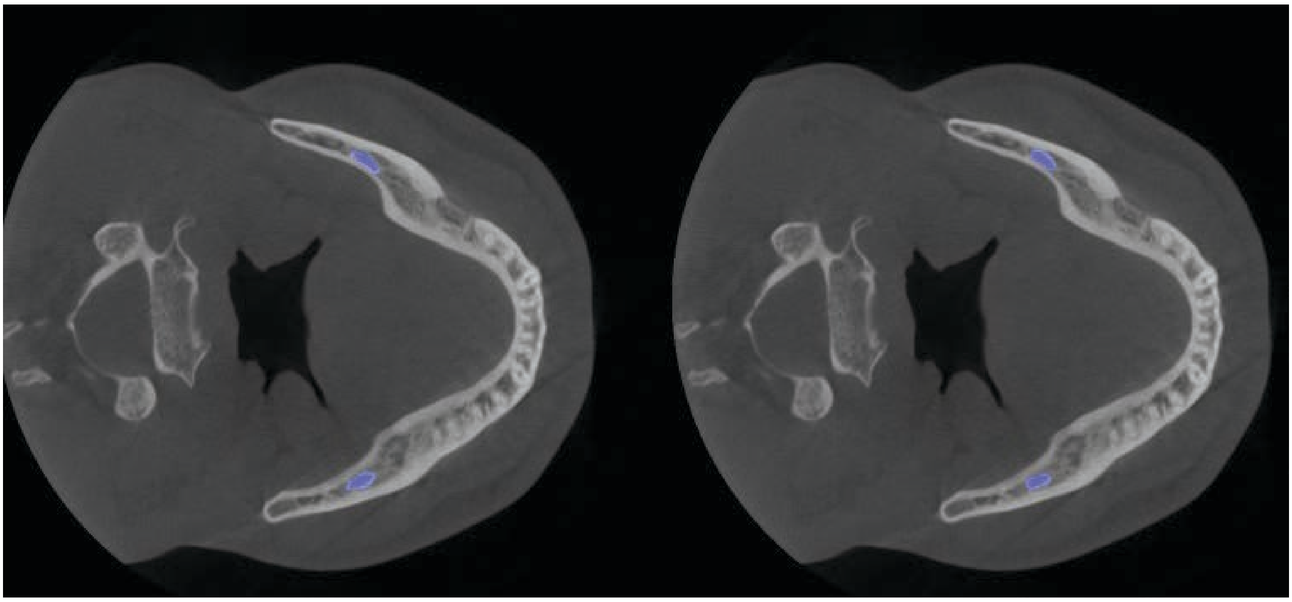

Figure 1. The image of the mandibular canal used for training (left) and the prediction of the deep learning algorithm (right) in axial sections of CBCT images.

Discussion

AI has significantly enhanced the analysis of medical and dental imagery, particularly through the implementation of deep learning models and CNNs. The recent and rapid development of deep learning has gained considerable attention[16, 17, 18].

The deep convolutional neural network (CNN) architecture appears to be the most frequently utilized deep learning strategy. This is most likely due to its effective self-learning models and high computational capacity,which provide superior classification, detection, and quantitative performance based on image data. In the studies reviewed, a variety of deep learning models have been applied to analyze the relationship between the mandibular canal and MM3 in panoramic images and CBCT scans[8, 19].

Vinayahalingam *et al.* worked on a deep learning-based algorithm for MM3 and mandibular canal detection and segmentation on panoramic images. CNNs were trained with a U-Net based deep learning approach to detect MM3 and mandibular canal on 81 panoramic radiographs. Subsequently, the DICE score was calculated for the success of the algorithm in detecting and segmenting both structures and was found to be 0.947 and 0.847 for MM3 and mandibular canal, respectively[20].

Yoo *et al.* used a CNN-based deep learning model on panoramic images to estimate the shooting difficulty of MM3s. A total of 1053 MM3 were examined from 600 preoperatively obtained panoramic radiographs. Pederson difficulty score was used to estimate the difficulty of extraction, and the final decision was reached based on the consensus of three physician observers. In the classification model, the ResNet 34 algorithm pre-trained on the ImageNet dataset was used, and the correlation was calculated between the Pederson difficulty score value determined by the proposed model and the values measured by experts. The prediction accuracies for depth, relationship with the ramus, and angulation of the tooth were found to be 78.91%, 82.03%, and 90.23%, respectively[21].

Zhu *et al.* used the YOLOv4 supported MM3-IANnet algorithm, a deep learning approach, to evaluate the actual relationship of MM3 and the mandibular canal on panoramic radiographs. 915 impacted teeth in 503 panoramic radiographs were included in the study. To accurately visualize the relationship between MM3 and the mandibular canal, the relationship of the parameters from the existing CBCT images was first determined and the accuracy, sensitivity and DICE score values of the algorithm's success on panoramic radiographs were calculated. These values were found to be 87.18%, 82.93%, 84.99%, respectively[22].

Büyük *et al.* examined the relationship between MM3 roots and the mandibular canal on 1880 panoramic radiographs. Each radiograph is segmented using a U-Net-like architecture, and the segmented images are classified by AlexNet. IoU score, DICE score, specificity value, sensitivity and AUC value were used to measure the performance of the models. Additionally, three dentists were asked to classify the same test data and success rates were evaluated using the intraclass correlation coefficient. With the algorithm used, 0.99 accuracy, 0.98 IoU score, 0.91 DICE score were obtained in all images. Additionally, for each classification, it achieved an accuracy of 0.80, a sensitivity of 0.74, 0.83, 0.86 and 0.67, respectively, a specificity of 0.92, 0.95, 0.88 and 0.96, respectively, and an AUC of 0.85 [23].

Fukuda *et al.* in their study, they aimed to evaluate three different CNN structures in terms of the relationship between MM3 and the mandibular canal in order to reduce the working time and storage space requirement. Using AlexNet, GoogLeNet, and VGG-16 algorithms, training was performed with only 70x70 pixel and 140x140 pixel images of the relevant region in 6600 panoramic radiographs, and the findings were observed as follows. Accuracy, sensitivity, specificity value and AUC value for AlexNet for 70x70 pixels were 0.90, 0.88, 0.92, 0.90, respectively; 0.84, 0.80, 0.88, 0.89 for 140x140 pixels; 0.92, 0.88, 0.96, 0.93 for 70x70 pixels for GoogleNet; For 140x140 pixels, it was found to be 0.82, 0.76, 0.88, 0.83, for VGG-16, it was found to be 0.87, 0.88, 0.86, 0.91 for 70x70 pixels, and 0.73, 0.80, 0.66, 0.75 for 140x140 pixels[24].

Sukugawa *et al.* used the ResNet50v2 algorithm to evaluate the relationship of MM3 and the mandibular canal. A total of 1279 MM3 images were used. The average accuracy, precision, sensitivity value, DICE score and AUC values were observed as 0.85, 0.81, 0.78, 0.79, 0.88, respectively[25].

Yoshiko *et al.* used total of 2260 panoramic radiographs were used in their study in 2022. U-net CNN was used for training and the DICE score was obtained as 0.857, the Jaccard index was 0.755 and the sensitivity was 0.839 [26].

Although there are studies on panoramic radiographs, artificial intelligence studies on CBCTs are limited. In CBCT imaging, Liu et al. employed 254 CBCT data, they worked with segmentation U-Net architecture to train and develop an artificial intelligence deep learning model to automatically determine the mandibular canal and the third mandibular molar teeth, as well as the connection between these two components. They also developed the classification of the relationship between components with the ResNet-34 architecture. DICE score and IoU values were used to test the segmentation, and accuracy, sensitivity, specificity and confusion matrix were used to examine the success of classifying the relationships between components. The average DICE score of the mandibular canal was 0.9248 and the average IoU value was 0.9003. The approximate IoU value of the third molar teeth was 0.9606 and the average DICE score was 0.9730. It was stated that the accuracy rate of the classification models was 93.3%, the specificity rate was 95.0% and the sensitivity rate was 90.2% [12].

Lahoud *et al*. developed an artificial intelligence model by applying the segmentation method for the mandibular canal on 235 CBCT images. Two CNNs were run together in this research. While the first CNN created a basic segmentation for the mandibular canal, the second CNN created a more precise segmentation in the area around this first segmentation. In this research, 3D U-Net architecture was developed, and they showed that the artificial intelligence algorithm can be used successfully for segmentation. Approximately the precision value was found to be 0.782, the sensitivity value was 0.792 and the accuracy value was 0.99 [27].

Orhan *et al.* aimed to evaluate MM3s on CBCT images. In total, in 113 MM3 images of 63 patients, the number of impacted teeth, root/canal numbers, and their relationship with adjacent anatomical points were compared with the human observer and the artificial intelligence algorithm, and the success rate of the observer with the CNN system was examined by kappa analysis. A total of 112 teeth (86.2%) were detected by artificial intelligence. The number of roots was determined correctly in 99 teeth (78.6%) and the number of canals was determined correctly in 82 teeth (68.1%). A good agreement was observed between the observer and the artificial intelligence algorithm in determining the mandibular canal according to the impacted third molars in the lower jaw (kappa: 0.762) and the number of roots (kappa: 0.620), and similarly, an excellent agreement was observed regarding the maxillary impacted third molar and maxillary sinus. There was agreement (kappa: 0.860). For the determination of the number of maxillary molar canals, moderate agreement was found between human observer and AI examinations (kappa: 0.424)[28].

The potential of deep learning to transform dental radiology is increasingly evident, as it offers significant improvements in the accuracy and efficiency of interpreting complex imaging data. Overall, the deployment of various deep learning techniques across different studies not only highlights the adaptability and robustness of these models in dental imaging but also underscores their potential to enhance diagnostic accuracy and operational efficiency in dental practices. As these technologies evolve, their integration into clinical workflows promises significant advancements in dental diagnostics and treatment planning.

Conclusions

The use of advanced deep learning techniques in the analysis of CBCT images for mandibular canal identification has shown considerable promise. The high accuracy, combined with commendable sensitivity, precision, and DICE score, signifies a substantial advancement in dental diagnostic tools, potentially revolutionizing preoperative assessments and reducing the risk of nerve injuries during mandibular surgeries. Continued advancements in AI technologies promise to further refine diagnostic procedures and therapeutic strategies in dentistry, ultimately improving patient care and surgical outcomes.

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References

1. Castro MA, Lagravere-Vich MO, Amaral TM, Abreu MH, Mesquita RA (2015). "Classifications of mandibular canal branching: A review of literature". *World J Radiol*. **7** (12): 531-537. doi: 10.4329/wjr.v7.i12.531. PMID: 26753068
2. Libersa P, Savignat M, Tonnel A (2007). "Neurosensory disturbances of the inferior alveolar nerve: a retrospective study of complaints in a 10-year period". *J Oral Maxillofac Surg*. **65** (8): 1486-1489. doi: 10.1016/j.joms.2007.03.023. PMID: 17656272.
3. Mukherjee S, Vikraman B, Sankar D, Veerabahu MS (2016). "Evaluation of outcome following coronectomy for the management of mandibular third molars in close proximity to inferior alveolar nerve". *J Clin Diagn Res*. **10** (8): ZC57-62. doi: 10.7860/JCDR/2016/20991.8273. PMID: 27656565
4. Weckx A, Agbaje JO, Sun Y, Jacobs R, Politis C (2016). "Visualization techniques of the inferior alveolar nerve (IAN): a narrative review". *Surg Radiol Anat*. **38** (1): 55-63. doi: 10.1007/s00276-015-1510-z. PMID: 26163825
5. Rood JP, Shehab BN (1990). "The radiological prediction of inferior alveolar nerve injury during third molar surgery". *Br J Oral Maxillofac Surg*. **28** (1): 20-25. doi: 10.1016/0266-4356(90)90005-6. PMID: 2322523
6. Keser G, Namdar Pekiner F (2023). „Artificial Intelligence Applications in Dentistry". In book: Current Researches in Health Sciences-I (pp.51-68), İstanbul: Özgür Publication. doi: 10.58830/ozgur.pub91.c383
7. Stafie CS, Sufaru IG, Ghiciuc CM, Stafie II, Sufaru EC, Solomon SM, Hancianu M (2023). "Exploring the Intersection of Artificial Intelligence and Clinical Healthcare: A Multidisciplinary Review". *Diagnostics (Basel)*. **13** (12): 1995. doi: 10.3390/diagnostics13121995. PMID: 37370890
8. Schwendicke F, Golla T, Dreher M, Krois J (2019). „Convolutional neural networks for dental image diagnostics: A scoping review". *J Dent*. **91**: 103226. doi: 10.1016/j.jdent.2019.103226. PMID: 31704386
9. Jung YH, Nah KS, Cho BH (2012). „Correlation of panoramic radiographs and cone beam computed tomography in the assessment of a superimposed relationship between the mandibular canal and impacted third molars". *Imaging Sci Dent*. **42** (3): 121-127. doi: 10.5624/isd.2012.42.3.121. PMID: 23071961
10. Suzuki K (2017). "Overview of deep learning in medical imaging". *Radiol Phys Technol*. **10** (3): 257-273. doi: 10.1007/s12194-017-0406-5. PMID: 28689314.
11. Corbella S, Srinivas S, Cabitza F (2021). "Applications of deep learning in dentistry". *Oral Surg Oral Med Oral Pathol Oral Radiol*. **132** (2): 225-238. doi: 10.1016/j.oooo.2020.11.003. PMID: 33303419.
12. Liu MQ, Xu ZN, Mao WY, Li Y, Zhang XH, Bai HL, et al. (2022). "Deep learning-based evaluation of the relationship between mandibular third molar and mandibular canal on CBCT". *Clin Oral Investig*. **26** (1): 981-991. doi: 10.1007/s00784-021-04082-5. PMID: 34312683
13. De Diego IM, Redondo AR, Fernández RR, Navarro J, Moguerza JM (2022). „General Performance Score for classification problems". *Appl Intell*, **52**: 12049–12063. https://doi.org/10.1007/s10489-021-03041-7
14. Goutte C, Gaussier E (2005). "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation". In European conference on information retrieval (pp. 345-359). Berlin, Heidelberg: Springer Berlin Heidelberg.
15. Zeiler MD, Fergus R (2014). "Visualizing and understanding convolutional networks". In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, (pp. 818-833). Springer International Publishing. doi: 10.13140/RG.2.2.12182.22080
16. He K, Zhang X, Ren S, Sun J (2015). "Delving deep into rectifiers:surpassing human level performance on image net classification," in Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp.1026–1034, Santiago, Chile.
17. Russakovsky OJ, Deng J, Suetal H (2015). "Imagenet large scale visual recognition challenge". *Int J Comput Vis*. **115** (3): 211–252. doi: 10.48550/arXiv.1409.0575
18. Hricak H (2018). "2016 New Horizons Lecture: Beyond Imaging-Radiology of Tomorrow". *Radiology*. **286** (3): 764-775. doi: 10.1148/radiol.2017171503. PMID: 29346031
19. Prados-Privado M, Villalón JG, Martínez-Martínez CH, Ivorra C (2020). "Dental Images Recognition Technology and Applications: A Literature Review". *Appl. Sci.* **10** (8): 2856. https://doi.org/10.3390/app10082856
20. Vinayahalingam S, Xi T, Bergé S, Maal T, de Jong G (2019). "Automated detection of third molars and mandibular nerve by deep learning". *Sci Rep*. **9** (1): 9007. doi: 10.1038/s41598-019-45487-3. PMID: 31227772
21. Yoo JH, Yeom HG, Shin W, Yun JP, Lee JH, Jeong SH, et al. (2021). "Deep learning based prediction of extraction difficulty for mandibular third molars". *Sci Rep*. **11** (1): 1954. doi: 10.1038/s41598-021-81449-4. PMID: 33479379

22. Zhu T, Chen D, Wu F, Zhu F, Zhu H (2021). „Artificial intelligence model to detect real contact relationship between mandibular third molars and inferior alveolar nerve based on panoramic radiographs". *Diagnostics (Basel)*. **11** (9): 1664. doi: 10.3390/diagnostics11091664. PMID: 34574005
23. Buyuk C, Akkaya N, Arsan B, Unsal G, Aksoy S, Orhan K (2022). "A fused deep learning architecture for the detection of the relationship between the mandibular third molar and the mandibular canal". *Diagnostics (Basel)*. **12** (8): 2018. doi: 10.3390/diagnostics12082018. PMID: 36010368
24. Fukuda M, Ariji Y, Kise Y, Nozawa M, Kuwada C, Funakoshi T, et al. (2020). "Comparison of 3 deep learning neural networks for classifying the relationship between the mandibular third molar and the mandibular canal on panoramic radiographs". *Oral Surg Oral Med Oral Pathol Oral Radiol*. **130** (3): 336-343. doi: 10.1016/j.oooo.2020.04.005. PMID: 32444332.
25. Sukegawa S, Tanaka F, Hara T, Yoshii K, Yamashita K, Nakano K, Furuki Y (2022). "Deep learning model for analyzing the relationship between mandibular third molar and inferior alveolar nerve in panoramic radiography". *Sci Rep*. **12** (1): 16925. doi: 10.1038/s41598-022-21408-9. PMID: 36209283
26. Ariji Y, Mori M, Fukuda M, Katsumata A, Ariji E (2022). "Automatic visualization of the mandibular canal in relation to an impacted mandibular third molar on panoramic radiographs using deep learning segmentation and transfer learning techniques". *Oral Surg Oral Med Oral Pathol Oral Radiol*. **134** (6): 749-757. doi: 10.1016/j.oooo.2022.05.014. PMID: 36229373.
27. Lahoud P, EzEldeen M, Beznik T, Willems H, Leite A, Van Gerven A, Jacobs R (2021). "Artificial intelligence for fast and accurate 3-dimensional tooth segmentation on cone-beam computed tomography". J Endod. **47** (5): 827-835. doi: 10.1016/j.joen.2020.12.020. PMID: 33434565
28. Orhan K, Bilgir E, Bayrakdar IS, Ezhov M, Gusarev M, Shumilov E (2021). "Evaluation of artificial intelligence for detecting impacted third molars on cone-beam computed tomography scans". *J Stomatol Oral Maxillofac Surg*. **122** (4): 333-337. doi: 10.1016/j.jormas.2020.12.006. PMID: 33346145

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