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A Deep Learning Approach to Automatic Tooth Detection and Numbering in Panoramic Radiographs: An Artificial Intelligence Study

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ABSTRACT

Objective: n this study, in order to test the usability of artificial intelligence technologies in dentistry, which are becoming widespread and expanding day by day, and to investigate ways to benefit more from artificial intelligence technologies; a tooth detection and numbering study was performed on panoramic radiographs using a deep learning software.

Methods: A radiographic dataset containing 200 anonymous panoramic radiographs collected from individuals over the age of 18 was assessed in this retrospective investigation. The images were separated into three groups: training (80%), validation (10%), and test (10%), and tooth numbering was performed with the DCNN artificial intelligence software.

Results: The D-CNN system has been successful in detecting and numbering teeth. of teeth. The predicted precision, sensitivity, and F1 score were 0.996 (98.0%), 0.980 (98.0%), and 0.988 (98.8%), respectively.

Conclusion: The precision, sensitivity and F1 scores obtained in our study were found to be high, as 0.996 (98.0%), 0.980 (98.0%) and 0.988 (98.8%), respectively. Although the current algorithm based on Faster R-CNN shows promising results, future studies should be done by increasing the number of data for better tooth detection and numbering results.

Keywords: Artificial intelligence, deep learning, panoramic radiography, tooth numbering.

1. INTRODUCTION

Since its inception in the 1950s, panoramic imaging has grown in popularity and importance as a diagnostic tool. It is a specific radiographic method used to provide a flat image of the jaws' curving surfaces. Curved surface tomography is the fundamental imaging concept. On a single film, entire maxilla, mandible, temporo-mandibular joints, and associated structures are visible. It is used as a pre-scan radiography to evaluate tooth and bone support, locate impacted teeth, and determine the site of dental implants, among other things. It also provides a basic evaluation of the bone state of the jaw and jaw joints, as well as a diagnosis of maxillary and mandibular fractures (1). On the other hand, panoramic radiographs can show significant geometric distortions and have relatively low spatial resolution compared to intraoral radiographs. Significant changes in image projection in the anterior region might arise depending on the patient's posture and the curvature of the jaws. It also lacks the delicate anatomical characteristics revealed in intraoral periapical radiography. However, it has a dosage advantage over several intraoral radiography (2-5).

Artificial intelligence (AI) is described as a machine's ability to replicate intelligent human behavior in order to execute complicated tasks such as problem solving, object and word recognition, and decision making. AI technologies have already achieved significant success in the modern world, and are integrated in our daily lives through search engines, online assistants, and video games. However, it is fast evolving in a variety of sectors, including medicine. In clinical medicine, a wide variety of AI models are being created for automatic disease risk prediction, detection of abnormalities/pathologies, disease diagnosis, and prognosis evaluation. Because of its capacity to provide digitally coded pictures that can be more readily translated into computer

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language, radiology serves as a form of entry point for the application of artificial intelligence in medicine (1, 3, 6-10).

The term machine learning (and its subcategories) refers to a situation where an agent learns whether it has improved its performance on future tasks after making observations about the data given to it. Machine learning is a term coined by Arthur Samuel in 1959 to describe a field of AI where computers learn automatically from a collection of data. Machine learning algorithms change as they are exposed to more data; they do not rely just on rules; they grow with experience, learning to provide precise responses by analyzing enormous volumes of data (11).

Machine learning is frequently separated into two types: supervised and unsupervised learning. The algorithm is provided annotated data ("basic truth" data) to use in the construction of the algorithm in supervised learning. Unsupervised learning requires the system to categorize itself using unlabeled input. Deep learning, and particularly deep convolutional neural networks (also known as DCNN (Deep Convolutional Neural Network) or CNN (Convolutional Neural Network)), are a subset of supervised machine learning that has gotten the most attention in recent years. DCNNs are a sort of supervised learning that use an algorithmic framework based on deep neural networks with several layers. The power of this method resides in its scalability and the neural network architecture's capacity to extract its own meaningful characteristics from data with no additional direction than the labeled input data (11). Neural networks must be "trained" with training datasets before they can "learn." In radiology, they are often hand-labeled picture datasets that are utilized by the algorithm to enhance its fit to the underlying reality. After a network has been trained using a training dataset, it will be evaluated using a different dataset (validation datasets) to assess the model's fit to the new data (3,10-12).

With the emergence of a digital picture archiving and communication network that produced vast volumes of imaging data, AI became a cornerstone of radiology, presenting significant potential for AI training (2,3,13,14). In a prior work, DCNN was used to learn by following a similarly graded component of the brain's visual cortex. Many research in the literature have proved the potential of DCNN approaches to aid practitioners in dentistry (11,12,16-18). Thus, the study aimed to evaluate the function of the diagnostic computer software designed for the evaluation of tooth detection and numbering on panoramic radiographs.

2. METHODS

In this retrospective study, a radiographic dataset containing 200 anonymous panoramic radiographs taken from patients over the age of 18 between January 2021 and January 2022 from the archive of Marmara University Faculty of Dentistry Department of Oral and Maxillofacial Radiology was evaluated. Panoramic radiographs with metal superposition, position errors, motion artifacts etc. were excluded from the dataset. Panoramic radiographs showing teeth such as dental caries, restorative fillings, crowns and bridges, implants etc. were included in the study. The study was conducted in accordance with the principles of the Declaration of Helsinki. The study protocol was approved by the Invasive Clinical Research Ethics Committee, Marmara University Faculty of Medicine on 04.11.2022 with protocol number 09.2022.1417.

2.1. Radiographic Data Set

All panoramic radiographs were obtained using the Planmeca Promax 2D (Planmeca, Helsinki, Finland) panoramic dental imaging unit with the following parameters:68 kVp, 16 mA,13 s. The radiographic dataset comprised of optimizing panoramic radiographs with the exposure parameters as low as reasonably achievable and as low as diagnostically acceptable.

2.2. Image Evaluation

Each tooth was labeled and numbered on the panoramic x-ray with the "area detection" option in the artificial intelligence assisted diagnosis software program Cranio-Catch (Cranio-Catch, Eskisehir, Turkey) according to the FDI tooth numbering system by the dentist (D.M.) (Figure 1,2).

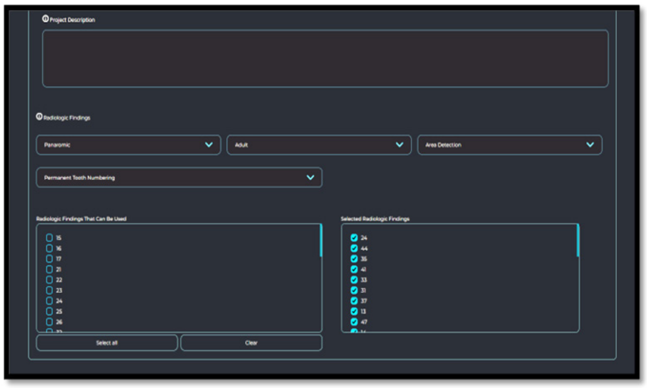

Figure 1. *Cranio-Catch software program, project creation and labeling information screen.*

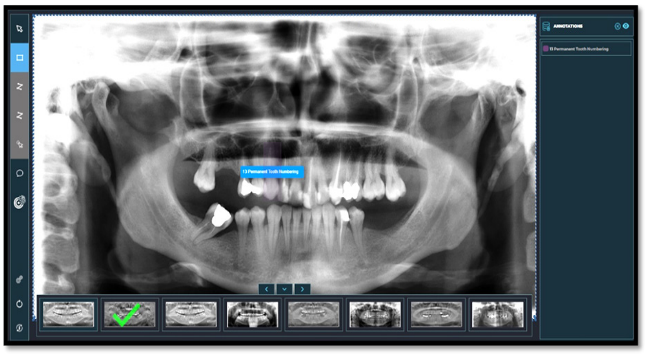

Figure 2. *Example of "Area detection" data labeling for tooth detection and numbering in panoramic radiography.*

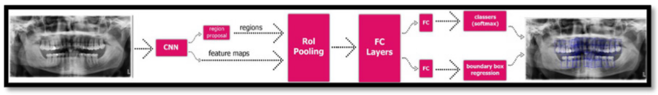

Figure 3. *System architecture and thread detection-numbering chain of operations.*

2.3. Deep Convolutional Neural Network (D-CNN)

A random sequence was generated using the open source Python programming language (Python 3.6.1, Python Software Foundation, Wilmington, DE, USA; retrieved on 01 August 2019 from https://www.python.org). The Inception v2 Faster R-CNN) network implemented with the TensorFlow library was used to build a model for thread detection and numbering. This method consists of 22 deep layers, which can obtain different scale features by applying convolutional filters of various sizes within the same layer.

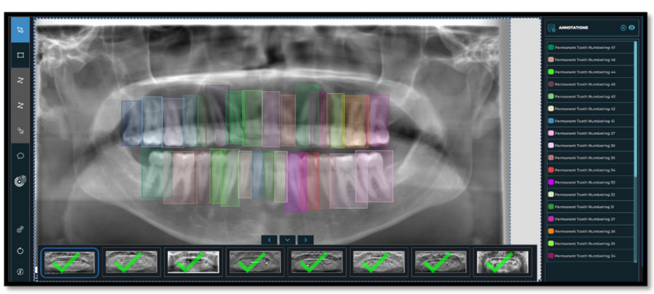

Figure 4. *Automatic tooth detection and numbering model of Craniocatch artificial intelligence software.*

2.4. Model Pipeline

In this study, an AI algorithm (CranioCatch, Eskişehir, Turkey) was developed to automatically detect and number teeth using deep learning techniques, including Faster R-CNN Inception v2 models, in panoramic radiographs. Using Inception v2 architecture as transfer learning, first the transfer values in the cache were recorded and then a fully connected layer and softmax classifier were used to create the final model layers (Figure 5). The training was conducted using 7000 steps on a computer with 16 GB RAM and NVIDIA GeForce GTX 1050 graphics card. The training and validation datasets were used to predict and generate optimal CNN algorithm weighting factors.

Before training, each radiograph was resized from its original dimensions of 2943×1435 pixels to 1024×512 pixels. The training dataset, in which 32 different teeth are labeled at the same time, consists of 160 images.

Numbering on 160 panoramic radiographs in the training group: 11-12-13-14-15-16-17-18-21-22-23-24-25-26-27-28-31-32-33-34-35-36-37-38-41-42-43-44-45-46-47-48 (tooth numbers).

2.5. Training Phase

Images were divided into training (80%), validation (10%) and testing (10%) groups. For each quadrant (regions 1, 2, 3, and 4), 160, 20, and 20 images were randomly allocated to the training, validation, and test groups, respectively.

The CranioCatch approach to detecting teeth is based on a deep CNN using 200,000 epochs trained with faster R-CNN initial v2 with a learning rate of 0.0002. After the model was trained, it was used to identify the presence of teeth (Figure 6).

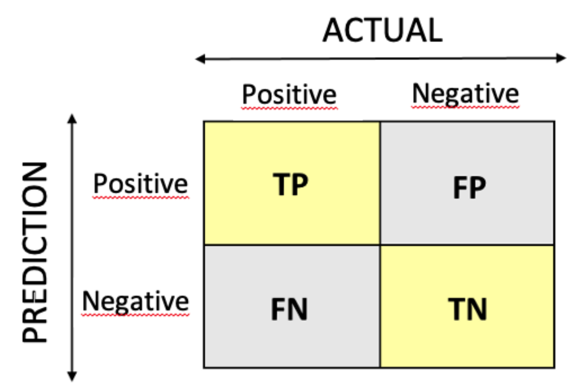

Figure 5. *Confusion matrix.*

2.6. Statistical Analysis

The confusion matrix, a useful table summarizing predicted and actual situations, was used as a metric to calculate the success of the model (Figure 5).

The following procedures and metrics were used to assess the success of the AI model:

• Initially true positive (TP), false positive (FP) and false negative (FN) rates were calculated.

TP: Result where the model accurately predicted the positive class (teeth were correctly detected and numbered on panoramic radiographs).

FP: Result where the model incorrectly predicted the positive class (teeth detected correctly but incorrectly numbered on panoramic radiographs).

FN: The result where the model incorrectly predicted the negative class (teeth were incorrectly detected and numbered on panoramic radiographs).

The following metrics were then calculated using the TP, FP and FN values:

Sensitivity (Recall): TP/ (TP+FN)

Precision: TP/ (TP+FP)

F1 Score: 2TP/ (2TP+FP+FN)

3. RESULTS

The D-CNN system has been successful in detecting and numbering teeth. TP, FP and FN results in all quadrants were determined as 4956, 18 and 100 tooth, respectively. Sensitivity and precision ratios are promising for the detection and numbering of teeth. The estimated precision, sensitivity, and F1 score were 0.996 (99.6%), 0.980 (98.0%), and 0.988 (98.8%), respectively (Table 1).

Table 1. *AI model performance measure value using the confusion matrix*

Measure	Value	Derivations
Sensitivity	0.980	TPR = TP/(TP + FN)
Precision	0.996	PPV = TP/(TP + FP)
F1 score	0.988	F1 = 2TP/(2TP + FP + FN)

TPR:True Positive Rate, Tp: True Positive, FN: False Negative, FP: False Positive, PPV: Positive Predictive Value

4. DISCUSSION

Artificial intelligence (AI) is the realization of tasks such as decision making, recognizing words and objects, and problem-solving using computer software and machines. Deep learning systems, which are a subset of artificial intelligence applications, have been gaining popularity recently and are stated to be promising (14,17). Artificial intelligence and deep learning applications are being used in many areas such as detection of caries in dentistry, detection of orofacial pathologies, orthodontic treatment planning, robotic surgery, dental implant construction and its usage area is expanding. Artificial intelligence applications in dentistry are promising in terms of saving time and effort for physicians, providing support in case of lack of experience, and accelerating archiving and reporting works. It has gained importance both clinically and academically for researchers to follow the developments related to artificial intelligence applications, which are becoming more common in the field of health and expanding their place in the literature and gaining experience in this field (4,18-20).

With the advent of modern imaging modalities and the development of archiving systems, radiology has experienced two significant digital revolutions. These developments were followed by the use of artificial intelligence, especially in radiographic analysis. Especially its compatibility with image processing methods has highlighted dental radiology studies (3,6,10).

Radiologists are using AI diagnostic models not only to assess and report numerous medical images, but also to improve job productivity and obtain more exact outcomes in the precise screening and diagnosis (4,6,20). The emergence of deep learning techniques has increased the performance of automated image analysis methods. The shape, number and position of the teeth are items that a dentist evaluates in the first step in a panoramic x-ray. Modeling tools have been proposed to assist experts as decision supporters for better diagnoses. The primary intent of image segmentation and detection is to aid other automated systems in later processing phases.

Although tooth segmentation and detection research is not new, the use of deep learning methods in the subject is. There are few research on tooth detection, segmentation, and numbering in panoramic radiography in the literature. To fill some of the gaps in the field of dental image analysis, Silva et al. (21) analyzed the performance of four network architectures, Mask R-CNN, PANet, HTC, and ResNeSt, on a dataset of 753 training, 452 validation, and 295 test datasets. The selection of these networks has been made based on their high performance over other datasets, for example for segmentation and detection. As a result of the study, they concluded that the Mask R-CNN solution with an F1 score of 0.902 (90.2%) is much better than the classical methods. This is the first study on sample segmentation, detection and numbering of teeth in panoramic dental x-rays. It has been found that detecting, segmenting, and numbering threads is entirely possible through any of the analyzed architectures, and performance can be significantly improved by choosing the appropriate neural network architecture.

Koch et al. (22) trained a U-Net model on the UFBA-UESC Dental Images dataset and found an F1 score of 0.936 (93.6%) in tooth segmentation in 1200 training and 300 test datasets in 1500 dental panoramic radiographs.

Jader et al. (23) were the first researchers to investigate the detection and segmentation of teeth in panoramic x-ray. They changed the UFBA-UESC Dental Images dataset to include the information of dental samples and created this new dataset as UFBA-UESC Dental Images Deep. A Mask R-CNN powered by ResNet-101 was trained and validated with 193 and 83 images, respectively. The remaining 1224 images of the data set were used for testing and the sensitivity, precision and F1 score were determined as 0.840 (84.0%), 0.940 (94.0)% and 0.880 (88%), respectively.

Tuzoff et al. (24) were the first researchers to apply deep learning to identify and number teeth on panoramic x-rays. On a dataset containing 1352 images for training and 222 images for testing, the sensitivity and precision were 0.994 (99.4%) and 0.994 (99.4%) for tooth detection, respectively, while these values were 0.980 (98.0%) and 0.994 (99.4%) for tooth numbering, respectively. They reported that the result of tooth detection and numbering in panoramic radiographs using a trained CNN-based deep learning model to generate automatic tooth detection according to FDI two-digit notation is promising and AI deep learning algorithms have the potential for practical application in clinical dentistry.

Celik et al. (25) tested the functionality of diagnostic computer program developed to assess missing teeth on panoramic radiography. For the identification of missing teeth, the dataset contains 153 images, 99 intact teeth and 54 missing teeth. The open-source Python programming language and the libraries OpenCV, NumPy, Pandas, and Matplotlib were used to generate a random sequence. For preprocessing, a pre-trained Google Net Inception v3 CNN network was employed, then dataset transfer learning was taught using 76 images. The model estimate of the images used in training has a success percentage of 94.7%. Estimating 32 images reserved for the exam but not utilized in training yields a 75% success rate. Bilgir et al. (3) found the predicted sensitivity, precision and F1 score measurement on a test data set consisting of 249 panoramic radiographs as 95.5%, 96.5%, and 96.5%, respectively. The deep convolutional neural network algorithm has been successful in detecting and numbering teeth.

Impacted supernumerary teeth are frequently observed in the maxillary incisor region, where they are known as mesiodens. Kuwada et al. (26) used different DL-based AI architectures to identify and classify the presence of impacted supernumerary teeth in the maxillary anterior region on panoramic radiography. Using various testing data, Detect Net obtained the greatest rate of diagnostic efficiency with 0.93 and 0.96 accuracy values for diagnosing the incisal area in terms of the presence or absence of an impacted supernumerary tooth. Detect Net also performed flawlessly, with recall, accuracy, and F-score values of 1.0. Similarly, Mine et al. (27) aimed to apply convolutional neural network (CNN)–based deep learning to detect the presence of supernumerary teeth in children during the early mixed dentition stage. The VGG16 model maintained a high performance in the detection of supernumerary teeth, with accuracy of 82.3%, sensitivity of 85.0%, and specificity of 79.0%. Although further improvements are needed for clinical applications, the CNN-based deep learning is a promising approach for detecting supernumerary teeth.

The artificial intelligence model applied by Prados-Privado et al. (28) obtained 0.992 (99.2%) accuracy in tooth detection and 0.938 (93.8%) accuracy in tooth numbering. In accordance with previous literature, the precision, sensitivity, and F1 scores achieved in our investigation were all high, at 0.996 (99.6%), 0.980 (98.0%), and 0.988 (98.8%). The comparatively low results achieved in investigations on periapical and bitewing radiography can be attributed to the fact that the system first assesses whether the image corresponds to the upper or lower jaw, while CNN-based deep learning in panoramic radiographs is accomplished in fewer steps. Despite the fact that the present approach, which is based on the Faster R-CNN, produced promising results, this study has certain limitations. Further study is needed to analyze different types of CNN architectures and algorithms, as well as to determine the estimation effectiveness of each tooth type (incisors, canines, premolars, and molars) using larger data sets. It is conceivable to develop a system that provides improved tooth detection and numbering results. Future study should also look at the advantages of applying AI to create radiographic images with less radiation exposure. Eventually, it should be also stated that AI is unlikely to replace the dentist-patient interaction in the near future, as humanistic qualities are equally critical in decision-making to manage dental treatment. The AI technologies are meant to assist dental professionals in decreasing misdiagnosis and to operate in harmony with the unique talents of dentists to deliver better, accessible treatment by automating routine elements of dentists' work.

5. CONCLUSION

A deep CNN was suggested in the current study for tooth detection and numbering. The model's high levels of accuracy and sensitivity demonstrated its value for teeth recognition and numbering. AI technology can help clinicians detecting and numbering teeth on panoramic radiographs. Artificial intelligence applications in dentistry are promising in terms of saving time and effort for physicians, providing support in case of lack of experience, and accelerating archiving and reporting works.

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Author Contributions:

Research idea: FNP, DM.

Design of the study: FNP, DM.

Acquisition of data for the study: DM, GK.

Analysis of data for the study: DM, GK, ISB.

Interpretation of data for the study: ÖÇ.

Drafting the manuscript: GK, DM, FNP.

Revising it critically for important intellectual content: DM, GK, FNP.

Final approval of the version to be published: FNP.

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