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ARTIFICIAL INTELLIGENCE METHODS IN DENTAL RADIOGRAPHY: CURRENT DEVELOPMENT OF SEGMENTATION AND IMAGE QUALITY ENHANCEMENT METHODS IN DIFFERENT MODALITIES

ANITA IVANOVIĆ[1], TATJANA MATIJAŠ[2]

Introduction: The application of artificial intelligence in dentistry can significantly improve the outcome of patient treatment and reduce human error. Computer systems and certain methods that use complex algorithms are able to encode digital data about the radiographic image, obtained by X-ray radiation, and transfer them to a computer language for processing a large set of data. Applied as an auxiliary tool, it can give information about the patient and diagnostics of teeth and surrounding dental structures on radiographic images (two-dimensional and three-dimensional).

The aim of the paper: The aim of the paper is to present the development and application of artificial intelligence in dentistry and at the same time emphasizing the importance of segmentation methods and methods of improving the quality of dental radiographic images.

Discussion: The common goal of the development and application of artificial intelligence methods in dental radiography is directed on obtaining radiograms from which diagnostically valuable information will be collected faster and easier for the purpose of successful treatment of the patients. Methods of segmentation of a dental structures have been developed to automatically number and localize the tooth or independently mark and display the desired structures on the image. Methods of image quality enhancement tend to work on, for example, improving image resolution or reducing metal artifacts. Research has shown that artificial intelligence can be applied in everyday clinical practice, but it has certain limitations.

Conclusion: Artificial intelligence methods in dental radiography are an useful auxiliary tool in clinical dental practice because they can speed up the process of retrieving patient data. Automatic localization of dental structure reduces the dentist's time for manual image analysis, but cannot completely replace human knowledge. For the full implementation of the mentioned methods, more development standards and resources are needed to overcome the ethical and legal problems of replacing humans with computer systems.

Keywords: ARTIFICIAL INTELLIGENCE, DEEP LEARNING, DENTAL RADIOGRAPHY, SEGMENTATION, IMAGE ENHANCEMENT

INTRODUCTION

Artificial intelligence (AI) is the process of training computers to imitate human intelligence for performing specific tasks such as learning, reasoning and problem solving (1-3). It includes a series of processes and behaviors generated by computer models and algorithms (3). To understand AI it is necessary to know several constituent subgroups as a part of it, namely: machine learning, neural networks and deep learning. The purpose of machine learning is to obtain a final outcome from already known algorithms based on a data set. Neural networks collect signals from artificial signals, forming a replication of neural networks of the brain (4). The purpose of deep learning is to create a neural network that automatically identifies patterns in input data for a purpose improvement of feature detection, and is most often identified with Convolutional Neural Networks (CNN) which are used in the processing of large and complex images and thus can give a good quantitative, not only qualitative image evaluation (4, 5).

The structure of a deep artificial neural network is made as a set of an interconnected layers of operational neurons with a large number of layers and neurons per layer (6). The architecture of basic neural networks enables information transmission to forward, from the input to the output layer, passing through the hidden layers. Architecture specificity of CNN are convolutional layers and compression layers which represent an upgrade over basic neural networks. Such a method is based on convolution operations which are obtained as a feature map whose pixel/voxel intensity is actually the sum of the pixels/voxels of the original image and the adjacent image (6-9). Deep learning, using CNN, has shown good results in the problems of computer vision in the image classification, object detection and image segmentation on radiographic modalities that include intraoral images, panoramic images and Cone Beam Computed Tomography (CBCT) images (6, 7). In their basic form, they can be easily detected on the image edges, lines, textures and patterns. By using additional algorithms, complex filters transmition can obtain information to higher layers of the network, which can show more complex features (6). In dental radiography, use of neural networks currently enables the segmentation of dental structures and the enhancement of image appearance (6).

Intensive research has been conducted in the field of AI application in dental radiography because the radiographic image obtained by X-ray radiation can be digitally coded and transferred into a computer language for processing large data sets (2). Improving the diagnostic interpretation of dental radiographic images with AI, it could contribute to dentists in easier diagnosis and making clinical decisions while saving time (1). Embracing the use of AI also means patient data management during the entire process, considering them as digitally stored and there is a great emphasis on design and implementation of algorithms related to privacy and confidentiality of patient data (1). The strength of the system is in reducing human error, establishing an earlier diagnosis of diseases, increasing efficiency and availability. Weaknesses of the system are the operator's dependence on computers and devices, the high initial costs of the system and legal and ethical problems due to the replacement of humans by computers (1).

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The aim of the work

The aim of this work is to highlight the advantages and limitations of the development and application of AI in dental radiography emphasizing the importance of segmentation methods and improving the quality of dental radiographs, which are one of a criterion for making diagnoses and clinical decisions while saving time in dental clinical practice. This professional work included relevant studies from PubMed/Medline in the last decade (predominantly in the last 6 years) using advanced search options with following keywords: artificial intelligence, deep learning, dental radiography, segmentation and image enhancement.

DISCUSSION

Application of segmentation methods

Segmentation is an essential procedure for maintaining oral health care, as it enables the localization of teeth enforcement of orthodontic treatments, surgical procedures and the assessment of the teeth condition during determination of caries or gum disease. Considering that manual delineation and delineation of tooth boundaries is a long and challenging procedure which depends on operator variability, new and proposed semi-automatic techniques for automatic tooth segmentation in research can be very useful because they independently delineate the boundaries and contours of the teeth (10). AI in tooth segmentation uses a deep learning approach based on convolution neural networks or transformers that can extract teeth from large and comprehensive sets from feature maps of training data (11). The fundamental effective models used for the segmentation of medical images so far are U-shaped encoder-decoder Network (U-Net), Mask Region-based Convolutional Neural Network (MASK R-CNN) and SEgmentation TRansformer (SETR) and numerous additional segmentation improvements and optimizations are achieved by upgrading existing models (12). Difficult development of newer models of automated computer tools variability is limited by the teeth of different patients, artifacts or image quality (12). According to Chen and Leung (2004), segmentation methods were divided into several general categories (shape, histogram, region, threshold, spatial correlation of pixels…) and based on these previous published classifications, Gil et al. (2018) adapted the classification of segmentation methods on dental structures (region-based, threshold-based, cluster-based, boundary-based, watershed-based) (12). Region-based segmentation is done by dividing the image into regions based on discontinuities in the pixel intensity level. Threshold-based segmentation (the most common method) of pixel values is a threshold value that segments parts of pixels above the threshold value into a region, and those below the threshold value to the adjacent region. Pixels above the threshold are connected and extracted, and pixels below the threshold are connected and shape the borders of the edges in the images and the method is limited by strong contrast and brightness due to the excess pixels (12, 13). Cluster-based segmentation groups data according to a certain degree of similarity, depending on the problem needed to be solved. Boundary-based segmentation methods are used to search discontinuities in the gray levels of the image (detection of points and edges), and the newer "active contour" method outlines object boundaries. The last one, based on the divider (transformation defined in the gray image), uses mathematical methods for image segmentation in adjacent regions (12). Based on the various proposed segmentation methods of teeth, research was carried out related to all types of dental images, two-dimensional (2D) and three-dimensional (3D).

Yasa et al. proposed a method of numbering and classifying teeth on 1125 bitewing photographs, using faster regional CNN (R-CNN). Research has shown a high rate of sensitivity and precision of numbering the teeth, which can save dentist's time required for manual dental preparation of the patient's record (Figure 1) (14). On 100 periapical recordings, Eun et al. used a CNN model to classify an existing or non-existing tooth, trained on a system for recognizing the number of tooth roots in different types of teeth. Also the system previously independently produced the border frames of the teeth. The method proved to be successful for localization of teeth and determining the presence of teeth (15).

Segmentation on the bitewing or periapical image is an easier procedure because it provides a clearer representation of the tooth with less interference from other bony structures compared to a pa-

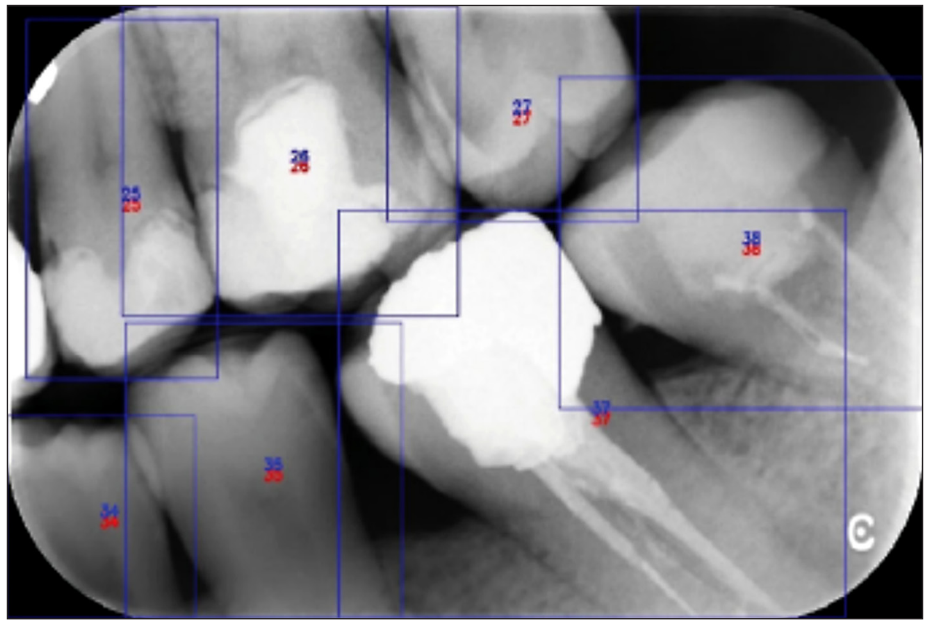

Figure 1.
Example of a bitewing image and teeth numbering with an applied CNN.
Source: https://sci-hub.se/https://www.tandfonline.com/doi/full/10.1080/00016357.2020.1840624

noramic image that shows other body parts (chin, spine and jaw). There are two types of tooth segmentation on panoramic radiographs. Semantic segmentation marks the entire distinguished object/tooth area from the background, i.e. all pixels/colours, with one label (category, class). In the instance segmentation case, each tooth has a special mark, and the goal is to identify and separate individual instances of the same class of objects and obtain a representation of the tooth of the same category. Dhar et al. used CNN to determine segmentation of teeth on panoramic radiographs and for later determining of the teeth orientation, with the aim of automatically creating a dental report. Their proposed model shows high applicability in practice, although there are disadvantages that need to be further investigated: overlapping molars and premolars, the presence of wires from braces or fillings in the teeth, and unclear root edges (Figure 2) (10).

Amer et al. proposed an automatic method of segmentation preparation on panoramic images for classification of wisdom teeth. The three stages of segmentation preparation included image pre-processing, extraction of region-based interest, based on tooth width, and stages of post-processing. The results showed that it was possible to successfully classify wisdom teeth even on post-processed segmented images. The proposed method can be used in wisdom teeth classification in dependence according to a specific problem, e.g. degree of impaction (Figure 3) (16).

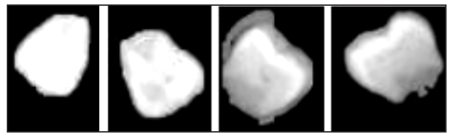

Figure 3.
Example of a segmented wisdom tooth image after post-processing.
Source: https://core.ac.uk/reader/82412360

AI is also applicable when determining reference points on cephalograms. In research by Hwang et al., AI was trained with 1983 cephalograms. The examiner manually outlined the reference points and by comparing the results of the examiner and AI, the point determination error was tolerated up to 2 mm. 11 out of 19 points showed more than 80% detection success rate. Some disadvantages of the method in detection success of the remaining points were the overlapping of the structures of the skull bases, and some points were invisible in the image. It was suggested to further investigate the analysis of angles and linear measurements of reference points obtained by AI (17).

Compared to 2D segmentation, 3D segmentation is a much more expensive method and is only applied in complex cases such as dental implantations (16). 3D application of AI is considered strong and useful when overcoming the limitations of algorithms on a 2D image because the 2D image is subject to distortion or superimposition of structures (18). Bayrakdar et al. examined the application of AI by using CNN when planning the dental implantation. CBCT images of 75 patients were manually measured, examined and an estimation for implantation was made as in the classic method. Images have been transferred in DICOM format and uploaded to the CNN network (Diagnocat, Inc.) which has prepared a report on implant planning based on a series of multiple pre-trained CNNs including segmentation voxels of teeth and surrounding structures. The results of the study showed that AI measurements were in accordance with manual measurements in the molar region and premolars of the upper jaw and premolars in the lower jaw and the marking of the mandibular canal was appropriate. Additional research should improve the measurement of bone length and height for dental implantation, the same as marking the nasal cavity, because these results were not sensitive enough (19).

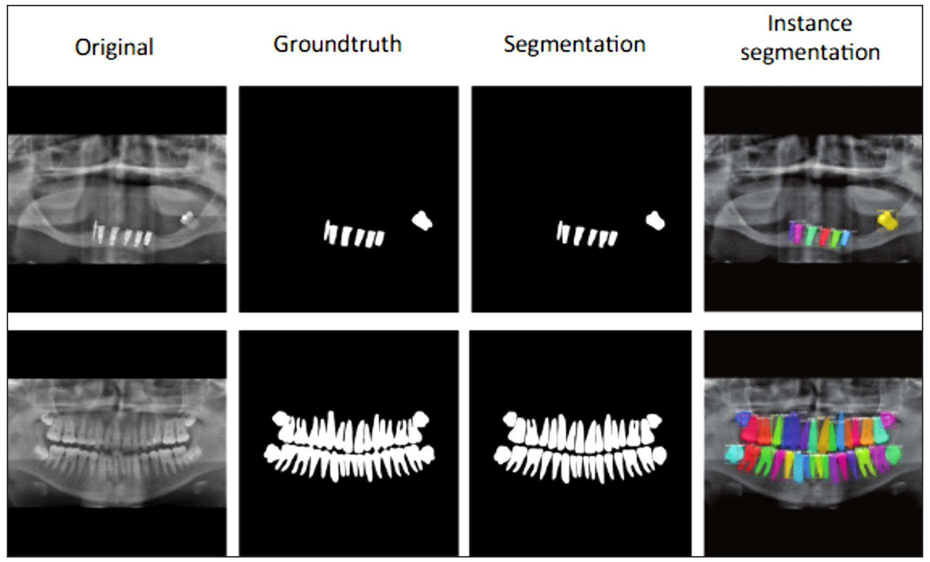

Figure 2.
Example of tooth segmentation on a panoramic radiograph.
Source:https://www.researchgate.net/publication/330472299_Deep_Instance_Segmentation_of_Teeth_in_Panoramic_X-Ray_Images

Application of methods for improving image quality enhancement

AI systems can be applied to computer systems that deal with improving the enhancement of the image, which consequently affects its quality. Thus, conducted research accorded on the possibility of reduction artifacts from metal fillings or implants and reduction of blurring and noise (20, 21). AI research that deals with the reduction of Metal Artifact Reduction (MAR) in the reconstructed image were mostly based on mathematical simulations of metal artifacts that do not follow physical foundations of photons and device detectors and are therefore not sufficiently reliable and practical for testing. Furthermore, due to the implementation of neural networks, they should be trained with an equal number of images with artifacts and without artifacts to make the results as precise as possible (22).

In the research on CBCT images, Minnema et al. suggested the use of a new Mixed-Scaled Dense neural network (MS-D) which was applied during image segmentation and not on the reconstructed image (previously U-Net, ResNet) and on stereolithography (STL) models. During the segmentation of the teeth, additional structures such as ramus, condyles and column vertebrae, were visible which means that bones were better distinguished from metal if they have not been affected by metal artifacts, compared to previously used networks. In the area of the teeth it was noticed less misinterpreted voxels. The results showed that all networks have a short segmentation time (less than 5 minutes), which affects saving time in clinical practice. Experimental results showed that the segmentation performance of the MS-D network was comparable to those as U-Net and ResNet CNNs architecture, while keeping more anatomical details in the resulting STL models and using less parameters which could be trained (Figure 4) (23).

Du et al. examined the effect of blurring on a panoramic radiograph that usually occurs in the front jaws due to wrong positioning of the patient's head which consequently leads to wrong position of the dental arch resulting in turbidity. This was the reason for CNN implementation in the research, which consisted of several stages of processing. During the first reconstruction of the image the method recorded the deviation of the position of the dental arch, thereby subtracting the movement of the structure "back and forth" in the image, and in the second reconstructed image there was less blurring visible. The results showed the effectiveness of the method in providing reconstructed images of stable quality and even though they were satisfactory, they should be additionally examined in order to achieve greater precision of the final assessment (24).

Super resolution methods based on deep learning models, where from one or more images with low resolution, an image with a higher spatial resolution is obtained. It was the subject of studies that could improve the resolution of radiograms, without limitation of the usual features of enlargement of the desired part of the image, due to diagnostically acceptable lower resolution images (25, 26). Rahimi et al. applied five types of deep learning networks to panorama radiographs with super-resolution but the combination of only two types of learning methods was successful when detecting caries or detecting periapical lesions (25). Moran et al. applied the super method resolution on the deep learning model on periapical radiographs, and their results showed that method can result in more detailed edges and less image blurring effect, but for a better quality results, only radiograms in DICOM format should be used, due to less information loss in the image (26).

CONCLUSION

The application of AI in dentistry is justified considering the advances it brings in the field of clinical dental practice. It makes the work of a dentist easier and saves time for manual preparation and analysis. Except that it is very helpful in making diagnoses and facilitating for the visualization of the pathology of dental structures, AI pointed out the importance of dental radiography. The use of CNN on 2D and 3D radiographs modalities requires knowledge

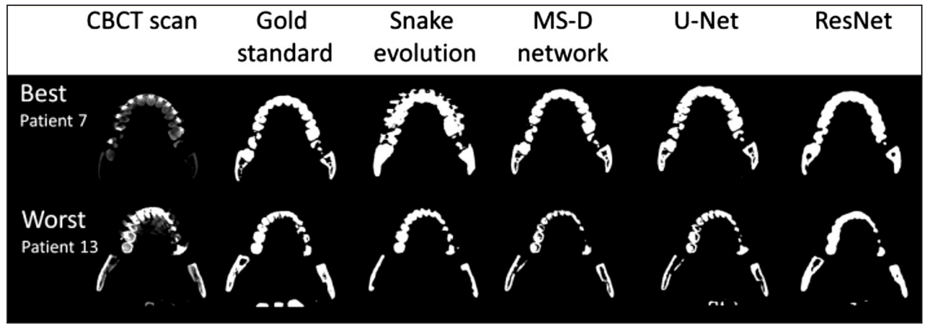

Figure 4.
Best (on the top) and worst (at the bottom) results of applying deep learning to different networks.
Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6900023/

of digital computer radiography. Other methods with the use of several types of CNN have shown success in segmenting teeth and surrounding structures and in improving the quality of the image itself, considering low resolution and artifacts. Although there are advantages, the use of AI is not without diasdvantages and obstacles, so, for example, the limitation of the teeth segmentation method is with insufficient number of radiograms, because complex AI systems need many images in order to train CNN to achieve the most accurate results. Furthermore, the image resolution differs in different modalities, and the manipulation of the reconstructed images always requires a pre-processing process due to low contrast or high noise. The implementation of AI requires financial resources and additional research should confirm its step forward in healthcare, while overcoming all ethical limitations and legal problems. AI cannot replace the knowledge and competence of experts, but it can be a valuable auxiliary tool in clinical practice for the benefit of patients.

Abbreviations:

2D - Two-Dimensional
3D - Three-Dimensional
AI - Artificial Intelligence
CBCT - Cone Beam Computed Tomography
CNN - Convolutional Neural Network
U-Net - U-shaped encoder-decoder Network
MASK R-CNN - Mask Region-based Convolutional Neural Network
SETR - SEgmentation TRansformer
R-CNN - Region-based Convolutional Neural Network
MAR - Metal Artefact Reduction
STL - Stereolithography
MS-D - Mixed-Scaled Dense (Neural Network)
ResNET - Residual Neural Network

NOVČANA POTPORA/*FUNDING*
Nema/*None*

ETIČKO ODOBRENJE/*ETHICAL APPROVAL*
Nije potrebno/*None*

SUKOB INTERESA/*CONFLICT OF INTEREST*
Autori su popunili *the Unified Competing Interest form na www.icmje.org/coi_disclosure.pdf (dostupno na zahtjev)* obrazac i izjavljuju: nemaju potporu niti jedne organizacije za objavljeni rad; nemaju financijsku potporu niti jedne organizacije koja bi mogla imati interes za objavu ovog rada u posljednje 3 godine; nemaju drugih veza ili aktivnosti koje bi mogle utjecati na objavljeni rad./ *All authors have completed the Unified Competing Interest form at www.icmje.org/coi_disclosure.pdf (available on request from the corresponding author) and declare: no support from any organization for the submitted work; no financial relationships with any organizations that might have an interest in the submitted work in the previous 3 years; no other relationships or activities that could appear to have influenced the submitted work.*

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Sažetak

METODE UMJETNE INTELIGENCIJE U DENTALNOJ RADIOGRAFIJI: TRENUTNI RAZVOJ METODA SEGMENTACIJE I POBOLJŠANJA KVALITETE SLIKE U RAZLIČITIM MODALITETIMA

Anita Ivanović, Tatjana Matijaš

Uvod: Primjena umjetne inteligencije u stomatologiji može značajno unaprijediti ishod liječenja pacijenta te ima tendenciju smanjenja ljudske pogreške. Računalni sustavi i određene metode umjetne inteligencije koje koriste složene algoritme, sposobni su kodirati digitalne podatke o radiografskoj slici dobivenoj rendgenskim zračenjem te ih prenijeti u računalni jezik za obradu velikog skupa podataka. Primijenjena kao pomoćni alat, može dati informacije o pacijentu te dijagnostici zuba i okolnih dentalnih struktura na svim radiografskim slikama (dvodimenzionalnim i trodimenzionalnim).

Cilj rada: Cilj rada je predstaviti način razvoja i primjenu umjetne inteligencije u stomatologiji, pritom naglašavajući važnost metoda segmentacije i metoda poboljšanja kvalitete dentalnih radiografskih slika.

Rasprava: Zajednički cilj razvoja i primjene metoda umjetne inteligencije u dentalnoj radiografiji usmjeren je na dobivanju radiograma iz kojih će se brže i lakše prikupiti dijagnostički vrijedne informacije u svrhu uspješnog liječenja pacijenata. Razvijene su metode segmentacije dentalnih struktura koje mogu automatski numerirati i lokalizirati zub ili samostalno označiti i prikazati željene strukture na slici. Metode unapređenja kvalitete slike nastoje djelovati na, primjerice, poboljšanju rezolucije slike ili smanjenju metalnih artefakata. Istraživanja su pokazala da se umjetna inteligencija može primjenjivati u svakodnevnoj kliničkoj praksi, no ima određena ograničenja.

Zaključak: Metode umjetne inteligencije u dentalnoj radiografiji koristan su pomoćni alat u kliničkoj praksi doktora dentalne medicine jer mogu ubrzati proces dohvaćanja podataka o pacijentu, a automatska lokalizacija dentalnih struktura skraćuje vrijeme stomatologu za ručnu analizu slike, no nikako ih mogu u potpunosti zamijeniti stomatologa. Za potpunu implementaciju navedenih metoda, potrebno je više razvojnih standarda i resursa te prevladavanje etičkih i pravnih problema zamjene čovjeka sa sustavom.

Ključne riječi: UMJETNA INTELIGENCIJA DUBOKO UČENJE, DENTALNA RADIOGRAFIJA, SEGMENTACIJA, POBOLJŠANJE SLIKE

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