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Artificial intelligence technologies in dentistry

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Abstract

One of the most important actors in the digitization process of our age has been the applications of artificial intelligence (AI). While the weak and strong AI sub-concepts and the different AI models within them are being utilized in many fields such as education, industry and medicine today, the interest of the dentistry field, which has started its integration into the digital world with CAD/CAM technology, in AI is increasing day by day. In different branches of dentistry; AI provides services to clinicians and researchers in many fields such as disease diagnosis, evaluation of the occurrence or recurrence of diseases such as oral cancer, and prediction of success in surgical and prosthetic treatments. In this article, studies in which AI models such as machine learning, convolutional neural networks have found research and usage areas on the basis of different branches of dentistry are reviewed.

Keywords: artificial intelligence, deep learning, dentistry, neural networks, prediction

1. Introduction

In dentistry, with the speed development of production options such as Computer-Aided Design/Computer-Aided Manufacturing (CAD/CAM) and Rapid Prototyping (RP) methods, the digital workflow has found an important place in clinical routine (Miyazaki and Hotta, 2011). Besides, artificial intelligence (AI) and machine learning (ML) technologies involved in the dental production phase; have carried out the most radical change in radiological imaging and diagnostic methods (Jones et al., 2017).

Artificial intelligence is defined as the ability to interpret the data uploaded to a system with high trueness, to make use of this data to sustain learning, and to use the adaptation capacity of the system in this learning process to achieve certain goals (Kaplan and Haenlein, 2019). The term "AI" basically consists of two sub-concepts, weak and strong AI (Park and Park, 2018). Researchers who support the concept of weak AI say that a running AI program is essentially a simulation of a cognitive process, whereas it itself does not have a cognitive base; on the other hand, strong AI advocates claim that AI is actually a mind of a (not yet designed) program running on a (not yet written) machine. Unlike weak AI, it is anticipated that strong AI will have free will and conscience like humans and can make the distinction between right and wrong independently (Scerri and Gresch, 2020). However, today AI does not have access to such consciousness as this claim, so both the practices in daily life and the studies in medicine and dentistry are shaped by weak AI.

Weak AI studies aim to build algorithms that can be fed with some inputs and then make various estimations (Mupparapu et al., 2018). Machine learning, is one of its branches that provides a computer model in order to enable AI to learn and make predictions through recognizing objects like image, speech, face, etc. (Hashimoto et al., 2018). The main advantage of machine learning is that, just as radiologists are constantly trained to work on medical images, the newly designed AI model enables them to develop more and increase their level of learning with a large database of new images (Kohli et al., 2017).

Furthermore, data mining methods (DMM) are utilized for more complex predictions. They have recently become common in many disciplines, including biology, medicine and dentistry. In this method, support vector machine (SVM) and convolutional neural networks (CNN) are mainly used, and they form a more successful alternative in modeling the non-linear relationships between the predicted variable and input data (Witten et al., 2011).

CNN feed on very large data clusters, thus they can be very efficient. AI is able to produce better results in disciplines such as medicine and dentistry than specialist doctors, thanks to the fact that AI models can be trained with hundreds of thousands of clinical cases. Therefore, it can transcend even the best experts in terms of the experience of clinical diagnosis and treatment (Bouletreau et al., 2019). Many of the dentistry practices make use of CNN models that are individually

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created. Looking at the literature, it appears that the pre-trained CNN models used are AlexNet, VGG16, ResNet, U-net, GoogLeNet, VGG19, densenet and V-net (Schwendicke et al., 2019).

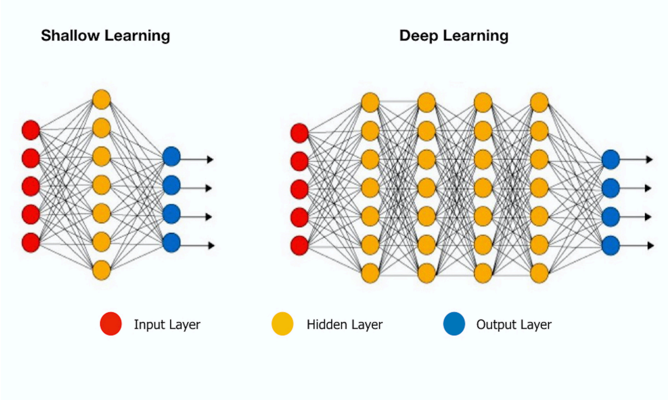

Fig. 1. Neural network designs

The accuracies of these networks depend on both the qualitative and quantitative features of training data that revises the weights of their attachments. Basic network structures with fewer layers are called "hallow learning" neural networks, while complex network structures with more layers are called "deep learning" (Burt et al., 2018) (Fig. 1). CNN based on deep learning, have started to gain a place in many fields of dentistry.

The aim of this study is to examine the applications of artificial intelligence that have been carried out in different branches of dentistry so far and which types of artificial intelligence are used in these studies.

2. Oral and maxillofacial radiology

In the fields of medicine and dentistry, many AI models have been produced to assess people's risk of getting sick, detect abnormal health data, diagnose and prognosis of diseases (Jiang et al., 2017; Litjens et al., 2017; Fazal et al., 2018). Since digital images are used for diagnosis in the field of radiology, it is quite easy to transfer these digital data into computer language. Thus, radiology is the most suitable branch of dentistry for AI use (Thrall et al., 2018). However, in order to make a high-accuracy prediction of 98% for deep learning accompanied by computed tomography data, it requires at least 1000 units and 4092 units for a success rate of 99.5%. (www.itnonline.com, 2020) (Fig. 2) As input data is increased, the success achieved in output increases (Cho et al., 2016).

Fig. 2. Deep learning reconstruction of computed tomography scan

Lee et al. (2020), pre-trained VGG16 networks with a limited training dataset by using deep CNN and evaluated the ability of this AI model to diagnose osteoporosis in dental panoramic radiography (DPR) images. While experimental results showed 84% accuracy, the researchers noted that DPR images had the potential to be used for prescreening of osteoporosis.

Kise et al. (2020), compared the diagnosis results of deep learning and three inexperienced radiologists on 100 patients who had been diagnosed with Sjogren Syndrome and 100 patients who had not been diagnosed before. As a result of the study obtained ultrasound images from salivary glands, deep learning had 89.5, 90.0 and 89.0% accuracy in parotid gland results, while radiologists had 76.7, 67.0 and 86.3% accurate diagnosis. Besides, Ekert et al. (2019) in the study they performed on panoramic radiographs, seven layers of the deep neural network were used in the Keras framework and it was reported that apical lesion detection could be made with high accuracy.

On the other hand, AI has also been found to provide good results in oral cancer prediction. In the study conducted by Alabi et al. (2019), artificial neural network (ANN) was trained with diagnostic parameters such as age, gender, T stage, WHO histologic grade, depth of invasion, tumor budding, the worst pattern of invasion, perineural invasion and lymphocytic host response in Microsoft Azure Machine Learning Studio (Azure ML 2019). In locoregional recurrence predictions performed on 311 patients, ANN was found to be successful at 92.7%, while the logistic regression model remained at 86.5% accuracy. In another study (Poedjiastoeti and Suebnukarn, 2018), the convolutional neural network (CNN) of The Google Net Inception-v3 architecture was compared with oral and maxillofacial specialists in the diagnosis of ameloblastoma and the keratocystic odontogenic tumor on panoramic radiography. CNN obtained diagnosis results with same accuracy in 38 seconds compared to the 23.1 minutes diagnostic time of the specialists. Therefore, AI may be a good alternative method to achieve a much faster diagnosis in oral cancer cases.

3. Oral and maxillofacial surgery

Zhang et al. (2018), estimated the amount of swelling with high accuracy that will occur in patients after mandibular third molar extractions, thanks to ANN working based on the conjugate gradient back-propagation algorithm. Besides, Kim et al. (2018), calculated the probability for the occurrence of bisphosphonate-related osteonecrosis after tooth extraction using five different machine learning methods based on drug holiday and CTX level values. As a result of the study, it was found that machine learning yielded better results than the conventional method, primarily the random forest model (97.3%) and ANN (91.5%).

Scrobotă et al. (2017), utilized fuzzy logic for predicting the risk of oxidative stress-related cancerization risk of the potentially malignant processes. The researchers noted that the system was highly successful in oral cancer screening. Polášková et al. (2013), developed a machine learning system (clinical decision support system) in a web application that gives recommendations on implant treatments. The system uses the data referencing anamnesis and medical examination such as 3-D measurements, information regarding treatment planning.

Artificial intelligence has also found extensive use in the field of maxillofacial surgery (www.dolphinimaging.it, 2020) (Fig. 3). In the study of Stehrer et al. (2019), among 950 patients undergoing orthognathic surgery between 2006 and 2017, training and test groups were created with 80% and 20% ratio in a Random Forest model. At the end of the study, a statistically significant correlation was determined between the estimated amount of blood loss and the amount of blood loss that occurred after the operations. In another study (Patcas et al., 2019), it was found out that the effect of orthognathic surgery on facial attractiveness and age estimation can be assessed fairly well with deep learning using Chicago Fire Dataset. Therefore, it is thought that in the near future deep learning algorithms trained with hundreds of thousands of clinical cases, will be equivalent to the best oral and maxillofacial surgeons, at least in diagnosing dento-facial dysmorphism; and the results that can be achieved in patients with orthognathic surgery can be predicted with high accuracy.

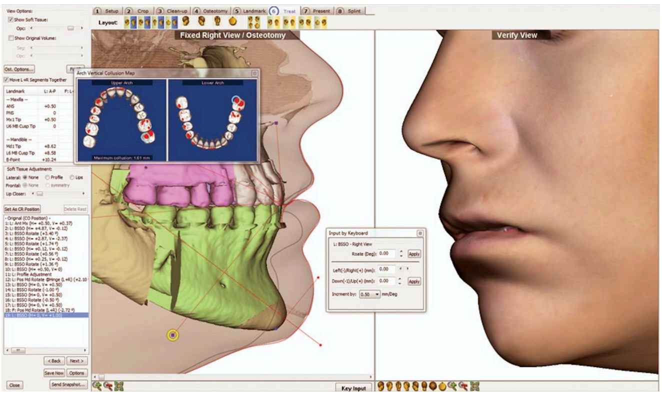

Fig. 3. 3D planning of maxillofacial surgery

4. Periodontics

Deep learning can be used to determine the prognosis of periodontally compromised teeth and to classify periodontal diseases. Lee et al. (2018), evaluated the prognosis of compromised teeth through periapical radiography by creating a deep CNN model with the Adam algorithm. They determined the prognosis with 81.0% accuracy in premolar and 76.7% accuracy in molar teeth. Furthermore, Kim et al. (2019) examined periodontal bone loss on panoramic radiographs using a deep learning-based DeNTNet system. DeNTNet system achieved a score of 0.75, while the performance of clinicians remained lower at 0.69.

Decision trees (DT), SVM and neural network (NN) have been used in current studies for the classification of periodontal diseases. Özden et al. (2015), formed a matrix with periodontium and bone loss data radiographically obtained from patients; and they identified 6 different classes. DT and SVM showed very successful results with calculation times of 7.00 and 19.91 seconds and 98% accuracy; while NN was the group that showed the worst correlation with 46% accuracy in this study. Nakano et al. (2014), performed oral halitosis classification by means of oral microbiota in saliva using DT, SVM and ANN methods. SVM yielded an accuracy level of >95% and it was reported that AI models using T-RFLP data may be useful in halitosis detection.

Currently, for the measurement of periodontal pockets, some researchers have been working on ultrasonographic probes that operate with non-invasive and pain-free techniques. To measure the depth, it applies echo waveforms that AI can then evaluate with the wavelet transformation technique. The model promptly offers the clinician two possible pocket depths with 90% legibility by using a binary classification algorithm (Rudd et al., 2009).

5. Pediatric dentistry

Looking at the current literature, it is pointed out that the branch in which AI finds perhaps the least use in pediatric dentistry. Baliga (2019), reported that early orthodontic movements can be performed with appliances customized by AI and pain control can be provided by using injection-free pedodontic practice with AI-based devices in pediatric dentistry.

6. Orthodontics

Four different NN models were used on 156 patients in a study that evaluated the diagnosis of tooth extraction before orthodontic treatment. The NN models were constructed with a back-propagation algorithm and the effectiveness of the models was evaluated. At the end of the study, the success rate of extraction vs non-extraction diagnosis was 93% (Jung and Kim, 2016). In addition to this study, Xie et al. (2010) conducted a study on 200 patients aged between 11-15 and the extraction decisions of NN models constructed with FORTRAN programming language and an orthodontist were compared. The researchers noted that the NN model yielded high accuracy with an 80% ratio.

Kunz et al. (2020), have developed an AI algorithm for automated cephalometric X-ray analysis. 12 experienced orthodontists identified 18 different landmarks on 1792 cephalometric X-rays to the AI model. At the end of the evaluation of 50 cephalometric X-rays, it was determined that the predictions carried out by the AI model did not differ statistically from the analysis carried out by orthodontists, which was accepted as the gold standard in orthodontics.

Frontal and profile pictures of 20 treated left-sided cleft patients and the control group of 10 healthy people were compared between VGG16 and the conventional rater group of lay people, orthodontists and oral surgeons, in terms of evaluation of facial attractiveness. AI evaluation of cleft patients (mean score: 4.75 ± 1.27) was similar to human ratings (lay people: 4.24 ± 0.81, orthodontists: 4.82 ± 0.94, oral surgeons: 4.74 ± 0.83); however, the results of people in the control group was higher at a statistically significant level. The researchers indicated the need for AI to be developed for safe use in facial attractiveness evaluation (Patcas et al., 2019).

Additionally, other studies have shown that fuzzy models can be used successfully for the assessment of the use of headgears by evaluating overjet, overbite and mandibular plane angle variables (Akçam and Takada, 2002) and to determine the cervical vertebral stage in patients with the cephalometric examination (Kök et al., 2019).

7. Endodontics

Kositbowornchai et al. (2013), have developed a probabilistic neural network that assesses whether tooth roots have a vertical fracture. As a result of testing the data, it was determined that the model can be detected with high sensitivity (98%), specificity (90.5%) and accuracy (95.7%). In another study conducted by Mallishery et al. (2019), 500 potential root canal patients were evaluated by both endodontists and ANN with the help of the standard American Association of Endodontists Endodontic Case Difficulty Assessment Form. The hidden and output layers have the rectified linear unit (ReLU) activation function, which is $f(x) = \max(0, x)$, and this function was used for the classification. The diagnosis determined by ANN was found to have 94.96% accuracy and it was stated that the degree of difficulty for these cases was able to be determined with high accuracy in endodontic terms.

ANN has also been applied in determining the working length of the root canal and locating minor apical foramen in the field of endodontics. In a study, the apical foramen on 50 human teeth before extraction was located by an endodontist with endodontic files and then by the ANN model in conjunction with the Otsu method. According to reference measurements made with a stereomicroscope, which is considered as the gold standard, the endodontist yielded results with 76% and ANN with 96% accuracy (Saghiri et al., 2012a). In another study conducted by also Saghiri et al. (2012b), apical foramen localization via radiography with ANN was performed with 93% accuracy. According to these data, it is stated that AI is one of the decision-making mechanisms that can be utilized in various clinical tables.

8. Restorative dentistry

Artificial intelligence is integrated into many systems, for instance intraoral scanners such as Cerec Primescan (Dentsply Sirona) and Trios 4 (3Shape) for removing the excessive images of intraoral scan and detect proximal caries. (my.cerec.com, 2020) (Fig. 4) NNs have been shown to be capable of high-accuracy caries detection with Near-Infrared-Light Transillumination (NILT) images (Schwendicke et al., 2020). Devito et al. (2008), compared NN to 24 examiners in terms of caries detection. The examiners were able to detect proximal caries with 71.7% and NN with 88.4% accuracy. Besides, the ANN model whose input fed with caries excavation methods and pre-streptococcus mutants for the detection of caries was introduced as an iOS application, entitled "Post-streptococcus mutans prediction (PSm)" (Javed et al., 2020).

Fig. 4. Full-arch maxillary scan

Haidan et al. (2014), evaluated the wear factors on dental surfaces of 96 patients using an ANN. Medical histories and data collected via eleven parameters were installed to an ANN software, Pythia. As a result of the study; age, consumption of pickles, oranges and acidic drinks and frequency of brushing were found the most effective factors in the wear of teeth surfaces. The researchers stated that 73.3% accuracy was achieved, and this value was clinically acceptable, while the dental wear assessment performed with ANN was timesaving.

Furthermore, in different studies, colorimetric values were used to predict the color change obtained by the bleaching system before the process (Thanathornwong et al., 2016). By using the initial chromatic values of a tooth, fuzzy logic can match the postbleaching CIELAB coordinates with the Vita shade to predict the approximate color of the tooth after bleaching (Herrera et al., 2010).

9. Prosthodontics

AI contributes to implant-supported fixed restoration production. After shaping the soft tissue with a temporary restoration, first soft tissue and then the scan body impressions are made. Then, two different images are superimposed on the CAD system with the help of AI and hybrid abutment production is performed in accordance with the soft tissue form (Mangano et al., 2019).

Yamaguchi et al. (2019), have developed a CNN model with the Keras library on top of TensorFlow in Python, which predicts the probability of debonding CAD/CAM composite resin crowns. Randomized 6480 training and validation images and 2160 test images were used to develop the model and the model was applied to the die images obtained with an intraoral scanner. As a result of the study; accuracy, precision, recall, F-measure values were found to be 98.5%, 97.0%, 100%, and

0.985% respectively, and the prediction level for debonding was detected successfully. Besides in another study, it has shown that a multilayer perceptron and Bayesian network using Verma and Pearl algorithm, can determine the most suitable type of restoration for different cases by predicting longevity (Aliaga et al., 2015).

Backpropagation of neural networks (BPNN) has been introduced to computer color matching in prosthodontics. The GA + BP system for color matching has been developed. The initial weights and threshold compared to conventional BPNN are primarily optimized by GA. It has been shown that BPNN improves convergence performance and stability by determining appropriate initial parameters rather than random selection of initial parameters and makes restoration's color matching more accurate (Li et al., 2015). The skin color of each region can also be determined with SVM and CNN models. Automatic analysis modules have been developed, especially in optical visagism systems through the use of skin color by eyewear virtual try-on software via a mobile device (Borza et al., 2018).

In the field of removable prosthodontics, it is possible to predict the changes of facial soft tissue that will occur in patients after complete denture applications with AI systems quickly and accurately (Cheng et al., 2015), and although it needs further development, AI can make case-specific removable partial prosthetics designs (Chen et al., 2016).

10.Temporomandibular disorders

Baş et al. (2012) measured the diagnostic determination ability of the neural networks (NN) on 58 patients after training the NN model with the clinical symptoms and diagnoses of 161 patients. They measured the sensitivity and specificity of ANN in determining TMD subgroups by comparing it with clinical diagnosis, which is considered the gold standard. The sensitivity and specificity of unilateral disc displacement with reduction detection of ANN were found to be 80% and 95%, while its without-reduction success was found to be 69% and 91%. Disc displacement sensitivity and specificity with bilateral reduction were 100% and 89%, while those without bilateral reduction were 37% and 100%. The success of disc displacement diagnosis with the reduction on one side and without-reduction on the other side remained at 44% and 93%. The researchers noted that ANN could help clinicians in the classification of TMD, with more input loading likely to increase accuracy.

There are also studies that have searched the effectiveness of AI-based Natural Language Processing (NLP) in diagnosing orofacial pain disorders. In their study Nam et al. (2018), after comparing the medical records of 29 TMD-mimicking patients with 290 genuine TMD patients, found out that the NLP model's success rate to predict TMD-mimicking condition is 96.6%, with 69.0% sensitivity and 99.3% specificity.

AI applications have not found enough place in dentistry clinical applications so far due to their technical difficulties and cost. However, AI models are expected to automatically diagnose diseases on 3-D images, to identify specific disease risks to individuals, and to contribute to clinicians in therapeutic applications by evaluating the prognoses of treatment types by feeding on more comprehensive data sets (Goldhahn et al., 2018).

11. Conclusion

AI technology, which is developing day by day, is expected to be given a greater role in the classification of diseases, utilization of treatment recommendations and prosthetic production stages soon. However, this requires that AI models prove their performance through clinical trials and their superior results on the success rate-time axis are supported by research data. The development of weak AI technologies continues to be human-oriented and may disrupt this process somewhat. If the use of strong AI is possible in the future, it will be possible to apply more accurate digital techniques rather than conventional techniques in dentistry as in all areas of life.

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