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An overview of deep learning in the field of dentistry

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ABSTRACT

Purpose: Artificial intelligence (AI), represented by deep learning, can be used for real-life problems and is applied across all sectors of society including medical and dental field. The purpose of this study is to review articles about deep learning that were applied to the field of oral and maxillofacial radiology.
Materials and Methods: A systematic review was performed using Pubmed, Scopus, and IEEE explore databases to identify articles using deep learning in English literature. The variables from 25 articles included network architecture, number of training data, evaluation result, pros and cons, study object and imaging modality.
Results: Convolutional Neural network (CNN) was used as a main network component. The number of published paper and training datasets tended to increase, dealing with various field of dentistry.
Conclusion: Dental public datasets need to be constructed and data standardization is necessary for clinical application of deep learning in dental field. ***(Imaging Sci Dent 2019; 49: 1-7)***

KEY WORDS: Artificial Intelligence; Deep Learning; Dentistry; Radiology

Introduction

Artificial intelligence (AI) has evolved from the concept of strong AI, which imitates human intelligence, to the implementation of weak AI that can solve certain problems.[1] Studies of weak AI explore ways to construct algorithms that can learn from data and make predictions. Machine learning is a branch of computer science that builds algorithms guided by data.[2] Among them, neural networks (NNs), which consist of nodes and weights, were one of the first types of AI algorithms to be developed. The computational power of these networks relies on the quality and quantity of training data, which allow these networks to update the weights of the connections. Simple network structures with only a few layers are known as "shallow" learning neural networks, whereas network structures that employ numerous and large layers are referred to as "deep" learning neural networks.[3] Deep learning structures referred to as convolutional neural networks (CNNs), which can extract many features from abstracted layers of filters, are mainly used for processing large and complex images. Deep learning is being accelerated by the development of self-learning back-propagation algorithms that progressively refine the results from the data, as well as by increases in computational power. Due to these rapid technological advances, AI, represented by deep learning, can be used for real-life problems and is applied across all sectors of society.[4] The diagnostic accuracy of deep learning algorithms in the medical field is approaching levels of human expertise, changing the role of computer-assisted diagnosis from a 'second-opinion' tool to a more collaborative one.[3] The development of AI applications in the dental field is also remarkable.[1,2] In this article, papers about deep learning applied to the field of oral and maxillofacial radiology will be reviewed.

Materials and Methods

Search strategy

In PubMed, Scopus, and the IEEE Xplore Digital Library,

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a search was performed for 'deep learning OR neural network' and 'dental AND (diagnosis OR detection OR classification OR segmentation)' extending through December 2018, and 144, 33, and 32 search results were obtained, respectively. A total of 25 peer-reviewed papers were obtained by removing articles not written in English, those focusing on non-dental fields, papers not related to imaging dentistry, as well as reviews, editorials, and in-press papers. The multilayer perceptron emerged as an early field of deep learning, and papers on this topic were excluded from this study because it is not a true end-to-end learning method—it learns features extracted from images using existing machine learning algorithms—and it has shallow networks and limited accuracy when the number of layers is increased.[5]

Data extraction

Study-specific data describing deep learning architecture, the size of the training datasets, evaluation results, advantages and disadvantages, the object of the study, and imaging modality were collected, in addition to other variables such as author and publication year.

Results

The data extracted from the selected papers are summarized in Table 1.

In all studies, CNN was used as a main network component, and there were also studies using various other types of networks, such as long short-term memory and siamese networks, in addition to CNNs. CNN-based papers have appeared in the field of dentistry since 2016, and subsequently, more and more dentistry papers using CNN have been published (Fig. 1).

The median size of the datasets used for training also tended to increase, from 100 units to 1000 units (Fig. 2).

Many papers that used pretrained networks such as Alexnet, VGG, GoogLeNet, and Inception v3 showed good results for general purposes.[31] However, the structure of CNN networks tends to change from networks with shallow layers to deeper or problem-specific home-made or complex networks.

These studies dealt with various field of dentistry. Most of them were related to teeth, but other subjects such as the gingiva and periodontium, the dental arch, osteoporosis, and anatomical landmarks were also studied using deep learning (Table 2).

Various imaging modalities have been studied in conjunction with the abovementioned subjects. Efforts are underway to diagnose dental disease using traditional 2-dimensional radiographs (intraoral and panoramic), as well as using 3-dimensional cone-beam computed tomography (CBCT). Other studies have investigated new modalities in dental applications, such as quantitative light-induced fluorescence, optical coherence tomography, and the use of intra-oral laser scanners.

Discussion

Computer assisted diagnosis (CAD) software in the medical field has been used to obtain second opinions, but the design and tuning of conventional CAD tends to be very arduous. Recently, deep learning techniques have been integrated into CAD, with promising results for various medical applications.[32,33] The qualitative and quantitative applications of deep learning in dentistry are also expanding, but certain areas need to be complemented to promote the continued development of deep learning research in oral and maxillofacial radiology.

However, because all the data sets used in the research analyzed herein were in-house, objective comparison of the studies was difficult. Only a single study tried to evaluate the accuracy of developed networks using other public datasets.[23] Efforts are needed to develop a public dataset, such as in the medical field,[34] to develop algorithms that can be used in clinical applications. In order to achieve this, researchers need to release the data used in their papers with appropriate removal of personal information, and legal and institutional support from each country is also necessary.[35,36] There is also a need to build a common, free repository that can reliably collect, catalog, and archive publicly available data in the dental field.

The overall increase in the size of training datasets is desirable for clinical applications of deep learning to the dental field. However, most studies used relatively small data sets (fewer than 1000 units per group), and the accuracy of most studies was less than 90%. This is below the clinically expected accuracy of 98%-99%.[37] Deep learning requires a large amount of data because it learns features directly from the data via an end-to-end process. In an anatomical classification study of CT data, at least 1,000 data sets per group were required to achieve 98% validation accuracy with deep learning, and 4,092 data sets per group were required to reach the desired accuracy of 99.5%.[38] CBCT, which is the most popular 3D imaging modality in the dental field, does not utilize defined Hounsfield unit values like medical CT, and the pixel values of the acquired images change at every exposure.[39] The image quality and magnification of panoramic radiographs, which are com-

Table 1. Summary of deep learning articles in the field of dentistry

	Author	Architecture	Number of training data	Evaluation (average accuracy if not mentioned)	Pros (+)/Cons(−)	Full name	Object	Modality	Year
1	Imangaliyev et al.[6]	CNN	427	0.75 (F1-score)	− No prominent CNN structure, small dataset	Deep learning for classification of dental plaque images	dental plaque	QLF	2016
2	Eun et al.[7]	CNN	600	0.7138 (MABO)	⊕ Conventional CNN approach − shallow layer, small dataset	Oriented tooth localization for periapical dental X-ray images via convolutional neural network	tooth	intraoral	2016
3	De Tobel et al.[8]	CNN (Alexnet)	400	0.51	⊕ Comparison against ML algorithms − manual ROI selection, small dataset	An automated technique to stage lower third molar development on panoramic radiographs for age estimation: A pilot study	tooth; age staging	panorama	2017
4	Rana et al.[9]	CNN	405	0.347 (precision), 0.621 (recall), 0.746 (AUC)	⊕ Conventional CNN approach − small dataset	Automated segmentation of gingival diseases from oral images	gingiva; gingivitis	QLF	2017
5	Lee et al.[10]	CNN	300	Not mentioned	⊕ Conventional CNN approach − shallow layer, small dataset	Cephalometric landmark detection in dental x-ray images using convolutional neural networks	skull; landmark detection	lateral cephalometric radiography	2017
6	Prajapati et al.[11]	CNN (VGG16)	251	0.8846	⊕ Conventional CNN approach − small dataset	Classification of dental diseases using CNN and transfer learning	tooth disease	intraoral	2017
7	Imangaliyev et al.[12]	CNN	427	0.76 (F1-score)	⊕ Comparison against ML algorithms − No precise CNN model description, small dataset	Classification of quantitative light-induced fluorescence images using convolutional neural network	dental plaque assessment	QLF	2017
8	Miki et al.[13]	CNN (Alexnet)	52 (CBCT)	0.888	⊕ Conventional CNN approach − manual ROI selection, relatively small dataset	Classification of teeth in cone-beam CT using deep convolutional neural network.	tooth classification	CBCT	2017
9	Yauney et al.[14]	CNN (truncated VGG)	47	0.8497∼0.8718	⊕ Conventional CNN approach − small dataset, patch based (suboptimal global information)	Convolutional neural network for combined classification of fluorescent biomarkers and expert annotations using white light images	dental plaque	QLF	2017
10	Oktay et al.[15]	CNN (modified Alexnet)	100	0.9174∼0.9432	⊕ Conventional CNN approach − small dataset, sliding window (suboptimal global information)	Tooth detection with convolutional neural networks	tooth	panorama	2017
11	Miki et al.[16]	CNN (Alexnet)	52 (CBCT)	0.774 (detection), 0.771(classification)	⊕ Conventional CNN approach − relatively small dataset	Tooth labeling in cone-beam CT using deep convolutional neural network for forensic identification	tooth	CBCT	2017
12	Murata et al.[17]	CNN, LSTM	352	0.648	⊕ CNN with LSTM − small dataset	Towards a fully automated diagnostic system for orthodontic treatment in dentistry	orthodontics	facial photo	2017
13	Xu et al.[18]	CNN	1200	0.9879∼0.9906	⊕3D analysis using feature vectors − relatively small dataset, complex system (different task, different network)	3D tooth segmentation and labeling using deep convolutional neural networks	tooth	dental model database	2018
14	Du et al.[19]	CNN	5166	0.362 (MSE)	⊕ Comparison among different architectures − simulated data set, manual ROI selection	A convolutional neural network based auto-positioning method for dental arch In rotational panoramic radiography.	dental arch	reconstructed panorama	2018
15	Zhang et al.[20]	CNN	1000	0.958 (precision) 0.961 (recall)	⊕ Comparison among different architectures − complex system (different task, different network), small dataset	An effective teeth recognition method using label tree with cascade network structure.	tooth	intraoral	2018

Table1. Continued

	Author	Architecture	Number of training data	Evaluation (average accuracy if not mentioned)	Pros (+)/Cons(−)	Full name	Object	Modality	Year
16	Yang et al.[21]	CNN	196	0.749 (F1)	⊕ automatic ROI detection − Inaccurate ROI detection, small dataset, few CNN layer	Automated dental image analysis by deep learning on small dataset	tooth; endodontic treatment result	intraoral	2018
17	Andreas et al.[22]	CNN (Unet)	10	0.744 (DSC), 0.790 (precision), 0.827 (recall)	⊕ Conventional CNN approach − small dataset, adopt machine learning method for segmentation	Automatic teeth segmentation in panoramic X-ray images using a coupled shape model in combination with a neural network	tooth	panorama	2018
18	Torosdagli et al.[23]	CNN (Tiramisu), LSTM	50 (CBCT)	0.9382 (DSC)	⊕ Comparison among different architectures, Comparison using public dataset − relatively small dataset, 2D (pseudo-3D) analysis	Deep geodesic learning for segmentation and anatomical landmarking	anatomical landmark	CBCT	2018
19	Karimian et al.[24]	CNN	5	Sensitivity 97.93∼99.85% Specificity 100%	⊕ Conventional CNN approach − small dataset, patch based (suboptimal global information)	Deep learning classifier with optical coherence tomography images for early dental caries detection	tooth (caries)	OCT	2018
20	Hatvani et al.[25]	CNN (Unet, subpixel net)	5680	0.9101 (DSC)	⊕ Comparison among different architectures − ex-vivo data	Deep learning-based super-resolution applied to dental computed tomography	tooth	CBCT	2018
21	Lee et al.[26]	CNN (GoogLeNet, Inception v3)	3000	0.82∼0.89 0.845∼0.917 (AUC)	⊕ Conventional CNN approach − relatively small dataset, cropped and downscaled images	Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm.	tooth (caries)	intraoral	2018
22	Lee et al.[27]	CNN (VGG19)	1740	0.767∼0.810	⊕ Conventional CNN approach − relatively small dataset, cropped and downscaled images	Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm	periodontitis	intraoral	2018
23	Egger et al.[28]	CNN (VGG16, FCN)	1680	0.9877	⊕ Conventional CNN approach − relatively small dataset	Fully convolutional mandible segmentation on a valid ground- truth dataset	mandible	CT	2018
24	Lee et al.[29]	CNN	1268	0.9763∼0.9987 (AUC)	⊕ Conventional CNN approach − relatively small dataset, cropped and downscaled images	Osteoporosis detection in panoramic radiographs using a deep convolutional neural network-based computer-assisted diagnosis system: a preliminary study	osteoporosis	panorama	2018
25	Chu et al.[30]	CNN (Octuplet Siamese Network)	108	0.8929∼0.9038	⊕ plus with texture and without texture compared − complex system (8 module), small dataset	Using octuplet siamese network for osteoporosis analysis on dental panoramic radiographs	osteoporosis	panorama	2018

CNN: Convolutional neural network, LSTM: long short-term memory, QLF: Quantitative light-induced fluorescence, OCT: Optical coherence tomography, MABO: mean average best overlap, DSC: dice similarity coefficient, AUC: area under the curve

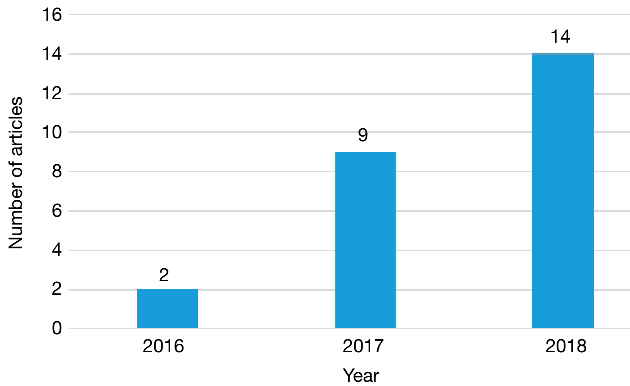

Fig. 1. Number of articles from 2016 to 2018.

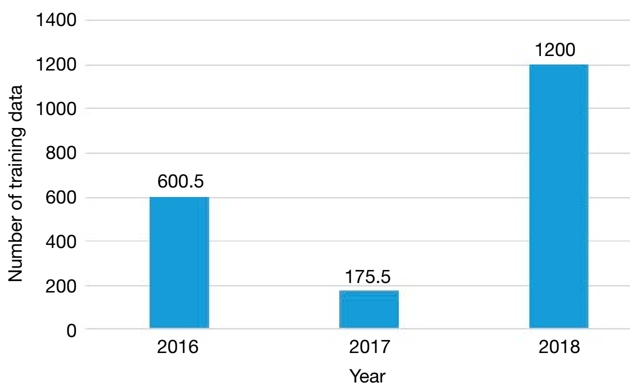

Fig. 2. Median size of training datasets from 2016 to 2018.

Table 2. Frequency of subjects in deep learning articles

Subject	Frequency
Tooth related	12
Dental plaque	3
Gingiva or periodontium	2
Osteoporosis	2
etc.	5

monly used in dental practice, depend on the positioning of the patient.[40] Therefore, to achieve clinically meaningful high accuracy, trans-hospital or hybrid data sets from multiple machines and conditions are likely to be needed due to the nature of dental images. For this reason, it is especially important to emphasize the need to construct a large-scale dental public dataset to make the clinical application of deep learning possible.

It is also necessary to emphasize the need for data standardization in the dental field, as well as for standardization of data set construction. In particular, CBCT exhibits large image variation according to brand, machine, and exposure conditions, which can be an obstacle to deep learning research. For example, collecting and learning data on a machine-by-machine basis is difficult because models learned on one machine do not apply to other machines. Although attempts have been made to develop guidelines in Europe, Germany, and England regarding the image quality of CBCT, no international standard has yet been established.[41] Therefore, in order for 3-dimensional diagnosis using deep learning to be practical, an international standard for the quality of CBCT images needs to be established in the near future.

Many papers have used preprocessed images via manual cropping of the region of interest. This makes it difficult to analyze and compare results accurately due to errors in the manual process. Some papers[9,10,19] have described networks that learned by dividing images into patches of a certain size. However, this method is limited because the network cannot learn the whole image, and instead only focuses on a small part of the image. Some papers[21,22,24] used downsampling, which might delete important details of the image. These choices seem to have been made due to limitations in the amount of data or computational power, as indicated in the limitations sections of some papers.[21,22] However, as computing power per cost increases, it is necessary to use entire images to learn, without any artificial manipulation in the preprocessing stage, in order to obtain more accurate and general results.

Currently, the use of AI is expanding in the medical field. For example, Watson, developed by IBM, has been used to support doctors' clinical decisions.[42] However, the clinical accuracy of AI in the dental field must be verified with a variety of cases and imaging modalities due to the difficulty of standardizing dental radiology before AI can take on a more important role in making diagnostic recommendations. Furthermore, current AI algorithms function as black boxes, making it difficult for humans to identify or adjust the criteria used for diagnoses.[43] Therefore, in order to increase the reliability of AI, it is necessary to develop a visualization and modification tool for deep learning networks that can be easily understood and edited by humans.

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