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Role of deep learning in dentistry an overview

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Abstract:
Purpose: Deep learning-based artificial intelligence (AI) can solve real-world problems in all fields, including medicine and dentistry. This study conducts a literature review focusing on oral and craniofacial radiology deep learning.
Martials and Method: Using PubMed, IEEE explore databases, and Scopus a systematic review identified English literature papers employing deep learning.25 studies examined number of training data, network architecture, assessment outcome, pros, cons, study topic, and imaging modalities.
Results: As the primary component of the network, a convolutional neural network, or CNN, was utilized. There has been a general trend towards an increase in the amount of published papers and training datasets that deal with various aspects of dentistry.
Conclusion: In order to put deep learning theory into practice in the field of dentistry, oral and dental data need to be created, and data needs to be standardized.

Keywords: Deep Learning; Artificial Intelligence; Dentistry; Radiology

Introduction:
Artificial intelligence (AI) has progressed from the idea of strong AI, which replicates human intelligence, to the application of weak AI, which can solve certain issues. Strong AI attempts to replicate human intelligence.[1]Research in the field of weak artificial intelligence looks into approaches to build algorithms that are able to learn from data and make judgments. The computer science field known as machine learning creates algorithms by following the capabilities of individuals by data.[2]Neural networks (NNs), which are made up of nodes and weights, were among the initial kinds of AI algorithms that were ever invented. They are one of the forms of AI. The quantity and quality of training examples are what enable these networks to adjust the connection weights, which in turn determines the amount of computational power that can be extracted from these networks. Network designs that employ a high number of layers and a big number of layers are alluded to as "deep" learning neural networks. On the other hand, simple network structures with just a few levels are referred to as "shallow" learning neural networks.[3] processing large and complicated images typically

requires the application of deep learning structures known as convolutional neural networks (CNNs). These structures are capable of extracting many characteristics from abstracted layers of filters, which makes them ideal for this task. The development of self-learning back-propagation algorithms, which progressively refine the conclusions derived from the data, as well as advancements in processing capacity, are helping to speed up the process of deep learning. Deep learning, which is a subfield of artificial intelligence, has made it possible to apply AI to the solution of issues that occur in real life and has spread its usage to all aspects of society.[4] Since the clinical diagnosis of deep learning algorithms in the medical profession is getting closer to that of human experts, the purpose of computer-assisted diagnosis is shifting from that of a tool for providing a "second opinion" to one that is more collaborative.[3] Artificial intelligence has also been used in astonishing ways in the dental industry.[1,2] This article reviews oral and maxillofacial radiology-related deep learning publications.

Substances and Techniques:

Search Strategy:

PubMed, Scopus, and IEEE Explore Digital Library searched for "deep learning OR neural network" and "dental AND (diagnostic OR recognition OR classification OR segmentation)" until December 2021.and the results were 144, 33, and 32 search results, respectively. After deleting publications that were not written in English, those that focused on subjects other than dentistry, papers that were not relevant 25 peer-reviewed imaging dentistry, review, editorials, and in-press articles were obtained. This study excluded papers on the multilayer perceptron, an initial field of deep learning, due to its lack of a truthful end-to-end learning method—it tools for various derived from pictures using established machine learning algorithms—with shallow networks as well as limited accuracy as layers increase.[5]

Data Extraction:

In addition to author and publishing year, study-specific data on deep learning architecture, trained data volume, evaluation findings, benefits and drawbacks, study purpose, and imaging modalities was collected.

Results:

The data Derive from the selected papers are compile In Table1.

In all studies, CNN was the main network component, but research also included Siamese networks, long-short-term memory since 2021, there have been articles released in the discipline of dental that are based on CNN, and as a result, there have been an increasing number of dental papers published that use CNN (Feg.1).

From 100 units to 1000 units, the maximum size of training datasets increased (Feg.2).

Results for general applications were favorable in the majority of the published works that made use of pretrained networks like Alex net, VGG, Google Net, and Inception v3.31However the management chart of CNN networks shifts from shallow layers to deeper, issue, home-made, or complex networks. Numerous dental fields were studied. Deep learning studied gums, inflamed gums, dental arch, bone loss, and anatomy landmarks (Table 2).

In combination with the aforementioned topics, research has been conducted on a number of different imaging modalities. Intraoral, panoramic, and concave computed tomography are used together to diagnose inflamed gums (CBCT). Restorative dentistry studies have examined confocal tomography, quantifiable light-induced fluorescence, and intra-oral laser scanners.

Table 1

Summary of deep learning articles in the field dentistry

Author	Year of publication	Modality	Number of Training Data	Methods	Architecture	Classes	Evaluation Metrics	Accuracy
AbdullahS.AL-Malaise AL-Gaudi et al.	2022	Image data set	371	DL	NAS.Net	3	Accuracy & Loss	96 %
Hahira Zhu et al.	2023	panoramic radiographs	3127	DL	CariesNet	4	Accuracy	93.64 %
Linhong Jiang et al.	2023	panoramic photographs	640	DL and IP	UNet and YOLO-v4	2	Loss and Accuracy	77 %
F. Casalegno al.	2021	Trans_illumination imaging (TI)	185	DL	CNNs	Binary	Accuracy	85 %
Sultan Imangaliyev et al.	2022	QLF-images	427	DL	Custom CNN	Multi class	Accuracy, loss and F-1 Score	75 %
Yoshihito Takahashi et al.	2021	oral photographic pictures	1904	Ensemble DL model	CNN model	2	Accuracy	93 %
Murcia Paul Murrain et al.	2023	X-Ray images	1000 images	DL and IP techniques	Optimized CNN	5	Accuracy, loss and F-1 Score, Recall and Presidi	89%

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							on	
Amir Hussein Abdi et al.	2022	X-Ray images	95 selected from 2000 images	DL	Segmentation	Binary	Coefficient Specificity and Sensitivity	94%
Vanessa De Araujo Farina et al.	2021	Py.Radiomics	105 images	DL	ANN	Binary	Accuracy and Loss	98%
Reyes LT et al.	2022	Dental images	Different datasets	ML and DL	N/A	Binary and Multi class	Accuracy, precision and Recall	74% to 98%
Joe Yang et al.	2023	X-Ray	196	DL	CNN	Binary	F1-Score	75%
Prerna Singh et al.	2023	panoramic image	400	DL and IP	Deep CNN	Binary	Accuracy	95%
Zhang et al.	2021	intraoral	1000	CNN	Deep CNN	Binary	Accuracy	96%
Imangaliyev et al.	2023	QLF	427	CNN	CNN Model	2	F1-Score	75%
Eun et al.	2023	intraoral	600	CNN	CNN Model	Binary	Accuracy & Loss	79%
De Tobel et al.	2023	panorama	400	ML	CNN Model	Binary	Accuracy	80%
Rana et al.	2023	QLF	405	DL	Deep CNN	2	Accuracy & Loss	92%
Lee et al.	2021	Lateral Cephalometr radiography	300	CNN	Deep CNN	Multi class	Accuracy & Loss	76%

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Milki et al.	2022	Radiography	1000	DL	ANN	3	Accuracy & Loss	96%
Yang et al.	2023	Image	196	DL	CNN	2	Accuracy & Loss	89%
Torosdagli et al.	2023	X-ray	500	DL and ML	ANN	Binary	F1-Score	93%
Karimian et al.	2022	panorama	800	Dl	UNet	2	Accuracy	98%
Egger et al.	2022	panoramic image	1150	DL	CNN Model	2	Accuracy	91%
Chu et al.	2022	panoramic radiographs	1400	DL and ML	CNN	3	Accuracy, Precision and Recall	98% to 95%
Lee et al.	2023	X-ray	1740	DL	CNN(VGG19)	Binary and Multiclass	Accuracy & Loss	99%

CNN: Convolutional neural network, Long-term short-term memory,
QLF: Quantitative light-induced fluorescence, OCT: confocal tomography, MABO: simple average best crossover, DSC: dice similarity coefficient. AUC: Curve area CNNs were the main network component in all studies, but some also used long-short-term memory and Siamese networks. Since 2021, CNN-based dentistry papers have increased (Figure.1).

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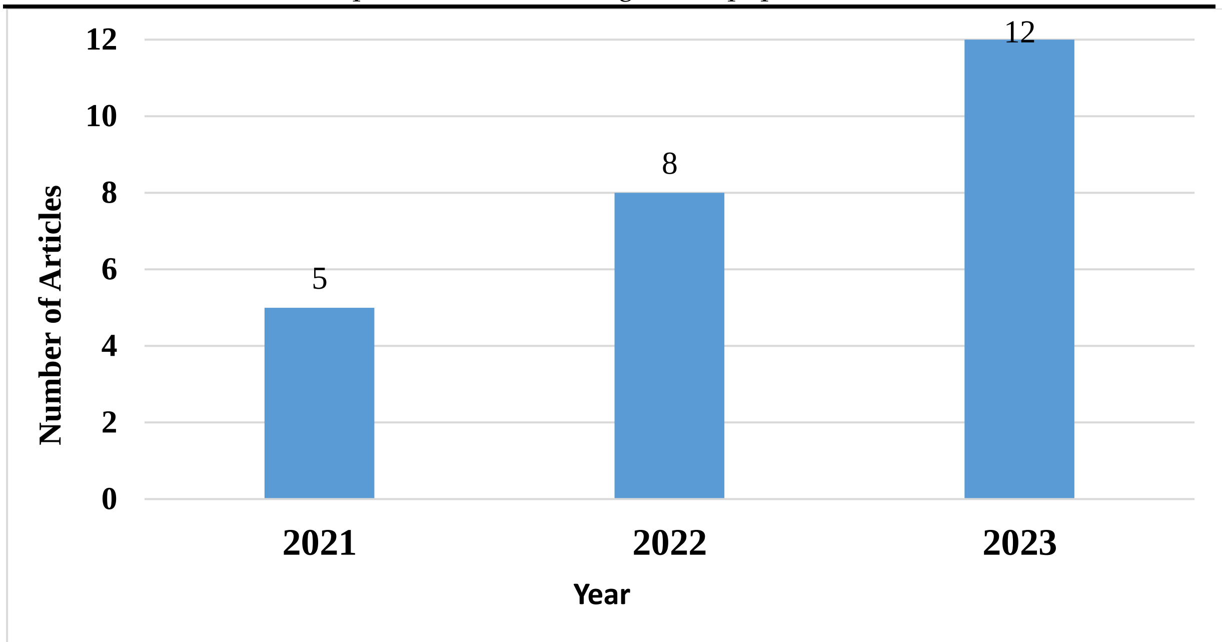

Figure. 1. Number of articles from 2021 to 2023.

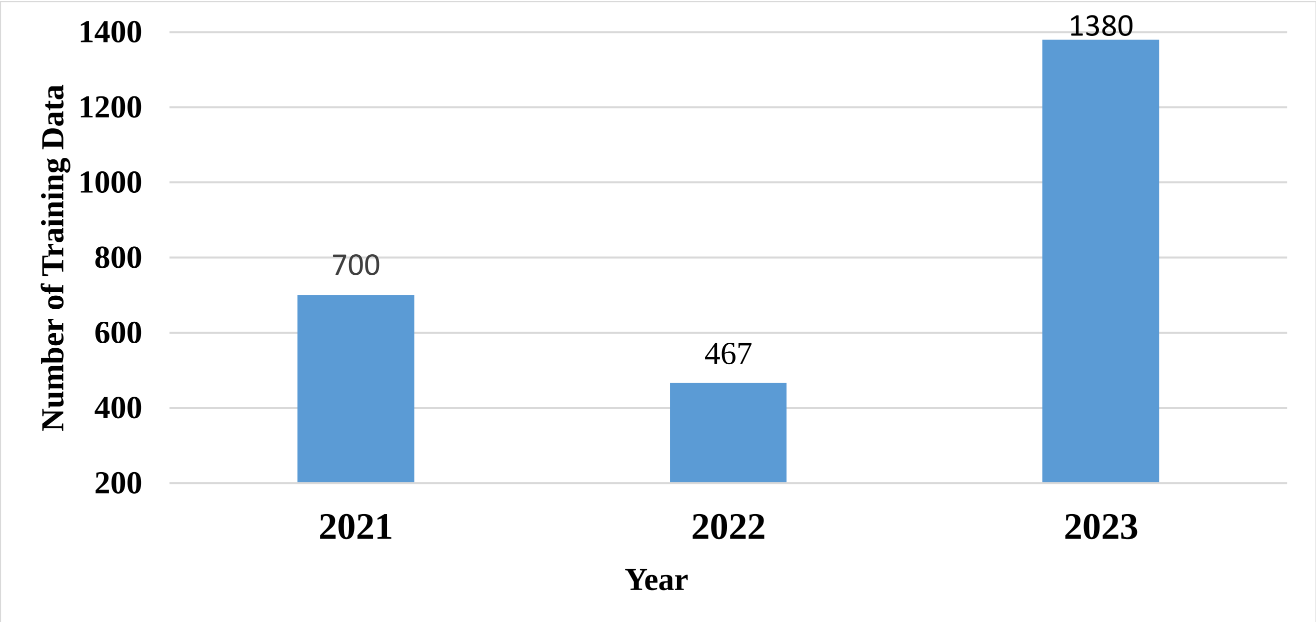

Figure. 2. Median size of training datasets from 2021 to 2023.

Pretrained networks like Alex net, VGG, Google Net, and Inception v3 performed well in general purpose papers. [31] CNN networks evolve from subsurface depth to deeper or issue residence or complex networks.

These studies covered various dental fields. Deep learning was used to study gingiva, periodontium, dental curve, bone loss, and anatomical landmarks (Table 2).

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Table 2. Frequency of subjects in deep learning articles.

Subject	Frequency
Tooth related	14
Dental plaque	4
Gingiva or periodontium	2
Osteoporosis	2
Etc.	3

Imaging techniques have been studied with the above subjects. Dental disease is being diagnosed using intraoral and panoramic radiographs and 3-D concave computed tomography (CBCT). Quantifiable lamp fluorescent dyes, optical coherence tomography (OCT), and intra-oral laser scanners have been studied in dentistry.

Discussion:

Although conventional CAD is challenging to construct and tune, medical professionals have used it to get an independent advice. CAD has recently integrated many deep learning methods, with promising results for medical applications. [32,33] Deep learning studies in maxillofacial and oral radiology must fill gaps to advance both quantitative and qualitative uses in dentistry.

However, because it was challenging to make impartial comparisons between the studies because all of the data sets utilized in the study that was analyzed in this article were housed internally. One and only one study attempted to assess the reliability of created networks by making use of other public datasets.[23] It is necessary to make efforts to build a public dataset, particularly in the area of medicine.[34] to create algorithmic solutions that can be implemented in clinical settings. Researchers must distribute their paper data after removing personal information, and each country must provide legal and institutional assistance.[35,36] In the field of dentistry, there is a further requirement for the establishment of a central, open repository that is capable of effectively collecting, cataloguing, and archiving data that is freely accessible to the public.

For deep learning to succeed in dentistry, training datasets should increase. However, most research had an accuracy of less than 90% and used small sets of data (with fewer than 1000 units in each group). This accuracy is below the clinically expected 98%–99%.[37] Due to its end-to-end nature and direct feature learning from data, deep learning calls for a great deal of data. To achieve 98% validation accuracy using deep learning for CT data anatomical classification, each group needed at least 1,000 data sets. For 99.5% accuracy, each group needed 4,092 data sets.[38]Cone beam calculated value tomography (CBCT), the most common dental 3D imaging modality, does not use clearly delineated Hounsfield unit values. Each exposure changes the pictures' image pixels.[39] The patient's position affects radiographic image quality and magnification in dental practices.[40] Thus, trans-hospital or hybrid data sets from multiple machines and circumstances may be needed to achieve clinically meaningful high accuracy. Due to dental pictures' nature. To make medical deep learning possible, a large-scale dental care public dataset is essential.

Additionally, dental data uniformity and data set standardization are crucial. CBCT images vary depending on brand, equipment, and exposure. Deep learning research may struggle.

Machine-by-machine data learning is difficult because models learned on one machine may not apply to others. Data collection and learning are difficult. Despite European, German, and English efforts to recommend CBCT picture quality, no standard has been established.[41] To make deep learning-based 3-dimensional diagnostics possible, a global standard for CBCT image quality must be established soon.

A significant number of publications have made use of preprocessed photos by manually trimming the area of interest. Because of this, it is difficult to accurately assess and compare the findings because of the inaccuracies that are caused by the manual procedure. There have been a few papers9,10,19 that have demonstrated networks that trained by extracting features into regions of a particular size. However, this method has its drawbacks due to the fact that the network cannot learn the entire image; rather, it concentrates its attention on a certain portion of the picture. Down sampling, which can result in the loss of essential image information, was utilized in some of the papers.21, 22,24According to the discussion of the limits in some articles, these decisions appear to have been taken because of restrictions on the quantity of data or the amount of computer power that was available.21,22 However, According to the explanation of the limitations in some publications, these judgments appear to have been made because there were restrictions on the data being collected or the amount of computing power that really was available.

Medicine is increasingly using AI. IBM's Watson helps doctors make crucial clinical decisions.[42] Due to the difficulty of unifying dental radiology, clinical accuracy of AI in the dental field must be verified using a broad range of instances and imaging modes before AI can play a larger role in diagnostic recommendations. Before AI becomes more important, this must be done.

AI algorithms operate like black boxes, making it difficult for people to recognize or change diagnostic criteria.[43] To improve artificial intelligence's dependability, a visualization and editing device for deep neural networks must be human-friendly (AI).

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