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PRINICPLES AND POSSIBILITIES OF ARTIFICIAL INTELLIGENCE IN ORAL RADIOLOGY

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ABSTRACT

With the deployment of AI, it is anticipated that during the next ten years, the quality, value, and depth of radiology's contribution to patient care and population health, as well as radiologists' work processes, will undergo a significant revolution. Dentists must use all of their knowledge to evaluate patients and choose the best course of treatment. When determining the prognosis, they must also make precise clinical judgements. Dentists occasionally, nonetheless, lack the information required to quickly determine the best clinical course of action. To make better judgements and perform better, they can employ AI programmes as a guidance. The majority of the literature focuses on artificial intelligence (AI) models that use convolutional neural networks (CNNs) and artificial neural networks (ANNs). Artificial learning's results are anticipated to lessen both the daily workload of doctors and the frequency of incorrect diagnoses and under diagnoses in the dentistry profession.

KEYWORDS: *Artificial Intelligence, Artificial Neural Intelligence, Convolutional Neural Networks, Deep Learning*

INTRODUCTION

Artificial intelligence made its birth officially in the Dartmouth conference in 1956 from Alan Turning's research related to machine intelligence.1969-1973-US Mansfield amendments refused funding by defense department, as it considered AI not to be having any scientific or economic potential and not having any applications in defense directly. Beginning of 80's AI reemerged as expert systems. Increased computing power makes AI surge forward in the beginning of 21st century. In 2017-Google-Alphago project made AI powered machines to beat the Go champion.[1]

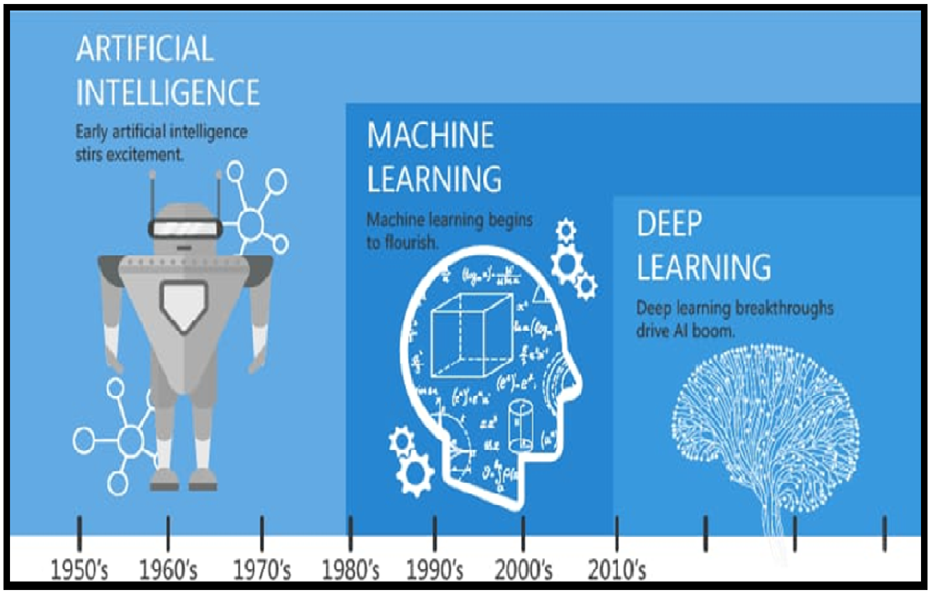

Figure 1:

Artificial Intelligence

Artificial Intelligence is defined as "A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and to mimic human tasks through flexible adaptations" mimicking human intelligence. Machine learning and Deep learning are subsets of artificial intelligence.[2]

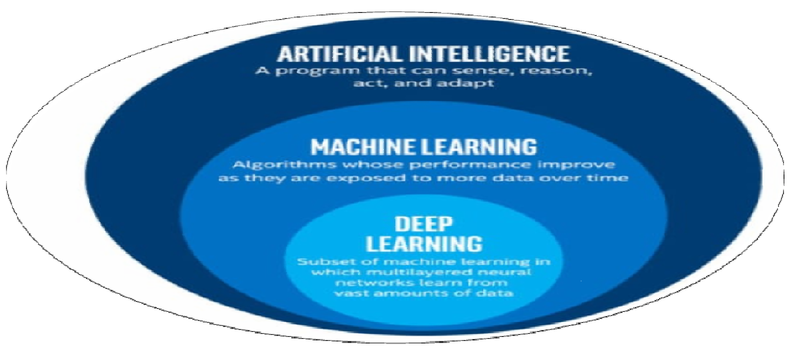

Figure 2.

Machine Learning-Supervised Learning

One of the most common forms of machine learning techniques is supervised learning where the task is to map an input to an output based on similar input-output pairs provided as a labelled dataset . Prentice Hall For an image classification task, the input would be an image to classify to a particular class and the output would be an array of scores which indicate the probabilities of the input image belonging to each of the particular classes.[3]

Deep Learning-Training Process

Deep learning is an upcoming area of study in the broad spectrum of machine learning techniques which has provided breakthroughs in various applications such as processing images, video, speech and audio. Making the application viable in a spectacular array of fields including medicine

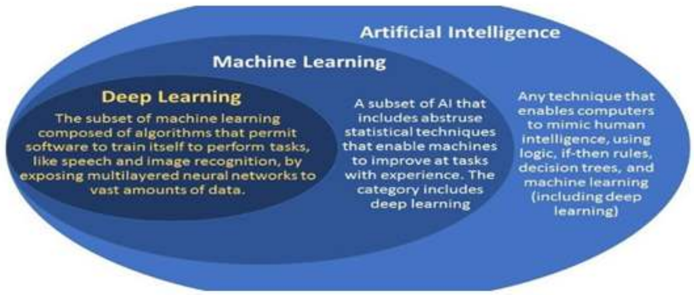

Figure 3:.

A typical deep learning algorithm consists of a network with many adjustable parameters which are also referred to as weights to serve as the function to map between the input and output pairs. The desired output scores are not expected before training the network. The training process starts with using an objective function to calculate the error between the output probabilities and the desired probabilities. The scores are fine tuned by the learning algorithm adjusting its internal weights as it is exposed to more and more labelled input and output pairs over several epochs or repetitions. Several hundreds of millions of these weights may be present in a typical deep learning network and hundreds of millions of labelled input output pairs may be used to train it

Convolution Neural Networks (CNNS)

Convolutional neural networks are the go to method in deep learning when faced with image based tasks. This largely stems from the success of convolutional neural networks reducing the number of parameters required to train a neural network on a set of images. The conventional idea would be to feed the entire image into an artificial neural network to achieve the desired results. The issue with this approach is even if we just consider two artificial neurons in the hidden layer such as in a multi layer perceptron and feed just an image of 32 x 32 pixels with 3 channels (RGB color channels), there would be over 6000 parameters required for it which is significantly high when considering the cost of computation. Convolution emerged as a more efficient method where only regions of the image are associated with a parameter or a weight and also allowed for stacking of several such layers or filters to detect various features in the image irrespective of its location in the image [4].Convolutional neural networks have also proved their usefulness in the field of radiology through different aspects such as classification, segmentation, detection and others.[5]

DIAGNOSTICS

One of the major potential roles of AI in radiology is in the diagnosis of pathology. It has been shown that a well-trained AI model could surpass the performance of human observers.

DEEP LEARNING

Deep learning is a form of machine learning that can utilized either supervised or unsupervised algorithms, or both. The word “deep” in deep learning comes from the many layers that are built into the deep learning models, which are typically neural networks.

A convolutional neural network (CNN) can be made up of many, many layers of models, where each layer takes input from the previous layer, processes it, and outputs it to the next layer, in a daisy-chain fashion.25 studies that used DL in dental imaging, with convolutional neural networks used as the predominant component of the DL model in all studies done by **Hwang et al.** [9].

TUMOR DETECTIONS

Different types of AI algorithms are used to detect and classify different types of cancers and all these techniques showed fluctuating accuracy across different years. This varying trend could be due to numerous factors, including network structure. In designing architecture for specific applications, the following selected parameters vary: network type, numbers of layers, number of nodes in hidden layers, activation function between layers, and the size of the dataset used (Dhokia, Kumar, Vichare, Newman, & Allen, 2008), (Peng, Jianmin, & Wu, 2009). Network generalization indicates how these networks are able to work with different data to decrease performance error to the lowest value.

Early detection of OC is for patients. Values obtained from cytology images, fluorescent images, CT images, and depth of invasion can be used in AI learning tools and can be diagnosed with more accurate results. Several experiments have carried out for early detection of the advanced stage of OC and it is reported that OC arise from different anatomical location subsites such as tongue, buccal mucosa, etc.

According to Poedjiastoeti and Suebnukarn et al.stated that of CNNs in the diagnosis of ameloblastomas and keratocystic odontogenic tumors on panoramic radiographs, showed the output of the CNN as a heatmap that fags potential regions of interest.[10]The sensitivity, specifcity and accuracy was same between the CNN and oral and maxillofacial surgeons, whereas the ‘interpretation time’ was 38 s for the former vs 23.1 min for the latter.

Sunny et al. he conducted an experiment using ANN for early detection of OC, using tele cytology (TC), which is digitization of the cytology slides [29]. The efficacy of AI was compared with conventional cytology and histology; 11,981 prepossessed images were loaded for AI analysis, based on the risk stratification model. Results showed of 80–84% in diagnosis with potentially malignant oral lesions are detected with low sensitivity, using telecytology. Malignant detection accuracy of 93%,and a potentially malignant lesion of 73% are found. The study used the brush biopsy method for sample collection.

Jeyaraj et al. observed that oral cancer was found with the help of regression-based deep-learning algorithm for the characterization of oral malignant growth . A deep-learning algorithm of CNN was formed with the help of a computer-aided OC detecting system and 100 hyperspectral images (HIS) were studied. It was found out that 91.4% sensitivity in detecting cancerous lesions using the regression-based algorithm, and the results were compared to the traditional algorithm using the same images. The quality of diagnosis was improved for the proposed model of the algorithm, as compared to the conventional.

Uthoff et al. conducted a study that detected OC by help of smart phone-based images and AI technology [28]. Based on this concept of , smart phone-based images are developed. Auto fluorescence and white light imaging are added to the pictures, later these pictures were stacked to AI algorithms for recognizing oral malignancy. 170 auto fluoresced pictures was found. This strategy was very convenient for application, and the accuracy was improved. However, the study needed to be conducted on a large population for further validation. Another observation made by Nayak et al.,using autofluorescent spectral images, and analysis was done using principal component analysis (PCA) and ANN . PCA is computing based on principal components of data and the results from ANN performance was slightly better than the PCA. The advantage of this technique is that fluorescence spectroscopy image uses a minimally invasive technique.[24]

Musulin et al. found that, AI showed better results in detecting OC, by using Histology images [25] Similarly, Kirubabai et al., showed CNN was better at differentiating malignant lesions as mild or severe, by using clinical images of patients [27].Kann et al. used deep-learning machines on 106 OC patients for the identification of nodal metastasis and tumor extra-nodal extension involvement [22.] The dataset com prised 2875 CT (computerized tomography) segmented lymph node samples. This study explored the capability of the deep-learning model to assist head and neck cancer patient management. Chang et al., observed an AUC of 0.90 for predicting the occurrence of OC, using AI based on genome markers .In this study, logistic regression analysis was used to compare with AI. but, the study was performed on 31 patients, which was considered less sample size.

MAXILLARY SINUS

The maxillary sinus is also an important part of the dental field, such as maxillary molar tooth disease, which causes maxillary sinusitis; if the maxillary molar implant has insufficient bone, maxillary sinus elevation is performed and bone grafts are performed.

Accordingly, it is very helpful to accurately diagnose, analyze, and evaluate maxillary sinus diseases. In a two-dimensional panoramic picture, the maxillary sinus area is distorted and overlapped by the vertebrae, which is difficult to evaluate .[19]

CT data, which are 3D images, are necessary for the accurate evaluation of the maxillary sinus. Deep learning analysis of 3D images is a much more difficult area than the analysis of 2D images. It is a complex area that needs to be reconstructed and evaluated again after analysis of the 2D slice image. The maxillary sinus is connected to various sinuses, such as the nasal cavity, ethmoid sinus, and frontal sinus, and is adjacent to the orbit and skull in the upper direction; therefore, it is very difficult to separate. Thus, it is even more difficult to segment the disease in the maxillary sinus.

Murata et al. performed a experiment that showed that CNNs for the detection of maxillary sinusitis on panoramic radiographs. [11] The AI's performance was slightly worse compared with experienced radiologists, but considerably higher than that of dental residents.

Using the previous studies, **Kavitha et al.** created a classification system that had a accuracy of 96% vs. lumbar spine bone mineral density (BMD) and 98.9% vs. femoral neck BMD [12]. Using the latter approach, **Chu et al**. exhibited an overall accuracy of 90% for a DL network that combined 8 regions of interest on panoramic radiographs.

Ai with Intraoral Radiographs

One of the major potential roles of AI in radiology is in the diagnosis of pathology. It has been shown that a well-trained AI model could reach or even surpass the performance of human observers. It could therefore be considered for more obscure lesions that could easily be missed by a clinician, or as a 'first pass' analysis with the aim of saving radiological interpretation time by highlighting potential pathology that warrant further investigation.

CNN is used in the detection of periodontally compromised teeth (PCT) on 1740 periapical radiographic images, for premolars and molars, the total diagnostic accuracy was 81.0% and 76.7%, , showing the highest diagnostic accuracy in severe cases [13]

Review was conducted by **Hwang et al**. in which it was identified that 25 studies that used DL in dental imaging, with convolutional neural networks used as the predominant component of the DL model in all experiments **Krois et al**. conducted a study which showed the use of CNN in evaluation of periodontal bone loss, showed a lower sensitivity, but higher specificity compared with dentists [14]

The annotation of the training data is done by a oral radiologist or a experienced clinician manually following which the AI software is trained, using those datasets to create a adapting dataset. The accuracy of the adapting data set is evaluated in the testing dataset (a fresh set of radiographs not evaluated previously). Thus AI helps in automated analysis of the dental radiographs.

In 2019 a study was conducted in which **Tuzoff et al** (2019) found a sensitivity of 0.9941 and a precision of 0.9945 for automated teeth detection whereas for tooth numbering, the sensitivity and specificity was 0.9893 & 0.9994 respectively.[15]

AI helps to identify interproximal caries using a series of bitewing radiographs. A pre-trained deep learning network can be used for diagnosis of dental caries in bitewing, periapical and as well as panoramic radiographs. **Lee et al (2018)** demonstrated the accuracy of identifying dental caries in premolars, molars, and both premolars and molars are 89%, 88%, and 82%, respectively which was found in 3000 radiographs.

A I can also be used detect the periapical pathologies such as periapical cyst, garnulomas and abscess which sometimes gets unnoticed by a clinicians eye. It locates the exact boundaries of the lesions and enable proper detection. [17]

ANN in future will help radiologists to reduce cognitive bias and diagnostic efforts and further increase the diagnostic accuracy of the periodontal pathology .**Koris et al (2019**) stated that neural network showed higher diagnostic performance, with accurate results of 81%, than individual clinicans, who showed an accuracy of 76%, in the radiographic detection of periodontal bone loss (P=0.067). [18]

ORAL CARCINOMAS ARTIFICIAL INTELLIGENCE IN DETECTING AND DIAGNOSING ORAL CANCER

Cytology images, fluorescent images, CT images, and depth of invasion can be used in AI learning tools, and OC can be diagnosed more accurately. Many studies have supported.

In the year 2019 **Kim et al** deep learning proved to help in predicting the cancer survival and helping the experts in selecting better treatment options and reducing unnecessary treatment protocols. The accurate results they found of the training and testing sets, were 81% and 78.1%, respectively.[19]

The usage of CNN enhanced the diagnosis of cervical lymph node metastasis was stated by **Arijiet et al** 2019. CNN image classification system showed overall results of accuracy of 78.2%, a sensitivity of 75.4%, and a specificity of 81.0%, when compared to radiologists[20]

DENTAL CT AND CBCT

Studies focusing on AI-based diagnosis in dental CT and CBCT are scarce as of yet, which could be attributed to the higher complexity of 3D images as well as practical difficulties in gathering a large training dataset and appropriate labels.

Johari et al found that the applied a neural network was used in both intra-oral and CBCT images for the diagnosis and vertical root fractures, and found to be high sensitivity for both modalities but a much higher specificity for CBCT images.

In 2011, an AI model was proposed to automatically localize anatomic landmarks on CBCT images. Cephalometric radiographs were gradually substituted by CBCT images to develop models for cephalometric analysis. Documented literature based on AI models of automatic 3 dimensional landmark annotation on CBCT images, demonstrated that the Cephalometric analysis on CBCT considered more versatile approach. However, automatic localization performance on existing models is still not found satisfactory [21]

Ariji **et al**. Found that the a CNN can be used for detecting the cervical lymph node metastasis in contrast-enhanced CT images of oral cancer patients, which showed no significant difference with the performance of radiologists (CNN AUC 0.80, radiologists AUC 0.83) [14], later it was found that the time for radiological reporting was much shorter for the CNN than for the radiologists.

CNN can also be used to detect the low bone mineral density and osteoporosis which clinically relevant to implant dentistry. AI models helps to differentiate to distinguish between normal and osteoporotic subjects using panoramic radiographs, based on reduction of mandibular cortical width and erosion of mandibular cortex have demonstrated 95% accuracy, sensitivity, and specificity. These promising results predicted the probable incorporation of these models into routine clinical practice in the near future [22, 23]

AI models are made to detect and to quantify the degree of alveolar bone loss. **Mol et al and Carmody et al** made models to find out the extent of periapical lesions. **Flores et al** [25, 26] made model, on CBCT images which can be easily differentiated from periapical cysts and granulomas.[24]

CONCLUSIONS

There is documented evidence that suggests that AI models have been developed for diverse applications including the detection of maxillary sinusitis, classification and staging of lower third molar development, and tooth types , detecting root canal orifices etc. Others include, the diagnosis of vertical root fractures on CBCT images of endodontically treated and intact teeth, forensic dental imaging using dental panoramic radiographs, three dimensional orthodontics visualization using patient models and panoramic radiographs[27] , automatic segmentation of mandibular canal[28] etc. This clearly shows that AI is being extensively explored and employed in various fields of DMFR, and hence its accuracy in clinical practice needs to be established soon.

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