CLINICAL APPLICATION OF ARTIFICIAL INTELLIGENCE IN ORAL RADIOLOGY

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Abstract:
Artificial intelligence systems actively applied in a broad range of industries in recent years are able to mimic humans' cognitive functions to perform problem-solving and learning tasks. Artificial intelligence applications are particularly promising in oral and maxillofacial radiology. Dentists could use them as an adjunct to other imaging modalities in making proper diagnoses and treatment plans. This system has reduced radiologists' workload by rapidly recording and presenting data, thereby observing the treatment response with a lowered risk of cognitive bias. In the field of oral and maxillofacial radiology, Artificial intelligence systems can perform image classification, detection, segmentation, registration, generation, and refinement. This article discusses the clinical applications and scope of intelligent systems such as machine learning, artificial intelligence, and deep learning programs in oral and maxillofacial radiology.

Key Words: Artificial intelligence, Oral and maxillofacial radiology, Machine learning, Deep learning, Convolutional Neural Network

DOI Number: 10.14704/nq.2022.20.12.NQ77003 **NeuroQuantology 2022; 20(12): 19-26**

Introduction:

Healthcare is shaping up in front of our eyes with advances in digital healthcare technologies such as artificial intelligence (AI), 3D printing, robotics, nanotechnology, etc. Digitized healthcare presents numerous opportunities for reducing human errors, improving clinical outcomes, tracking data over time, etc.[1] Advanced imaging techniques like computed tomography, cone beam computed tomography, magnetic resonance imaging, positron emission tomography, panoramic radiography, cephalometric imaging, ultrasound and other modalities, including optical coherence tomography, have also found a place in modern dentistry. [2]Radiologists interpret 2-dimensional (2D) and 3-dimensional (3D) volumetric images for effective patient management. With radiology's beginning as a field at the end of the 19th century, image interpretation has usually been subjective.

The broader use of these modalities to detect and diagnose dental conditions includes plain radiography, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography, and ultrasonography, leading to analyzing large volumes of data increases radiologists' workload. In the modern era, new technologies - artificial intelligence, machine learning, and deep learning - have revolutionized ways of working with data. With these modalities' help, they can detect abnormalities within images that may go unnoticed by the naked eye or solve problems not resolved by human cognition.[3]

Introduction: Artificial Intelligence: Machine learning, Deep learning, Convolutional Neural Network (CNN)

Artificial intelligence (AI): Artificial intelligence, a branch of computer science, can be defined as the capability of machines to imitate intelligent human behaviour' (i.e., the ability of a computer program to function like the human brain). [4] It performs tasks such as learning and problem-solving based on the data input. AI has become popular amongst radiologists and has the potential to revolutionise the way we work in the twenty-first century. [3]Machine learning: Machine learning, a subset of artificial intelligence, predicts the outcome based on the dataset loaded to it using algorithms. It refers to the scientific study of computer models that improve their performance by learning from experience without explicit instructions[5]; that is, decisions are mostly data-driven rather than strategically programmed for a particular task. Machine learning can improve prediction performance by dynamically adjusting the output model when data change over time. Machine learning is classified into supervised, unsupervised, and reinforcement learning categories. Furthermore, machine learning may provide quantitative tools that will increase the value of diagnostic imaging, augment image quality with shorter acquisition times, and improve workflow and communication.[6]Deep learning: Deep learning is a category of machine learning 'concerned with algorithms inspired by the structure and function of the brain and a subset of intelligent systems comprising multiple layers of algorithms interconnected and stratified into more or less meaningful data. [7] Deep learning systems are distinct from conventional machine learning models due to their ability to derive high-level abstractions and complex features from big data through several nonlinear transformations using artificial neural networks. [8]These programs are mainly used for processing large and complex images such as 2D radiographs or 3D CT. Convolutional Neural Network (CNN): A Convolutional Neural Network (CNN) is a profound learning algorithm designed to display a high object recognition capability in image data, consisting of multiple building blocks stacked together, namely convolution layers, pooling layers, and fully connected layers. [9]A convolutional neural network learns directly from the data, identifies patterns within images, and categorizes the final output based on its task. The convolution and pooling layers deal with feature extraction, whereas fully connected layers deliver the outcome, and the last activation layer categorizes extracted features into categories. A set of learnable parameters (known as kernels) are applied at each image position. The convolution layer's training process optimizes these kernels to minimize the mismatch between the output and ground values by applying an optimization algorithm known as back propagation. [7,10]

Clinical applications of intelligent systems:

A. Computer-aided diagnosis

Computer-aided diagnosis (CAD) represents the earliest clinical application of artificial intelligence in the medical field and oral radiology. CAD is rapidly entering the radiology mainstream by becoming an integral part of the routine clinical work for detecting breast cancer with mammograms. Doi carried out foundational research related to CAD systems, as reported in articles between 1963 and 1973, and found it beneficial for detecting lung, breast, and colon cancer. [10]A CAD system makes a diagnosis for which it has been explicitly trained. By providing additional datasets, the performance of CAD algorithms can only be improved. The systems' performance does not need to be better than, or even comparable to, that of clinicians; instead, the computer output is employed as a second opinion to assist clinicians in detecting pathologies. The main limitation of CAD is the high rate of false-positive detections, and some CAD systems may also miss specific lesions. In the modern era, early CAD diagnostic systems are being replaced by artificial intelligence approaches characterized by autonomous learning, which detects and solves problems based on computer algorithms similar to the human brain. These systems have reduced the burden on radiologists by eliminating the need to perform segmentation manually and provide vital information on the functional performance of vital organs and tissues and the extent of disease. [11]

B. Dentomaxillofacial imaging

1. **Location of radiographic landmarks:** Convolutional neural networks allow accurate edge detection, and edge-based, region-based, and knowledge-based algorithms are used to locate cephalometric landmarks. These networks can locate the landmarks in partially hidden, low-contrast, overlapping areas that are not visible to the naked human eye. Convolutional neural network algorithms enable pixel-by-pixel elaboration, and knowledge-based algorithms help locate new anatomic landmarks more robustly and precisely. On panoramic images, neural networks have been used to detect and number the teeth according to World Dental Federation Notation and the FédérationDentaireInternationale 2-digit notation system more precisely. [12]

2. **Periapical pathologies:**Periapical granulomas, abscesses, and cysts are the most common periapical lesions in daily clinical practice. Most of these lesions are apparent on radiographs, but some may go unnoticed as images may be noisy or have low contrast. Artificial intelligence systems can accurately find tooth areas inclined to caries and complex periapicalpathosis, use automated segmentation to describe the boundaries of lesions more precisely, and enable their differentiation. In the future, these systems may benefit implant dentistry by enabling the early detection of peri-implantitis with appropriate interventions. [13,14]

3. **Maxillary sinus pathologies:** The conventional Waters and paranasal sinus views are used to screen suspected patients for maxillary sinusitis. Confirmation is made using a CT scan, the preferred imaging modality for assessing the air-fluid level and sinus opacifications. These conventional radiographs pose diagnostic difficulties due to overlapping the maxillary sinus by facial bony structures, which may

eISSN 1303-5150

produce false-negative results. Deep learning programs boost the diagnostic ability of conventional radiographic views, thereby helping avoid unnecessary referrals of patients for CT examinations with high radiation doses.[15]

4. **Periodontal disease and bone density assessment:** Deep analysis tools assist periodontists in the early detection of alveolar bone loss, bone density changes, and areas of furcation involvement. Krois et al.[16] found that a convolutional neural network showed higher diagnostic performance, with an accuracy of 81% than individual examiners, who showed an accuracy of 76%, in the radiographic detection of periodontal bone loss (P=0.067). They suggested that automated systems can be used as reliable and accurate adjunctive tools for detecting periodontal bone loss on panoramic radiographs.

5. **Oral oncology:** CT and MRI are the imaging modalities most normally used to identify cervical lymph node metastasis and sentinel lymph nodes. Recently, Ariji et al [17]found that using a convolutional neural network improved the CT-based diagnosis of lymph node metastasis. The performance of a convolutional neural network image classification system resulted in an accuracy of 78.2%, a sensitivity of 75.4%, and a specificity of 81.0%, comparable to trained radiologists. Kim et al.[18] used a deep learning program to predict the survival of oral cancer patients. He found that the diagnostic performance of the program was superior to that of the classical statistical model. Their analysis suggested that deep learning survival predictions might guide clinicians in determining the best treatment choice for oral cancer patients, thereby preventing unnecessary treatment interventions.

6. **Temporomandibular joint osteoarthritis:**Osteoarthritis, the most common degenerative disease affecting the temporomandibular joint (TMJ), is characterized by the destruction of the articular cartilage and subchondral bone resorption. [19]No method has been designed to assess morphological changes in the early stages of the disease. de Dumast et al. [20] described a non-invasive technique, referred to as the shape variation analyzer, that uses neural networks to categorize morphological variations of 3D models of the mandibular condyle into 7 different categories (G1, normal; G2, close to normal; and G3-6, various stages of degeneration). A rainbow color-coded map on 3D models described the exact location of the morphological changes on the condylar surface. Categorization by neural networks will improve clinicians' understanding of the shape changes that occur in patients with TMJ osteoarthritis.

7. **Headache:** Primary headaches, like migraine and tension headaches, significantly affect the quality of life of individuals in the working population. There is no associated underlying organic cause of Primary headaches, whereas secondary headaches are usually the symptoms of an underlying disease process. Physicians treat patients with chronic headache symptoms based on a clinical examination and imaging modalities such as MRI and usually prefer medical management as an

appropriate treatment intervention. However, some patients suffer delays in diagnosis, undergo multiple consultations, and complain of continuing headache symptoms.[21,22]For a precise diagnosis of headache, Vandewiele et al. [21] and Krawczyk et al. [22]designed an automated 3-component system for classifying headache disorders by a decision tree algorithm. They found that automated techniques were highly precise (97.85%) and reduced classification errors (P<0.05). These systems enable trigger management by the automated detection of possible triggers, enabling patients to adjust their lifestyle to prevent triggers and the happening of headache attacks.

8. **Sjögren syndrome:**Sjögren syndrome indicates a systemic autoimmune disease that primarily affects the salivary and lacrimal glands, causing intense dryness of the mouth and eyes. Lately, software algorithms have appeared as a promising method for analyzing big datasets from large groups of patients affected by systemic autoimmune diseases.[23]Kise et al. [23]used a deep learning system to detect Sjögren syndrome on CT and discovered accuracy, sensitivity, and specificity of 96.0%, 100%, and 92.0%, respectively. The corresponding values of inexperienced radiologists (83.5%, 77.9%, and 89.2%) suggest that the performance of the diagnostic of the deep learning system was better than that of inexperienced radiologists. The results of their study indicate that deep learning systems could be used as a diagnostic aid for analyzing CT images of patients with Sjögren syndrome.

9. **Miscellaneous applications:**In endodontic practice, artificial intelligence software works precisely in establishing working length by determining the accurate location of the apical foramen and detecting vertical root fractures on cone-beam computed tomography (CBCT) images. [14]Devito et al. [13]found that neural networks improved the diagnosis of proximal caries by 39.4% compared to bitewing radiography. Intelligent systems help orthodontists find the necessity of tooth extractions, monitor tooth movements, stage tooth development, and mark landmarks on cephalograms. Intelligent systems have transformed the field of oral and maxillofacial surgery by introducing image-guided surgery. Preoperative CT and MRI images are registered with CBCT images for intraoperative imaging due to the less radiation exposure and high resolution of CBCT.[24] Surgical removal of lower third molars are challenging due to the proximity of the mandibular third molar (M3) and inferior alveolar nerve (IAN). These procedures can damage the IAN, causing neurosensory impairment in the chin and lower lip. In order to address this issue, Vinayahalingam et al. [25]conducted automated segmentation on panoramic radiographs to detect the proximity of M3 regarding the IAN before surgical removal of M3 and suggested that it was a promising approach to the segmentation of anatomical structures.

Prospects and Challenges:

Intelligent systems have helped the radiologists a lot by reducing the workload by boosting automated segmentation, detecting subtle anomalies within an image that a human eye may unnoticed, providing data on the functional performance of tissues and organs and diseases etc., and facilitating early screening for cancers, identifying patients at risk of cancer, and eliminating errors due to cognitive bias. Despite those above benefits, the dilemma is whether this technology will be able to substitute radiologists in the future. Intelligent systems have reduced radiologists' workload, but it is challenging to replace human intelligence (3). These systems require a massive database of knowledge to perform accurately. When applied to images from other contexts, the incorrect interpretation of images may ensue, producing false-positive or false-negative results. Furthermore, radiologists should be trained in computational algorithms, data science, biometrics, and genomics to enhance their use of this technology. A search of the recent literature regarding the use of intelligent systems in dentomaxillofacial radiology revealed only in vitro studies, studies on skulls, and anatomic models. [3]No studies have been performed in real clinical situations to verify the actual applicability of these systems. Soon, more clinical trials about intelligent systems should be funded by the government to encourage the testing and execution of this technology in clinical practice.

Conclusion:

Artificial intelligence is rapidly growing to serve an ever-expanding niche in medicine and dentistry, playing an essential role in dento-maxillofacial radiology in making diagnostic recommendations. Data-driven AI will reduce workload of radiologists save time and eliminate human errors in diagnosis. Few issues need to be solved to use artificial intelligence in actual clinical practice in the future, such as building up a massive amount of fine-labelled open data set, understanding the judgment criteria of artificial intelligence, and DICOM hacking threats using artificial intelligence. With the solutions to these problems, artificial intelligence will develop further and is expected to play an essential role in the development of automatic diagnosis systems, the establishment of treatment plans, and the fabrication of treatment tools. . These systems have a promising and bright future in general dentistry and maxillofacial radiology.

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