Artificial Intelligence-Finding New Frontiers in Oral and Maxillofacial Radiology

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Abstract

Artificial intelligence (AI), particularly deep learning algorithms, is gaining extensive attention for its exceptional performance in image-recognition tasks. Artificial intelligence (AI) is rapidly moving from an experimental phase to an implementation phase in many fields, including medical and dental imaging. Major performance breakthroughs in its development have been possible due to the proportionate amalgamation of augmented computing capacity, better availability of vast datasets and advanced learning algorithms. They can automatically formulate a quantitative assessment of complex medical image characteristics and achieve an increased accuracy for diagnosis, with higher efficiency. AI is extensively used and gaining worldwide popularity in the medical imaging of the liver, ultrasonography, and nuclear medicine. AI can reduce physicians' workload by assisting to make more accurate and reproducible imaging diagnosis. AI is slowly but steadily permeating in the field of Oral & Maxillofacial Radiology too. This article reviews a general understanding of AI methods, particularly those pertaining to image-based tasks in Oral & Maxillofacial Radiology. We explore how these methods could impact multiple facets of imaging and the impact of AI on oral radiologists.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Oral Radiologist.

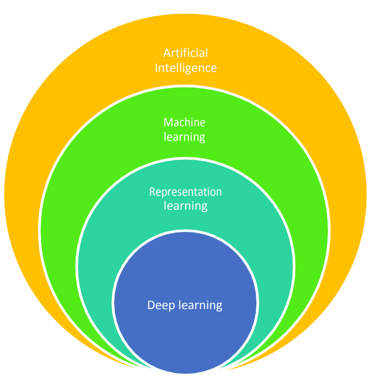
1. Introduction

The scientific arena has witnessed innumerable innovations with the advent of technology for creating a near perfect model that can successfully simulate the functioning of the human brain. This constant search has given rise to what is known as artificial intelligence (AI), which is a highly evolved system capable of mimicking the functioning of the human brain. The term 'artificial intelligence was first coined by Allan Turner in the year 1955[1]. AI refers to that branch of computer science devoted to the development of computer algorithms, to achieve tasks conventionally associated with human intelligence, such as the capacity to learn and resolve problems[2]. Computer-based diagnosis is gaining momentum due to its ability to detect and diagnose lesions which may go unnoticed to the human eye, thereby paving way for a holistic practice.

Over the past 2 decades, advances in medical imaging technology and related research have revolutionized the storage of medical imaging data to digital format. This data must be processed such that it can be used with AI to ascertain appropriateness, optimize patient outcomes and improve the accessibility and efficiency of the existing health care system. Being experts who employ imaging for the identification and management of disease conditions, it is crucial that radiologists not only provide guidance, but also actively contribute to the implementation of data-driven systems that interface with clinical workflows, thereby enhancing patient care. Oral and maxillofacial radiology is a specialty that has always been at the forefront of adapting new technology and has led dentistry into capturing newer "fields of view." Whether it is for looking between teeth or around lesions, we can use deep learning algorithms to detect what the human gray scale cannot discern. In head-and-neck imaging modalities, AI provides additional leverage owing to its unique ability to learn and it can be integrated with imaging systems such as magnetic resonance imaging and cone-beam computed tomography to identify minute deviations from normalcy that could have gone unnoticed by the human eye. They have the ability to make very-high resolution images with pixel and voxel sizes of a few microns. AI is helping to streamline the oral radiology workflow by managing patient appointments as well as data archival, retrieval, and reporting models. With the application of cleverly written programs that extract information from massive clusters of data clouds, use of these programs for diagnosis and treatment planning is becoming increasingly common. With the development of AI technology and its eventual integration into clinical workflow in near future, radiologists will need to familiarize the terminologies and understand its fundamental concepts.

2. Artificial Intelligence (AI)

Artificial intelligence (AI) is defined as 'the capability of a machine to imitate intelligent human behavior to perform complex tasks, such as problem solving, object and word recognition, and decision-making[3,4]. In a broader sense it designates an array of fields and techniques. This includes 'machine learning (ML)', 'representation learning' and 'deep learning' (Figure 1).



a. Machine Learning

Machine learning (ML) is that component of AI research that imparts knowledge and other inputs to computers through data and observations, without the need for explicit programming[5]. ML algorithms evolve as they are exposed to more data. Nearly all ML algorithms analyze pixel data of radiology examinations and 'learn' to give specific answers (whether the image is normal or abnormal) by evaluating a large number of examinations that have been hand-labeled. Similar to radiologists who acquire clinical acumen and experience by repeated evaluation of radiographs, AI models can 'self-improve' and 'learn with experience' by undergoing enhanced training based on evaluation of extensive image data sets[6].

b. Representation Learning

Representation learning is a subtype of ML in which there are no 'hand-crafted' features available. Instead, the computer algorithm learns the features required to classify the data provided. The quantity of training data impacts the competence of ML algorithms. The performance is greatly augmented on adding data. When provided with ample data, systems based on representation learning may have an edge over conventional ML systems that utilize 'hand-crafted' features[1].

c. Deep Learning

It is that part of representation learning relying on multiple processing layers, to learn the representation of data with various levels of abstraction. This algorithm uses multiple layers to detect simple features like line, edge and texture to more advance and intricate shapes, lesions, or entire organs in a hierarchical configuration. Deep learning can greatly outperform by learning a hierarchical standard representation of a particular type of image from an extensive array of normal examinations[7,8].

3. Neural Networks

Neural networks are computing systems which are inspired by, but not identical to, biological neural networks that constitute animal brains. Such systems 'learn' to perform tasks by considering examples, generally without being programmed with task-specific rules. This involves a network of highly interconnected computer processors that has the ability to learn from past examples, analyse non-linear data, handle imprecise information and generalize enabling application of the model to independent data has making it a very attractive analytical tool in the field of medicine. Neural networks are the algorithms that are most commonly used for image analysis today[2].

4. Clinical Applications

AI applications must tackle unmet necessities and improve upon existing clinical solutions in order to be incorporated into routine practice. Basically, there are 3 methods to categorize clinical applications of AI in radiology: clinical workflow, types of applications, or classes of use cases[1].

I. Clinical Workflow

Clinical AI applications could be envisioned as diagnostic tests, incorporated into existing clinical pathways. In the present setting, radiologists conduct imaging tests in a sample population. For instance, when a patient requires a diagnostic imaging, a radiologist is the one who decides the image selection and other protocols. Alternatively, AI applications could be applied using various scenarios to reduce the radiologist's burden. Different scenarios used in clinical work flow are triage, replacement and add-on which are based on the conceptual framework developed by Bossuyt, *et al*[9]. AI could be employed in a triage situation as a novel screening tool to sort examinations depending on the probability of disease (eg, positive or negative result according to AI). For example, AI algorithms could determine the triage of unread radiographs based on the likelihood of disease, as per the content of the images or other data obtained. Such applications could even decide which examination should be conducted first.

AI might even substitute radiologists in certain scenarios, if the results are constantly precise, replicable, quicker and effortless to obtain. For example, AI software could consistently outperform a radiologist in bone age estimation. AI may be employed on a subset of patients as an add-on, subsequent to an existing clinical pathway which relies on a radiologist's interpretation. The utilization of add-on tools may be justifiable when it can be used as a time saver in certain situations; for instance, when used in automated lesion segmentation to estimate total tumor volume, for prioritizing patients with hepatocellular carcinoma, for liver transplant.

II. Types of Applications

The applications of ML in radiology are;

- Detection - To correctly spot an anomaly within an image (eg, a lung nodule)
- Segmentation - Isolation of a structure of significance from the rest of the study (eg, delineating the margins of an organ)
- Classification – Categorizing a particular lesion, identified from the image.

III. Use Cases

Yet another method to approach clinical applications is based on classes of use cases', i.e. differentiating normal from abnormal. The basis of any radiologic interpretation would consist of an implied perceptual task of categorizing an image or a sequence of images as normal or abnormal performed by an expert radiologist. In this context, deep learning can perform better by learning a standard hierarchical representation of a specific image from multiple regular examinations. AI can detect minor changes in the images saving the observers' time and also can help by retrieving previous data of the patient or finding similar findings in other images providing a list of possibilities. The 'ACR Reporting and Data Systems' (RADS) provides assessment, structure for Grading and categorization of images[10].

Radiomics is a process that extracts a large number of quantitative features from medical images. It can potentially be applied to any medical condition, but it is currently applied mostly in oncology for quantification of tumour phenotype and for development of decision support tools[11]. Deep learning and convolutional neural networks have the potential to automatically extract the significant features from images to help predict an important outcome.

5. Applications of AI In Maxillofacial Radiology:

Numerous pre-clinical studies have commented positively on the capability of AI diagnostic models to precisely locate root canal orifices[12, 13], identify vertical root fractures[14] and detect proximal caries[15].

I. AI Applications to Localize Cephalometric Landmarks

Several studies[16, 17] proposed an automated approach based on AI techniques using different algorithms for the localization of cephalometric landmarks, to enhance the efficiency of orthodontic treatment planning. Quite a few studies reported successful outcome, in accordance with the standard of automatic landmark localization. In 2011, an AI model was proposed[18] to automatically localize anatomic landmarks on CBCT images. Cephalometric radiographs were gradually substituted by CBCT images to develop models for cephalometric analysis. Documented literature on AI based models of automatic 3dimensional landmark annotation on CBCT images, demonstrates that Cephalometric analysis on CBCT images is considered as a more versatile approach. However, automatic localization performance on existing models is still not satisfactory[19, 20].

II. AI Applications for Detecting Bone Disorders

AI for detecting low bone mineral density and osteoporosis is clinically relevant to implant dentistry. AI models 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 predict the probable incorporation of these models into routine clinical practice in the near future[21, 22].

III. AI Application to Classify / Segment Maxillofacial Cysts and/ or Tumors

Of late, AI models for automated diagnosis of various jaw cysts and tumors are being researched and developed extensively. These models basically employ four main steps;

a. Lesion detection
b. Segmentation
c. Extraction of texture features and
d. Classification.

At present, the initial step of 'lesion detection' in these models is still being performed manually so that these models can automatically perform the subsequent steps. The development of a fully automated model that can accurately diagnose cysts and tumors, is still in infancy stage[23,24].

IV. AI Applications to Detect Periapical and Periodontal Disease

The field of periodontics has witnessed the development of AI models to detect and quantify the degree of alveolar bone loss[25, 26]. Mol et al[27] and Carmody et al[28] proposed models to classify the extent of periapical lesions. The contribution of Flores et al[29] towards clinical practice is highly regarded. His model, based on CBCT images can easily differentiate periapical cysts from granulomas.

V. AI Application for Dental Caries Detection:

Automated caries detection models had been documented (Logicon Caries Detector™ program, Logicon Inc., USA) for the detection and characterization of proximal caries[30] Numerous studies[31,32,33] have outlined innumerable attempts to develop ideal caries detection models that utilize 2 dimensional images acquired from extracted teeth. Though the diagnostic efficiency of such models in pre-clinical studies demonstrated satisfactory results, its potential in real life clinical scenarios needs to be validated.

VI. AI Applications for Other Diagnostic Purposes

There is documented evidence that suggests that AI models have been developed for diverse applications including the detection of maxillary sinusitis[34], classification and staging of lower third molar development[35], and tooth types[36], detecting root canal orifices[37] etc. Othersinclude, the diagnosis of vertical root fractures on CBCT images of endodontically treated and intact teeth[38], forensic dental imaging using dental panoramic radiographs[39], three dimensional orthodontics visualization using patient models and panoramic radiographs[40], automatic segmentation of mandibular canal[41] 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.

6. Limitations and Future Outlook

For successful development and bench marking of AI applications in dental radiology large representative data sets are required. All AI algorithms may not be applicable for different clinical scenarios, image artefacts may interfere with the accurate interpretation, and may not adapt to different imaging softwares used in different CBCT machines. In spite of the initial promising performance demonstrated by various AI models, it still requires to confirm the generalizability and dependability of these models by using sufficient data obtained from newly-recruited patients or collected from other dental establishments. In future, it can be expected that we can not only witness an improvement in AI efficiency that parallels that of experts, but also one that outperforms them by even detecting early lesions that cannot be visualized by human eyes.

7. Conclusion

AI is gradually turning smarter, quicker, precise and more reliable. Repetitive tasks in all fields, including medical imaging would soon be automated. Radiologists must keep abreast with the changing tides and make themselves familiar with its terminologies and concepts in order to analyze new frontiers and identify the shortcomings and potential challenges associated with it. Automation cannot completely outsmart the image interpretation and diagnostic skills of a radiologist; instead can aid in alleviating the workload by quicker screening, prediction of disease risks, and enhanced radio diagnosis and patient care. The role of AI would be certainly of great value to screen patients in remote areas with limited access to specialists. Radiologists must work hand in hand with scientists and engineers to contribute towards research and development of AI.

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