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Mini Review

Artificial Intelligence in Dento-Maxillofacial Radiology

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Abstract

Advanced breakthroughs in image recognition techniques using artificial intelligence (AI) and media researcher statements has led to the impression of AI being equated with the demise of radiologists. However, the work performed by radiologists includes many other tasks apart from image recognition that require common sense and general intelligence for solving tasks that cannot be achieved through AI. A thorough knowledge regarding the adaptation of technology will not only help in better and precise patient care but also reducing the work burden of the radiologist. This review focuses on artificial intelligence and its application in dento-maxillofacial radiology perspective.

Keywords: Artificial Intelligence; Dental Radiology; Maxillofacial Radiology; Digital Dentistry

Abbreviations

AI: Artificial Intelligence; ANNs: Artificial Neural Networks; CBCT: Cone Beam Computed Tomography; CDSS: Clinical Decision-Support Systems; CT; Computed Tomography; ML: Machine Learning; MRI: Magnetic Resonance Imaging; NLP: Natural Language Processing; OPG: Orthopantomogram.

Introduction

Radiologists are primarily known for their image interpretation skills [1]. Advanced breakthroughs in image recognition introduced by deep learning techniques, and media statements by researchers have portrayed artificial intelligence as the cause of demise of radiologists. However, the complex work performed by radiologists includes many other tasks that require common sense and general intelligence for problem solving tasks that cannot be achieved through AI. Understanding a case requires multiple basic medical and clinical specialities to provide plausible explanations for imaging findings. Also, advanced imaging modalities necessitate specialized intelligence for detection of anomalies, segmentation, and image classification [2-5].

Artificial intelligence (AI) is a technology, which has shifted from science fable into reality in the radiology practice in the last two decades [6]. Allan Turner one of the founders of AI defined it as the ability to achieve human-level performance in cognitive tasks by computers [7]. Implementation of AI in radiology is anticipated to significantly revolutionize the quality, value, and depth of radiology's contribution to patient care and population health, and radiologists work flow in next decade [6]. This makes it imperative that a radiologist be aware of AI and its applications in their field. This mini review provides an insight to the various concepts and terminologies used in AI from a dento-maxillofaial radiology perspective.

Artificial intelligence

AI is a branch of computer science dedicated to the development of computer algorithms to accomplish tasks traditionally associated with human intelligence, such as the ability to learn and solve problems [1]. This includes machine learning (ML), representation learning and deep learning (Figure 1).

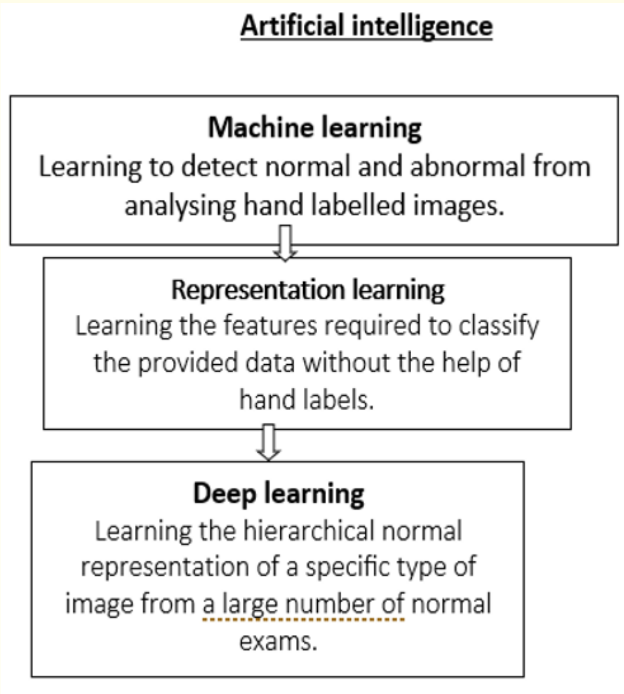

Figure 1: Hierarchy of Artificial Intelligence fields.

Machine learning (ML)

Is a part of research on AI that seeks to provide knowledge to computers through data and observations without being explicitly programmed [8].

This allows a computer to correctly generalise a setting by tuning of parameters within the algorithm to optimize the goodness of fit between the input (ie, text, image, or video data fed into the algorithm) and output (ie, classification). For example, for a ML algorithm can detect a lymph node in head and neck image as normal or abnormal provided it is trained Radiologist by analysing thousands of such images which are labelled as normal or abnormal [1]. To sum it up ML algorithms are trained to give a specific answer by evaluating or learning a large number of exams that have been hand-labelled.

Representation learning

Is a subtype of ML in which the computer algorithm learns the features required to classify the provided data? This does not require a hand labelled data like ML [1].

Deep learning

Is a subfield of representation learning relying on multiple processing layers (hence, deep) to learn representations of data with multiple layers of abstraction. This algorithm uses multiple layers to detect simple features like line, edge and texture to complex shapes, lesions, or whole organs in a hierarchical structure. Basis of any radiologic interpretation is logical elimination of possible diagnosis. In this context, deep learning can potentially excel by learning a hierarchical normal representation of a specific type of image from a large number of normal exams [1,7,9].

Clinical decision-support systems (CDSSs)

AI programs that are designed to provide expert support for health professionals are known as CDSS. They are designed to support healthcare workers in their everyday duties, assisting with tasks that rely on the manipulation of data and knowledge. These systems include Artificial neural networks (ANNs), fuzzy expert systems, evolutionary computation and hybrid intelligent systems. Each AI technique has its own strengths and weaknesses. Neural networks are mainly concerned with learning, fuzzy logic with imprecision and evolutionary computation with search and optimisation [10].

Artificial neural networks (ANNs)

Are the most popular AI analytic tool in used for image analysis inspired by the biological nervous system [1,10]. This involves a networks of highly interconnected computer processors that has the ability to learn from past examples, analyse non-linear data, handle imprecise information and generalise enabling application of the model to independent data has making it a very attractive analytical tool in the field of medicine [1]. ANNs have been used to interpret plain radiographs, ultrasound, CT, MRI, and radioisotope scans.

Fuzzy logic

Is the science of reasoning, thinking and inference that recognises that everything is a matter of degree of shades of grey rather than conventional white and black? It has the ability to recognise that most things would fall somewhere in between with varying shades of grey. This data handling methodology that permits ambiguity and hence is particularly suited to medical applications. They have been used to characterise ultrasound images of the breast, ultrasound and CT scan images of liver lesions and MRI images of brain tumours [1].

Evolutionary computation

Are a class of stochastic search and optimisation algorithms based on natural biological evolution. The most widely used form of it being used for 'genetic algorithms'. It has better application in medical field where they work by creating many random solutions to the problem at hand. Commonly used in computerised analysis of mammographic microcalcification, MRI segmentation of brain tumours to measure the efficacy of treatment strategies and for analysing computerised 2-D images to diagnose malignant melanomas [1].

Hybrid intelligent systems

Has the advantages of all the above technologies combined together to work in a complementary manner. The synergetic system allows to accommodate common sense, extract knowledge from raw data, use human-like reasoning mechanisms, deal with uncertainty and imprecision, and learn to adapt to a rapidly changing and unknown environment. There are varoius hybrid systems available, the popular ones being ANNs for designing fuzzy systems, fuzzy systems for designing ANNs, and Genetic Algorithms for automatically training and generating neural network architectures [1].

Applications

Adapting of AI in maxillofacial radiology its clinical applications can be divided into 3 types [1] (Table 1).

1. Clinical workflow,
2. Types of applications
3. Classes of use cases.

Clinical workflow	Types of applications	Classes of use cases
Triage scenario	Detection	For workflow optimization and quality assurance
Replacement scenario	Segmentation	Separate normal from not normal
Add on scenario	Classification	Grading and classification of images
		Computer aided detection
		Radiomics
		Natural language processing, computer-assisted reporting, and knowledge management

Table 1: Clinical application of AI.

Clinical workflow these are the diagnostic tests inserted in existing clinical pathways.

For example, when a patient requires a diagnostic imaging, radiologist is the one who decides the image selection and other protocols. Alternatively, AI applications can be applied using various scenarios to reduce the radiologist burden.

Different scenarios used in clinical work flow are triage, replacement and add-on which are based on the conceptual frame work developed by Bossuyt., *et al* [11].

Triage scenario adapted from is used as a screening tool to sort examinations based on the probability of disease being positive or negative according to AI.

For example, AI will assess the not interpreted x-rays for highest probability of disease determined by an algorithm according to the content of images or other data available and determine which examination should be interpreted first.

Replacement scenario, AI may replace radiologists if results are consistently more accurate, rapid, reproducible, and easier to obtain. Most common application of it being estimation of bone age by an AI software. AI is found to consistently provide better performance than a radiologist in bone age estimation.

Add-on scenario may use AI in a subgroup of patients where the existing clinical pathway is dependent on the radiologist interpretation. This tool is applied only if the imaging findings warrant a time-consuming application best left to ML algorithms.

Types of application

This can be divided into

- **Detection:** To identify an anomaly within an image (eg, a nodule);
- **Segmentation:** To isolate a structure from the remainder of the study (eg, defining the boundary of an organ); and
- **Classification:** To assign an image or lesion within an image is assigned to a category (eg, is presence or absence of pulmonary embolism on a CT scan).

Classes of use Cases

This approach is based on use cases I, e.

- To Separate normal from abnormal
- For workflow optimization and quality assurance: 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.
- Grading and classification of images: The ACR Reporting and Data Systems (RADS) provide assessment structure and classification for reporting in patient imaging [12].
- Radiomics process extracts a large number of quantitative features from medical images. Though t can potentially be applied to any medical condition, it is currently applied mostly in quantification of tumor phenotype and development of decision support tools in oncology [13].
- Natural language processing (NLP): NLP is commonly defined as the conversion of unstructured text into a structured form to allow for the automated extraction of information, synonymous with text mining or information extraction. AI analyses the large amount of unstructured information in full-text radiology reports to extract potentially invaluable source of information for clinical care quality improvement and research, which would have been a challenge otherwise due varied and individual reporting styles of narrative reports [1,14].

Applications in maxillofacial radiology

As the easiest fields for the evaluation of efficiency of application of AI are diagnostics of lung nodules and breast cancer screening most of the researches involving radiology are focused on it [15].

Following aspect of the dento-maxillofacial radiology has been researched with respect to AI.

1. Interpretation of radiographic lesions and automated interpretation of dental radiographs [10]
2. Using the radiologists work as data, AI may enable programs to identify details of individual radiologists' practice pattern and categorizing them to create a sophisticated radiology report card [1].
3. Caries detection: Logicon Caries Detector™ program (Logicon Inc., USA) is designed to assist dentists in the detection and characterization of proximal caries [16]
4. Diagnosis of vertical root fractures on CBCT images of endodontically treated and intact teeth [17]
5. To stage tooth development [18]
6. Computer based digital subtraction imaging [19]
7. Computer-assisted image analysis is useful to visualize and evaluate the bone architecture directly from the dental panoramic radiograph [20]
8. 3 dimensional orthodontics visualisation using patient models and OPGs [21]
9. Bone density evaluation to predict osteo porosis using OPGS [20]
10. Automatic segmentation of mandibular canal [22]

    Gerlach reported accuracy of automatic segmentation of the mandibular canal by the AAM and ASM methods is inadequate for use in clinical practice.
11. Forensic dental imaging: Personal Identification System Using Dental Panoramic Radiograph based on Meta_Heuristic Algorithm reported to have 97.7% precision [23]
12. Dental biometrics [24].

Advantages of AI

- It is a powerful tool to identify patterns, predict behaviour or events, or categorize objects [1].
- Improve radiology departmental workflow through precision scheduling, identify patients most at risk of missing appointments, and empower individually tailored exam protocols [1].
- Machine Learning directly with medical data can help in preventing the errors due to cognitive bias [25].

Limitations

Requires a very huge and sound data base of knowledge, if not may result in inappropriate answers when presented with images outside of their knowledge set [26,27].

For example, when iamge techniques not appropriate or if there are any artefacts may result in faulty interpretation of image.

May not adapt with new imaging software or new machine immediately.

Not all the algorithms used are apt for clinical application [22]. More trials to recommend the apt analytic programmes for different scenarios.

Future Recommendations

- Radiologists should be familiar with AI terminology and hierarchy.
- Radiology programs should begin to integrate health informatics, computer science and statistics courses in their curriculum.
- To train the radiologist for logic, statistics, and data science and be aware of other sources of information such as genomics and biometrics, insofar as they can integrate

data from disparate sources with a patient's clinical condition.

- Radiologists should understand the challenges related to preparation of training datasets for supervised learning.

Conclusion

Integration of artificial intelligence eases the radiologist's job rather than take it away. If artificial intelligence becomes adept at screening for diseases in images, it could screen populations faster than radiologists and at a fraction of cost. The radiologist could ensure that images are of sufficient quality and that artificial intelligence is yielding neither too many false-positive nor too many false negative results.

Economically it could translate into better patient care specially in developing countries hampered by access to specialists. A single specialist, with the help of artificial intelligence, could potentially manage screening for a large population at reduced time and cost.

Key Message

- Use of artificial intelligence decreases the workload of the radiologist.
- It cannot replace a radiologist but definitely redefines radiologists job.
- AI integration helps in reaching larger population with accuracy enhancing patient care.

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Conflict of Interest

None

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