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Prospect of Artificial Intelligence in Radiology

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Abstract

Without doubt, artificial intelligence (AI) is the most discussed topic today in medical imaging research, both in diagnostic and therapeutic. This paper aims to provide a review of the basis for application of AI in radiology, to discuss the immediate ethical and professional impact in radiology, and to consider possible future evolution. Researchers have applied AI to automatically recognizing complex patterns in imaging data and providing quantitative assessments of radiographic characteristics Radiomics, the extraction of a large number of image features from radiation images with a high-throughput approach, is one of the most popular research topics today in medical imaging research. AI coupled with CDS can improve the decision process and thereby optimize clinical and radiological workflow. AI is the essential boosting power of processing massive number of medical images and therefore uncovers disease characteristics that fail to be appreciated by the naked eyes.

Keywords

Radiology,
CT,
MRI,
artificial intelligence,
imaging,
application

The paper aims to provide a review of the basis for application of AI in radiology, to discuss the immediate ethical and professional impact of AI in radiology, and to consider possible future evolution of such technology within diagnostic imaging.

The term “artificial intelligence” (AI) includes computational algorithms that can perform tasks considered typical of human intelligence, with partial to complete autonomy, to produce new beneficial outputs from specific inputs [1].

Artificial Intelligence (AI) represents the capacity of machines to mimic the cognitive functions of humans (in this context, learning and problem solving). AI can be subdivided into artificial narrow intelligence, where a computer can perform a very specific task as well as or better than humans, and artificial general intelligence, where a computer goes beyond specific tasks to perform higher-order syntheses, emulating human thought processes [2].

Artificial Intelligence (AI) is one of the fastest-growing areas of informatics and computing with great relevance to radiology. Practicing radiologists, trainees, and potential future radiologists need to understand the implications of AI for the specialty, what it means, how it can contribute to the radiological profession, and how may change it in the future. They are aware of the impact that AI is having on the field of Radiology, from technical, professional, scientific, ethical, and economic perspectives.

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Although premises to the development of AI were achieved in the early era of computers, it has only been with the introduction of new powerful computational hardware, in association with the capability of collecting and storing huge amounts of data, that it has become feasible to explore its potential in tasks most relevant to the field of radiology. Indeed, although healthcare represents a challenging field for AI application, medical imaging is currently one of the most promising areas to apply this technology [3].

The use of artificial intelligence (AI) in diagnostic medical imaging is undergoing extensive evaluation. AI has shown impressive accuracy and sensitivity in the identification of imaging abnormalities and promises to enhance tissue-based detection and characterization. [4]

At present, many AI imaging studies estimate diagnostic accuracy by calculating sensitivity and specificity, while others assess clinically important outcomes. [5,6] However, as AI can detect minor image alterations but the occurrence of clinically meaningful events should be the focus of AI-based investigations. Even though numerous studies show that AI has higher specificity and lower recall rates than standard reading. Non patient-centric endpoint selection might increase sensitivity at the expense of increasing false positives and possibly over diagnosis as a result of identifying minor changes.

From the beginning, it has been quite clear that computers could be potentially useful in assisting the radiologist in the routine tasks of detection and diagnosis. The idea fostering the use of the so-called computer-aided detection/ diagnosis (CAD) systems, precursors of modern AI, was to provide radiologists with the assistance in the detection and interpretations of potential lesions in order to discriminate between benign and malignant lesions, reduce false negatives, and boost radiologists' productivity, especially in terms of discovery and identification of significant findings requiring a prompt human validation [7].Main limitations of CAD systems were their task-specific orientation which is suited to only one particular given task in a corresponding specific imaging modality and, moreover, their reliability and the risk of false positive results implied mandatory validation by a trained radiologist [7]. Since then, ever-increasing attempts have been made to improve upon the diagnostic performance of AI.

However, it is difficult to discriminate papers related to the use of CAD and those reporting the pure application of machine or deep learning, since both terms are included in the wider term "artificial intelligence."Some of many recent applications of AI include the RSNA pediatric bone age machine learning challenge on plain radiographs [8], breast cancer detection in mammography and MRI [9-11], chest radiograph interpretation [12-13], liver lesion characterization on ultrasound and CT [14-15], brain tumor [16-17], and prostate cancer detection [18-19].

The development of AI is largely based on the introduction of artificial neural networks (ANN) in the early 1950s [20] and their subsequent further evolution (from single to multilayer ANN), introducing the concepts of "computational learning models," machine learning (ML) and deep learning (DL).

ML is based upon the so-called "reverse training" method, in which computer systems focus on specific pathological features identified during a training period [21]. Thus, ML applications require a set of data on a specific pathology on which the computer can train itself, and those data must necessarily contain the desired outcome that needs to be predicted (e.g., nodules or emphysema on chest X-rays, focal liver lesions, hemorrhage in head CT, and soon). Big data is the type of data that may be supplied into the analytical system so that an ML model could learn, improving the accuracy of its predictions. Once trained, the computer can apply this information even to new cases never seen before [22-23]. ML can be supervised or unsupervised, depending, respectively, on the "labeled" input previously selected by human experts, or directly extracted by the machine using several computational methods [24].

Deep learning is a subset of machine learning and is the basis of most AI tools for image interpretation. Deep learning means that the computer has multiple layers of algorithms interconnected and stratified into hierarchies of importance (like more or less meaningful data). These layers accumulate data from inputs and provide an output that can change step by step once the AI system learns new features from the data. Such multi-layered algorithms form large artificial neural networks [13].

ML/DL image processing with clinical and when available pathological/histological data, to correlate intrinsic diagnostic patterns and features of a CT or MRI scan to a specific pathology and histological subtype, has opened a new window in research establishing so-called radiomics [25-27].

A great challenge is that, unlike discrete findings derived from sophisticated conventional radiographic studies, AI might identify imaging pattern changes that are not easily amenable to human identification.[28] For example, analysis of brain MRI using machine learning has the potential to identify tissue changes reflective of early ischemic stroke within a narrow time window from symptom onset with greater sensitivity than a human reader.[29]

Despite the promise of early diagnosis with machine learning, the relationship between very subtle parenchymal brain alterations detected by AI, either in the natural history of small evolving infarcts or non-ischemic processes, and gross neurological outcomes is unknown. Further, difficult circumstances might ensue in which a recommendation for treatment might be given in the absence of a well-defined abnormality detected by routine imaging.[29] At the patient level, such discordance might cause confusion and potentially mistrust and will necessitate public education regarding the new concept of deep learning in imaging analysis. It might also introduce medical liability issues (such as failure to diagnose or potentially unnecessary surgery) that could materialize if AI becomes the standard of care.10 The public and especially physicians should also be reassured that AI is unlikely to replace radiologists, but a radiologist who uses AI might be more productive than a radiologist who does not.[30]

Another high-yield niche for AI imaging is cancer detection and characterization. High-power quantitative analysis of fine structural image alterations could be used to predict the odds of malignancy and anticipated tumor kinetics and help tailor management plans.

The rise and dissemination of AI in clinical medicine will refine our diagnostic accuracy and rule-out capabilities. However, unless AI algorithms are trained to distinguish between benign abnormalities and clinically meaningful lesions, better imaging sensitivity might come at the cost of increased false positives, as well as perplexing scenarios whereby AI findings are not associated with outcomes.

Despite the excitement AI has generated in the medical imaging research, there are challenges before it can become more robust and be widely adopted in the clinic. AI is constrained by a lack of high quality, high volume, longitudinal, outcomes data. Each patient cohort associated with a clinic is different. The way each clinic practices is also different. How to organize the data generated from different practices in a more standard way is a big challenge on AI-based medical imaging research. Medical imaging data organization itself might deserve to be a major research field.

To conclude, AI is playing a significant role in medical imaging researches. It changed the way people process the enormous number of images. There are still challenges to be resolved before AI can eventually impact clinical practices.

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