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► **To cite this version:**

Tom Boeken, Jean Feydy, Augustin Lecler, Philippe Soyer, Antoine Feydy, et al.. Artificial intelligence in diagnostic and interventional radiology: Where are we now?. *Diagnostic and Interventional Imaging*, 2023, 104 (1), pp.1-5. 10.1016/j.diii.2022.11.004 . hal-03949288

HAL Id: hal-03949288

<https://hal.science/hal-03949288v1>

Submitted on 8 Jan 2025

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Artificial intelligence in diagnostic and interventional radiology: Where are we now?

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Abstract

The emergence of massively parallel yet affordable computing devices has been a game changer for research in the field of artificial intelligence (AI). In addition, dramatic investment from the web giants has fostered the development of a high-quality software stack. Going forward, the combination of faster computers with dedicated software libraries and the widespread availability of data has opened the door to more flexibility in the design of AI models. Radiomics is a process used to discover new imaging biomarkers that has multiple applications in radiology and can be used in conjunction with AI. AI can be used throughout the various processes of diagnostic imaging, including data acquisition, reconstruction, analysis and reporting. Today, the concept of “AI-augmented” radiologists is preferred to the theory of the replacement of radiologists by AI in many indications. Current evidence bolsters the assumption that AI-assisted radiologists work better and faster. Interventional radiology becomes a data-rich specialty where the entire procedure is fully recorded in a standardized DICOM format and accessible via standard picture archiving and communication systems. No other interventional specialty can bolster such readiness. In this setting, interventional radiology could lead the development of AI-powered applications in the broader interventional community. This article provides an update on the current status of radiomics and AI research, analyzes upcoming challenges and also discusses the main applications in AI in interventional radiology to help radiologists better understand and criticize articles reporting AI in medical imaging.

Keywords

Artificial intelligence; Diagnosis; Interventional radiology; Medical imaging; Radiomics

List of abbreviations

3D: Three-dimensional

AI: Artificial intelligence

CPU: Central processing unit

GPU: Graphics processing unit

IR: Interventional radiology

1. Introduction

During the last two decades, the rapid growth in the number of medical imaging examinations and the improvement of calculation capabilities led to a dramatic development of artificial intelligence (AI) in medical imaging [1]. AI is now implicated in all aspects of medical imaging whichever the modality or the organs concerned. Even if most published AI studies refer to diagnostic imaging, there is no doubt about the fact that AI has also a promising future in the field of interventional radiology (IR) [2]. Whether or not AI will overachieve or deceive is still unknown [3]. Bluemke et al. published a brief guide with nine essential questions to address when assessing an AI model in radiology [4] and similar recommendations were also published by Gong et al. [5]. These considerations pave the way for a more standardized and formalized way of publishing results. Essentially, this might alleviate concerns non-specialists feel about the use of specific AI-based solutions.

The purpose of this article was to provide an updated status of radiomics and AI research and upcoming challenges and also discusses the main applications in AI in IR to help radiologists understand and criticize articles reporting AI in medical imaging.

2. Up-to-date status of AI research and upcoming challenges

The emergence of AI models as useful tools in radiology results from a decade-long industrial effort. From the development of new computing chips to the construction of curated image repositories, this technological leap has been made possible by a conjunction of progresses at multiple levels.

First, the emergence of massively parallel yet affordable computing devices has been a game changer for research in the field. Whereas central processing units (CPU) provide a few dozens of compute units (cores) at most, graphics processing units (GPU) pack thousands of cores on a single device. Going beyond their initial use as accelerators for the rendering of three-dimensional (3D) scenes, GPUs can now be used for a wide range of scientific applications and provide the computational power of a traditional cluster at a fraction of the price. As a consequence, they currently power the vast majority of AI computations. Second,

a significant investment from the web giants has fostered the development of a high-quality software stack. Except for a few exceptions, all AI models developed since 2017 have been written using accessible software libraries that are maintained by Google or Facebook and rely on numerical routines provided by the GPU constructor Nvidia [6]. Finally, in healthcare, the main stakeholders have catered to the needs of this new generation of image analysis software. Thanks to a clarification of the legal framework and significant investments from the public and private sectors, large datasets have been made available to researchers [7].

This favorable environment has led to multiple breakthroughs in radiology. As detailed below, we may cite the improvement of acquisition and denoising pipelines, pattern detection with ResNets and automatic organ segmentation with U-Nets [8]. Going forward, the combination of faster computers with dedicated software libraries and the widespread availability of data has opened the door to more flexibility in the design of AI models. The past few years have seen the arrival of AI-specific circuits in GPUs and advances in compilers technology that are enabling the deployment of new types of models such as transformers, graph neural networks or scalable kernel machines [9, 10]. Going beyond the analysis of grid images and volumes, this has led to significant progress in the processing of natural language, 3D point clouds and surfaces [11]. The subsequent interest in AI solutions has led to a remarkable increase in collaborations between medical doctors and AI researchers, with great promises for the future.

Nevertheless, caution should be exercised when evaluating AI methods and making optimistic predictions about the next decade. First, because the constraints of a clinical environment are seldom considered in research publications. Turning a promising AI software into a certified solution for radiology is an arduous and expensive process. Second, because the funding and maintenance of an open AI software ecosystem has been, so far, entirely dependent upon the goodwill of a few tech companies which are currently experiencing sharp fluctuations of their stock valuations. And finally, because the supply chain of hardware accelerators that powers the AI revolution is coming under risk. With current AI research relying almost exclusively on GPUs that are designed by Nvidia and manufactured by TSMC in Taiwan, progress in the field is tributary to a stable geopolitical environment. The global chip shortage caused by the COVID-19 pandemic or the recent ban imposed by the United States on the exports of high-end GPUs to mainland China are having significant impact on researchers worldwide and may well curtail optimistic growth projections.

3. Radiomics

Radiomics is a high-throughput data mining process used to discover new imaging biomarkers. It is a data-driven, hypothesis-free research field that consists of the extraction of large sets of quantitative imaging descriptors that can feed machine learning algorithms to find correlations with diagnostic, prognostic or predictive targets [12]. The exponential growth of radiomics research has been built on the premises that medical images contain biological information that cannot be analyzed by the naked eye but can be quantified using high throughput methods similar to those used in genomics [13].

Radiomics was initially studied in oncology imaging where predictive models have yielded encouraging performances in varying tasks such as distinguishing benign vs malignant lesions, predicting histopathological tumor types, genetic mutations or even survival [14, 15]. These results encouraged researchers to develop radiomics signatures for other diseases, including neurodegenerative disorders, pulmonary fibrosis or Sars-CoV-2-induced pneumonia [16, 17, 18].

Radiomics process is classically separated in seven steps: (i), data acquisition; (ii), lesion segmentation; (iii), preprocessing; (iiii), feature extraction; (v), feature reduction; (vi), model building, and (vii), validation. Each step may be performed in different ways. This process may involve traditional machine learning methods, but deep learning can also be used, either as an end-to-end process, or only for certain steps [19]. Extracted imaging descriptors include shape descriptors, histogram-based features describing signal intensity content of voxels, and texture features describing spatial distribution of signal intensities and therefore tumor heterogeneity [19].

The complexity of this seven-steps process is the major limitation of radiomics that hinders the reproducibility of studies and the clinical application [20, 21]. Guidelines have been developed to improve the quality of radiomics research, which every author, reader or reviewer of radiomics studies should keep in mind to help radiomics overcome its daemons [22]. Specifically, the Image Biomarker Standardization Initiative and the Radiomics Quality Score develop recommendations for each step of the process that should be reported in studies to standardize research and improve reproducibility of the results. Low-code tools such as autoradiomics or workflow for optimal radiomics classification have also been recently developed to offer clinicians with little time or experience in radiomics and programming the opportunity for initial exploration of imaging data using radiomics in an automated and

standardized way. The combination of radiomics and non-radiomics data in large clinical trials will likely pave the way for the future of this data-driven research field [23].

4. Main applications of AI in diagnostic imaging

AI can be used throughout the various processes of diagnostic imaging acquisition, reconstruction, analysis and reporting. AI has a potential to impact all the various steps of the daily radiological workflow, helping radiologists dealing with a constantly increase in workload [24]. Studies report that, usually, an average radiologist must interpret one image every 3–4 seconds in an 8-hour workday to meet workload demands [25]. Therefore, errors are inevitable, especially under such constrained conditions. The development of AI is driven by the desire for greater efficacy and efficiency in clinical care.

First, image acquisition can be achieved more quickly using AI, with various techniques, such as the undersampling of the k space, the creation of synthetic images obtained from a single image, or the use of higher acceleration factors without compromising the quality of the images obtained.

Second, there used to be a widening gap between advancements in image acquisition hardware and image- reconstruction software, a gap that could potentially be addressed by new deep learning methods for suppressing artefacts and improving overall quality. Image reconstruction can be substantially improved by AI, with various advantages, such as the decrease of contrast doses needed, the dose optimization, the improvement of registration techniques or the reduction of the reconstruction time itself [26]. Overall, AI can help obtain a higher image quality for diagnosis. Dose optimization can be done with AI algorithms [27]. AI can be an optimizing tool for assisting the radiologist in choosing a personalized patient's protocol, in tracking the patient's dose parameters, and in providing an estimate of the radiation risks associated with cumulative dose and the patient's susceptibility, such as age and other clinical parameters. Many current research works investigate the accuracy of deep learning-based reconstruction algorithms and their ability to recreate rare, unseen structures, as initial errors propagated throughout the radiology workflow can have adverse effects on patient outcome [28].

One of the most interesting fields of clinical application of AI remains centered on image analysis, such as lesion detection and characterization, response to treatment or disease monitoring. AI might help triage exams by screening all the exams completed during a shift to rule out normal exams and to alert the radiologist on the most urgent exams to review. AI is a

great aid to radiologists in the emergency setting and improves their workflow by decreasing reading time in some areas [29, 30].

Many AI algorithms are now available in clinical practice. As their number is constantly evolving and increasing, online platforms are helpful to identify them, such as <https://grand-challenge.org>. Such platforms check whether the proposed AI algorithms are Food and Drug Administration or Commnauté Européenne marked and more importantly whether their performance is supported by published peer-reviewed research articles. At the time of the writing of this article, there were more than 200 AI software available on the market with a Commnauté Européenne or Food and Drug Administration approval. Among them, and not exhaustively, radiologists can be helped with tools providing automated detection and prioritization of acute intracerebral hemorrhage on non-contrast CT, aiding the assessment of acute ischemic stroke, automatically detecting and prioritizing acute large vessel occlusions on CT angiography, automatically measuring the maximum transverse diameter of the aorta to detect aneurysms, assisting radiologists or clinicians in the interpretation of chest x-ray, automatically analyzing the main anatomical structures of the knee and detecting lesions, detecting and characterizing lung nodules, estimating pediatric bone age, monitoring child growth and development from digital X-rays of the hand, detecting pulmonary embolism, detecting bone fractures, detecting mammogram abnormalities, assessing a tuberculosis risk score, providing objective cardiac ultrasound images analysis, providing a workflow for detection of prostate abnormalities on magnetic resonance imaging examination, detecting and localizing pneumothorax, pleural effusion or alveolar syndrome, characterizing brain tumors, detecting brain aneurysms, measuring the volume fraction of fat in liver tissue or liver iron concentration, providing the subject's level of risk of having or progressing to Alzheimer's disease dementia, labeling and volumetric quantification of segmented central nervous system structures, assessing (sub)clinical disease activity in patients with multiple sclerosis, measuring brain atrophy, calculating, quantifying volumetric breast density or automatic coronary artery calcium scoring [1, 3, 31].

Another strength is to allow automated segmentation in clinical practice as well as in research to reduce the burden on radiology workflow of the need to perform segmentation manually. Multiple studies have been published about various organ segmentation using a deep learning approach, showing its interest to reduce the human reader variability as well as to reduce the time and exhaustion dedicated to this task. AI can also aid the reporting workflow, especially its standardization. It can integrate into a report data arising from various sources, such as quantitative data, radiomics data, volumetric data or data coming

from computer-assisted reporting systems. It can help the linking between reports from various imaging modalities to increase the quality of the report and to adapt the management and treatment of the patient. It can help radiologists achieve this laborious and routine time-consuming task of generating an accurate and complete report [32]. It can improve communication between radiologists and referring physicians, such as in oncology.

Today, the concept of “AI-augmented” radiologists is preferred to the theory of the replacement of radiologists by AI in many indications [3]. Current evidence bolsters the assumption that AI-assisted radiologists work better and faster. However, the promise of advanced AI methods should not be overstated, as most state-of-the-art advances in the field of AI remain “weak AI”, where AI is trained for one task and one task only, with only a few applications actually exceeding human capabilities.

5. Main applications in interventional radiology

Most deep learning models are based on large datasets, which are commonly available in diagnostic imaging. Unfortunately, IR does not generate ready-to-use multicentric labelled images, and this may contribute to the idea that IR might be less suited for AI applications. This is a question of perspective, and IR should not be opposed to diagnostic imaging. It should rather be compared to other interventional specialties such as surgery or endoscopy. With this viewpoint, IR becomes a data-rich specialty where the entire procedure is fully recorded in a standardized DICOM format and accessible via standard picture archiving and communication system systems. No other interventional specialty can bolster such readiness. In this setting, IR could lead the development of AI-powered applications in the broader interventional community, working on specific research on how to generalize and translate into clinical applications models trained on mono or oligo-centric routine interventions.

The practical use of AI in IR can be divided into three areas including pre-procedural, peri-procedural and post-procedural settings, even though these situations are intertwined.

5.1. Pre-procedural AI towards better patient selection

Better patient selection is both a challenge for interventional and non-interventional radiologists. This is particularly true in oncology where human-powered intelligence is put to work in a translational and multidisciplinary approach. Ultimately, prognostic and predictive biomarkers will help tumor boards make clinical decisions towards personalized strategies.

The use of AI in generating risk profiles for patients who will benefit from IR is described on every level of the decision process, such as pathology [33, 34], circulating tumor DNA analysis [35], genomic analysis [36, 37] or response to treatment [38]. [

The possibility to predict responses to interventional therapies in oncology will have to be rigorously evaluated. Research amongst the specific field of clinical decision assistance is particularly challenging when it comes to generalization. For example, following the nine-point guide provided by Bluemke et al., the second recommendation suggests using an external validation set to avoid overfitting bias [4]. Practically, this means that prospective trials will eventually be run to show that AI-based guided approaches yield better outcomes. Such biomarker-based approaches are already seen in major cancer publications [39]. Not only should interventional radiologists train AI models, but eventually interventional radiologists will have to lead prospective studies validating these new biomarkers.

5.2. Peri-procedural AI to enhance intervention

Enhancing the intervention is probably the most futuristic vision of how AI will help interventional radiologists in daily work. Interventional radiology was built on two elementary pillars that include a human manipulation of devices into the patient and a live human analysis of the images provided by different modalities. Both tasks can conceivably be assisted by AI.

The manipulation of devices is the subject of research in the field of robotics. Not only does robotics use AI for faster and more precise movements, but this field is also studying the potential of force sensors coupled with image analysis for automation. This will eventually shift robotics-assisted interventions towards more automatic procedures [40]. This naturally leads to questions regarding the connection between a manipulation (device or retreat for instance a guidewire or a probe) and the effect within the patient as observed on the image. Research on how the image is processed could lead to lower radiation exposure, shorter procedures and lower amount of injected contrast material [41]. Next-generation fusion, with real-time registration deep learning algorithms, could help interventional radiologist use pre-operative imaging concomitantly with live fluoroscopy, similar to automated detection software [42]. Moreover, synthetic images can be produced from unsubtracted angiographic images, reducing misregistration artifacts [43, 44].

5.3. Post-procedural AI for follow-up

IR techniques suffer from a lack of standardization when it comes to evaluating treatment response. Criteria used in diagnostic radiology are not necessarily adapted to IR and this could lead to suboptimal patient care and to a misrepresentation of IR success rates. The Response Evaluation Criteria In Solid Tumours criteria, for example, are not necessarily adapted to endovascular therapies in oncology and could be outperformed by AI models [45, 46, 47].

Precision medicine will eventually integrate molecular biology, follow-up imaging and clinical data for prognosticating patients and rapidly adapting treatment strategies after IR procedures [48].

6. Conclusion

AI may enhance the future of radiology throughout every aspect of our daily patient care [1, 3, 16, 49]. The recent structuration of research in AI for imaging enables a more rigorous development and evaluation of AI-powered solutions, a mandatory turning point in this new field.

Human rights

The authors declare that the work described has been performed in accordance with the Declaration of Helsinki of the World Medical Association revised in 2013 for experiments involving humans.

Informed consent and patient details

The authors declare that this article does not contain any personal information that could lead to the identification of the patients.

Funding

This work did not receive any funding

Contribution of authors

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

Author credit statement

Conceptualization: All authors

Methodology: All authors

Investigation: All authors

Writing – original draft: Tom Boeken, Loïc Duron

Writing - review and editing: Jean Feydy, Augustin Lecler, Philippe Soyer, Antoine Feydy, Maxime Barat

Final draft approval: All authors

Declaration of Competing Interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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