

Artificial intelligence: new applications in neuro-oncology.

Evans John*

Department of Neurology, University of Illinois, Chicago, USA

Abstract

Artificial intelligence (AI) techniques have the potential to increase the accuracy of medical diagnostic and treatment procedures due to the exponential rise of computer algorithms. The spearhead of this revolution has been and most likely will remain the field of radiomics in neuro-oncology. Different AI techniques applied to conventional and advanced neuro-oncology MRI data can already distinguish between pseudo progression and real progression, delineate infiltrating margins of diffuse gliomas, and predict recurrence and survival more accurately than techniques currently used in clinical practise. By enabling non-invasive molecular environment sampling with great spatial resolution and offering a systems-level insight of underlying diverse cellular and molecular processes, radio genomics will also increase our understanding of cancer biology. These AI-based radiomic and radio genomic tools have the potential to stratify patients into more accurate initial diagnostic and therapeutic pathways and enable better dynamic treatment monitoring in this era of personalised medicine by providing in vivo markers of spatial and molecular heterogeneity. Although there are still many obstacles to overcome, as AI technology is developed and approved for clinical use, radiologic practise is expected to undergo significant change.

Keywords: Artificial intelligence, radio genomic tools, Radiomics, Neuro-oncology.

Introduction

Explicit rule-based systems and computer algorithms that don't require hard-coded rules are both included in the wide definition of artificial intelligence, which covers any work carried out by a computer that would typically require human intellect. A subfield of data science known as "machine learning," which is included in the AI umbrella, allows computers to learn from pre-existing "training" data without the need for explicit programming in order to generate predictions about future data points. Recent developments in computing have made it possible for deep learning, a subtype of machine learning that uses neural networks and has several layers. Radiomics research, which uses medical imaging data as quantitative imaging biomarkers, is rapidly adopting machine learning and deep learning methodologies. In order to improve patient outcomes, the ultimate goal of AI-based research in neuro-oncologic imaging is to better comprehend the complicated presentations of heterogeneous central nervous system (CNS) neoplasms [1].

The area of radiomics pulls data from clinical images for use as quantitative imaging biomarkers, despite the fact that clinical radiology typically depends on subjective and qualitative visual assessment of images. Lesion segmentation is typically the first crucial step in radiomics, and it is typically preceded by image pre-processing procedures such skull

stripping, intensity normalisation, and alignment of image volumes from various modalities. For segmentation, a range of techniques have been used, from manual labelling and/or annotation, semi-automated techniques, and more recent deep learning techniques. The extraction of quantitative features, such as fundamental shape, size, and intensity metrics, as well as more complex features derived from a variety of statistical techniques applied to the images, such as histogram-based features, texture-based features, fitted biophysical models, spatial patterns, and deep learning features, is the next step in radiomics with traditional machine learning. In order to "mine" the intermediate quantitative data for meaningful relationships, a range of alternative machine learning models can then be used [2].

This enables them to forecast critical information about a tumour, such as infiltrating tumour margins, molecular markers, and prognosis. High-quality ground truth data, generalizable and interpretable methodologies, and user-centric workflow integration pose significant obstacles to the promises of AI in radiology. Given the ongoing development of techniques like saliency mapping or principal component analysis that may "unbox" the networks by examining internal algorithm feature vectors, worries about the "black box" character of these algorithms have somewhat subsided. Both clinical acceptance and increasing the biologic and treatment

*Correspondence to: Evans John, Department of Neurology, University of Illinois, Chicago, USA, E-mail: john.evan@gmail.com

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relevance of the patterns identified by these approaches will benefit from a greater mechanistic understanding of the relationship between feature patterns and underlying biology [3].

The lack of huge, thoroughly annotated data sets is one of the biggest problems facing AI research. Studies with relatively small sample numbers, however, are more likely to have measurement error. While non-glioma-based research has been constrained by the absence of publicly available data sets, TCIA and BraTS have made significant strides in the creation of consolidated, well-labelled data for glioma image processing. However, the great bulk of the data are still isolated within various organisations and hospital systems. The generalizability of an algorithm's performance across various imaging sites, acquisition parameters and patient groups may need to be improved, which will require larger and more heterogeneous data sets [4].

There are significant barriers to the effective and reliable application of these advanced algorithms in a healthcare environment, despite the expanding usage of AI algorithms in research settings. To be adopted, the system must be simple to include into the radiologist's workflow. Additionally, a lot of segmentation and radiomic techniques take a long time to process, call for user involvement, and use a variety of internal pipelines. There hasn't been a lot of effort put into creating tools for quickly sharing and translating these methods. In actuality, most publications don't give readers enough details to independently recreate their process. Modelhub, Pyradiomics, and the Cancer Imaging Phenomics Toolkit are a few examples of open source applications that could ease the sharing of various methodologies.

Conclusion

This research program's overarching objective is to enhance CNS neoplasm patient outcomes by developing more effective diagnostic and therapeutic approaches. The use of AI technologies to create prediction models using clinical, radiomic, and genomic data holds great potential for directing and monitoring tailored therapies. To realise this field's potential, however, there are numerous obstacles to overcome and a lot of work that has to be done. Nevertheless, as AI technology advances and allows radiologists to work more accurately and efficiently, radiologic practise will significantly change. As these potent tools become further integrated into routine clinical practise over the next few years, it will be vital for the radiologist of the future to comprehend and effectively apply them.

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