

Artificial intelligence- image learning and its applications in neurooncology: a review

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Abstract

Image learning involves using artificial intelligence (AI) to analyse radiological images. Various machine and deep-learning-based techniques have been employed to process images and extract relevant features. These can later be used to detect tumours early and predict their survival based on their grading and classification. Radiomics is now also used to predict genetic mutations and differentiate between tumour progression and treatment-related side effects. These were once completely dependent on invasive procedures like biopsy and histopathology. The use and feasibility of these techniques are now widely being explored in neuro-oncology to devise more accurate management plans and limit morbidity and mortality. Hence, the future of oncology lies in the exploration of AI-based image learning techniques, which can be applied to formulate management plans based on less invasive diagnostic techniques, earlier detection of tumours, and prediction of prognosis based on radiomic features. In this review, we discuss some of these applications of image learning in current medical dynamics.

Keywords: Artificial Intelligence, Radiomics, Deep Learning, Neoplasms, Prognosis, Biopsy, Morbidity, Mutation, Machine Intelligence, Brain tumours, Neurooncologist, Artificial neural networks, Convolutional neural networks.

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Introduction

Artificial intelligence (AI) refers to working a computational system in tasks that normally require human thinking. Since its inception, AI has been aimed to substitute for human intelligence and has revolutionized the theory of consciousness and judgment. Consequently, it has also been implemented in medicine to help diagnose, treat, and predict the prognosis of diseases. Artificial neural networks (ANN) and

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convolutional neural networks (CNN) are some of the more well-known AI deep learning techniques in medicine. ANN implies a network of interconnected computer processors that are capable of analyzing input data in real-time, performing parallel processing and presenting plans.¹ CNN involves deep neural networks capable of analyzing images more accurately than ANN and extracting more in-depth image features and patterns.² Other AI techniques include fuzzy expert systems, evolutionary computation and hybrid intelligent systems, all of which have been employed in medicine, including managing brain tumours. One such application is analyzing radiological images, i.e., image learning (IL).¹

IL can be based on deep learning (DL) or radiomics and involves the extraction of quantitative features that may not be as apparent to human operators and can be used to diagnose types of disease and predict prognosis. One of the most significant applications of this breakthrough has been the initiation, continuation, stopping and switching of therapies. Not only can the machine IL deduce whether the tumour is showing resolution or progression with the instituted therapy, but it also differentiates between true tumour progression (TTP) versus pseudo-progression (PsP) and treatment-related effects (TREs) such as radiation necrosis (RN).³ These deductions can help reduce management errors based on humane radiological image interpretations ranging from withholding effective treatment to induction and continuation of ineffective treatment, with overall survival benefits. Hence, AI-based image interpretation can potentially improve treatment strategies and decision-making in neuro-oncology research and practice. Medical professionals have not widely adopted IL due to a lack of understanding of machine learning mechanics and real-world applications. This has limited the knowledge of AI and its applications among healthcare workers and hindered the evaluation of its feasibility and reliability in everyday medical use.

Review of Evidence

This review discusses possible applications of image-based learning and feature extraction in neuro-oncology, their implementation in diagnostic and therapeutic

oncology, and prognosis prediction. We also discuss using these IL techniques to devise precise management plans in clinical practices for prognostication.

Brain Tumour Diagnosis Using Machine Learning

Soomro et al. published that the incidence of brain tumours has increased from 2004 to 2020.⁴ Brain tumours, specifically malignant brain tumours, carry a poor prognosis. As per a United States registry report by Ostrom et al., malignant CNS tumours had a mortality rate of 4.42% between 2012 and 2016. The 5-year survival rate following a nonmalignant brain tumour was observed to be 91.5% while following malignant brain tumours, it was reported to be 35.8%.⁵ However, low-grade gliomas can turn malignant if not managed promptly. Hence, early and accurate diagnosis is important. This can be done using deep learning (DL) or machine learning (ML).

ML works by learning from structured algorithms and predicting output. Meanwhile, DL, a branch of ML, involves multi-layered algorithms that learn and adapt with parallel input, processing real-time information to reach conclusions more accurately. IL begins with pre-processing the image to filter the most appropriate data set and processing and analysis using ML and DL techniques. ML techniques include algorithms such as support vector machines (SVM) classifier, K-nearest neighbour, Naive Bayes classifier and random forest. These can be used to make input data-based decisions and prognostications and have been implemented in brain tumour classifications. DL techniques include advanced algorithms such as ANN, CNN, long-short-term memory (LSTM) and generative adversarial networks (GAN). DL techniques can perform more accurate image analysis and segmentation and are more commonly used in diagnosing and classifying tumours.^{2, 4, 6}

Radiomics has been used to predict tumour grades, and now, in the form of radio-genomics, DL allows correlation between genetic markers and their imaging phenotypes. In neuro-oncology, this is being used to predict prognostic molecular markers such as isocitrate dehydrogenase (IDH) mutation, methylguanine-DNA methyltransferase methylation, and 1p/19q co-deletion with accuracies of 83-94%. LSTM networks also gather time-series data, further improving diagnostic accuracy.⁷ The IDH and 1q/19q co-deletion have been predicted as AUC using ML and DL methods such as SVM and CNN, with accuracies of over 80%.⁸ This is of great importance in limiting the morbidity attributed to invasive procedures such as histopathological biopsy and also is more appropriate in patients for whom biopsy is not feasible.

Image Learning in Differentiating True Versus Pseudo Tumour Progression Versus Response to Treatment

Radiologically, pseudo-progression (PsP) is defined as the increase in contrast uptake, usually within 3 months following radiotherapy, which is not associated with actual tumour growth and resolves spontaneously. This is in contrast with true tumour progression (TTP), which involves an increase in tumour size and mostly requires switching chemotherapeutic agents or considering repeat surgical resection. TTP can also be confused with treatment-related effects (TREs), such as radiation necrosis (RN), which can appear similar on single radiological imaging but occurs around 3 months after radiotherapy. Imaging may be equivocal in such cases; therefore, various criteria such as the MacDonald criteria, Response Evaluation Criteria in solid tumours (RECIST), WHO criteria, and Response assessment in neuro-oncology (RANO) criteria and modified RANO are used to differentiate between TTP and PsP.⁹⁻¹³ Inter-observer variability further compounds this issue.¹⁴ A surgical biopsy would be the only method of determining between the two pathologies: PsP shows gliosis on biopsy, while RN shows gliosis, necrosis, oedema, endothelial thickening and thrombosis. However, this is impractical considering procedural morbidity.

AI-based image interpretations are being explored to lead the world toward "virtual biopsy" by extracting features that are not visible to the human eye and by eliminating interpersonal variability.^{3, 14} Radiomics, including CNN and SVM techniques, have been used to analyze MRI and PET scan images to differentiate TTP from PsP with diagnostic accuracies ranging from 75-92%, with MRI scans being more accurate than PET scans and further improving with clinical correlation.⁸ However, the diagnostic accuracy percentage still needs to be improved to a more consistent value to make it a feasible option for regular medical use. TREs and brain metastases have also been differentiated using MRI, dynamic amino acid, and static FET PET scans, with diagnostic accuracy increasing up to 89% with both modalities combined.⁸

Prediction of Survival and Prognosis

Radiomics is also being used to predict the survival and prognosis of various brain tumours. This has been based on IL models that can predict overall survival and progression-free survival.⁸ Prognosis can also be determined by predicting the type of brain tumour using radio-genomics.

Conclusion

Artificial intelligence is being applied in all specialties of medicine, including neuro-oncology and has introduced

oncology to the possibility of better diagnostic and management options. Image analysis, an application of AI, is now being used for early detection, classification, prognostication and treatment decisions of brain tumours, as well as noninvasive means of predicting molecular markers and differentiating tumour progression from treatment effects. However, being relatively new, it has not shown widespread application and uptake and has not reached a consistent diagnostic accuracy. Further, the complicated techniques currently pose a challenge to healthcare workers in terms of implementation and understanding. Hence, there still remains a need for further research and validation of image learning and the feasibility of its application in daily medical use.

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