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Review Article

A review on recent advancements in artificial intelligence for the detection, monitoring, and treatment of brain cancers

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Abstract

Brain tumors, such as gliomas and glioblastomas, provide substantial diagnostic and therapeutic hurdles due to their heterogeneity, aggressive activity, and treatment resistance. Recent advancements in artificial intelligence (AI), notably machine learning (ML) and deep learning (DL), have transformed how brain tumors are diagnosed, tracked, and treated. AI applications in radiomics, histopathology, genomics, and multimodal data integration provide earlier diagnosis, improved prognosis, and more tailored treatment options. This study gives a complete overview of cutting-edge AI approaches utilized in neuro-oncology, emphasizing their integration into clinical workflows, advantages, and limits. Ethical concerns and the potential for AI-driven brain cancer treatment are also highlighted.

Keywords: Glioblastoma, Deep Learning, Radiomics, Neuro-oncology, Histopathology, Personalized Medicine, Liquid Biopsy.

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1. Introduction

AI has revolutionized brain tumor management by combining imaging, histopathology, and genetic technologies to improve detection, classification, outcome prediction, and treatment planning. When measured across all aspects of malignant brain tumor management--diagnosis, prognosis, and therapy - AI models surpass human evaluations in terms of accuracy and specificity. Their capacity to detect molecular features from imaging may eliminate the need for invasive diagnostics and shorten the time to molecular diagnosis. The study examines AI approaches ranging from classical machine learning to deep learning, emphasizing contemporary applications and problems. Multimodal data integration, generative AI, massive medical language models, accurate tumor identification and characterization, and tackling racial and gender inequities are all promising future research avenues. Adaptive tailored therapy options are also highlighted to improve clinical results.

2. Discussion

Brain tumors, particularly high-grade gliomas and glioblastoma multiforme (GBM), remain among the most fatal cancers, with few treatment choices.[1] Despite substantial study, the prognosis for GBM patients is dismal, with a median survival of only 15 months.[2] Detecting and segmenting brain tumors is the most complicated and critical operation in many medical imaging applications since it frequently demands a large amount of data and information. Tumors exist in many forms and sizes. Automatic or semiautomatic detection/segmentation, aided by AI, is becoming essential in medical diagnosis. Before undergoing therapies such as chemotherapy, radiation, or brain surgery, medical personnel must authenticate the borders and regions of the brain cancer, as well as determine where it lays and the specific affected areas. The use of AI in neuro-oncology provides a disruptive approach to improving diagnostic accuracy, tracking disease progression, and personalizing therapy.[3]

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2.1. An overview of brain cancers and clinical challenges

Brain tumors result from uncontrolled and rapid cell growth. Early cancer identification is critical to saving many lives. Brain tumors are classified into numerous groups based on their kind, location of origin, rate of development, and stage of progression; therefore, tumor classification is critical for targeted therapy. Brain tumor segmentation seeks to properly identify the regions of brain tumors. A professional with a solid grasp of brain diseases is required to manually identify the correct sort of brain tumor. Additionally, processing many photos takes time and is tiring. As a result, automated segmentation and classification approaches are necessary to accelerate and improve brain tumor diagnosis. Brain scans, such as computed tomography (CT) and magnetic resonance imaging (MRI), can detect tumors swiftly and safely. Machine learning (ML) and artificial intelligence (AI) have showed promise in building algorithms for autonomous categorization and segmentation using a variety of imaging modalities. To improve diagnosis and treatment of individuals with brain tumors, the appropriate segmentation approach must be applied.

A brain tumor is an uncontrolled and abnormal growth of brain cells. Any unexpected development may have an impact on human functioning because the human skull is a rigid and volume-restricted structure, depending on the area of the brain involved. Furthermore, it may spread to other organs, jeopardizing human functions.[4] Early cancer detection enables effective treatment planning, which is critical in the healthcare sector.[5] Cancer is difficult to treat, and the chances of survival decrease significantly if it spreads to nearby cells. Undoubtedly, many lives could be saved if cancer was detected at an early stage using quick and inexpensive diagnostic methods. Both invasive and noninvasive methods can be used to diagnose brain cancer. A biopsy involves making an incision to extract a sample of the lesion for analysis. It is regarded as the gold standard for cancer diagnosis, in which pathologists examine various cell characteristics of the tumor specimen under a microscope to confirm the malignancy.

Noninvasive techniques include physical examinations of the body and imaging modalities used to image the brain. [6] In comparison to brain biopsy, other imaging modalities, such as CT scans and MRI pictures, are more quick and secure. Radiologists employ these imaging methods to diagnose brain disorders, evaluate the progression of illnesses, and plan procedures.[7] However, brain scans or image interpretation to identify disorders are subject to inter-reader variability and accuracy, which is determined by the medical practitioner's expertise.[6] To decrease diagnostic mistakes, the kind of brain illness must be identified precisely. Using computer-aided diagnostic (CAD) technology can help enhance accuracy. The primary idea behind CAD is to provide a computer result as an extra reference to assist radiologists in interpreting pictures and minimize image reading time. This improves the accuracy and consistency of radiological diagnoses.[8]

The World Health Organization (WHO) classified brain tumors into 120 types. This classification is based on the cell's origin and behavior, which range from less aggressive to more aggressive. Even specific tumor types are graded, with I being the least malignant (e.g., meningiomas, pituitary tumors) and IV being the most malignant. Despite variances in grading systems based on the kind of tumor, this indicates the rate of growth.[9] Glioma is the most common kind of brain tumor in adults, and it can be categorized as HGG or LGG based on histological and molecular criteria. High-grade gliomas are recognized for their infiltrative development, which makes total surgical excision very difficult.[10] The WHO further classified LGG as I-II grade tumors and HGG as III-IV grade. To prevent diagnostic mistakes, accurately identifying the precise kind of brain illness is critical for therapy planning. A synopsis of the many forms of brain tumors proposed by Kaifi[11] is shown below (**Figure 1**).

Furthermore, traditional imaging makes it difficult to distinguish between tumor recurrence and treatment-related alterations (for example, radiation necrosis). These difficulties demand new tools, such as artificial intelligence, for improved discrimination and result prediction.[12]

2.2. AI for early detection and diagnosis

1. Radiomics and Imaging Analytics: Extracting quantitative information from medical imaging data. Machine learning techniques use these data to categorize cancers and forecast genetic alterations such as IDH1 or MGMT methylation.[13,14] Models such as convolutional neural networks (CNNs) and autoencoders have been used to detect tumor margins, grade tumors, and assess perfusion.[15]
2. AI-enabled digital pathology can automatically classify tumor subtypes from whole-slide photos.[16] Deep neural networks can distinguish oligodendrogliomas, astrocytomas, and GBMs with above 90% accuracy.[17]
3. Integrating genomes and transcriptomics with AI models to understand tumor biology. Predictive models may identify molecular subtypes based on gene expression patterns, which helps with targeted therapy decisions.[18,19]

Types of Tumors Based on	Type	Comment
Nature	Benign	Less aggressive and grows slowly
	Malignant	Life-threatening and rapidly expanding
Origin	Primary tumor	Originates in the brain directly
	Secondary tumor	This tumor develops in another area of the body like lung and breast before migrating to the brain
Grading	Grade I	Basically, regular in shape, and they develop slowly
	Grade II	Appear strange to the view and grow more slowly
	Grade III	These tumors grow more quickly than grade II cancers
	Grade IV	Reproduced with greater rate
Progression stage	Stage 0	Malignant but do not invade neighboring cells
	Stage 1	Malignant and quickly spreading
	Stage 2	
	Stage 3	
	Stage 4	The malignancy invades every part of the body

Figure 1: Types of brain tumors.[11]

2.3. AI for monitoring and prognosis of brain cancer

1. AI techniques enable long-term monitoring of tumor growth and therapy response using time-series imaging analysis. Deep learning methods like as Recurrent Neural Networks (RNNs) use tumor volume changes over time to discriminate between pseudo-progression and actual recurrence.[20]
2. AI can analyze circulating tumor DNA (ctDNA), exosomes, and microRNAs for real-time monitoring via liquid biopsies. Machine learning models increase sensitivity and specificity in diagnosing minimum residual illness.[21]
3. AI-based survival prediction models use radiological, histological, and clinical data. Models such as DeepSurv and Cox-nnet have showed promise in calculating customized survival curves.[22,23]

2.4. AI applications in brain cancer therapy

1. AI-based intraoperative techniques like augmented reality (AR) and real-time segmentation algorithms improve surgical accuracy and minimize tissue damage.[24] CNNs are used to guide surgeons during resections using fluorescence or intraoperative MRI.
2. AI algorithms support autonomous segmentation and dosage optimization in radiation treatment. Adaptive radiation planning systems change treatment settings based on the tumor response observed by imaging.[25]
3. AI enables high-throughput drug discovery, repurposing, and personalized treatment for brain cancer. Deep learning techniques, such as Graph Neural Networks (GNNs), have sped the discovery of drugs that penetrate the blood-brain barrier.[26]

2.5. AI technologies and model architectures for neuro-oncology

Different model architectures are used for specialized tasks: CNNs for image classification, RNNs for time-series prediction, and transformers for integrative data processing. Federated learning is being developed to enable model training over decentralized datasets while protecting patient privacy.[19,27]

2.6. Ethical, regulatory, and data privacy challenges

Artificial Intelligence (AI) is revolutionizing the landscape of neuro-oncology by enhancing diagnostic accuracy, predicting treatment responses, and assisting in personalized care. While these technological advancements offer hope for improved brain tumor outcomes, they simultaneously raise profound ethical concerns. As AI becomes an integral tool in the treatment and management of brain tumors, careful ethical scrutiny is imperative to ensure that it serves patients' best interests without compromising privacy, autonomy, or equity. AI models must be explainable and generalizable across multiple patient groups. Data privacy, model bias, and lack of interpretability are all important issues to overcome. Regulatory authorities such as the FDA are developing new avenues for AI-powered clinical tools.[28] Here are some points to be taken care of while implementing the artificial intelligence models for treatment and management of brain tumor.

2.6.1. Patient autonomy and informed consent

AI-driven tools often operate through complex algorithms that are difficult for patients—and even clinicians—to understand. This lack of transparency complicates the process of obtaining informed consent. Patients must be fully aware of how AI systems impact their diagnosis and treatment, including the limitations and uncertainties involved. Ensuring genuine informed consent requires clinicians to explain AI outputs in accessible language, thereby empowering patients to make autonomous decisions about their care.

2.6.2. Data privacy and confidentiality

AI systems rely heavily on vast amounts of patient data, including MRI scans, genomic profiles, and electronic health records. The collection, storage, and analysis of such sensitive data present significant risks to patient privacy. Ensuring data security through robust encryption, de-identification protocols, and transparent data governance is crucial. Breaches in confidentiality not only violate ethical norms but can also erode trust in healthcare systems.

2.6.3. Algorithmic bias and health equity

One of the major concerns in AI-based brain tumor management is algorithmic bias. AI models trained on non-representative datasets may yield inaccurate results for underrepresented populations. This can lead to disparities in diagnosis or treatment recommendations, particularly among racial minorities, children, or individuals from low-resource settings. Ethical deployment of AI necessitates inclusive training datasets and continuous validation to minimize such biases.

2.6.4. Clinical responsibility and accountability

The integration of AI into clinical workflows raises questions about responsibility when outcomes are adverse. If an AI system recommends an incorrect treatment pathway, who is liable—the software developer, the clinician, or the institution? Ethical integration demands clear guidelines delineating accountability. Clinicians must maintain ultimate responsibility for patient care and use AI as a support tool rather than a decision-maker.

2.6.5. Psychological impact on patients

AI-generated prognostic information, such as survival prediction models, can have a psychological impact on patients and their families. While some may appreciate the transparency, others may find such data distressing, especially if it suggests poor outcomes. Ethically, clinicians must be trained to deliver AI-derived information sensitively and consider the patient’s emotional readiness to receive such data.

2.6.6. Regulatory and oversight challenges

There is a lack of standardized regulatory frameworks guiding the ethical use of AI in neuro-oncology. Without clear oversight, AI applications may be implemented prematurely or without proper validation. Regulatory bodies must enforce rigorous clinical testing, ethical review, and continuous monitoring of AI tools to ensure they meet safety and ethical standards.

2.7. The road ahead

The healthcare business is about to undergo substantial changes because of advances in big data analytics, artificial intelligence, and personalized therapies. These advancements offer immense promise for optimizing healthcare delivery, improving patient care, and health outcomes. However, to ensure responsible and fair deployment, their introduction into healthcare systems raises serious ethical concerns that must be properly addressed. This section examines the future of healthcare, emphasizing the importance of collaboration among many stakeholders, the impact of evolving technology, and ethical problems. Amalgamated Learning and Secure Data Sharing: Training models without data transfer will enable privacy-compliant collaboration across institutions.[26]

1. Explainable AI (XAI): Enhancing model transparency to gain clinical trust.
2. Multimodal AI Platforms: Integrating imaging, omics, and clinical data.
3. Real-time AI Systems: Embedded AI in surgical and monitoring tools.
4. Global Open Datasets: Efforts like TCGA and TCIA will facilitate robust model development.
5. Clinical Trials: Trials such as NCT04508934 are evaluating AI’s clinical utility.

AI-driven breakthroughs are on track to improve diagnosis and treatment, with algorithms already improving medical imaging, predicting disease progression, and customizing care. AI has exhibited improved early detection skills, notably in cancer, and is likely to increase diagnostic precision and personalized therapy as it advances. Big data analytics may also help advance healthcare by providing insights into illness prevention, treatment efficacy, and population health patterns. However, using vast amounts of patient data creates privacy and security risks. Strong data protection mechanisms and regulatory frameworks stressing patient consent are required to ensure that individuals retain ownership over their data. As AI, big data, and customized medicine become more prevalent, healthcare personnel must be taught in both technical capabilities and ethical considerations. Education should concentrate on the best practices for incorporating this technology into care while adhering to ethical norms. Healthcare institutions may use technology responsibly to enhance patient outcomes by cultivating an ethical culture [29].

3. Conclusion

AI is no longer a secondary adjunct in oncology; rather, it is becoming an important, inherent component in the advancement of cancer therapies. AI is revolutionizing cancer care at every stage: detection, diagnosis, therapy, follow-up, and research. It is revolutionizing brain cancer care by improving diagnosis accuracy, tracking therapy success, and tailoring therapeutic tactics. While there are problems with data quality, ethics, and regulatory processes, the incorporation of AI is already boosting therapeutic results. Continued multidisciplinary collaboration will hasten AI's influence in neuro-oncology, making cancer treatment more efficient, focused, and egalitarian.

The use of artificial intelligence into brain cancer diagnosis, therapy planning, and prognosis represents a paradigm change in disease management. AI-driven technologies have the potential to reset the standards in neuro-oncology by enhancing diagnostic accuracy, treatment planning, medication development, and outcome prediction. The integration of AI into the treatment and management of brain tumors presents enormous potential, yet it brings with it a host of ethical dilemmas. Addressing these concerns requires a multidisciplinary approach involving ethicists, clinicians, data scientists, and patient advocates. Upholding ethical principles—such as respect for autonomy, justice, beneficence, and non-maleficence—is vital to ensure that AI enhances care without undermining human dignity or social trust.

By resolving many of these issues and encouraging openness, inclusion, and creativity, AI can realize its great promise in the battle against brain cancer. However, the objective remains the same: to improve patient outcomes, extend survival, and improve the quality of life for patients with brain cancer. The future of enhanced brain cancer care is at the crossroads of fresh and transformational technology and improved clinical practice, providing optimism in the face of one of contemporary medicine's most difficult challenges.

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None.

5. Conflict of Interest

None.

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