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Artificial Intelligence and Radiomics in Glioblastoma Surgery: Current Applications, Clinical Challenges, and Future Directions - A Narrative Review

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Abstract: Glioblastoma (GBM) remains the most aggressive primary malignant brain tumor in adults despite advances in neurosurgical techniques, radiotherapy, chemotherapy, and molecular diagnostics. The marked heterogeneity of GBM, coupled with its infiltrative growth pattern and poor prognosis, continues to pose substantial challenges in diagnosis, surgical planning, treatment selection, and postoperative surveillance. In recent years, artificial intelligence (AI) and radiomics have emerged as promising technologies capable of extracting quantitative information from medical imaging that extends beyond conventional visual interpretation. Machine learning and deep learning algorithms have demonstrated considerable potential in tumor segmentation, molecular characterization, surgical planning, intraoperative guidance, prognostic modeling, and prediction of therapeutic response.

This narrative review summarizes current evidence regarding the integration of AI and radiomics into the management of glioblastoma from a neurosurgical perspective. The review discusses recent developments in preoperative imaging analysis, automated tumor segmentation, prediction of molecular biomarkers, intraoperative applications, survival prediction, and postoperative monitoring. Current limitations including data heterogeneity, limited external validation, algorithm interpretability, ethical concerns, and regulatory challenges are also examined. Finally, future directions involving multimodal data integration, explainable AI, federated learning, and prospective clinical validation are highlighted.

Although AI has not yet replaced clinical judgment, growing evidence suggests that AI-assisted decision-making may substantially improve diagnostic accuracy, surgical precision, personalized treatment planning, and clinical outcomes in patients with glioblastoma. Continued multidisciplinary collaboration between neurosurgeons, radiologists, computer scientists, and data engineers will be essential for translating these technologies into routine clinical practice.

Keywords: *Glioblastoma; Artificial Intelligence; Radiomics; Machine Learning; Deep Learning; Neurosurgery; Magnetic Resonance Imaging; Precision Medicine.*

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I. INTRODUCTION

Glioblastoma (GBM), classified as a World Health Organization (WHO) grade 4 diffuse glioma, represents the most common and aggressive primary malignant brain tumor in adults. Despite advances in microsurgical techniques, neuronavigation, molecular diagnostics, radiotherapy, and systemic therapies, the prognosis remains poor, with median overall survival typically ranging from 14 to 18 months following standard treatment [2]. The current standard of care

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consists of maximal safe surgical resection followed by concurrent chemoradiotherapy with temozolomide and maintenance chemotherapy[3]. However, extensive intratumoral heterogeneity, diffuse infiltration into surrounding brain tissue, and inevitable recurrence continue to limit therapeutic success [4].

Magnetic resonance imaging (MRI) plays a central role in the diagnosis and management of glioblastoma [5]. Conventional MRI provides valuable anatomical information regarding tumor size, location, edema, and contrast enhancement, yet visual interpretation alone often fails to accurately characterize tumor biology, differentiate treatment-related changes from recurrence, or predict molecular alterations that influence prognosis and therapeutic response. These limitations have stimulated increasing interest in computational approaches capable of extracting more detailed imaging information [6].

Artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), has rapidly transformed medical image analysis over the past decade [7]. Radiomics, an AI-driven approach that converts standard medical images into large sets of quantitative features, enables comprehensive assessment of tumor morphology, texture, intensity, and spatial heterogeneity [8]. When combined with clinical, histopathological, and molecular data, these imaging biomarkers have demonstrated promising applications in precision neuro-oncology [9,10].

Recent advances suggest that AI-assisted tools may support multiple stages of glioblastoma management, including automated tumor segmentation, prediction of molecular biomarkers such as isocitrate dehydrogenase (IDH) mutation and O6-methylguanine-DNA methyltransferase (MGMT) promoter methylation status, surgical planning, intraoperative decision-making, postoperative surveillance, and individualized survival prediction. Nevertheless, widespread clinical implementation remains limited by challenges related to dataset quality, algorithm generalizability, interpretability, regulatory approval, and ethical considerations [8-11].

This narrative review aims to summarize the current landscape of artificial intelligence and radiomics in glioblastoma surgery by discussing their applications, clinical utility, existing limitations, and future prospects. Through synthesizing recent evidence, this review seeks to provide neurosurgeons, clinicians, and researchers with an updated understanding of how AI may contribute to more personalized and effective management of patients with glioblastoma.

II. METHODOLOGY

This narrative review was conducted to provide a comprehensive overview of the current applications of artificial intelligence and radiomics in glioblastoma surgery. Relevant literature published primarily in the last ten years was identified through electronic searches of PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar. Search terms included combinations of *glioblastoma*, *artificial intelligence*, *machine learning*, *deep learning*, *radiomics*, *MRI*, *neurosurgery*, *tumor segmentation*, *survival prediction*, and *precision medicine*. Additional articles were identified by manually reviewing the reference lists of selected publications.

Peer-reviewed original research articles, systematic reviews, meta-analyses, and consensus statements published in English were considered for inclusion. Studies focusing on AI-based imaging analysis, radiomics, neurosurgical applications, molecular prediction, and clinical outcome assessment in glioblastoma were prioritized. Editorials, conference abstracts without full manuscripts, duplicate publications, and studies unrelated to neurosurgical management were excluded. Given the narrative design of this review, no formal risk-of-bias assessment or quantitative meta-analysis was performed. The selected literature was synthesized thematically to provide an integrated overview of current evidence, clinical applications, limitations, and future directions.

III. BODY OF THE REVIEW

➢ *Artificial Intelligence in Modern Neurosurgery*

Artificial intelligence has emerged as one of the most transformative technologies in modern neurosurgery, enabling the analysis of large and complex clinical datasets beyond the capabilities of conventional statistical methods [12-15]. AI encompasses machine learning algorithms that learn from structured data and deep learning models, particularly convolutional neural networks, that automatically recognize complex patterns within medical images [13-15]. These approaches have shown considerable promise in improving diagnostic accuracy, surgical planning, and individualized treatment strategies [12,13,44,45].

In glioblastoma management, AI assists clinicians by integrating multimodal information obtained from conventional MRI, diffusion-weighted imaging, perfusion imaging, spectroscopy, genomic profiling, and electronic health records [12,13,44]. Unlike traditional image interpretation, AI-based systems can identify subtle imaging features associated with tumor biology, aggressiveness, and treatment response [13,17,44]. Such computational approaches support more objective decision-making and may reduce interobserver variability in radiological assessments [12,44,45].

Beyond diagnosis, AI has demonstrated utility in automating labor-intensive tasks such as tumor segmentation, volumetric analysis, and longitudinal disease monitoring [21-25]. These capabilities are particularly valuable in high-volume clinical settings where rapid yet accurate interpretation of imaging studies is essential [21,23,44]. Moreover, AI-driven predictive models are increasingly being developed to estimate patient survival, identify molecular alterations, and support personalized therapeutic planning, highlighting their growing role in precision neuro-oncology [26-30,36-39].

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- *Radiomics: Transforming MRI into Quantitative Biomarkers*

Radiomics refers to the extraction of a large number of quantitative imaging features from standard radiological examinations. These features describe tumor characteristics such as shape, texture, intensity, spatial relationships, and heterogeneity, many of which are imperceptible to the human eye [16-20]. The radiomics workflow typically includes image acquisition, tumor segmentation, feature extraction, feature selection, and predictive model development [16-18].

Glioblastomas exhibit remarkable spatial and biological heterogeneity, making them well suited for radiomic analysis [16,17]. Studies have demonstrated that radiomic signatures derived from preoperative MRI can distinguish tumor grades, predict molecular subtypes, estimate treatment response, and provide prognostic information [20,26-30,36,37]. When combined with machine learning algorithms, radiomic models have achieved encouraging performance in identifying clinically relevant biomarkers such as IDH mutation status and MGMT promoter methylation, potentially reducing the need for invasive diagnostic procedures [27-30].

Despite these advances, challenges remain in standardizing image acquisition protocols, ensuring reproducibility across institutions, and validating predictive models in diverse patient populations [17-19,40]. Addressing these limitations will be essential before radiomics can be routinely integrated into neurosurgical practice [17,19,40,44].

- *Artificial Intelligence for Automated Tumor Segmentation*

Accurate tumor segmentation is a fundamental component of glioblastoma management, influencing surgical planning, radiation treatment, disease monitoring, and assessment of therapeutic response [21,22]. Traditionally, segmentation relies on manual delineation of tumor boundaries by neuroradiologists or neurosurgeons, a process that is labor-intensive, time-consuming, and subject to considerable interobserver variability [21,23]. The infiltrative nature of glioblastoma further complicates the identification of precise tumor margins, particularly in regions where infiltrating tumor cells extend beyond contrast-enhancing areas [21,22].

Artificial intelligence, particularly deep learning techniques based on convolutional neural networks (CNNs), has transformed automated brain tumor segmentation by enabling rapid and reproducible analysis of multimodal magnetic resonance imaging (MRI) [23-25]. These algorithms integrate information from T1-weighted, contrast-enhanced T1-weighted, T2-weighted, and fluid-attenuated inversion recovery (FLAIR) sequences to distinguish enhancing tumor, necrotic core, non-enhancing tumor, and peritumoral edema [21-25]. Publicly available datasets such as the Brain Tumor Segmentation (BraTS) challenge have played a pivotal role in the development and validation of these models, providing standardized benchmarks for algorithm performance [21,22].

Several studies have demonstrated that deep learning models achieve segmentation accuracy comparable to expert neuroradiologists while substantially reducing processing time [23-25]. Automated segmentation facilitates accurate volumetric assessment of tumor burden, assists in preoperative planning, and enables objective monitoring of disease progression and treatment response [21,23,24]. Furthermore, standardized segmentation provides the foundation for radiomic feature extraction, thereby supporting downstream applications such as molecular prediction and prognostic modeling [17,20,26-30].

Despite these advances, important challenges remain. Variability in MRI acquisition protocols, differences in scanner hardware, image artifacts, and heterogeneous patient populations may reduce algorithm performance when applied outside the institutions in which they were developed [17-19,40]. Continued efforts toward multicenter validation, standardized imaging protocols, and externally validated algorithms will be essential before fully automated segmentation can be routinely integrated into neurosurgical practice [17,19,40,44].

- *Radiogenomics: Predicting Tumor Biology Through Imaging*

The molecular characterization of glioblastoma has become increasingly important for diagnosis, prognosis, and treatment selection [26–30]. Molecular alterations such as isocitrate dehydrogenase (IDH) mutation, O6-methylguanine-DNA methyltransferase (MGMT) promoter methylation, epidermal growth factor receptor (EGFR) amplification, and telomerase reverse transcriptase (TERT) promoter mutations significantly influence tumor behavior and therapeutic response [27-30]. However, conventional determination of these biomarkers requires surgical biopsy or tumor resection, limiting their availability during preoperative decision-making [26,27].

Radiogenomics represents an emerging discipline that integrates radiomic imaging features with genomic and molecular data to non-invasively predict tumor biology [17,20,26]. Machine learning algorithms analyze quantitative imaging characteristics that may reflect underlying cellular architecture, angiogenesis, metabolic activity, and genetic alterations [17,20,27]. By identifying imaging signatures associated with specific molecular profiles, radiogenomic models have the potential to support precision medicine without requiring additional invasive procedures [26-30].

Among the most extensively investigated applications is the prediction of IDH mutation status using conventional MRI combined with radiomic feature extraction [27,30]. Similar approaches have demonstrated encouraging performance in predicting MGMT promoter methylation, a clinically relevant biomarker associated with improved response to temozolomide chemotherapy [28,29]. Additional studies have explored imaging-based prediction of EGFR amplification, TERT promoter mutations, and other genomic alterations that influence tumor aggressiveness and survival [26,29,30].

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Although radiogenomics remains primarily a research tool, continued improvements in machine learning methodology, standardized imaging protocols, and multicenter validation may facilitate its integration into routine clinical practice [17,19,40,44]. Future models incorporating imaging, genomic, clinical, and histopathological information may provide increasingly accurate and personalized predictions for patients with glioblastoma [17,26,30,45].

- *Artificial Intelligence in Surgical Planning and Intraoperative Decision-Making*

Maximal safe resection remains one of the most important determinants of survival in patients with glioblastoma [31,32]. Achieving this objective requires careful balancing of extensive tumor removal with preservation of eloquent cortical and subcortical structures responsible for language, motor function, sensory processing, and cognition [31-33]. Artificial intelligence has emerged as a valuable adjunct in preoperative planning and intraoperative decision-making by integrating multimodal imaging and patient-specific anatomical information [32,33].

Machine learning algorithms can analyze structural MRI, functional MRI, diffusion tensor imaging (DTI), and tractography to identify critical white matter pathways and predict regions at increased risk of postoperative neurological deficits [31,33]. These computational models assist neurosurgeons in selecting optimal surgical approaches while minimizing injury to essential functional networks [31-33].

Artificial intelligence also enhances neuronavigation systems by improving image registration, compensating for intraoperative brain shift, and facilitating real-time interpretation of intraoperative ultrasound and MRI [33-35]. Deep learning algorithms capable of rapid image processing may improve the accuracy of tumor localization throughout the procedure, particularly when anatomical landmarks change during resection [32-35]. In addition, AI-assisted analysis of intraoperative imaging may help distinguish residual tumor from postoperative changes, supporting more complete yet safer resections [33-35].

Beyond image guidance, emerging applications include robotic-assisted neurosurgery, intelligent surgical workflow recognition, and computer vision systems capable of identifying surgical instruments and procedural stages [32,33]. Although these technologies remain under active investigation, they illustrate the expanding role of AI in supporting rather than replacing neurosurgical expertise [32-35].

- *Artificial Intelligence for Prognostic Modeling and Personalized Treatment*

Predicting survival and treatment response remains a major challenge in glioblastoma due to the considerable biological heterogeneity of the disease [36-39]. Traditional prognostic assessment relies on clinical factors such as patient age, functional status, tumor location, extent of resection, and molecular biomarkers [36,37]. While these variables provide useful information, they often fail to capture the complex interactions that influence individual patient outcomes [36-38].

Artificial intelligence enables the integration of high-dimensional datasets derived from imaging, genomics, pathology, and clinical records to develop individualized prognostic models [36-39]. Machine learning algorithms can identify complex nonlinear relationships among these variables that are difficult to detect using conventional statistical approaches [36,39]. As a result, AI-based models have demonstrated improved performance in predicting overall survival, progression-free survival, treatment response, and risk of recurrence [36-39].

Radiomic features extracted from preoperative MRI have shown particular promise in prognostic modeling [20,26,29,36,37]. Quantitative measures of tumor heterogeneity, shape, texture, vascularity, and peritumoral edema have been associated with patient survival and therapeutic response [20,26,36,37]. When combined with molecular biomarkers such as IDH mutation status and MGMT promoter methylation, these imaging-derived signatures provide more comprehensive risk stratification than either modality alone [27-30,36,37].

Personalized prognostic models may also support individualized treatment planning by identifying patients most likely to benefit from aggressive surgical intervention, targeted therapies, or enrollment in clinical trials [36–39]. Nevertheless, prospective validation, external multicenter evaluation, and demonstration of clinical utility remain necessary before these models can be routinely implemented in patient care [40,42,44].

IV. LIMITATIONS AND CHALLENGES

Despite the considerable advances in artificial intelligence (AI) and radiomics for glioblastoma management, several scientific, technical, and clinical challenges continue to limit their widespread adoption in routine neurosurgical practice. While numerous studies have demonstrated promising diagnostic and prognostic performance, many AI-based models remain in the experimental stage, and their translation into real-world clinical settings has been slower than anticipated. Addressing these limitations is essential to ensure the safe, reliable, and equitable integration of AI into patient care [17,19,44].

- *Data Heterogeneity and Limited Generalizability*

One of the most significant challenges in AI development is the heterogeneity of medical imaging data. Variations in MRI acquisition protocols, scanner manufacturers, magnetic field strengths, image resolution, and preprocessing techniques can substantially influence radiomic feature extraction and algorithm performance [17-20]. Consequently, models trained using data from a single institution often demonstrate reduced accuracy when applied to external datasets [17,19]. Furthermore, differences in patient demographics, tumor characteristics, and treatment protocols across institutions may limit the generalizability of predictive models [19,44]. Establishing standardized imaging

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protocols, adopting harmonized image acquisition methods, and developing large multicenter datasets are therefore essential to improve the robustness, reproducibility, and clinical applicability of AI algorithms [17,18,20].

- *Small and Retrospective Datasets*

Most published AI studies in glioblastoma rely on retrospective datasets collected from individual institutions [19,40,44]. Although retrospective analyses provide valuable proof-of-concept evidence, they are inherently susceptible to selection bias, incomplete clinical information, and inconsistent follow-up [40,42]. In addition, deep learning models generally require large, diverse, and well-annotated datasets to achieve optimal performance [19,44]. The limited availability of high-quality, labeled neuroimaging data remains a major obstacle to developing clinically reliable algorithms [17,19,45]. Collaborative data-sharing initiatives, standardized data collection protocols, and prospective multicenter studies will be critical for generating representative datasets capable of supporting robust model development and validation [17,40,42].

- *Lack of External and Prospective Validation*

While many AI models report excellent performance in internal validation cohorts, relatively few have undergone rigorous external validation using independent patient populations [40,42,44]. Internal validation alone may overestimate model performance because algorithms can inadvertently learn institution-specific characteristics rather than clinically meaningful patterns [40,45]. Moreover, only a limited number of studies have prospectively evaluated the impact of AI-assisted decision-making on surgical planning, patient outcomes, or healthcare efficiency [44,45]. Future research should prioritize multicenter prospective clinical trials to establish the clinical utility, safety, generalizability, and cost-effectiveness of AI technologies before widespread implementation [17,40,42].

- *Interpretability and the "Black Box" Problem*

Many advanced machines learning and deep learning algorithms function as highly complex computational systems whose decision-making processes are not readily interpretable by clinicians [41,43]. This lack of transparency, commonly referred to as the "black box" problem, presents an important barrier to clinical adoption [41]. Neurosurgeons and radiologists may be reluctant to rely on algorithmic predictions when the underlying reasoning cannot be adequately explained [43,45]. The development of explainable artificial intelligence (XAI) methods that provide interpretable predictions and highlight clinically relevant imaging features may improve physician confidence, facilitate integration into clinical workflows, and enhance trust in AI-assisted decision-making [41,43,45].

- *Ethical, Legal, and Regulatory Considerations*

The incorporation of AI into neurosurgical practice raises several ethical and regulatory concerns [43,44,46]. Protecting patient privacy while enabling large-scale data sharing remains a significant challenge, particularly when imaging data are transferred across institutions or international borders [46,47]. In addition, algorithmic bias may occur when training datasets underrepresent specific demographic or clinical populations, potentially leading to unequal diagnostic performance and healthcare disparities [43,44,46]. Questions regarding accountability also remain unresolved, particularly in situations where AI-assisted recommendations influence clinical decisions that result in adverse outcomes [43,46]. Comprehensive regulatory frameworks, standardized reporting guidelines, and transparent governance strategies will be necessary to ensure patient safety, fairness, and public trust in AI-based technologies [42,46,47].

- *Integration into Clinical Workflow*

Successful implementation of AI requires seamless integration into existing neurosurgical workflows without increasing clinician workload or delaying patient care [43,44,47]. Current hospital information systems, Picture Archiving and Communication Systems (PACS), and electronic health records often lack standardized infrastructure for incorporating AI-based decision-support tools [45,47]. Additional challenges include the need for clinician training, software maintenance, cybersecurity, interoperability, and ongoing model updates as new clinical data become available [44,47,49]. For AI to achieve widespread acceptance, algorithms must demonstrate not only high diagnostic accuracy but also ease of use, interoperability, cost-effectiveness, and measurable improvements in clinical efficiency and patient outcomes [43,45,47].

- *Economic and Resource Constraints*

The implementation of AI technologies may require substantial financial investment in computational infrastructure, specialized software, secure data storage, and personnel with expertise in data science and machine learning [43,47,48]. These requirements may pose particular challenges for low- and middle-income countries and resource-limited healthcare systems, where access to advanced imaging technologies and computational resources may already be constrained [48,49]. Additional costs associated with software validation, cybersecurity, regulatory compliance, and continuous algorithm maintenance may further limit adoption in routine clinical practice [46,47]. Ensuring equitable access to AI-assisted healthcare will require cost-effective solutions, open-source platforms, international collaborative initiatives, and scalable implementation strategies that reduce barriers to adoption while maintaining high standards of safety and performance [43,47-49].

V. CONCLUSION

Although artificial intelligence and radiomics have demonstrated considerable promise in improving the diagnosis, surgical planning, molecular characterization, and prognostic assessment of glioblastoma, several challenges continue to hinder their routine clinical adoption. Addressing issues related to data standardization, external validation, model interpretability, ethical governance, workflow integration, and resource availability will be essential for translating AI from experimental research into reliable

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clinical practice. Continued multidisciplinary collaboration among neurosurgeons, neuroradiologists, computer scientists, engineers, and regulatory authorities will play a pivotal role in ensuring that AI technologies are implemented safely, transparently, and in ways that meaningfully improve patient care.

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