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Artificial Intelligence and Precision Medicine: Transforming the Landscape of Brain Tumors Treatment

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A B S T R A C T

Brain Tumors represent a significant and life-threatening neurological challenge, requiring innovative approaches for accurate diagnosis and effective treatment. Advances in artificial intelligence (AI) have revolutionized medical research by enabling computational models to mimic neural networks, facilitating the analysis of high-dimensional imaging data of brain Tumors. AI-driven imaging techniques provide deeper insights into Tumor characteristics, leading to improved diagnostic accuracy and personalized treatment strategies. The convergence of AI and precision medicine (PM) is transforming the landscape of healthcare, particularly in oncology. AI enhances cancer imaging interpretation through more precise Tumor genotyping, volumetric delineation, and prognostic modeling. Additionally, AI-assisted brain surgery has emerged as a promising approach, offering improved precision and safety in Tumor excision. This review explores various AI and PM-based techniques that are reshaping brain Tumor treatment, including genomic profiling, microRNA panels, quantitative imaging, and radiomics. While these technologies hold immense potential, their widespread clinical adoption faces challenges, such as data integration, algorithm validation, and ethical considerations. Addressing these barriers is essential to fully harness the capabilities of AI and precision medicine in enhancing patient outcomes and advancing neuro-oncology.

Keywords: Artificial intelligence; autonomous precision medicine; brain Tumors; artificial intelligence; imaging technology; gene targeting

1. Introduction

Brain Tumors are among the most challenging forms of cancer, often affecting critical brain regions and contributing to cancer-related mortality, accounting for approximately 2.3% of all cancer deaths (World Health Organization [WHO]) [1]. Among these, glioblastoma (GBM), a grade IV Tumor of the central nervous system (CNS), represents over 60% of adult brain Tumors [2]. The standard treatment for glioblastoma includes radiation therapy, which, while effective, may have significant drawbacks. One major concern is its potential to weaken the blood-brain barrier (BBB), increasing the risk of secondary brain metastases [3]. Reports have documented cases of radiation-induced secondary brain Tumors, highlighting the long-term risks associated with this approach [4]. The process of Tumor metastasis is biologically complex, requiring cancer cells to overcome multiple barriers before establishing metastatic lesions. Additionally, intraTumor heterogeneity—the presence of genetically distinct subpopulations of cancer cells within the same Tumor—poses a significant challenge in developing effective treatments [5]. Addressing these complexities requires innovative technological interventions, such as brain-inspired computing, which mimics neural networks and has the potential to transform cancer diagnosis and management [6]. Artificial intelligence (AI) has demonstrated remarkable capabilities in medical diagnostics, particularly in brain Tumor detection and classification. AI-powered algorithms analyze medical imaging data, enabling the identification of hidden Tumor characteristics that may be imperceptible to human experts. In one study, AI successfully identified 98% of brain Tumors with high precision, highlighting its potential as a diagnostic tool [7,8]. Machine learning (ML) techniques, when applied to medical imaging, can extract critical Tumor features, improving the accuracy of cancer diagnosis, prognosis, and treatment planning [9]. A notable study using deep learning on 1,991 healthy samples and 12 cancer types achieved an impressive accuracy of 94.7% in cancer identification, further solidifying AI's role in oncology [10]. Beyond diagnostics, AI is also transforming surgical precision and patient outcomes. According to the National Academy of Medicine, AI in healthcare offers advantages such as enhanced access to specialized care, reduced human error, and improved procedural efficiency [11]. Studies indicate that AI-assisted surgical interventions lead to fewer complications and shorter hospital stays, making it a promising avenue for neurosurgical applications [12]. The application of AI in healthcare and drug development is expanding rapidly. The global AI healthcare market is projected to reach $150 billion by 2026, driven by the digitization of healthcare data and AI's ability to derive actionable insights [13,14]. AI has already shown promise in early disease detection, precision diagnosis, treatment optimization, and personalized medicine strategies [15]. Moreover, AI is playing a transformative role in small-molecule drug discovery, particularly in target selection, hit identification, and lead optimization [16]. For instance, eToxPred, a machine-learning-based model, demonstrated a 72% accuracy in predicting the toxicity and synthesis feasibility of small organic molecules, illustrating AI's potential in accelerating drug development pipelines [17]. Precision medicine (PM) is an emerging paradigm in oncology, leveraging genomic, molecular, and environmental data to tailor treatments to individual patients. Since the late 1990s, PM has been instrumental in customizing cancer therapies based on genetic profiles [20,21]. The concept of

"precision" in medicine extends beyond oncology, influencing public health, personalized treatments, and evidence-based interventions [22-25]. By integrating multiple data types—genetic, environmental, and lifestyle factors—PM enables more accurate predictions of disease progression and treatment response [26-29]. One of the greatest challenges in cancer treatment is intraTumoral heterogeneity—the presence of diverse genetic and epigenetic profiles within a single Tumor [31,32]. This variability complicates targeted therapy, as different subpopulations of cancer cells may respond differently to treatments [33]. Furthermore, Tumor plasticity allows cancer cells to adapt and develop resistance to therapies over time, leading to treatment failures [32]. IntraTumoral heterogeneity arises from microenvironmental, genetic, and epigenetic factors, many of which remain poorly understood [34,35]. However, advancements in PM and AI offer a potential solution by enabling individualized treatment plans tailored to each patient's unique cancer profile [36]. AI models are proving invaluable in non-invasive glioma detection and classification. For example, a newly developed AI system has demonstrated the ability to distinguish urine samples from glioma patients and healthy individuals, providing a potential biomarker-based approach for early detection [37,38]. Additionally, proteomics-based biomarker discovery offers a promising avenue for fluid-based glioma diagnostics, aiding in treatment stratification and precision targeting [39-41]. However, precision medicine faces several challenges, particularly in the management of patient data, population diversity, and ethical concerns [42]. Ensuring the privacy, security, and equitable application of AI-driven PM remains a priority for researchers and policymakers alike.

1.1. Molecular and Genomic Profiling of Brain Tumors and the Role of Precision Medicine

The treatment of brain Tumors has evolved significantly with the advancement of molecular and genomic profiling, enabling more precise and targeted therapeutic approaches. Molecular profiling involves analyzing the genetic composition of a Tumor to identify gene mutations that contribute to Tumor development. By understanding these mutations, clinicians can tailor personalized treatment regimens using drugs that are most effective for a patient's unique genetic profile [43,44]. Despite its advantages, traditional molecular profiling often overlooks certain molecular features that may be clinically significant. These include drug-target group predictions, molecular fingerprint representation, Tumor profile-to-cell line matchmaking, and drug-target interactions [45-49]. Currently, tissue biopsies are the primary method for identifying Tumor sensitivity and resistance predictors, but these procedures can be invasive and pose risks to patients [50]. Recent studies have demonstrated that AI-powered diagnostic models can accurately predict whether a brain Tumor is benign or malignant with an accuracy of 95% [51,52]. This suggests that AI could potentially reduce the need for invasive biopsies and provide faster, non-invasive diagnostic solutions [53]. The integration of genomic profiling in clinical practice has paved the way for targeted cancer therapies, fundamentally reshaping treatment paradigms. By identifying genomic alterations within Tumor cells, oncologists can design treatments that specifically target these mutations, leading to more effective and personalized cancer therapies [55]. However, brain Tumors and metastases have traditionally demonstrated poor responses to immunotherapy [56]. Recent research, however, has suggested that precision medicine (PM)-driven immunotherapies can enhance treatment efficacy for patients with brain metastases [57]. The role of Tumor-derived genetic markers in understanding cancer progression is becoming increasingly recognized [58,59]. One study linked Tumor biology to circulating Tumor DNA (tDNA) levels, showing that genomic alterations detected in plasma tDNA assays could be used as biomarkers for real-time cancer monitoring [60]. Next-generation sequencing (NGS) and gene expression arrays have further expanded the potential of genomic profiling, allowing physicians to predict patient responses to specific therapies with greater accuracy [61-63]. Precision medicine has proven to be particularly effective in treating aggressive brain Tumors such as glioblastoma (GBM) [64]. One promising approach is photodynamic therapy (PDT), which targets Tumor cells selectively while minimizing damage to surrounding healthy tissue [65]. Several studies have highlighted the molecular classification of GBM, revealing new genomic subtypes that could help optimize treatment strategies [66]. A fully integrated precision medicine service incorporates multiple advanced methodologies, including microbiome analysis, clinical phenotyping, genomic imaging, and molecular diagnostics [67-69]. By leveraging AI and big data analytics, these strategies can refine personalized treatment plans and predict patient outcomes with improved accuracy. Cancer immunotherapy is another area of significant interest, particularly in immune checkpoint targeting to enhance T-cell responses against Tumors [70]. Neoantigen recognition, which involves identifying Tumor-specific antigens derived from somatic mutations, has shown great potential in improving immune responses in cancer patients [71]. In addition to optimizing treatment selection, precision medicine can also benefit patients with rare or treatment-resistant brain Tumors, offering tailored therapies that conventional treatments may not provide [72,73]. A study published in Nature reported that targeting IDH1 gene mutations in brain Tumors significantly improved survival rates, highlighting the potential of genomic-driven interventions [74]. Despite the remarkable progress in precision oncology, several challenges persist in its large-scale clinical application. Complexity of Tumor Heterogeneity – Brain Tumors exhibit significant intraTumoral heterogeneity, making it difficult to develop universal treatment strategies [88,89]. Clonal evolution within Tumors means that different parts of a Tumor may have distinct genetic profiles, complicating treatment decisions. Ethical and Logistical Challenges – Recruiting patients for PM-based clinical trials is challenging due to population heterogeneity and informed consent complexities. Patients and their families may struggle to understand the implications of participating in genomic-driven treatments [82]. Data Integration and Standardization – Precision medicine relies on large-scale genomic data, but a lack of standardized protocols for data collection and analysis makes cross-institutional collaboration difficult. Informatics-driven solutions are needed to streamline patient recruitment for clinical trials, integrating genomic data with eligibility criteria for more efficient study designs [84-86]. Biomarker Development and Sampling Bias – Identifying reliable biomarkers remains a significant challenge due to the variability in Tumor samples. Sampling bias in biopsies and tissue banks can affect the precision of molecular classifications, necessitating the need for multi-sample Tumor profiling to improve clinical accuracy [87-89]. Limitations of Targeted Therapy – While targeted drugs have shown promise, they cannot fundamentally alter Tumor formation mechanisms. Some Tumors do not respond to standard therapy, requiring the use of angiogenesis inhibitors or combination therapies for effective treatment [90,91]. Additionally, gene mutations within Tumors can evolve over time, reducing the efficacy of initial targeted treatments [81].

AI and deep learning algorithms are increasingly being utilized to improve precision medicine approaches in brain Tumor treatment. AI-powered predictive modelling can help:

- Identify optimal treatment regimens based on a patient's genomic profile.
- Improve drug-target selection by analyzing Tumor-specific biomarkers.
- Reduce false-positive rates in diagnostic screenings [79].

By integrating genomic profiling, AI-based drug discovery, and patient-specific treatment plans, precision medicine is poised to transform neuro-oncology, making brain Tumor treatment more effective, personalized, and adaptive. Although significant challenges remain, the rapid progress in AI-driven genomics and precision oncology is paving the way for breakthroughs in brain Tumor treatment, ensuring better patient outcomes and long-term survival.

1.2. MicroRNA (miRNA) Panels as Biomarkers in Brain Tumors

Brain Tumors, particularly gliomas and glioblastomas, are often characterized by distinct microRNA (miRNA) expression profiles. MiRNAs, a class of small non-coding RNAs, play a critical role in Tumor biology by regulating gene expression and influencing Tumor growth, invasion, and response to therapy [94,95]. Depending on their dysregulation in different cancer types, miRNAs can function as Tumor suppressors or oncogenes [96]. Given their stability in bodily fluids, miRNA panels are emerging as promising non-invasive biomarkers for the early detection, classification, and prognosis of brain Tumors [97]. A large-scale study conducted in China involving 2170 glioma patients and 1456 healthy controls reinforced previous findings that miRNAs can serve as effective diagnostic markers for glioma detection [98]. Another study examining miRNA expression levels in serum exosomes from cancer patients found that hsa-miR-576-3p is a strong biomarker for predicting brain metastases in breast cancer patients [99]. These studies highlight the potential of miRNA signatures in real-time monitoring and early detection of metastatic brain Tumors. Certain miRNA expression profiles are associated with Tumor prognosis, distinguishing aggressive Tumors from less malignant forms. For instance, the upregulation of miR-21 has been identified as both a prognostic and diagnostic marker, correlating with Tumor progression and poor survival rates [100-102]. Various miRNA panels have also been proposed as diagnostic tools for Tumor grading, enabling more precise classification of gliomas and glioblastomas [103]. Furthermore, miRNAs have shown the ability to differentiate primary central nervous system (CNS) lymphoma from glioblastoma, an essential distinction for treatment planning and clinical decision-making [104]. Beyond diagnostics, miRNAs are also being investigated as therapeutic targets in brain Tumor treatment. Some miRNAs have been found to increase Tumor sensitivity to radiation therapy, potentially enhancing treatment efficacy while reducing side effects [105]. However, due to their involvement in key biological processes such as cell cycle regulation, apoptosis, proliferation, and differentiation, careful evaluation is required before implementing miRNA-based therapies in clinical settings [106]. Recent research has also explored miRNA-based therapies for treating inflammatory diseases, demonstrating their therapeutic versatility and potential applications in neuro-oncology [107]. To enhance the safety and specificity of miRNA-based treatments, nanocarrier-based delivery systems are being developed. These platforms ensure targeted and controlled miRNA delivery to Tumor cells while minimizing off-target effects [108]. As research progresses, miRNA biomarkers and targeted therapies hold the potential to revolutionize the diagnosis, prognosis, and treatment of brain Tumors. Their integration into clinical practice will depend on further validation through large-scale clinical trials and advancements in precision medicine technologies.

Table 1. Relevant studies in relation to the role of miRNAs in the oncogenesis of malignant primary brain Tumors.

Tumor Type	miRNA	Gene-Target	Biological Function		Signalling Pathway	References
Glioblastoma	miR-128-3p	platelet-derived growth factor alpha receptor	promotes glioblastoma	Down	receptor tyrosine kinase	[109]
Glioblastoma	miR-218	hypoxia-inducible factor 2 alpha	promotes glioblastoma	Down	receptor tyrosine kinase	[110]
Glioblastoma	miR-95	Hepatocyte Growth Factor and Mitogen-Activated Protein Kinase Kinase 3	improved clinical outcome in the neural subtype	Down	Signal transducer and activator of transcription 3	[111]
Glioblastoma	miR-21	Integrin b8 [112]	improved clinical outcome in the neural subtype	Up	Signal Transducer and Activator of Transcription [113]	[111]
Glioblastoma	miR-381	lymphoid enhancer-	Inhibits metastases	Down	Wnt	[114]

2. Artificial Intelligence in Brain Tumor Imaging

The rapid growth of artificial intelligence (AI) in medical imaging has significantly enhanced the ability to detect, classify, and monitor brain Tumors. The increasing investment in AI-driven healthcare projects has led to major breakthroughs in automated diagnostic procedures, making AI a key player in modern neuro-oncology [115,116]. The global brain Tumor diagnostics market, valued at $844.63 million in 2021, is projected to reach $2.47 billion by 2028, growing at a compound annual growth rate (CAGR) of 16.6%. This rapid expansion underscores AI's growing impact on medical imaging and cancer diagnosis [117,118]. AI-driven approaches have revolutionized Tumor detection and characterization, improving early diagnosis, precision treatment planning, and patient monitoring. AI-based imaging technologies can track Tumor progression, predict treatment responses, and detect early-stage malignancies before they become symptomatic [119,120]. Radiologists increasingly rely on computer-aided diagnosis (CAD) systems, which use supervised and unsupervised machine learning, deep learning, and transfer learning to identify brain Tumors with high precision. Deep neural network models, such as the Xception model, have demonstrated superior accuracy in medical imaging, with continued improvements expected as AI technology advances [121]. Molecular imaging provides a more refined framework for Tumor diagnosis, enabling the visualization of molecular and cellular activity in brain tissues. This technique enhances Tumor detection and classification, providing crucial insights into the biological characteristics of Tumors that conventional imaging might overlook [122]. AI-based imaging models, including CXR-Vision, LIDC-IDRI, LUNA16, and CT-based volumetric analysis, have been successfully applied in lung, breast, and brain cancer diagnosis [123,124]. These AI-driven tools analyze distinct Tumor characteristics, such as contrast enhancement, metabolic activity, and morphological patterns, improving diagnostic accuracy. MRI-based AI algorithms exploit biological differences in Tumors, such as the breakdown of the blood-brain barrier, which can be visualized using gadolinium-enhanced T1-weighted imaging [125]. Emerging AI techniques, such as orthogonal wavelet transforms and deep learning models, are being used to detect and classify brain Tumors with high specificity [126]. The deep wavelet autoencoder (DWAE) model, combined with support vector machines, has been shown to predict Tumor location and classify Tumor volumes using multimodal data from MRI and PET scans [127]. One of the most significant applications of AI in neuro-oncology is medical image segmentation, where AI partitions MRI and CT scans into meaningful regions to enhance Tumor visualization and tracking [128]. The ability to automatically segment brain Tumors allows clinicians to analyse Tumor growth patterns, measure treatment efficacy, and plan surgical interventions more effectively. Deep learning-based segmentation has proven highly effective in distinguishing Tumors from healthy tissue, with models such as CapsNet (deep capsule network) and LDCRF (latent-dynamic condition random field) showing promising results [129]. However, studies have also identified challenges—while deep learning methods work well for large, well-defined Tumors, they often struggle with detecting smaller lesions, leading to misclassifications [130]. The integration of AI with molecular imaging has paved the way for customized treatment strategies in metastatic brain Tumors (MBT). AI-driven imaging techniques can assess molecular expression profiles, which provide personalized Tumor characterizations. Loss of MGMT DNA expression in 20–40% of MBT cases has been identified using AI-based analysis, offering potential therapeutic targets for precision oncology [131]. AI models are increasingly used to identify Tumor-specific receptors and signal transduction molecules, allowing for personalized, molecule-targeted therapies. This is particularly crucial for patients with treatment-resistant brain Tumors, where AI can assist in selecting the most effective therapeutic options based on the Tumor's unique molecular makeup.

As AI technology continues to evolve, its role in brain Tumor imaging and diagnostics is expected to expand significantly. Future advancements will likely include:

Improved AI models for small Tumor detection, minimizing misclassification rates.

- AI-assisted multimodal imaging, combining MRI, PET, and molecular imaging for a comprehensive Tumor assessment.
- Real-time AI-guided image analysis, enhancing the precision of neurosurgical interventions.
- Integration of AI with genomic data, enabling more accurate treatment selection based on a patient's genetic profile.

Despite current challenges, AI remains a game-changer in neuro-oncology, offering faster diagnoses, enhanced precision, and improved patient outcomes. As AI-based models continue to refine their capabilities, their adoption in clinical workflows will further revolutionize brain Tumor detection, classification, and treatment.

2.1. Quantitative Imaging of Brain Tumors

Quantitative imaging plays a crucial role in detecting, characterizing, and monitoring brain Tumors, utilizing various imaging modalities such as magnetic resonance tomography (MRT), computed tomography (CT), and positron emission tomography (PET). These techniques enable precise localization and volumetric analysis of Tumors, essential for accurate diagnosis and treatment planning. Contrast agents are frequently used to enhance image resolution, providing clearer differentiation between Tumor tissue and normal brain structures [132]. PET imaging, in particular, offers a functional perspective on Tumor metabolism, allowing for real-time assessment of Tumor progression, treatment response, and recurrence. It enables measurement of transcapillary transport of water-soluble compounds, enhancing our understanding of Tumor vascularization and its impact on therapy [133]. Studies suggest that PET imaging can detect Tumor regions with high metabolic activity, often correlating with aggressive Tumor growth and resistance to standard treatments [134,135]. Specific PET tracers, such as 18F-fluorodeoxyglucose (FDG), 18F-fluoroethyltyrosine, 11C-methionine, and 18F-L-3,4-dihydroxyphenylalanine, have demonstrated high sensitivity in distinguishing malignant from nonmalignant brain lesions and identifying residual or recurrent cancer [136]. Additionally, 3D-U-Net convolutional neural networks (CNNs) have been employed to segment gliomas from PET scans, achieving up to 99% specificity and 88% sensitivity in Tumor detection [137]. Emerging AI techniques, such as machine learning-based MRI analysis, have shown superior predictive accuracy in brain Tumor grading and treatment outcome predictions compared to conventional

imaging methods [138]. AI-powered classifiers have been developed to automatically segment pathological tissue in brain MRIs, significantly improving diagnostic precision [139]. Further advancements in nanotechnology and molecular imaging have introduced aptamers, highly specific DNA/RNA molecules that bind to Tumor markers, improving targeted PET imaging and biomarker research [140]. Additionally, autofluorescence imaging, a noninvasive technique that distinguishes normal from Tumor-affected brain tissue based on fluorescence emission, has been successfully applied in brain Tumor detection and surgical guidance [141].

2.2. Radiomics in Brain Tumor Diagnosis

Radiomics is an emerging field that utilizes high-dimensional data extracted from medical images to predict Tumor characteristics, treatment response, and patient prognosis. Unlike conventional radiological assessments that rely on qualitative markers (e.g., Tumor density, enhancement patterns), radiomics translates imaging features into quantitative, computable data, improving diagnostic precision [150]. Since the 2016 WHO classification of brain Tumors integrated genetic markers, radiomics has gained increasing relevance in Tumor stratification and individualized treatment selection. Studies have demonstrated its ability to differentiate low-grade from high-grade gliomas, with significant correlations between radiomic signatures and Tumor biology [151,152]. AI-driven radiomic analysis can also be applied to assess Tumor response to therapy by integrating data from functional imaging modalities such as diffusion-weighted imaging (DWI) and perfusion imaging, providing early indications of treatment success or failure [154]. A study comparing deep radiomic features with traditional imaging biomarkers found that deep radiomics achieved an AUC of 89.15%, significantly outperforming standard radiomic models (AUC of 78.07%) in predicting short- and long-term survival in glioblastoma patients [155]. However, the limited availability of large, well-annotated imaging datasets remains a key challenge in radiomics research. Transfer learning techniques, where AI models trained on one dataset are adapted for use in a related domain, offer a potential solution to this constraint [149]. Researchers have identified a set of 11 radiomic features that improve Tumor survival predictions and treatment response assessments, providing a more comprehensive approach to personalized oncology [156]. As radiomics continues to integrate with AI, machine learning, and big data analytics, it is expected to redefine precision diagnostics and predictive oncology.

2.3. Radio genomics: Bridging Imaging and Genomics

The field of radiogenomics (also referred to as imaging genomics) explores the relationship between imaging biomarkers and underlying genomic alterations in Tumors. By analyzing textural, functional, and morphological imaging features, radio genomics provides insights into Tumor heterogeneity, genetic mutations, and molecular subtypes [125]. One of the main challenges in oncology is the spatial and temporal heterogeneity of Tumors, where different regions of the same Tumor may exhibit distinct genetic and phenotypic profiles. Radio genomic approaches address this limitation by analyzing the entire Tumor volume, rather than relying on single-site biopsies, thereby reducing sampling bias and improving treatment stratification [158]. As cancer therapies increasingly incorporate immunotherapy, targeted therapy, and precision medicine, radiomics and radio genomics will play an essential role in optimizing treatment selection and monitoring therapeutic responses.

2.4. Convolutional Neural Networks for Clinical Diagnostics

Convolutional neural networks (CNNs) have emerged as powerful AI tools for automating medical image analysis. CNN architectures, when optimized using stochastic gradient algorithms, enable faster and more accurate processing of radiological data, facilitating Tumor classification, segmentation, and treatment planning [159]. In a ground-breaking study, Ker et al. demonstrated that CNN models classified brain histological samples into high- and low-grade gliomas with 98% and 100% accuracy, respectively [162]. Another study by Havaei et al. showed that a CNN-based segmentation algorithm was 30 times faster and more precise than traditional segmentation methods, proving CNNs' superiority in brain Tumor imaging [79]. Deep CNN models can extract highly discriminative Tumor features from histopathological images, significantly enhancing diagnostic accuracy in glioblastoma patients [163]. The use of CNN-based Raman spectroscopy probes in neurosurgery has also enabled real-time Tumor detection, allowing surgeons to identify Tumor margins with millimetre-level precision during operations [164]. Furthermore, CNN-assisted 3D imaging models have demonstrated remarkable accuracy in Tumor classification, enhancing treatment planning and personalized therapy selection. AI-driven CNN architectures continue to evolve, promising further breakthroughs in clinical diagnostics and neuro-oncology [165-167].

2.5. Future Prospects of AI in Brain Tumor Imaging

The integration of AI-driven imaging techniques, radionics, and radio genomics is set to revolutionize neuro-oncology. Future AI applications in brain Tumor imaging may include:

- Improved early-stage Tumor detection using AI-enhanced multimodal imaging (MRI, PET, and molecular imaging).
- Real-time AI-assisted surgical navigation, improving precision in Tumor resection procedures.
- Automated AI-driven pathology analysis, reducing interobserver variability and enhancing diagnostic consistency.
- Personalized AI models for patient-specific Tumor progression prediction, optimizing treatment planning and post-treatment monitoring.
- Integration of AI with wearable biosensors and telemedicine, enabling continuous monitoring of high-risk brain Tumor patients.

As AI technologies continue to refine their diagnostic capabilities, their adoption in routine clinical workflows is expected to significantly improve patient outcomes, reduce diagnostic errors, and advance precision medicine in brain Tumor management.

3. The Future of AI in Brain Tumor Diagnosis and Treatment

The integration of artificial intelligence (AI) into diagnostic radiology and brain Tumor management has significantly improved Tumor detection, segmentation, and classification. However, many challenges remain that must be addressed to enhance clinical accuracy, efficiency, and patient outcomes [168]. AI-based systems have recently been incorporated into clinical workflows, demonstrating their potential to streamline diagnostics and improve personalized treatment strategies [169]. One of the most promising applications of AI is its ability to enable early glioma diagnosis, even in cases where visual contrast is absent in medical imaging. However, the full potential of AI in glioma detection is currently limited by the availability of high-quality imaging datasets, which are essential for training deep learning models. Addressing this limitation will require standardized data-sharing frameworks and enhanced imaging techniques that ensure greater accuracy in AI-driven diagnostic tools. A key future development in AI-based brain Tumor diagnostics is the recognition of pre-metastatic niches. These early-stage Tumor microenvironments provide an accurate assessment of a patient's likelihood of developing metastatic or micro metastatic disease. Early detection of these niches through AI-powered imaging will allow for earlier interventions and more effective personalized treatment plans.

AI applications in medical imaging can be broadly categorized into two domains:

- Upstream AI applications, which focus on operational analytics, including workflow optimization and automation of clinical decision-making [170].
- Downstream AI applications, which deal directly with imaging data processing, enabling enhanced Tumor segmentation, phenotype classification, and volumetric assessment.

One of the major advancements in AI-driven imaging analysis is the combination of different types of annotations to improve accuracy and efficiency. However, the conventional separation of annotation types limits the potential of AI models. Integrating global labels and local annotations into a unified framework will enhance supervised medical image analysis, resulting in higher diagnostic precision and more reliable AI-generated assessments [171]. Beyond brain Tumor detection, AI is expected to revolutionize neurology and neuro-oncology. In addition to Tumor grading [173], AI has the potential to predict seizures based on neural activity patterns, which could improve seizure management and patient care [172]. One study demonstrated that AI-based segmentation models, trained using multitasking approaches with global and local annotations, significantly improved the accuracy of brain Tumor segmentation on MRI scans [174]. Moreover, AI models have been shown to accurately detect and segment intracranial hemorrhages on CT scans, enabling the measurement of hemorrhage volumes with high precision. This capability could also be extended to detect and quantify head and neck vascular Tumors or malformations, further expanding AI's role in neuroimaging [175]. Another area where AI is expected to make significant advances is in cancer imaging interpretation. AI-based radiomics will allow for the extrapolation of Tumor genotypes, volumetric delineation of Tumors over time, and prediction of clinical outcomes based on radiographic phenotypes. By integrating AI with advanced imaging modalities such as MRI, PET, and CT, clinicians will be able to track Tumor progression more accurately, assess treatment responses, and optimize therapeutic strategies [151]. Despite these promising advancements, the future of AI in brain Tumor research and treatment will require continued innovation in data quality, model interpretability, and clinical integration. Addressing privacy concerns, ethical considerations, and regulatory challenges will be crucial to ensuring that AI becomes a trusted and effective tool in brain Tumor management. As AI technologies continue to evolve, their integration into precision oncology and personalized medicine will transform diagnostics, treatment planning, and long-term patient care, leading to improved survival rates and quality of life for patients with brain Tumors.

4. Challenges of Using AI in Brain Tumor Diagnosis and Treatment

The application of artificial intelligence (AI) in brain Tumor diagnosis and treatment presents several challenges, particularly in the detection and classification of gliomas, one of the most difficult cancers to diagnose. Gliomas often appear small and indistinct on imaging scans, and their symptoms can be vague, mimicking other neurological conditions. While deep learning and machine learning have the potential to revolutionize glioma diagnosis, existing limitations hinder their widespread clinical adoption [176,147]. One of the significant challenges in AI-driven healthcare is the lack of resources and investment in information technology. Many healthcare institutions struggle with insufficient infrastructure, making it difficult to implement AI models effectively [177,178]. Additionally, the lack of training on big data analytics prevents medical professionals from utilizing AI tools optimally. Big data in healthcare requires advanced analytical techniques capable of handling massive datasets with diverse formats and rapid updates. To address this, intelligent tutoring systems and process-oriented e-learning platforms could be integrated into medical training programs, equipping personnel with the skills needed for AI-driven diagnostics. Another pressing concern is data security and privacy. AI-driven healthcare systems rely on vast amounts of sensitive patient data, raising ethical and legal challenges related to data access, storage, and sharing. Robust access control models and privacy-preserving protocols must be implemented to safeguard patient confidentiality and comply with global healthcare regulations [179]. To mitigate the issue of limited data availability for machine learning model training, centralized AI systems have been employed, aggregating patient data across multiple healthcare facilities. However, this centralized approach poses logistical and privacy-related difficulties, as transferring sensitive patient records between hospitals requires significant time and resources. Additionally, inter-center research collaborations may be restricted due to institutional policies and ethical constraints [179]. An alternative to centralized AI is federated learning, a decentralized machine

learning approach that allows multiple healthcare institutions to collaboratively train AI models without directly sharing patient data. This method enables institutions to retain control over their data while benefiting from a collective AI training process. Federated learning has the potential to enhance AI model accuracy and generalizability, ensuring that medical AI systems perform reliably across diverse patient populations while maintaining data privacy and security. Despite these advancements, several fundamental challenges remain in brain Tumor research. One of the most significant issues is Tumor grading, which currently relies on human interpretation of medical images. This subjective process often leads to variability in Tumor classification, as different radiologists may assess the same Tumor differently based on morphological features. AI-driven automated image analysis offers a promising solution by providing a quantitatively objective Tumor classification system, reducing diagnostic inconsistencies and improving accuracy [180]. Emerging AI-based radiology techniques have demonstrated significant potential in improving medical imaging interpretation. However, for AI to become fully integrated into clinical practice, healthcare providers must address barriers related to infrastructure, data security, standardization, and physician training. By overcoming these challenges, AI has the potential to significantly enhance early Tumor detection, treatment planning, and overall patient outcomes in neuro-oncology [149].

5. Conclusion

Artificial intelligence (AI) has emerged as a powerful support tool in cancer diagnostics, intervention, and prevention, demonstrating remarkable potential in improving brain Tumor detection, classification, and treatment. AI-assisted neurosurgery has been shown to enhance precision and safety, reducing surgical risks and improving patient outcomes. By integrating clinical, radiological, and molecular markers, AI-driven models are enabling personalized treatment strategies, which hold immense promise for the future of brain Tumor management. Recent advancements in precision medicine (PM) have shifted the focus toward targeted therapies and customized treatment regimens, tailored to each patient's molecular and genetic profile. Although the large-scale implementation of AI and PM in neuro-oncology still faces significant challenges, the rapid pace of technological progress suggests that remarkable breakthroughs in brain Tumor treatment are on the horizon. With continued research, improved AI training methodologies, and greater collaboration between healthcare institutions, AI and PM are poised to revolutionize brain Tumor care, ultimately leading to more effective treatments and better patient outcomes.

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