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A Review of Artificial Intelligence-Assisted Diagnostic Imaging Tools in the Detection and Characterization of Brain Tumors

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Abstract

Background:
Brain tumors represent a diverse group of central nervous system neoplasms that require precise diagnosis and characterization for effective treatment. Advances in neuroimaging have improved the detection of these tumors; however, conventional interpretation methods remain time-intensive and subject to variability. Artificial intelligence (AI), particularly through machine learning and deep learning, has emerged as a powerful tool in neuro-oncological imaging, offering automation, consistency, and enhanced diagnostic performance.

Objective:
This review aims to provide a comprehensive overview of AI-assisted imaging tools used in the detection and characterization of brain tumors. It highlights key AI technologies, their clinical applications, performance compared to human experts, and the emerging trends shaping the future of AI in neuro-oncology.

Methods:
A narrative review was conducted of recent peer-reviewed studies focused on the application of AI in brain tumor imaging. Emphasis was placed on machine learning and deep learning models used for tumor segmentation, histopathologic and molecular subtype prediction, prognostic modeling, and treatment response monitoring. Technical challenges, ethical concerns, and regulatory considerations were also examined.

Results:
AI models have demonstrated high accuracy in tasks such as tumor segmentation, classification of tumor types and grades, non-invasive prediction of molecular markers (e.g., IDH mutation, MGMT methylation), and survival prediction. Emerging techniques such as federated learning, multimodal data integration, and explainable AI are addressing key limitations, including data privacy, generalizability, and clinical trust.

Conclusion:
AI-assisted imaging holds considerable promise in improving the accuracy, speed, and personalization of brain tumor diagnosis and management. For widespread clinical adoption, future efforts should focus on multi-institutional collaboration, prospective validation, regulatory alignment, and clinician education. With continued advancement, AI can become a

valuable adjunct in the neuro-oncology diagnostic arsenal, ultimately contributing to better patient outcomes.

Keywords: Artificial Intelligence, Neuro-Oncology, Brain Tumors, Medical Imaging, Deep Learning

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1. Introduction

1.1. Background on Brain Tumors and Diagnostic Challenges

Brain tumors are a heterogeneous group of neoplasms that affect the central nervous system (CNS), comprising both primary tumors (originating in the brain or spinal cord) and secondary tumors (metastatic lesions from extracranial sites). Primary brain tumors account for approximately 1.4% of all cancers and 2.5% of cancer-related deaths globally, with glioblastoma multiforme (GBM) representing the most aggressive and common malignant subtype in adults (Miller et al., 2021; Ostrom et al., 2021). Despite significant advances in neurosurgical techniques, radiotherapy, and chemotherapy, brain tumors continue to pose diagnostic and therapeutic challenges due to their complexity, infiltrative growth patterns, and variability in radiographic appearance. Early and accurate diagnosis is critical for optimal clinical management and improved prognosis. However, brain tumors often present with nonspecific symptoms, such as headaches, seizures, or cognitive changes, which can delay referral and diagnosis, particularly in resource-limited settings (Ellor et al., 2014). Moreover, tumor grading and classification rely heavily on radiological features, which can be subjective and prone to interobserver variability. This diagnostic uncertainty has led to an increasing demand for objective, automated, and high-throughput diagnostic tools to support clinical decision-making. Neuroimaging plays an indispensable role in the diagnosis, treatment planning, and follow-up of patients with brain tumors. Magnetic Resonance Imaging (MRI) remains the gold standard modality, providing high-resolution anatomical and functional imaging, including diffusion-weighted imaging (DWI), perfusion-weighted imaging (PWI), and MR spectroscopy (MRS) (Weller et al., 2021). Computed Tomography (CT) is often employed in emergency settings and for assessing calcifications or hemorrhage, while Positron Emission Tomography (PET), particularly with tracers like ^18F-FDG or ^11C-methionine, contributes valuable metabolic information for tumor grading and recurrence assessment (Albert et al., 2016).

Despite these advancements, manual interpretation of imaging studies can be time-intensive, subjective, and limited by the radiologist’s expertise. Furthermore, distinguishing tumor progression from treatment-related changes, such as pseudoprogression or radiation necrosis, remains a significant diagnostic dilemma. These challenges underscore the need for robust, automated diagnostic systems that can assist radiologists by enhancing accuracy, consistency, and efficiency in tumor assessment. Artificial intelligence (AI) has emerged as a powerful tool to address existing limitations in medical imaging. With the rise of machine learning

(ML) and, more recently, deep learning (DL), AI systems have demonstrated exceptional performance in image classification, segmentation, and anomaly detection tasks across multiple medical domains (Esteva et al., 2019; Litjens et al., 2017). In neuro-oncology, AI algorithms are being applied to tasks such as automated tumor segmentation, classification of glioma grades, prediction of molecular markers (e.g., IDH mutation, 1p/19q co-deletion), and prognostic modeling (Bauer et al., 2013).

Deep convolutional neural networks (CNNs), radiomics pipelines, and ensemble learning approaches have shown promising results in both research and early clinical implementation. These technologies aim to augment the radiologist's workflow, reduce diagnostic errors, and support personalized treatment strategies. However, challenges remain regarding data heterogeneity, model generalizability across institutions, lack of interpretability, and the regulatory hurdles required for clinical integration (Series et al., 2023; Topol, 2019).

1.2. Objectives and Scope of the Review

This review aims to comprehensively examine the current landscape of artificial intelligence-assisted diagnostic imaging tools in the context of brain tumor detection and characterization. Specifically, it focuses on AI applications in widely used imaging modalities such as MRI, CT, and PET. The review will explore various AI methodologies, including deep learning, radiomics, and hybrid approaches, and analyze their performance, advantages, and limitations. In addition to discussing the clinical applicability and potential of these tools, the paper will address challenges related to data availability, model validation, reproducibility, and ethical considerations. It also highlights trends in multimodal data integration and explainable AI (XAI) that are shaping the future of neuro-oncological diagnostics. Through this synthesis, the review aims to inform clinicians, radiologists, and researchers about the state-of-the-art developments in AI-assisted imaging and identify critical gaps and opportunities for future research and clinical translation.

2. Overview of Imaging Modalities in Neuro-Oncology

Magnetic Resonance Imaging (MRI) is the gold standard in neuro-oncology for evaluating brain tumors due to its exceptional soft-tissue contrast and multiparametric imaging capabilities. Standard sequences such as T1-weighted, T2-weighted, FLAIR (Fluid-Attenuated Inversion Recovery), and contrast-enhanced T1-weighted imaging are routinely used for tumor localization, edema assessment, and evaluation of blood–brain barrier disruption(Weller et al., 2021).

MRI enables detailed visualization of intracranial anatomy and offers advanced techniques for functional and metabolic evaluation. Diffusion-Weighted Imaging (DWI) is sensitive to cellularity and often used to differentiate high-grade from low-grade tumors (Essig et al., 2013). Perfusion-Weighted Imaging (PWI) assesses tumor vascularity and neoangiogenesis, correlating with tumor grade. Magnetic Resonance Spectroscopy (MRS) provides metabolic profiling, helping distinguish tumor recurrence from post-treatment effects. These techniques, when combined with radiomics and deep learning algorithms, have become a foundation for non-invasive tumor characterization and treatment response monitoring. MRI's non-ionizing nature also makes it preferable for longitudinal follow-up and pediatric imaging. However, access to high-quality MRI remains limited in some low- and middle-income countries, where resource constraints and technical expertise may pose challenges (Nittas et al., 2023).

Computed Tomography (CT) is frequently used in emergency neurological imaging, particularly for patients presenting with acute symptoms such as seizures, trauma, or altered consciousness. While CT offers lower soft-tissue resolution than MRI, it remains indispensable in detecting intracranial hemorrhage, calcifications, and mass effect, as well as for assessing bone involvement (Schröder & Thomalla, 2017).

Contrast-enhanced CT can aid in identifying enhancing brain lesions, although its sensitivity to tumor boundaries is inferior to MRI. Nevertheless, CT is faster, more widely available, and often the first imaging modality encountered, particularly in resource-limited healthcare systems where MRI infrastructure may be lacking. In such settings, AI-enhanced CT image analysis holds promise for bridging diagnostic gaps by improving tumor detection using machine learning approaches trained on minimal-resource input (Pekcevik et al., 2015). Positron Emission Tomography (PET) complements structural imaging by offering molecular and metabolic insights into tumor biology. Traditional ^18F-FDG PET has limited sensitivity in brain imaging due to high physiological glucose uptake in gray matter. Therefore, amino acid PET tracers such as ^11C-methionine, ^18F-FET (fluoroethyltyrosine), and ^18F-DOPA are increasingly used for improved tumor visualization, especially for delineating tumor margins, grading, and detecting recurrence (Albert et al., 2016).

PET imaging is particularly useful in differentiating tumor progression from post-treatment changes, such as pseudoprogression or radiation necrosis. Hybrid imaging platforms like PET/MRI provide simultaneous functional and anatomical data, offering comprehensive insight into tumor biology. These datasets are increasingly being utilized for AI-based predictive modeling and outcome forecasting in neuro-oncology (Morana et al., 2015). Advanced MRI techniques provide deeper insights into tumor infiltration, white matter disruption, and metabolic alterations. Diffusion Tensor Imaging (DTI), an extension of DWI, maps white matter tracts and is invaluable for pre-surgical planning, helping avoid damage to eloquent brain areas. Tractography based on DTI is often used to assess tumor displacement or infiltration of functional pathways, particularly in gliomas (Zhang et al., 2012).

Magnetic Resonance Spectroscopy (MRS) offers a non-invasive method to assess biochemical changes within tumor tissue. Elevated choline and decreased N-acetylaspartate (NAA) levels are typically seen in high-grade gliomas. The detection of lactate and lipid peaks can further aid in distinguishing necrotic tissue from active tumor (Sibtain et al., 2007). These metabolic markers are increasingly being incorporated into AI algorithms to improve diagnostic performance and predict molecular subtypes. Other specialized MRI techniques include Arterial Spin Labeling (ASL) for perfusion without contrast, and Functional MRI (fMRI) for localizing brain activity during tasks. These modalities enhance surgical planning and have growing roles in radiogenomics and personalized neuro-oncology.Table1, shows the Imaging modalities in neuro-oncology

Table 1: Overview of Imaging Modalities in Neuro-Oncology

Modality	**Key Features**	**Clinical Applications**	**Strengths**	**Limitations**
Magnetic Resonance Imaging (MRI)	Gold standard; multiparametric imaging (T1, T2, FLAIR, contrast-enhanced T1)	Tumor localization, edema assessment, BBB disruption, grading, treatment response	Excellent soft-tissue contrast; advanced tools (DWI, PWI, MRS); non-ionizing; useful for follow-up & pediatrics	Limited availability in LMICs; high cost; requires expertise
Computed Tomography (CT)	X-ray–based cross-sectional imaging, with contrast options	Emergency use (trauma, seizures, hemorrhage); detection of calcification & bone involvement	Fast; widely available; essential in acute care; useful where MRI not accessible	Lower soft-tissue resolution than MRI; limited sensitivity for tumor boundaries
Positron Emission Tomography (PET)	Molecular & metabolic imaging; tracers (^11C-methionine, ^18F-FET, ^18F-DOPA)	Tumor grading, recurrence detection, distinguishing progression vs. treatment effects	Complements MRI/CT; useful in pseudoprogression vs. necrosis; PET/MRI hybrid offers comprehensive insight	^18F-FDG limited in brain due to high glucose uptake; tracer availability & cost issues
Advanced MRI Techniques (DTI, MRS, fMRI, ASL)	Functional & metabolic extensions of MRI	Pre-surgical planning (DTI tractography), metabolic profiling (MRS), perfusion (ASL), task localization (fMRI)	Non-invasive insight into white matter, tumor infiltration, biochemical changes; supports radiogenomics & AI integration	Technically demanding; variable availability; interpretation requires expertise

3. Artificial Intelligence in Neuroimaging

Artificial Intelligence (AI) has become increasingly integrated into neuroimaging workflows, offering the potential to enhance diagnostic accuracy, reduce observer variability, and improve clinical efficiency. In the context of brain tumor imaging, AI systems are being developed to automate or augment key tasks such as tumor detection, segmentation, classification, and prognostic modeling. With the increasing availability of imaging data and computational power, the use of AI-based tools is expanding rapidly in both research and clinical environments.

AI in neuroimaging primarily encompasses machine learning (ML) and deep learning (DL) approaches. Traditional machine learning techniques such as support vector machines (SVM), random forests, and logistic regression require manual feature engineering and are often used in radiomics pipelines to classify tumor subtypes or predict clinical outcomes (Aerts et al., 2014). In contrast, deep learning, particularly convolutional neural networks (CNNs), has revolutionized medical image analysis by learning hierarchical features directly from raw image data. CNNs have demonstrated exceptional performance in various neuro-oncological tasks, including tumor segmentation and grade classification (Akkus et al., 2017)). More recent advancements such as U-Net architectures, transformer-based models, and generative adversarial networks (GANs) are being explored to improve robustness and generalizability of AI models. While deep learning often outperforms traditional ML in terms of accuracy, it typically requires larger annotated datasets and is more computationally intensive. The "black-box" nature of deep learning models also raises concerns about interpretability, especially in high-stakes clinical decision-making (Topol, 2019).

Radiomics is a quantitative imaging approach that involves extracting a large number of handcrafted features from medical images, capturing tumor shape, texture, intensity, and spatial relationships. These features are then used to build predictive models for diagnosis, prognosis, and therapeutic response (Gillies et al., 2016). In neuro-oncology, radiomic signatures derived from MRI have been linked to molecular markers such as IDH mutation, 1p/19q co-deletion, and MGMT promoter methylation (Osman, 2019). Radiomics typically follows a structured pipeline: image acquisition and preprocessing, tumor segmentation, feature extraction, feature selection, and model construction. While this approach allows for greater model interpretability compared to deep learning, its performance is highly dependent on image standardization, reproducibility of features, and robustness across scanners and institutions. Hybrid models that combine radiomic features with clinical or genomic data (radiogenomics) are gaining traction, offering a more holistic view of the tumor's biological behavior.

AI models in neuro-oncology imaging are developed for a range of tasks:

> Tumor segmentation involves delineating the tumor boundaries from surrounding brain tissue. CNN-based models, especially 3D U-Nets, have achieved state-of-the-art performance in segmenting enhancing tumor, necrotic core, and peritumoral edema on MRI (Isensee et al., 2021). Accurate segmentation is crucial for volume estimation, treatment planning, and monitoring.
>
> Tumor classification aims to differentiate between tumor types (e.g., glioblastoma vs. low-grade glioma) or grades (e.g., WHO Grade II vs. Grade IV). Deep learning models trained on multiparametric MRI inputs have shown high accuracy in predicting histological subtypes and even molecular markers (Chang et al., 2018).

Outcome prediction includes survival estimation, recurrence risk, and treatment response forecasting. AI-based prognostic models can integrate imaging features with clinical data to support personalized medicine strategies.

These tasks are increasingly supported by open datasets such as the Brain Tumor Segmentation (BraTS) challenge, which have accelerated model development and benchmarking.

The development of robust AI models requires rigorous training, validation, and testing using well-annotated, diverse datasets. Training involves feeding labeled examples into the model to learn feature patterns, while validation is used for hyperparameter tuning and early stopping to prevent overfitting. External testing on independent datasets is essential to evaluate generalizability.

Common performance metrics in neuroimaging AI include:

Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) for segmentation accuracy

Accuracy, sensitivity, specificity, precision, and F1-score for classification tasks

Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) for evaluating discriminative performance

Model robustness, reproducibility, and explainability are increasingly emphasized by journals and regulatory agencies. Techniques such as saliency maps, Grad-CAM, and SHAP values are used to provide insights into model decisions and foster clinician trust(Lundervold & Lundervold, 2019; Mazurowski et al., 2019). Figure 1, present AI in neuroimaging: Key components and applications.

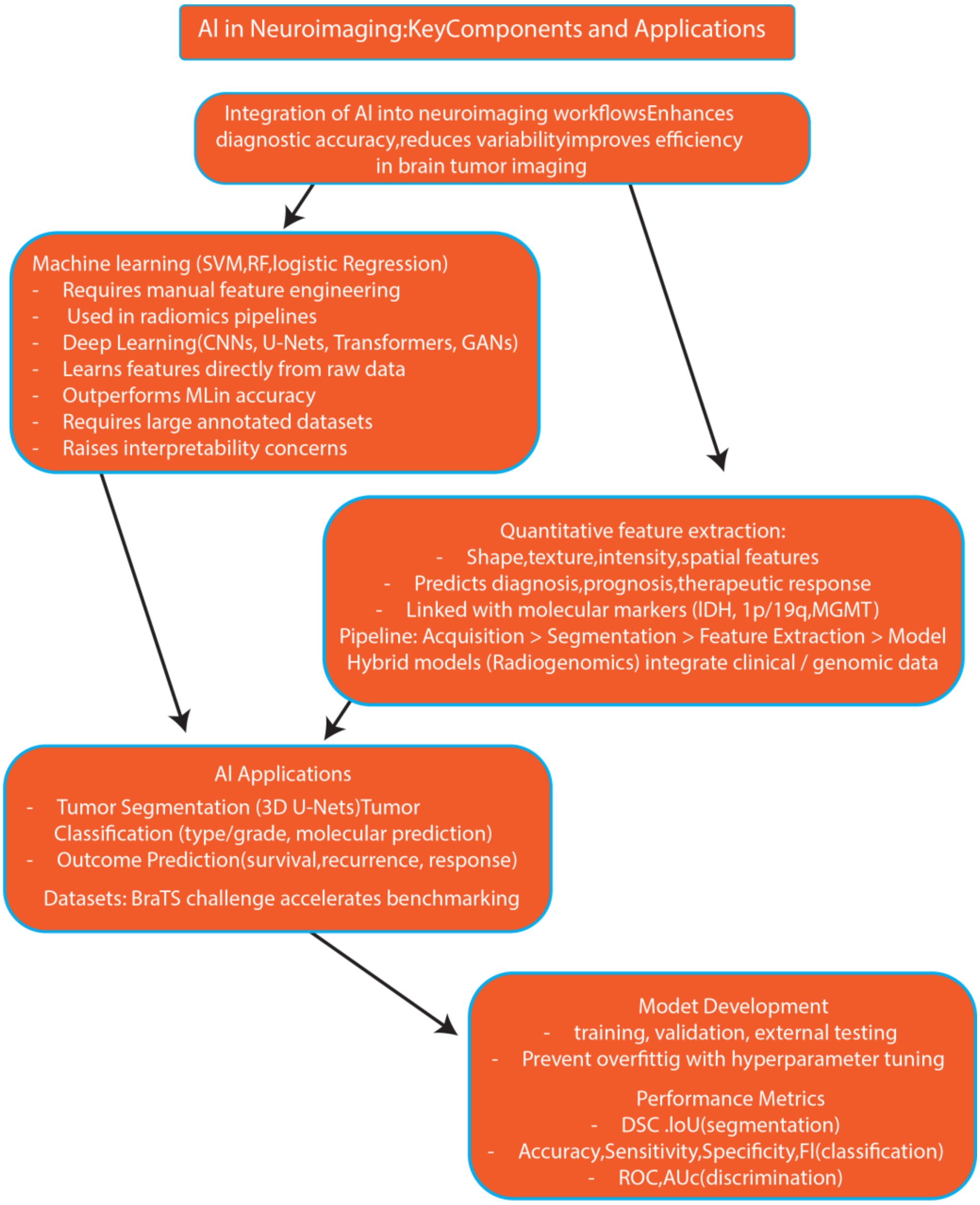

Figure 1. AI in Neuroimaging: Key Components and Applications

4. Applications of AI in Brain Tumor Detection

Artificial intelligence has significantly advanced the field of neuro-oncological imaging by enabling automated, reproducible, and high-throughput analysis of complex medical data. In the context of brain tumor detection, AI tools can perform various diagnostic tasks with increasing accuracy, often complementing or even surpassing human expertise in specific domains. This section outlines the major applications of AI in tumor segmentation, diagnosis, early screening, and performance comparison with radiologists. Accurate tumor segmentation is critical for diagnosis, surgical planning, radiotherapy targeting, and monitoring treatment response. Traditional manual segmentation is time-consuming and prone to interobserver variability, particularly in heterogeneous tumors such as glioblastomas. AI-based tools, especially deep learning models like U-Net, V-Net, and nnU-Net, have demonstrated high accuracy and efficiency in segmenting tumor sub-regions including the enhancing core, necrotic tissue, and peritumoral edema across multiple MRI sequences (Isensee et al., 2021). These models are often trained on public datasets such as the Brain Tumor Segmentation Challenge (BraTS), which provide standardized benchmarks for evaluating performance. Reported Dice Similarity Coefficients (DSC) for AI-based segmentation frequently exceed 0.85 for the whole tumor region, rivaling expert manual annotations (Bakas et al., 2018). Additionally, AI-enabled volumetric analysis provides objective and reproducible measurements essential for tracking tumor progression.

AI algorithms have also been applied to classify brain tumors by histological type and grade using imaging data. Deep learning models trained on multiparametric MRI can differentiate between high-grade and low-grade gliomas, glioblastomas, meningiomas, metastases, and other tumor entities with notable accuracy. For example, CNN-based systems have achieved classification accuracies above 90% in differentiating glioma grades and even predicting molecular biomarkers such as IDH mutation and 1p/19q co-deletion (Chang et al., 2018; Osman, 2019). These AI tools often utilize radiomics features, deep features, or hybrid approaches for tumor classification. Some advanced systems incorporate clinical and genomic data, contributing to radiogenomics models that can non-invasively predict molecular subtypes from imaging alone. Such tools can support decision-making in cases where biopsy is contraindicated or surgical access is limited.

While brain tumors are often diagnosed only after the onset of clinical symptoms, AI holds potential in facilitating early detection especially in high-risk populations or incidental findings. Algorithms capable of scanning large datasets for subtle or early-stage abnormalities could enable opportunistic screening, particularly when integrated into routine head imaging workflows. Studies have shown that AI models can detect small or asymptomatic lesions that are easily overlooked by radiologists, suggesting a role in early triage, incidentaloma evaluation, or as part of population health strategies (Jun, 2024; Lui et al., 2020). However, the rarity of brain tumors and the lack of large-scale screening programs remain challenges for developing and validating such tools in a clinical context.

Multiple studies have assessed how AI models compare to human radiologists in brain tumor diagnostics. In segmentation tasks, AI systems have demonstrated equivalent or superior accuracy to neuroradiologists, with significantly reduced processing time (Bathla et al., 2021). For classification tasks, models trained on curated datasets can match or outperform expert performance particularly in consistency and sensitivity although real-world generalizability remains a concern. Importantly, AI tools are best viewed as assistive technologies that augment human expertise rather than replace it. Integration into clinical practice must consider workflow design, user trust, and explainability. Tools that offer visual outputs (e.g., saliency maps or heatmaps) and decision support dashboards are more likely to be adopted and trusted in radiological workflows (Lundervold & Lundervold, 2019). Figure 2, shows applications of AI in Brain Tumor Detection.

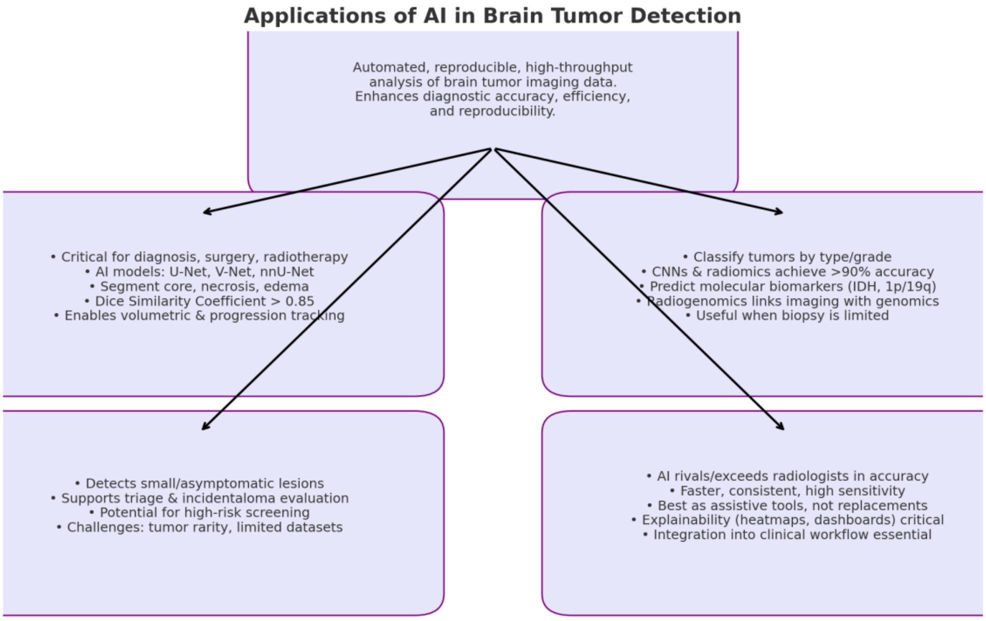

Figure 2. Applications of AI in Brain Tumor Detection

5. AI in Tumor Characterization and Prognosis

The characterization of brain tumors is essential for guiding treatment decisions, estimating prognosis, and personalizing therapeutic approaches. Traditionally, this has relied on histopathological examination following surgical biopsy or resection. However, non-invasive approaches using artificial intelligence (AI) have shown growing potential to predict tumor grade, molecular profile, and treatment outcomes from imaging data alone. This section explores the major AI applications in tumor grading, molecular classification, outcome prediction, and treatment response assessment.

5.1. Grade Prediction and Histopathologic Correlation

Tumor grade remains a critical factor in determining treatment aggressiveness and expected clinical trajectory. The 2021 WHO classification of CNS tumors places significant emphasis on integrated histopathological and molecular grading. AI models trained on multiparametric MRI (mpMRI) have demonstrated promising performance in predicting tumor grades non-invasively, thus aiding in pre-surgical decision-making. Studies utilizing radiomics and deep learning have reported high accuracy in distinguishing low-grade gliomas (LGG) from high-grade gliomas (HGG) based on texture, shape, and intensity features extracted from T1, T2, and FLAIR sequences (Zhou et al., 2018). These models are particularly useful when surgical access is risky or tissue sampling is inconclusive. Integration of advanced imaging such as perfusion and diffusion metrics further improves grading accuracy by capturing underlying tumor vascularity and cellularity(Kim et al., 2019; Park et al., 2020).

5.2. Molecular Subtype Classification Using Imaging Biomarkers

In modern neuro-oncology, molecular classification is indispensable for diagnosis and prognosis. Genetic alterations such as IDH mutation, 1p/19q co-deletion, and MGMT promoter methylation are now essential components of glioma classification. However, genetic testing is not always available or feasible, particularly in low-resource settings. AI models using radiomic features and deep learning architectures have achieved significant success in predicting these molecular markers from imaging data. For instance, Chang et al. (2018) demonstrated that CNNs trained on mpMRI could classify IDH mutation status with accuracies exceeding 85%. Similarly, other studies have developed radiogenomic models to predict 1p/19q status, ATRX loss, and TP53 mutation, using features such as contrast enhancement, tumor heterogeneity, and border sharpness (Osman, 2019). Such non-invasive molecular profiling supports precision medicine, enabling tailored therapies and reducing dependence on invasive procedures.

5.3. Prognostic Modeling and Outcome Prediction

Prognostic assessment plays a key role in determining treatment intensity and counseling patients. AI-driven prognostic models integrate imaging features, clinical data (e.g., age, performance status), and molecular markers to predict survival, recurrence risk, and progression-free intervals. Machine learning algorithms such as random forests, gradient boosting machines, and deep neural networks have been trained on large imaging datasets (e.g., BraTS, TCGA) to forecast overall survival in glioma patients with good accuracy (Kickingereder et al., 2019). Some models generate risk scores or nomograms to stratify patients into low-, intermediate-, and high-risk categories. Importantly, the explainability and interpretability of these models are crucial for clinical adoption. Tools like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) help clinicians understand the contribution of individual features to model predictions.

5.4. Response Monitoring and Treatment Planning

Assessing treatment response in brain tumors remains a major clinical challenge, especially in distinguishing true progression from pseudoprogression or radiation necrosis. AI-based tools can aid in early and accurate response monitoring using both anatomical and functional imaging. For example, models using serial MRI data have been developed to detect subtle changes in tumor volume, texture, and perfusion that may indicate treatment efficacy or failure earlier than conventional radiological criteria (Kickingereder et al., 2019). Advanced deep learning architectures can also integrate multimodal inputs (e.g., T1-Gd, FLAIR, DWI, PWI) to provide a more holistic view of treatment response. In radiotherapy planning, AI-based segmentation ensures precise target delineation and helps in adaptive radiotherapy, where treatment plans are modified based on changes observed during therapy. Furthermore, AI-assisted prediction of radiation sensitivity or chemotherapy response holds promise for guiding personalized therapeutic regimens.

6. Challenges and Limitations

Despite the growing promise of artificial intelligence (AI) in neuro-oncological imaging, numerous technical, clinical, and ethical challenges hinder its widespread clinical integration. From limitations in data availability to concerns about model transparency and regulatory frameworks, these issues must be addressed to ensure safe, effective, and equitable deployment of AI tools in real-world settings. High-performing AI models require large, diverse, and high-quality datasets for training and validation. In neuro-oncology, acquiring such datasets is challenging due to the rarity of brain tumors, variability in imaging protocols, and patient privacy concerns. Many public datasets (e.g., BraTS, TCIA) are relatively small, homogeneous, or institution-specific, limiting their representativeness of global clinical populations (Menze et al., 2014). Moreover, the creation of annotated datasets is labor-intensive, relying on expert radiologists or pathologists to delineate tumor boundaries and provide ground-truth labels. These annotations are subject to interobserver variability, introducing label noise and bias into the training process. Over-reliance on single-center datasets can also result in overfitting and poor model generalization.

A major limitation of current AI models is their limited generalizability across institutions, scanners, and populations. Models trained on data from one hospital or imaging protocol may perform poorly when applied to external datasets due to variations in scanner hardware, acquisition parameters, and patient demographics a phenomenon known as the domain shift (Yamashita et al., 2018). Efforts to improve generalizability include data augmentation, domain adaptation, and federated learning, which allows models to be trained collaboratively across institutions without sharing patient data. However, these approaches are still in early stages, and external validation remains a critical requirement before clinical adoption.

Many AI models, particularly those based on deep learning, operate as “black boxes”, providing predictions without easily interpretable explanations. In clinical practice, this lack of transparency raises significant concerns for trust, accountability, and decision validation, particularly when AI outputs conflict with radiologist assessments (Doshi-Velez & Kim, 2017). To address this, researchers are developing explainable AI (XAI) methods such as Grad-CAM, saliency maps, and SHAP values, which highlight the input regions or features most responsible for a given prediction. While these tools improve insight into model behavior, they do not always offer clinically actionable explanations, and standard guidelines for interpretability are lacking.

The deployment of AI tools in clinical environments involves navigating complex regulatory pathways and ethical considerations. Medical AI systems must be approved by regulatory bodies such as the U.S. FDA or the European Medicines Agency (EMA), requiring robust evidence of safety, effectiveness, and reproducibility. However, existing frameworks are not fully adapted to the dynamic and self-updating nature of AI models (Topol, 2019). Ethical challenges include concerns about algorithmic bias, data privacy, informed consent, and liability in case of diagnostic error. Models trained on non-representative datasets may inadvertently perpetuate health disparities by underperforming on minority or underserved populations (Char et al., 2018). Finally, clinical integration is hindered by the need for infrastructure upgrades, training of healthcare providers, and alignment with existing workflows. Without seamless interoperability and clinician buy-in, even technically robust AI tools may fail to achieve impact at the bedside.

7. Emerging Trends and Future Directions

The integration of artificial intelligence (AI) into neuro-oncological imaging is progressing rapidly, driven by advances in algorithmic methods, data sharing, and translational research. As technical challenges are addressed and clinical infrastructure matures, several key trends are poised to shape the next generation of AI applications in brain tumor diagnosis and management. This section discusses four critical areas of innovation: federated learning, multimodal integration, explainable AI, and real-time applications.

One of the most significant barriers to building robust AI models is access to large, diverse, and annotated datasets. Federated learning is an emerging paradigm that enables collaborative model training across multiple institutions without sharing raw patient data (Sheller et al., 2020). Instead, local models are trained independently, and only model weights or gradients are aggregated on a central server. In neuro-oncology, federated approaches allow for the development of AI systems that generalize across scanners, protocols, and populations critical for deployment in real-world settings. Projects like FeTS (Federated Tumor Segmentation) and Federated BraTS have demonstrated the feasibility of this model in brain tumor segmentation, showing comparable performance to models trained on pooled data while preserving data privacy (Wang et al., 2017). Federated learning also facilitates international collaboration, promoting equity in AI development by including institutions from low- and middle-income countries in the training loop.

The convergence of imaging, genomics, and clinical metadata is ushering in a new era of multimodal AI. By combining structural and functional imaging with genomic profiles (e.g., IDH mutation, MGMT methylation), electronic health records, and pathology data, AI models can generate more comprehensive, biologically informed predictions. Multimodal models have been shown to outperform unimodal counterparts in tumor grading, molecular subtype classification, and survival prediction (Senders et al., 2018). For example, hybrid deep learning architectures can process imaging data via CNNs and clinical variables via fully connected networks, improving prognostic accuracy. The field of radiogenomics exemplifies this trend by linking image-based phenotypes to genetic alterations, potentially enabling personalized therapy without invasive biopsy (Zhou et al., 2018). These approaches are also well-suited to AI-driven clinical decision support systems (CDSS), which integrate diverse inputs to assist with diagnosis, risk stratification, and treatment planning.

As AI models become more complex, the need for transparency and interpretability in clinical applications has grown. Explainable AI (XAI) techniques are designed to make model decisions understandable to clinicians, enhancing trust, accountability, and regulatory compliance.

Popular XAI methods in medical imaging include:

Saliency maps and Grad-CAM for visualizing important image regions

SHAP (SHapley Additive exPlanations) for feature-level insights

Counterfactual explanations for simulating decision changes

In neuro-oncology, XAI has been used to highlight tumor regions contributing to diagnosis or to interpret why certain features predict poor prognosis (Lundberg & Lee, 2017). However, there remains a tension between model performance and interpretability, and no consensus exists on which XAI methods are best suited for clinical deployment. Future work will likely involve standardizing interpretability metrics, integrating XAI into user interfaces, and validating explanations with clinician feedback.

A major frontier in neuro-oncological AI is the transition from research settings to real-time, point-of-care (POC) clinical use. This involves embedding AI tools into Picture Archiving and Communication Systems (PACS), radiology workstations, and electronic health record (EHR) platforms for seamless integration. Edge computing and lightweight models (e.g., MobileNet, EfficientNet) are enabling faster inference times, making it feasible to provide instant diagnostic support in resource-constrained environments. Such systems could assist in emergency triage, surgical planning, or intraoperative imaging, especially where specialist access is limited (Esteva et al., 2019). Real-time applications are particularly relevant in settings like tele-neurooncology, where AI tools can aid remote radiologists in evaluating urgent scans. However, ensuring robustness, minimizing false positives/negatives, and navigating regulatory approvals remain key hurdles before full-scale adoption.

8. Conclusion

Artificial intelligence is reshaping the landscape of neuro-oncological imaging, offering promising solutions to longstanding challenges in the detection and characterization of brain tumors. This review highlights how AI, particularly through machine learning and deep learning approaches, has demonstrated high accuracy in tumor segmentation, classification, and molecular profiling, all while reducing the reliance on time-consuming manual interpretation. The ability of AI models to predict key biomarkers such as IDH mutation and MGMT promoter methylation from imaging data supports the growing role of non-invasive, image-based diagnostics in personalized neuro-oncology. Additionally, emerging innovations such as federated learning, multimodal data integration, and explainable AI are actively addressing critical barriers to clinical adoption, including data privacy, generalizability, and interpretability. However, despite these advancements, significant work remains to ensure the safe, equitable, and effective deployment of AI systems in real-world settings. To bridge the gap between research and practice, future efforts must prioritize prospective validation, robust regulatory pathways, and clinician engagement through training and education. Ultimately, with responsible development and interdisciplinary collaboration, AI has the potential to become a valuable and trusted tool that enhances diagnostic accuracy, supports clinical decision-making, and improves patient outcomes in the management of brain tumors..

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