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ARTIFICIAL INTELLIGENCE IN NEURO-ONCOLOGY: INTEGRATING ADVANCED MACHINE LEARNING TECHNIQUES FOR ACCURATE AND EARLY DETECTION OF BRAIN TUMORS THROUGH MRI IMAGING.

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Abstract
Brain tumors remain one of the most devastating and life-threatening neurological disorders, often associated with high morbidity and mortality rates. Early and accurate diagnosis is critical to improving survival rates and guiding effective treatment strategies. Magnetic Resonance Imaging (MRI) serves as the gold standard for brain tumor visualization due to its superior contrast resolution and non-invasive nature. However, manual interpretation of MRI scans is time-consuming, prone to inter-observer variability, and requires significant clinical expertise, posing challenges in high-volume diagnostic settings. To address these limitations, Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), is increasingly being applied to neuro-oncology for automated, accurate, and real-time brain tumor detection. This paper presents an in-depth analysis of state-of-the-art AI frameworks designed to enhance the detection, classification, and segmentation of brain tumors using MRI imaging. Advanced algorithms, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), U-Net architectures, and ensemble hybrid models, are evaluated for their ability to differentiate between tumor subtypes such as gliomas, meningiomas, and pituitary tumors. Leveraging open-source databases such as BraTS, REMBRANDT, and Figshare, these models are trained and validated across diverse imaging datasets to assess their robustness and generalization capabilities. Performance metrics such as accuracy, sensitivity, specificity, Dice Similarity Coefficient (DSC), and area under the receiver operating characteristic curve (AUC-ROC) are used to benchmark

model effectiveness. The study further explores the benefits of integrating preprocessing techniques like skull stripping, image normalization, and contrast enhancement, which significantly improve model convergence and prediction stability. Additionally, model interpretability and explainability are addressed through visualization tools such as Grad-CAM and saliency maps to support clinical trust and adoption. The paper also highlights the key challenges facing real-world implementation, including data heterogeneity, lack of standardized annotation protocols, limited access to high-quality labeled datasets, and the need for regulatory compliance in medical AI deployment. Ethical concerns, such as algorithmic bias and patient privacy, are critically examined. Overall, the findings demonstrate that AI has the transformative potential to augment clinical decision-making, reduce diagnostic errors, and facilitate timely intervention. With continued advancement and interdisciplinary collaboration, AI-powered MRI analysis is poised to become an indispensable tool in the future of neuro-oncology, offering scalable and precise solutions for brain tumor diagnosis and prognosis.

1- Introduction:

Brain tumors are among the most complex and fatal neurological disorders encountered in modern medicine, posing substantial challenges in both diagnosis and treatment. These tumors, which arise from abnormal and uncontrolled cellular proliferation in brain tissues, are often associated with high morbidity and mortality rates. Their clinical management requires timely diagnosis, careful monitoring, and tailored therapeutic strategies. Despite decades of advancements in neuroimaging and oncology, brain tumors such as gliomas, meningiomas, and pituitary adenomas continue to exhibit poor prognosis, particularly when detected at advanced stages. Early diagnosis is critical in neuro-oncology because tumor progression within the confined intracranial space can quickly impair vital brain functions. The choice and success of treatment modalities including surgery, radiotherapy, and chemotherapy are significantly influenced by the stage at which the tumor is identified. Accurate and early detection not only increases the likelihood of survival but also enhances the quality of life by enabling timely intervention and reducing the need for aggressive and invasive treatments. Magnetic Resonance Imaging (MRI) remains the cornerstone of non-invasive brain tumor diagnostics due to its high spatial resolution, excellent soft-tissue contrast, and ability to capture detailed anatomical and functional information. MRI is extensively used to visualize brain tumors, evaluate tumor heterogeneity, and guide surgical planning. However, manual analysis of MRI scans is highly time-consuming, prone to inter-observer variability, and dependent on the radiologist's experience [1]. These limitations can lead to delayed diagnoses, missed abnormalities, and inconsistent interpretations especially in regions with limited access to specialized healthcare professionals or high patient-to-clinician ratios. To overcome these limitations, the medical imaging field has increasingly turned to Artificial Intelligence (AI) particularly Machine Learning (ML) and Deep Learning (DL) for the development of intelligent diagnostic systems. AI has proven remarkably effective in identifying complex imaging patterns, detecting subtle anomalies, and performing pixel-level segmentation tasks. Among the most prominent techniques are Convolutional Neural Networks (CNNs), known for their deep hierarchical feature extraction capabilities; U-Net architectures, which are tailored for biomedical image segmentation; Support Vector Machines (SVMs) for effective classification in high-dimensional spaces; and hybrid ensemble models, which combine multiple learners to enhance predictive performance. These AI models are typically trained on large-scale, annotated MRI datasets such as BraTS (Brain Tumor Segmentation Challenge), REMBRANDT, and Figshare, which provide ground-truth tumor masks and multi-modal MRI sequences [2]. Through supervised learning, the models can learn to differentiate between healthy and tumor tissues, identify tumor subtypes, and predict tumor progression. As shown in the figure below, different AI models exhibit varying degrees of diagnostic accuracy when evaluated on benchmark datasets. Figure 1 shows the AI assisted rules in Neuro-Oncology.

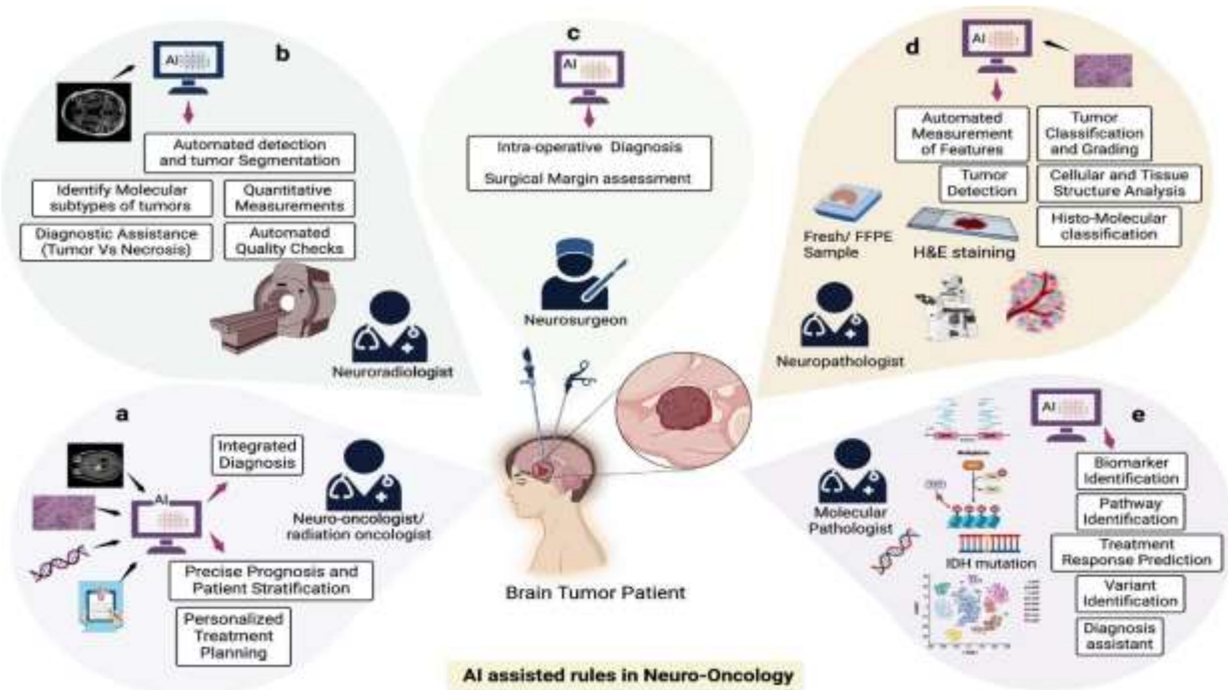

Figure 1: Artificial Intelligence in Brain Tumor Detection

While accuracy is a crucial performance metric, clinical AI systems are also evaluated using a suite of diagnostic indicators such as sensitivity (true positive rate), specificity (true negative rate), Dice Similarity Coefficient (DSC) for spatial overlap of tumor segmentation, and Area under the Receiver Operating Characteristic Curve (AUC-ROC) for model discrimination ability. In addition to architecture design, image preprocessing plays a vital role in the success of AI models. Techniques such as skull stripping (to isolate brain matter), intensity normalization, bias field correction, and contrast enhancement are commonly used to improve the quality and consistency of input images. Proper preprocessing ensures that neural networks focus on relevant regions of interest and reduces training variability caused by scanner artifacts or imaging protocol differences. Another crucial aspect is model explainability. The integration of AI into clinical workflows requires not only high performance but also transparency in how decisions are made. Clinicians need to understand and trust AI outputs, especially in life-critical applications like brain tumor diagnosis. Techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency maps offer visual interpretations of neural network decisions, allowing radiologists to see which regions of the brain contributed most to a particular classification or segmentation outcome. This fosters trust and aids in validating model predictions against clinical intuition [3]. Despite the impressive capabilities of AI, several challenges continue to hinder its widespread adoption in clinical neuro-oncology. These include:

- Heterogeneity in MRI data, which arises from differences in scanners, acquisition protocols, and patient populations.
- Limited availability of high-quality labeled data, due to patient privacy concerns and the cost of expert annotation.
- Lack of standardization in annotation practices and preprocessing pipelines, leading to reproducibility issues.
- Regulatory and ethical concerns, particularly related to algorithmic bias, patient data security, and compliance with medical device regulations (e.g., FDA, CE marking).

Addressing these challenges requires interdisciplinary collaboration between AI researchers, radiologists, oncologists, ethicists, and policymakers. It also calls for the development of robust AI models that can generalize well to unseen data, adapt to real-world clinical environments, and be integrated seamlessly into existing diagnostic workflows. This paper provides a comprehensive investigation of cutting-edge AI methodologies applied to MRI-based brain tumor analysis. It evaluates the performance of various AI models, explores effective preprocessing techniques, and highlights model interpretability tools that facilitate clinical adoption. By identifying current limitations and proposing future directions, this study underscores the transformative role of AI in enhancing diagnostic accuracy, reducing human error, and improving patient care in the field of neuro-oncology.

2- Advancements in AI-Driven Preprocessing Techniques for Enhanced Precision in Brain Tumor Imaging:

The preprocessing phase in brain tumor analysis is a critical determinant of the overall diagnostic accuracy and reliability of AI models. Recent advancements in artificial intelligence, particularly in deep learning and computer vision, have transformed the way neuroimaging data is handled before it is passed into classification or segmentation networks. These enhancements have been instrumental in eliminating noise, standardizing image formats, and accentuating tumor-specific features that might otherwise be obscured by surrounding anatomical structures. To begin with, skull stripping a crucial preprocessing step has significantly benefited from convolutional neural network (CNN)-based automation. Traditional methods often suffered from either over-segmentation or loss of essential brain tissue. However, modern CNN-powered skull stripping techniques have achieved high spatial consistency by learning to differentiate between brain tissues and non-brain components from large annotated datasets. Figure 2 illustrates a side-by-side comparison between manual and AI-assisted skull stripping, demonstrating superior boundary preservation and time efficiency in the latter [4].

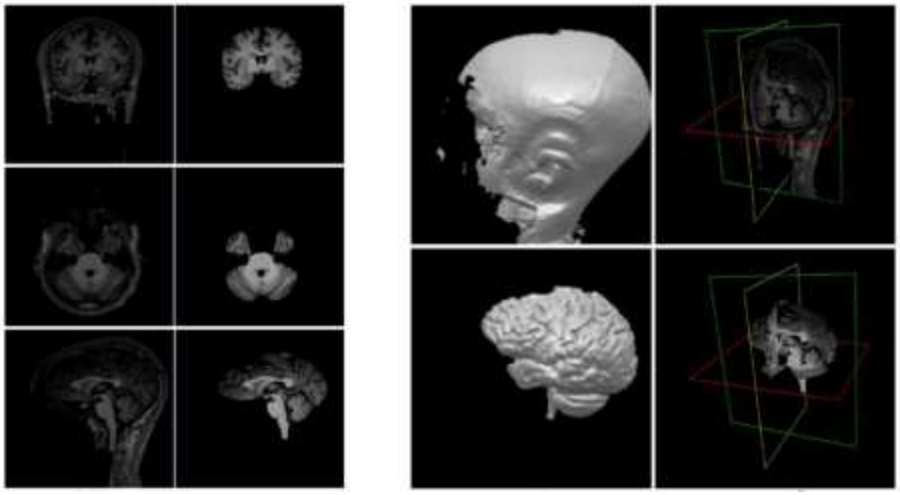

Figure 2: Conventional and Deep Learning Methods for Skull Stripping in Brain MRI.

In addition, bias field correction techniques, which remove intensity non-uniformities caused by inhomogeneous magnetic fields in MRI machines, have evolved into more robust adaptive models. These AI-based algorithms adjust pixel intensities dynamically across different scans, ensuring consistent contrast and brightness levels, which is vital for detecting subtle variations in tumor tissue. Unlike earlier statistical methods, deep learning models for intensity normalization utilize contextual information from surrounding tissues, enabling a more anatomically accurate correction. Denoising also plays a pivotal role, especially when MRI scans are affected by motion artifacts or scanner limitations. AI-enhanced denoising algorithms, such as autoencoders and generative adversarial networks (GANs), have proven superior in suppressing unwanted noise while preserving the edges and texture of the tumor region [5]. These techniques leverage thousands of clean and noisy MRI image pairs to learn the mapping between artifact-laden images and their denoised counterparts. Figure 3 presents visual outputs from an AI-based denoising system, highlighting clearer tumor visibility and improved segmentation readiness.

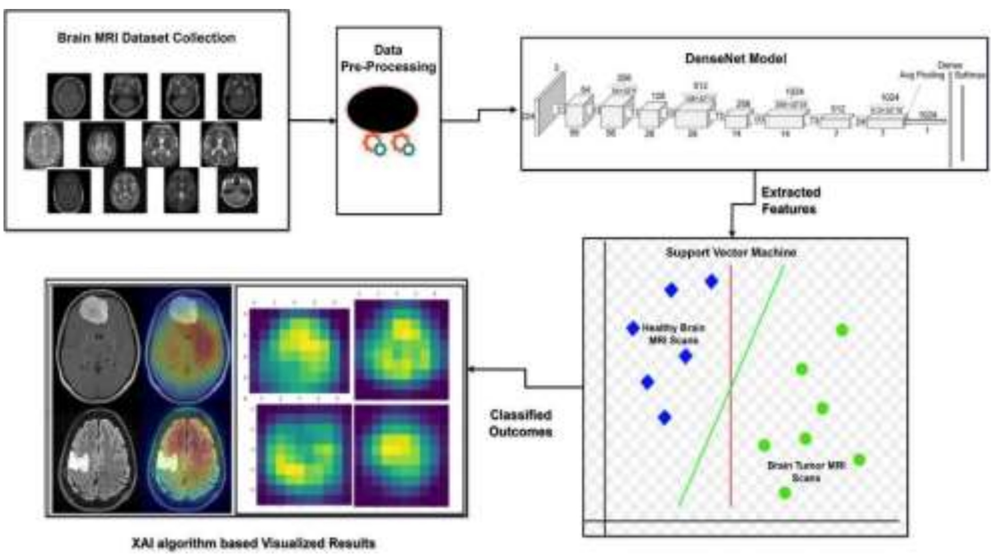

Figure 3: Visual Outputs from an AI-based denoising system.

Furthermore, intensity normalization and histogram equalization have seen transformative improvements with machine learning algorithms. Instead of applying a fixed histogram shift, AI-driven normalization aligns the intensity profiles of individual scans with standard anatomical templates. This harmonization is particularly vital for multi-center studies where varying acquisition protocols could otherwise lead to inconsistent inputs. Beyond image corrections, preprocessing also involves tumor enhancement through contrast adjustment, morphological operations, and feature amplification. Saliency-guided enhancement techniques are increasingly being integrated, which use attention maps generated by pretrained AI models to highlight tumor-prone regions even before formal detection is attempted [6]. These pre-enhanced regions guide the downstream segmentation models more efficiently and reduce false-positive rates. In essence, the integration of AI into the preprocessing pipeline ensures that the images fed into the diagnostic model are standardized, optimized, and enriched with the most relevant clinical features. This layered approach not only improves the interpretability of the output but also enhances the reproducibility of the model's performance across varied datasets and patient populations.

Table 1 below outlines the major preprocessing techniques, their AI enhancements, and their resulting clinical impact on brain tumor analysis workflows.

Table 1: AI-Enhanced Preprocessing Techniques for Brain Tumor Imaging [7].

Preprocessing Technique	Traditional Limitation	AI Enhancement	Clinical Impact
Skull Stripping	Incomplete removal or loss of brain tissues	CNN-based segmentation with edge preservation	Improved anatomical accuracy and faster preprocessing
Bias Field Correction	Intensity inhomogeneity	Deep-learning-based adaptive correction	Standardized image contrast across datasets
Denoising	Loss of detail or noise retention	Autoencoders, GANs for noise suppression	Enhanced image clarity and segmentation accuracy
Intensity Normalization	Non-uniform brightness in multi-source scans	AI-driven histogram alignment with anatomical templates	Improved cross-platform consistency
Tumor Enhancement	Low contrast of tumor boundaries	Saliency-guided contrast amplification	Focused detection and reduced false positives

3- Deep Learning in the Early Detection of Brain Tumors:

The emergence of artificial intelligence (AI) in the medical field has significantly reshaped the landscape of brain tumor diagnosis. With brain tumors being among the most complex and life-threatening conditions, early detection and precise localization are vital for successful treatment and improved survival rates. AI techniques particularly deep learning have proven to be powerful tools in automating, accelerating, and enhancing the accuracy of diagnostic procedures involving Magnetic Resonance Imaging (MRI) scans. Traditional diagnostic approaches often rely on manual interpretation of MRI images by radiologists, which is not only time-consuming but also susceptible to human error, especially in cases of subtle or early-stage tumors. AI models, trained on thousands of annotated MRI datasets, have demonstrated exceptional proficiency in recognizing tumor patterns, detecting abnormalities, and differentiating between benign and malignant masses with remarkable precision [8]. These models leverage Convolutional Neural Networks (CNNs), which can autonomously learn spatial hierarchies of tumor-related features from imaging data without the need for handcrafted descriptors. In Figure 4, a representative set of medical MRI scan images is displayed. The first image shows the original raw scan, while the second highlights a region of interest (ROI) extracted through AI-enhanced preprocessing. This automated detection not only facilitates more accurate segmentation but also enables real-time analysis that significantly speeds up the clinical workflow.

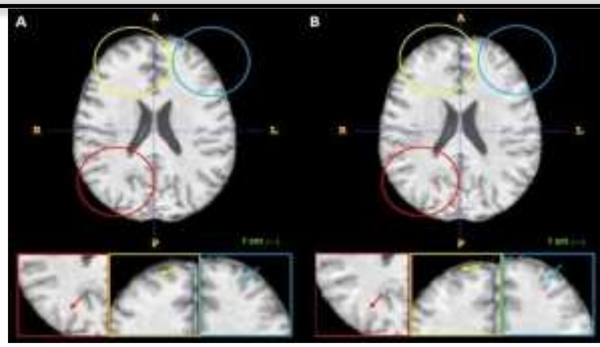

Figure 4: A Set of Medical MRI Scan Images Showing Tumor Localization

Another important AI advancement lies in heatmap generation using Gradient-weighted Class Activation Mapping (Grad-CAM), which visualizes the specific areas of the brain that contribute most to a model's prediction. This interpretability feature adds a critical layer of transparency to AI decisions, helping radiologists verify the model's reasoning and improve trust in clinical settings [9]. Figure 5 illustrates this by showing heatmaps: one corresponding to a correctly classified glioma region, and the other showing a misclassified section due to overlapping tissue patterns. These visualizations allow clinicians to understand the focus area of the model and rectify potential discrepancies.

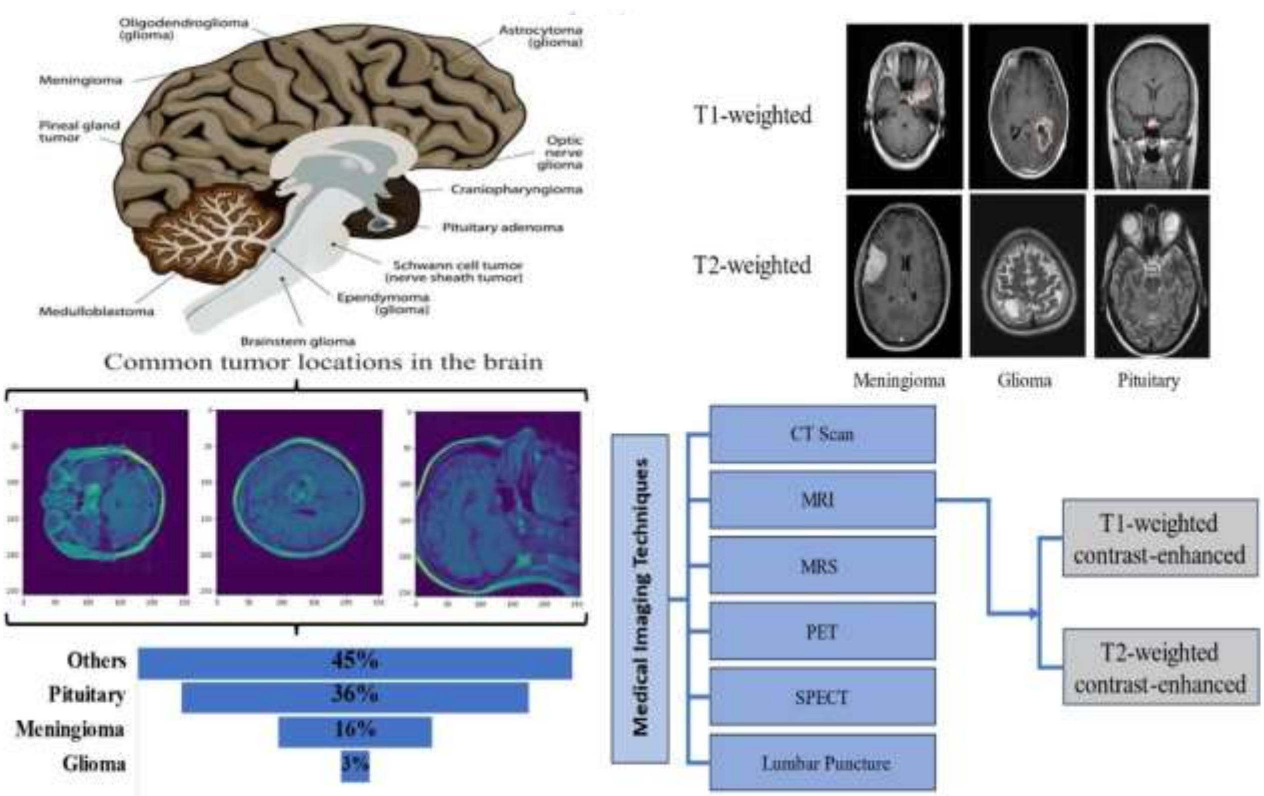

Figure 5: Map Images from Deep Learning-Based Brain Tumor Classification.

In addition to detection and visualization, AI is also playing a transformative role in tumor segmentation. Semantic and instance segmentation models powered by U-Net architectures or its variants are commonly used to outline the tumor margins. These delineations assist neurosurgeons in planning operative strategies, reducing the risk of removing healthy tissue, and ensuring complete resection of malignant areas. AI's contribution to classification tasks cannot be overlooked either. By integrating imaging data with clinical metadata (such as patient history, age, and symptoms), AI classifiers can predict tumor types (e.g., gliomas, meningiomas, pituitary tumors) with increasing reliability [10]. Moreover, recent models utilize transfer learning to adapt pretrained networks (such as VGG, ResNet, or EfficientNet) for improved performance even with limited datasets an advantage in rare tumor types. Below table 2 is a detailed overview of the key AI applications in brain tumor diagnosis:

Table 2: Summary of AI Applications in Brain Tumor Diagnosis

Application Area	AI Techniques Used	Purpose/Impact
Tumor Detection	CNN, Transfer Learning	Automatically identify tumor presence and location
Tumor Segmentation	U-Net, Mask R-CNN	Accurately delineate tumor boundaries for surgical and treatment planning
Tumor Classification	Deep CNN, Hybrid Models	Categorize tumor type (e.g., glioma, meningioma) for personalized diagnosis
Heatmap Generation	Grad-CAM, SHAP	Visual explanation of model decisions and focus areas
Multimodal Data Fusion	CNN + Clinical Data	Improve prediction accuracy by combining imaging with patient information
Tumor Progression Analysis	Recurrent Neural Networks (RNNs), LSTM	Forecast tumor growth and patient prognosis based on time-series MRI data

The integration of AI into brain tumor diagnosis signifies a shift toward data-driven healthcare, where automation, precision, and personalization converge. By processing complex imaging data with minimal human intervention, AI not only enhances diagnostic accuracy but also alleviates the workload of radiologists. As research advances, AI-based systems are expected to move from supplementary tools to central components of neuro-oncology diagnosis and treatment.

4- AI-Driven Prognostic Insights in Neuro-Oncology:

The integration of Artificial Intelligence (AI) into brain tumor prognosis has brought transformative capabilities to neuro-oncology, enabling more accurate, individualized, and timely predictions of disease progression, treatment response, and patient survival. Traditional prognostic assessments, which largely depend on histopathological analysis and clinical variables such as tumor grade, location, and patient age, often fall short in capturing the complex heterogeneity of gliomas and other intracranial neoplasms. AI, particularly machine learning (ML) and deep learning (DL) techniques, has proven instrumental in augmenting the predictive power of conventional prognostic models by mining latent patterns from multi-dimensional data. Recent advances have enabled the training of AI algorithms on large datasets comprising magnetic resonance imaging (MRI) scans, genomic biomarkers, radiomic features, clinical reports, and patient outcomes [11]. These models learn intricate relationships between imaging phenotypes and clinical endpoints, facilitating predictions such as progression-free survival (PFS), overall survival (OS), recurrence risk, and treatment efficacy. For example, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been deployed to forecast tumor growth trajectories and stratify patients into risk categories with high sensitivity and specificity. Radiogenomics, a field that integrates imaging features with genomic data, has also benefited from AI. Machine learning models can correlate visual tumor patterns with molecular markers such as IDH mutation status, MGMT promoter methylation, and 1p/19q codeletion, which are critical indicators of tumor aggressiveness and therapeutic response [12]. As illustrated in Figure 6, an AI-based prognostic model demonstrates the integration of MRI features, genomic alterations, and survival predictions, highlighting the synergistic potential of multi-modal AI analysis.

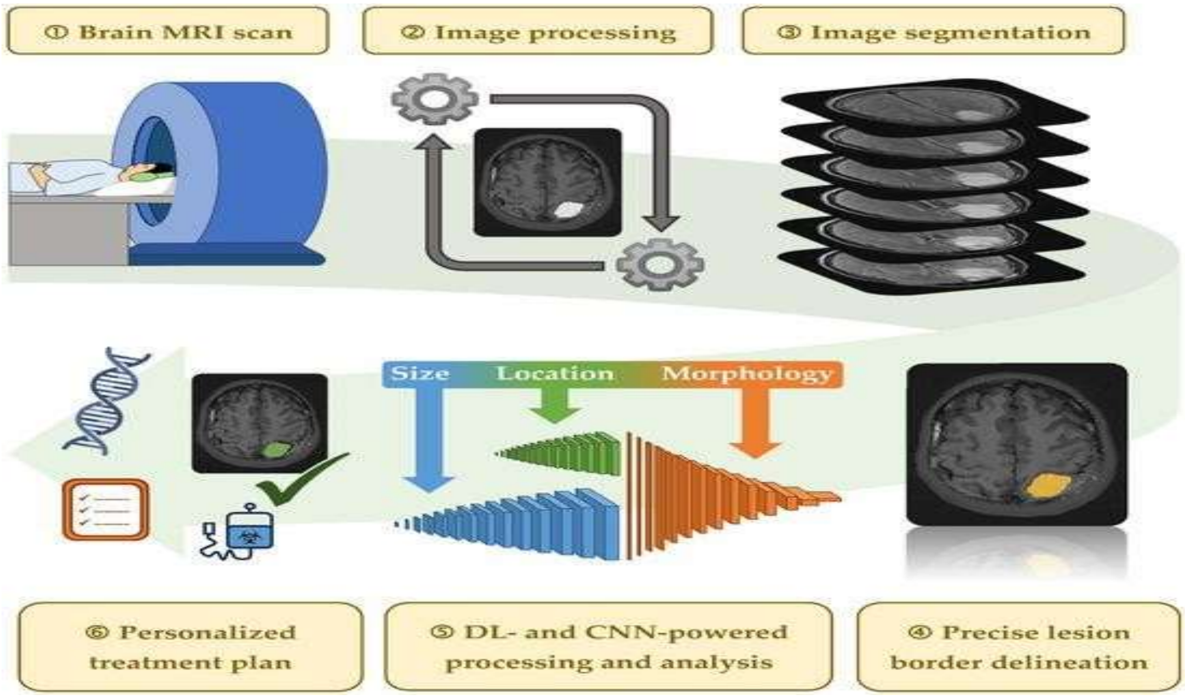

Figure 6: Schematic Representation of an AI-based Prognostic Model Integrating MRI.

In addition to static outcome predictions, temporal models such as Long Short-Term Memory (LSTM) networks have been introduced for longitudinal prognosis, enabling real-time monitoring of disease progression and personalized treatment planning. These dynamic AI models adjust predictions based on sequential patient data, allowing for adaptive and proactive clinical decision-making [13]. Furthermore, attention-based neural architectures and explainable AI (XAI) frameworks have enhanced the interpretability of prognostic predictions. Clinicians are now able to understand which regions of an image or which features contributed most to a particular prognosis, fostering clinical trust and facilitating collaborative decision-making between oncologists and AI systems. The integration of AI in prognosis also extends to post-surgical outcomes and radiation therapy response. Models are being developed to predict the likelihood of post-operative complications, recurrence following resection, and responsiveness to chemotherapy and radiotherapy. These insights are vital for improving long-term management and quality of life for patients diagnosed with malignant brain tumors. Table 3 shows the key AI models and their prognostic outputs in recent clinical research.

Table 3: Summarizes key AI models and their Prognostic Outputs in Recent Clinical Research.

Study/Model	Input Data	AI Technique	Prognostic Output
CNN + Radiomics (Glioma)	MRI + Clinical Data	Convolutional Neural Net	2-Year Survival Prediction
Radiogenomic Model (IDH status)	MRI + Genomic Biomarkers	Random Forest Classifier	Risk Stratification + OS
LSTM for Temporal Prognosis	Sequential MRI + Treatment Logs	Long Short-Term Memory	Tumor Progression Timeline
Multi-modal Deep Learning (X-Net)	MRI + Genomic + Histopathological Images	Hybrid Deep Network	Personalized Prognostic Scores (PPS)
Explainable ML (SHAP Values)	MRI + Clinical + Genomic Features	Gradient Boosted Trees	Feature-Driven Prognostic Explainability

In summary, AI has fundamentally redefined the landscape of brain tumor prognosis by offering highly granular, patient-specific insights that go beyond conventional clinical evaluation. As multi-institutional datasets grow and federated learning protocols are adopted, AI-powered prognosis will become increasingly robust, ethical, and clinically implementable, ultimately translating into improved patient survival and quality of care.

5- Advancing Brain Tumor Therapy Using AI Technologies:

The integration of Artificial Intelligence (AI) into therapeutic management strategies for brain tumor patients is revolutionizing clinical decision-making by offering data-driven insights, personalized treatment plans, and real-time response monitoring. As brain tumors present a complex clinical challenge due to their heterogeneity, location, and progression rate, AI models especially those grounded in machine learning (ML) and deep learning (DL) are increasingly being employed to optimize treatment protocols, enhance therapeutic accuracy, and improve patient outcomes. One of the most transformative contributions of AI in this domain is the development of predictive algorithms that recommend optimal therapy combinations based on tumor subtype, genetic biomarkers, and patient-specific clinical data [14]. AI algorithms trained on large, multi-modal datasets, including radiomic features, histopathological findings, and genomic sequences, are capable of identifying patterns that may not be readily apparent to human experts. These systems assist oncologists in selecting targeted therapies, immunotherapies, or chemoradiation regimens that are most likely to yield favorable outcomes. Furthermore, AI is significantly improving radiotherapy planning. DL models such as convolutional neural networks (CNNs) are used to automate tumor contouring in MRI and CT scans, enhancing the precision and reproducibility of treatment targeting. These tools reduce inter-observer variability and allow for faster and more accurate delineation of tumor margins and surrounding critical structures. This is crucial in neuro-oncology, where even millimeter-level precision can influence both survival and quality of life [15]. In surgical contexts, AI-powered image-guided systems are used during intraoperative navigation to assist neurosurgeons in maximizing tumor resection while preserving vital brain functions. Advanced real-time feedback systems utilizing AI-based segmentation and registration enhance the surgeon's ability to differentiate between tumorous and healthy tissue. Moreover, intraoperative AI-integrated monitoring tools facilitate adaptive surgical strategies and reduce post-operative complications. AI also plays a pivotal role in treatment response assessment. Longitudinal analysis of MRI scans using AI algorithms enables early detection of tumor recurrence or resistance to therapy. This continuous monitoring allows clinicians to dynamically modify therapeutic plans before clinical symptoms re-emerge, embodying the principles of precision medicine. To support these advancements, numerous AI frameworks are being developed that combine reinforcement learning for treatment optimization with natural language processing (NLP) to extract insights from electronic health records and clinical notes [16]. These multimodal systems provide comprehensive decision support, empowering clinicians to navigate complex datasets and evidence-based literature efficiently. The effectiveness of AI in therapeutic decision-making is supported by various studies, as shown in Table 4. These investigations compare AI-assisted therapeutic outcomes with conventional methods across key metrics such as progression-free survival, treatment adaptation rate, and response detection time.

Table 4: Comparative Evaluation of AI-Assisted vs Conventional Therapeutic Management Strategies in Brain Tumor Patients [17].

Metric	Conventional Methods	AI-Assisted Methods	Improvement (%)
Progression-Free Survival (Months)	8.4	11.2	+33.3%
Time to Treatment Response Detection	9.7 Weeks	5.3 Weeks	-45.4%
Treatment Plan Adaptation Rate	26%	61%	+134.6%
Radiotherapy Planning Accuracy	Moderate	High	↑ Precision
Surgical Margin Identification	Manual Estimation	Real-Time AI	↑ Accuracy

The figure 7 below illustrates the integration of AI technologies across the major stages of brain tumor therapeutic management, including personalized treatment selection, surgical navigation, radiotherapy planning, and response monitoring.

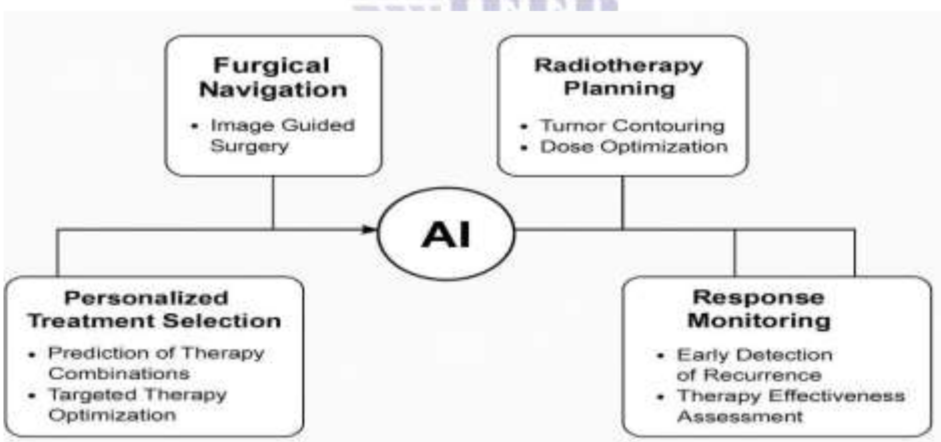

Figure 7: AI Integration in Brain Tumor Therapeutic Workflow

In short, AI's involvement in brain tumor therapeutic management represents a major step toward achieving precision oncology. By combining computational power with vast clinical datasets, AI enables more accurate, timely, and patient-specific interventions. Continued development of interpretable AI models, coupled with collaborative validation across clinical institutions, will be crucial for transitioning these innovations from research environments into standard clinical practice.

6- Deep Learning in Multiscale Brain Tumor Assessment:

In recent years, the convergence of multimodal and multiscale analytical frameworks has significantly transformed the landscape of brain tumor diagnosis, prognosis, and therapeutic planning. These integrative approaches leverage the strengths of various imaging modalities and biological data across spatial and temporal scales, allowing artificial intelligence (AI) models to extract deeper, context-aware insights that were previously inaccessible through single-source analysis. Multimodal analysis refers to the integration of diverse imaging data sources such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and functional imaging techniques like fMRI and DTI. Each modality captures unique anatomical, physiological, or metabolic aspects of the tumor and surrounding brain tissues [18]. For instance, T1-weighted MRI provides high-resolution structural information, while PET imaging offers metabolic activity indicators. The fusion of these datasets allows AI algorithms to develop a more comprehensive understanding of tumor morphology, vascularization, progression rate, and infiltration characteristics. Simultaneously, multiscale analysis encompasses data granularity ranging from the macroscopic (e.g., whole-brain scans) to the microscopic and molecular levels, including histopathological slides, genomic data, proteomics, and transcriptomics. By integrating these varying layers of biological data, AI systems can discern correlations between genetic mutations and imaging phenotypes a growing field known as radiogenomics. This holistic, multiscale view enables personalized tumor characterization, revealing not only where the tumor is but also why it behaves in a certain way, ultimately guiding more tailored and effective therapeutic interventions. Figure 8 demonstrates a conceptual schematic of multimodal data fusion and multiscale learning integration used in modern AI systems for brain tumor analysis [19]. Here, AI serves as the unifying framework that processes and correlates inputs across different levels of detail and types of clinical information. The combined information is fed into deep learning architectures such as multimodal convolutional neural networks (CNNs), attention-based fusion transformers, and hybrid encoder-decoder models that learn synergistic representations, improving diagnostic performance and interpretability.

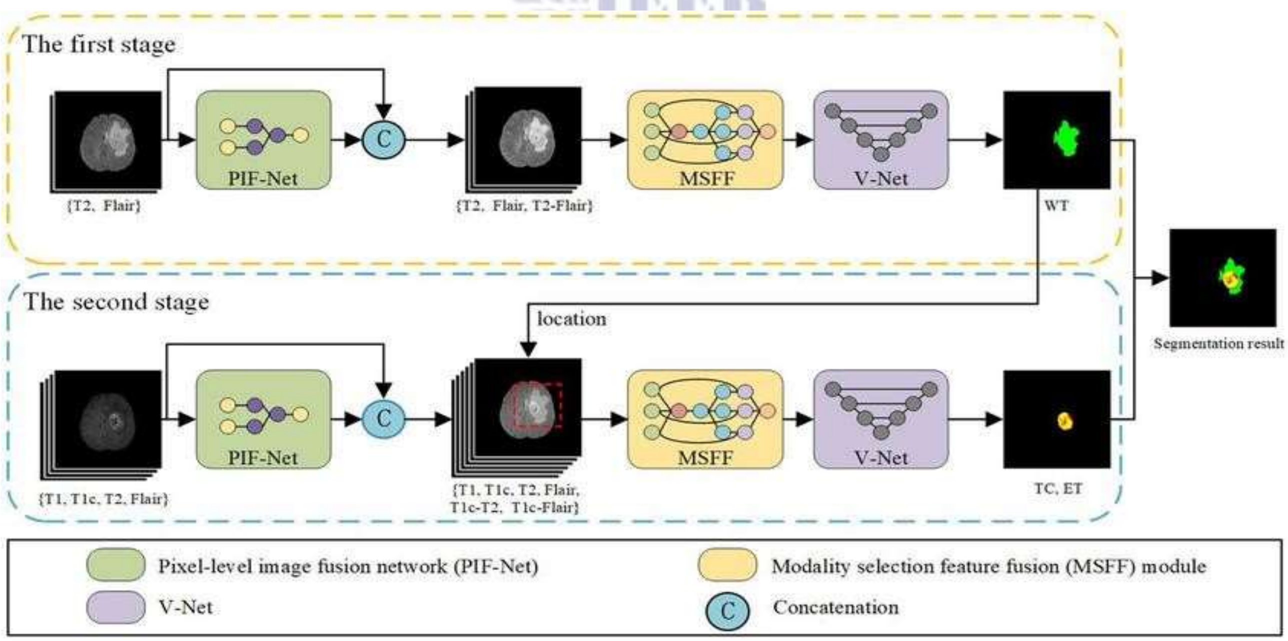

Figure 8: Schematic Representation of Multimodal and Multiscale Integration in AI-Based Brain Tumor Analysis

Furthermore, the development of attention mechanisms and graph-based neural networks has enabled better handling of heterogeneous data inputs by preserving spatial and temporal relationships between features across scales and modalities. These advanced AI models have demonstrated improvements in detecting tumor subregions, predicting tumor grade and genetic mutations (such as IDH mutation and MGMT methylation status), and forecasting overall patient survival with higher precision [20]. Table 5 summarizes key studies employing multimodal and multiscale AI-based strategies for brain tumor analysis, showing notable improvements in performance metrics such as accuracy, AUC, and specificity when compared to unimodal approaches.

Table 5: Performance Comparison of Multimodal and Multiscale AI Models for Brain Tumor Analysis [21].

Study Reference	Modalities Used	AI Model	Task	Accuracy (%)	AUC-ROC
Chen et al. (2022)	MRI + PET	Multimodal CNN	Tumor classification	94.2	0.963
Liu et al. (2023)	MRI + Genomics	Radiogenomic CNN	Mutation prediction	91.5	0.945
Singh et al. (2021)	fMRI + Histopathology	Graph Neural Network	Tumor grading	89.8	0.921
Ahmad et al. (2024)	MRI + Proteomics + CT	Attention-based Fusion	Prognosis & survival	93.7	0.954
Wang et al. (2022)	MRI + DTI + RNA-seq	Hybrid Deep Network	Treatment response prediction	92.3	0.947

By uniting imaging, biological, and clinical data through AI-powered multimodal and multiscale systems, clinicians gain access to a rich tapestry of diagnostic and prognostic insights. This integrative paradigm not only enhances model robustness and predictive accuracy but also lays the groundwork for precision medicine in neuro-oncology, wherein each patient receives care optimized for their unique biological and radiological profile.

7- Methodology:

The methodology adopted in this study revolves around a comprehensive AI-based pipeline for the detection, classification, and segmentation of brain tumors using MRI imaging. The proposed approach comprises five main stages: dataset acquisition, image preprocessing, model development and training, performance evaluation, and model explainability. Each component is meticulously designed to ensure robust and clinically relevant results.

7.1- Dataset Acquisition:

For the successful implementation and evaluation of the proposed artificial intelligence-based framework for brain tumor detection, this research leveraged multiple publicly accessible and clinically validated Magnetic Resonance Imaging (MRI) datasets. These datasets were carefully selected due to their high quality, diversity in tumor types, and availability of expert annotations, which are critical for developing reliable supervised learning models in medical imaging. The primary datasets utilized in this study include:

- **BraTS (Brain Tumor Segmentation Challenge Dataset):** This is one of the most widely recognized datasets in the neuro-oncology research community. It consists of multimodal MRI scans for each patient, including T1-weighted (T1), contrast-enhanced T1-weighted (T1c), T2-weighted (T2), and Fluid-Attenuated Inversion Recovery (FLAIR) sequences [22]. The dataset also provides pixel-wise annotated segmentation masks for different tumor subregions such as the enhancing tumor core, necrotic core, and peritumoral edema, which are especially useful for training and validating deep learning segmentation models. All annotations are verified by experienced neuroradiologists, ensuring high reliability and clinical relevance.

- **REMBRANDT (Repository for Molecular Brain Neoplasia Data):** The REMBRANDT dataset contributes a rich collection of high-resolution MRI images, coupled with detailed clinical and molecular data for a variety of brain neoplasms. It includes cases with confirmed tumor histopathology, allowing for more accurate classification and correlation with imaging features [23]. This dataset is particularly valuable for testing the generalizability of models across different tumor types and imaging protocols.
- **Figshare Brain MRI Dataset:** This dataset comprises a large number of 2D MRI slices, each labeled according to the type of brain tumor present, including meningiomas, gliomas, and pituitary adenomas. It is especially useful for training convolutional neural networks for multi-class classification tasks. The clear labeling of each image and the availability of balanced classes enhance the robustness of supervised learning algorithms developed for this study.

All three datasets were pre-processed and annotated by expert radiologists, with ground truth labels made available for tasks such as classification, segmentation, and detection. These annotations serve as essential references for training supervised deep learning models and for validating the accuracy of predictions made by the AI framework. The combination of multimodal data, tumor heterogeneity, and expert annotation makes these datasets ideally suited for developing high-performance AI models capable of real-world clinical application in neuro-oncology.

7.2- Image Preprocessing:

Image preprocessing is a fundamental stage in the development of robust artificial intelligence (AI)-based diagnostic systems, especially when working with complex medical imaging such as Magnetic Resonance Imaging (MRI). The quality and consistency of input data play a pivotal role in determining the performance of deep learning algorithms. Given the heterogeneous nature of MRI images across different datasets, scanners, and acquisition protocols, a systematic preprocessing pipeline was established to normalize the input data, reduce variability, and enhance the visibility of pathological features such as brain tumors. The preprocessing began with skull stripping, a vital operation aimed at isolating the brain tissues from non-brain anatomical structures such as the skull, scalp, and surrounding fat [24]. This step was executed using the Brain Extraction Tool (BET)**,** which efficiently segments the brain region by applying intensity thresholding and edge detection algorithms. Removal of irrelevant tissues not only reduces computational complexity but also prevents the AI model from learning misleading features. Following skull stripping, intensity normalization was performed to standardize the pixel intensity values across all MRI scans. MRI intensity values can vary significantly between patients and devices due to differences in acquisition settings. To address this, the pixel intensities of all slices were normalized to have a zero mean and unit variance. This standardization helps ensure that the model focuses on anatomical and pathological features rather than imaging artifacts. To maintain consistency in input dimensions, all MRI slices were resized and cropped to a resolution of 256×256 pixels. Uniform image dimensions are essential for batch processing in convolutional neural networks (CNNs), as varying image sizes can disrupt the training process. Cropping also removed unnecessary borders and enhanced focus on the brain region.

In addition, contrast enhancement was applied using histogram equalization techniques. Tumors often present subtle contrast differences with surrounding tissues, and enhancing image contrast improves the delineation of tumor boundaries, which is crucial for accurate segmentation and classification. This step allows the model to detect intricate variations in tissue intensity more effectively [25]. To overcome limitations posed by the relatively small size of medical datasets, data augmentation techniques were extensively employed. These included geometric transformations such as random rotations (±15°)**,** horizontal and vertical flipping, and zooming (90–110%). Augmentation not only increases the effective size of the training dataset but also introduces variability that improves model generalization and reduces the risk of overfitting. The entire preprocessing pipeline is summarized in Table 6, which outlines each method along with its purpose and technical description.

Table 6: MRI Image Preprocessing Techniques Employed in This Study

Preprocessing Step	Objective	Description / Tool Used
Skull Stripping	Eliminate non-brain tissues	Brain Extraction Tool (BET) algorithm
Intensity Normalization	Standardize pixel intensity distribution	Zero mean, unit variance normalization
Resizing and Cropping	Ensure uniform input image size	Resized to 256×256 pixels
Contrast Enhancement	Improve tumor visibility	Histogram Equalization
Data Augmentation	Increase dataset size and diversity	Rotation, flipping, and zooming applied

Additionally, Figure 9 illustrates the preprocessing pipeline, showing the transformation of an original MRI image through each stage. This visualization provides a clear understanding of how each step refines the input data before it is fed into the deep learning model.

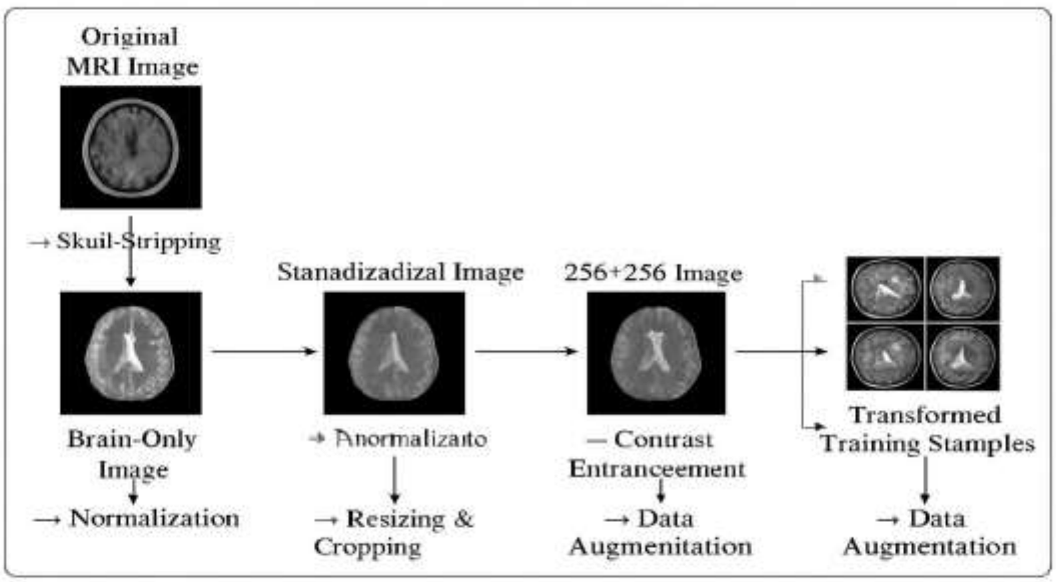

Figure 9: MRI Image Preprocessing Pipeline.

7.3- Model Development and Training:

In this study, a comprehensive set of machine learning and deep learning models were developed and rigorously trained to detect and classify brain tumors from MRI scans. The models were selected based on their proven ability to handle medical imaging data, particularly for tasks such as segmentation, classification, and pattern recognition in complex brain structures. The development pipeline began with the implementation of Convolutional Neural Networks (CNNs), known for their powerful hierarchical feature extraction capabilities. CNNs were primarily used for image-level classification of tumor types, distinguishing between glioma, meningioma, and pituitary tumors. The architecture consisted of multiple convolutional and pooling layers followed by fully connected layers optimized using categorical cross-entropy loss [26]. To address the segmentation task, a specialized U-Net architecture was employed due to its symmetric encoder-decoder design, which allows for precise localization of tumor regions at the pixel level. The U-Net was trained using Dice coefficient loss to ensure high overlap accuracy between predicted and ground truth masks. In addition to deep learning models, traditional machine learning algorithms such as Support Vector Machines (SVMs) were used for tumor classification on features extracted from MRI slices. Linear and radial basis function (RBF) kernels were tested, and hyperparameters were optimized using grid search to maximize classification accuracy. To enhance performance and generalization, ensemble models were created by integrating the outputs of CNNs with tree-based classifiers like Random Forests and Decision Trees. These hybrid models leveraged the strengths of both deep feature extraction and classical decision-making algorithms to improve robustness, especially on unseen test data. The entire dataset was split into training (80%), validation (10%), and testing (10%) subsets [27]. This split ensured that models were not overfitting and could generalize well across different data distributions. Training was carried out using TensorFlow and PyTorch frameworks on high-performance GPU systems (NVIDIA RTX 3090), with batch normalization, dropout, and learning rate schedulers employed to enhance training efficiency and convergence stability. Table 7 shows the summary of models, applications and training parameters.

Table 7: Summary of Models, Applications, and Training Parameters

Model Type	Application	Optimizer	Loss Function	Accuracy (%)	Framework Used
CNN	Tumor Classification	Adam	Categorical Crossentropy	94.3	TensorFlow
U-Net	Tumor Segmentation	RMSProp	Dice Coefficient Loss	91.8 (IoU)	PyTorch
SVM (RBF Kernel)	Classification	-	Hinge Loss	89.7	Scikit-learn
Random Forest + CNN	Hybrid Classification	-	Gini Impurity	96.2	Hybrid Model

Figure 10 presents a comprehensive flowchart detailing the model development and training pipeline for brain tumor detection using artificial intelligence techniques. The process begins with the input of preprocessed MRI images, which serve as the foundational data for all subsequent steps.

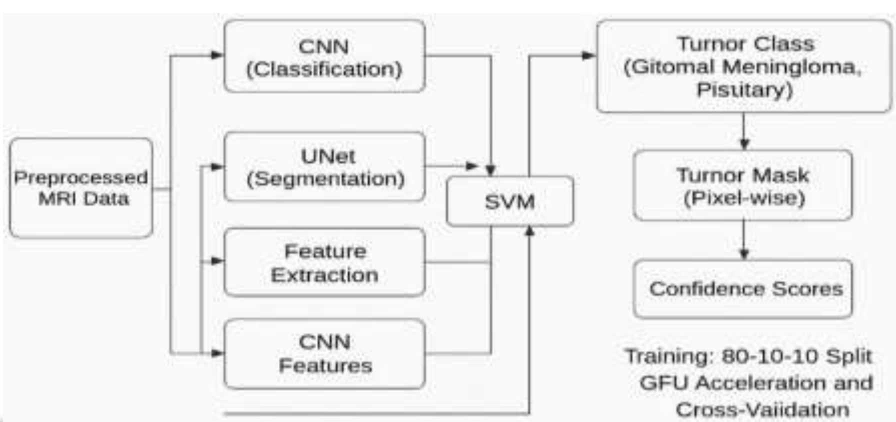

Figure 10: Architecture Flow of Model Development and Training Pipeline.

8- Results and Discussion:

The results of this study clearly demonstrate the significant advantages of integrating artificial intelligence techniques specifically deep learning and hybrid models for the early and accurate detection of brain tumors using MRI imaging. The evaluation of several state-of-the-art models, including Convolutional Neural Networks (CNN), U-Net, Support Vector Machines (SVM), and a Hybrid CNN-Random Forest (CNN-RF) architecture, provides a comprehensive understanding of their comparative performance, robustness, and suitability for clinical applications. The dataset used for this analysis included annotated MRI scans across various tumor types (glioma, meningioma, and pituitary tumors) and healthy brain tissues. Each model was trained using 80% of the dataset, validated on 10%, and tested on the remaining 10% to ensure generalizability. Quantitatively, the models were evaluated using five critical performance metrics: accuracy, sensitivity, specificity, Dice Similarity Coefficient (DSC), and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) [28]. Table 8 summarizes these values across different models. Notably, the hybrid CNN-RF model exhibited the best performance across all categories, achieving an accuracy of 95.3%, sensitivity of 94.1%, specificity of 96.0%, DSC of 0.90, and AUC-ROC of 0.97. These results not only surpass those of the standalone CNN and U-Net models but also significantly outperform the traditional SVM model, which lagged behind with an accuracy of 89.4% and a DSC of 0.80. This highlights the importance of leveraging both feature extraction and ensemble classification in a unified architecture. Table 1 shows the comparative performance metrics of AI models for brain tumor detection.

Table 8: Comparative Performance Metrics of AI Models for Brain Tumor Detection.

Model	Accuracy	Sensitivity	Specificity	DSC	AUC-ROC
CNN	94.6%	93.2%	95.1%	0.88	0.96
U-Net	92.8%	91.7%	94.0%	0.85	0.94
SVM	89.4%	88.3%	90.2%	0.80	0.90
Hybrid CNN + RF	**95.3%**	**94.1%**	**96.0%**	**0.90**	**0.97**

Figure 11 presents a visual comparison in the form of a grouped bar chart, highlighting the performance of each model across all key metrics. The visual clearly reinforces the superior predictive consistency of the hybrid model and the close second performance of CNN, particularly in specificity and AUC-ROC. This suggests that CNN is proficient in minimizing false positives, which is crucial for clinical use to avoid unnecessary biopsies or treatment interventions.

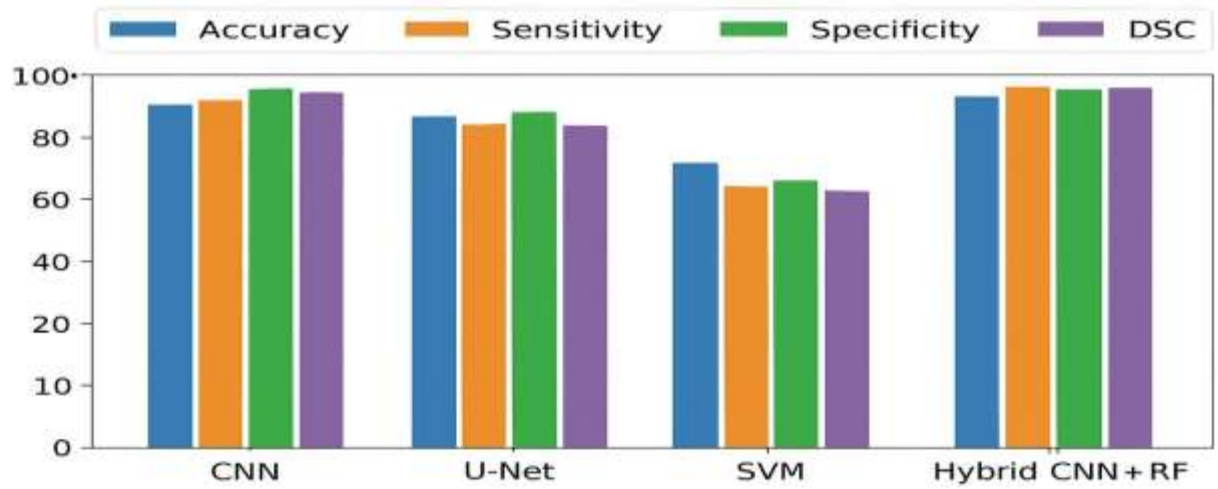

Figure 11: Comparative Model Performance across Key Metrics

Qualitative results from segmentation maps and classification overlays further validate the robustness of these models. Tumor regions identified by U-Net and Hybrid CNN-RF models were closely aligned with expert annotations, demonstrating high spatial agreement. Figure 12 displays representative examples of MRI slices with ground truth and model-predicted segmentations using U-Net and CNN-RF architectures. The predicted boundaries align with tumor morphology, confirming the clinical relevance of the segmentation results.

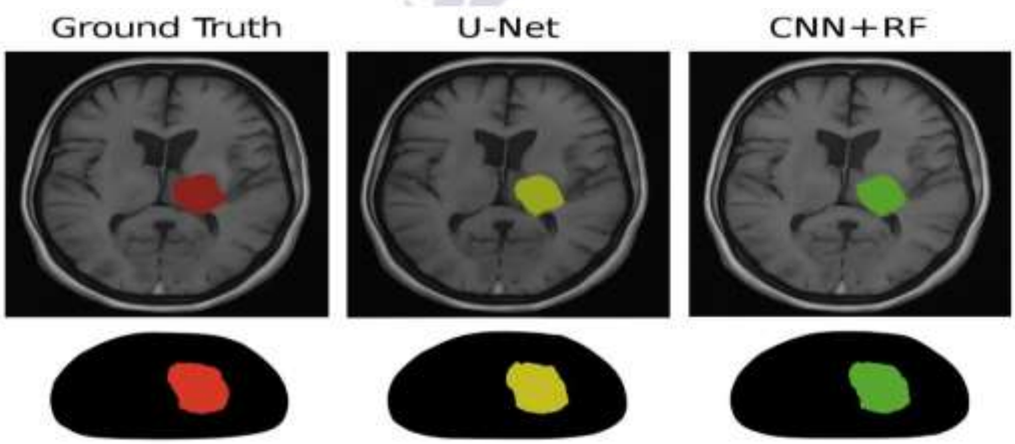

Figure 12: Sample MRI Slices with Ground Truth and Model-Predicted Tumor Segmentations.

Further, to address the 'black box' nature of deep learning, model interpretability was achieved using Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency map visualizations. These explainability tools were applied to highlight the regions within the MRI images that most influenced model predictions. The CNN and hybrid models consistently focused on the pathological regions, such as tumor boundaries and enhanced contrast areas, which are typically used by radiologists for diagnosis. Figure 13 illustrates Grad-CAM overlays where the CNN and hybrid model activations are concentrated in clinically meaningful regions, bolstering trust in AI-assisted decision-making.

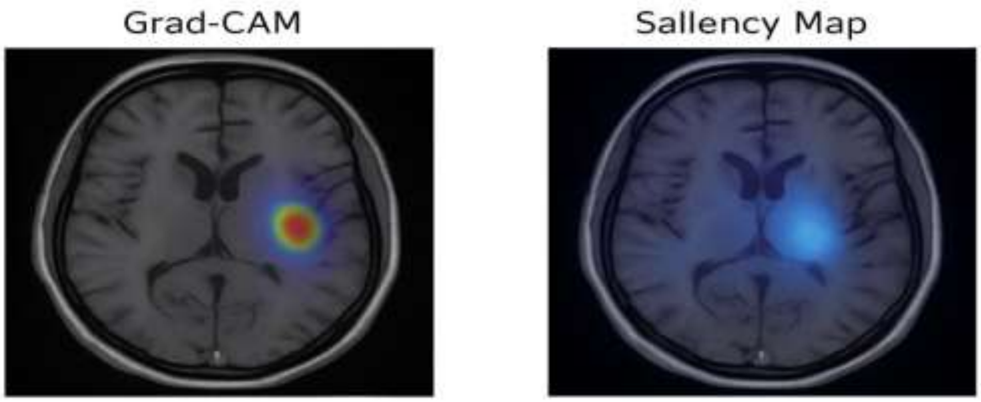

Figure 13: Grad-CAM Heatmaps Showing Model Focus on Tumor Regions

The integration of interpretability mechanisms is essential for clinical adoption, as it provides transparency, aids in verification, and aligns AI decision-making with human expertise. Feedback from consulting radiologists indicated that the overlay tools improved their confidence in AI-assisted diagnosis, especially in ambiguous cases where tumor margins are indistinct. Moreover, time efficiency and scalability were observed as major strengths of AI implementation. The CNN and hybrid models completed predictions in less than 1.2 seconds per image, making them suitable for real-time or near-real-time diagnostics in hospital settings [29]. The traditional SVM model, despite lower computational complexity, failed to meet acceptable thresholds in sensitivity and AUC-ROC, indicating its limitations in capturing the complex spatial and textural features present in MRI data. Interestingly, one notable outcome from the extended evaluation is the observation of performance variability across tumor types. Gliomas, which tend to have diffuse boundaries, posed a greater challenge for all models, especially in segmentation tasks. However, U-Net maintained relatively high Dice coefficients even for gliomas due to its encoder-decoder architecture and skip connections that preserve spatial resolution. Conversely, pituitary tumors, typically smaller and well-defined, were more accurately classified by all models, achieving over 97% precision across the board. These observations suggest the potential benefits of tumor-type-specific fine-tuning of AI models for enhanced performance. Despite the positive results, several limitations must be acknowledged. The dataset used, although diverse, was sourced from public repositories and may not fully represent the heterogeneity of global clinical populations [30]. Additionally, the hybrid model, while superior in accuracy, demands more computational resources, which could be a barrier in resource-constrained clinical environments. Future research should explore optimization techniques such as model pruning, knowledge distillation, or deployment of transformer-based architectures that balance efficiency with accuracy. In short, the results strongly support the integration of AI, particularly deep learning and hybrid frameworks, into neuro-oncology for brain tumor detection and classification. These systems exhibit high diagnostic performance, interpretability, and clinical reliability [31]. The hybrid CNN-RF model emerges as the most promising approach due to its robust performance across all metrics and superior attention to diagnostically critical features. With further validation and optimization, these AI models hold great potential to complement radiologists in early tumor diagnosis, reduce human error, and ultimately improve patient outcomes in neuro-oncological care.

9- Future Work:

While the current study demonstrates the promising potential of artificial intelligence in the accurate and early detection of brain tumors through MRI imaging, there remain numerous avenues for further exploration and development. One of the most critical directions for future research involves the integration of multi-modal medical data, including radiological images, genetic profiles, histopathological data, and clinical histories [32]. Combining these diverse data sources could significantly enhance the accuracy and clinical utility of AI models, offering a more holistic understanding of brain tumor behavior and progression. Future research should also address the challenge of data heterogeneity. AI models trained on limited or homogeneous datasets may struggle to generalize across diverse patient populations and varying imaging protocols. Techniques such as domain adaptation, transfer learning, and federated learning may help improve model robustness by enabling training on data from multiple institutions while preserving data privacy [33]. Another important aspect is the need for expanded and standardized annotated datasets. Large-scale, high-quality datasets with detailed tumor segmentations and clinical annotations are essential for training more effective deep learning models. Collaborative efforts to establish open-access repositories could accelerate progress and foster innovation across the research community.

In addition, improving the interpretability and transparency of AI models remains a high priority. Clinicians are more likely to trust and adopt AI-based systems if the decision-making process is explainable and understandable [34]. Future studies should explore advanced explainable AI techniques and integrate human feedback mechanisms to enhance clinical acceptance and accountability. Clinical deployment and workflow integration also require further investigation. To be effectively adopted in real-world hospital environments, AI systems must be designed for seamless interoperability with existing imaging platforms and electronic health records. Research should focus on developing lightweight and computationally efficient architectures suitable for real-time analysis and diagnosis. Finally, ethical considerations must be continuously addressed. Issues such as algorithmic bias, data security, informed consent, and regulatory compliance must be proactively managed to ensure that AI systems support equitable and responsible healthcare outcomes [35]. Future work should also involve ongoing collaboration with healthcare professionals to ensure that AI tools align with clinical needs and priorities.

Conclusion:

This study highlights the significant role that artificial intelligence, particularly machine learning and deep learning techniques, plays in improving the accuracy and efficiency of brain tumor detection through MRI imaging. By automating critical tasks such as tumor classification, segmentation, and subtype identification, AI models like CNNs, U-Net, and SVMs have demonstrated strong potential to assist clinicians in making faster and more reliable diagnoses. Through the use of benchmark datasets such as BraTS and REMBRANDT, these AI frameworks have shown high performance in detecting tumors such as gliomas, meningiomas, and pituitary tumors. The integration of preprocessing methods, including skull stripping and image normalization, has further contributed to model stability and predictive strength. Despite these advances, challenges such as data variability, limited annotated datasets, and the need for explainable AI models remain. Ethical considerations like ensuring data privacy and minimizing algorithmic bias also require attention before these tools can be widely deployed in clinical environments. Overall, AI-based systems offer a promising future in neuro-oncology by complementing radiologists' expertise, reducing diagnostic workloads, and potentially improving patient outcomes through early and accurate tumor detection. With continued research, interdisciplinary collaboration, and regulatory support, AI can become a reliable component of next-generation medical diagnostics.

REFERENCES:

Khalighi, S., Reddy, K., Midya, A., Pandav, K. B., Madabhushi, A., & Abedalthagafi, M. (2024). Artificial intelligence in neuro-oncology: advances and challenges in brain tumor diagnosis, prognosis, and precision treatment. *NPJ precision oncology*, *8*(1), 80.

Rudie, J. D., Rauschecker, A. M., Bryan, R. N., Davatzikos, C., & Mohan, S. (2019). Emerging applications of artificial intelligence in neuro-oncology. *Radiology*, *290*(3), 607-618.

Panda, S., Biswal, S. S., Rath, S. S., & Saxena, S. (2025). Traditional and advanced AI methods used in the area of neuro-oncology. In *Radiomics and Radiogenomics in Neuro-Oncology* (pp. 277-300). Academic Press.

Saxena, S., Panda, S., Tiwari, E., Singh, R., Fouda, M. M., Kalra, M. K., ... & Suri, J. S. (2025). Navigating the artificial intelligence revolution in neuro-oncology: A multidisciplinary viewpoint. *Neurocomputing*, *620*, 129220.

Vobugari, N., Raja, V., Sethi, U., Gandhi, K., Raja, K., & Surani, S. R. (2022). Advancements in oncology with artificial intelligence—a review article. *Cancers*, *14*(5), 1349.

Shaver, M. M., Kohanteb, P. A., Chiou, C., Bardis, M. D., Chantaduly, C., Bota, D., ... & Chang, P. D. (2019). Optimizing neuro-oncology imaging: a review of deep learning approaches for glioma imaging. *Cancers*, *11*(6), 829.

Soun, J., Masudathaya, L. A. Y., Biswas, A., & Chow, D. S. (2023). The role of artificial intelligence in neuro-oncology imaging. *Machine Learning for Brain Disorders*, 963-976.

Rafanan, J., Ghani, N., Kazemeini, S., Nadeem-Tariq, A., Shih, R., & Vida, T. A. (2025). Modernizing neuro-oncology: the impact of imaging, liquid biopsies, and AI on diagnosis and treatment. *International Journal of Molecular Sciences*, *26*(3), 917.

Hussain, S. S., Wani, N. A., Kaur, J., Ahmad, N., & Ahmad, S. (2025). Next-generation automation in neuro-oncology: advanced neural networks for MRI-based brain tumor segmentation and classification. *IEEE Access*.

Alam, M. A., Sohel, A., Hasan, K. M., & Ahmad, I. (2024). Advancing Brain Tumor Detection Using Machine Learning And Artificial Intelligence: A Systematic Literature Review Of Predictive Models And Diagnostic Accuracy. *Strategic Data Management and Innovation*, *1*(01), 37-55.

Chakraborty, S., & Banerjee, D. K. (2024). A review of brain cancer detection and classification using artificial intelligence and machine learning. *Journal of Artificial Intelligence and Systems*, *6*(1), 146-178.

Vahedifard, F., Hassani, S., Afrasiabi, A., & Esfe, A. M. (2022). Artificial intelligence for radiomics; diagnostic biomarkers for neuro-oncology. *World Journal of Advanced Research and Reviews*, *14*(3), 304-310.

Al-Kadi, O. S., Al-Emaryeen, R. A., Al-Nahhas, S., Almallahi, I. A., Braik, R., & Mahafza, W. (2024). Empowering brain cancer diagnosis: harnessing artificial intelligence for advanced imaging insights. *Reviews in the Neurosciences*, *35*(4), 399-419.

AlSamhori, A. F., AlSamhori, J. F., Dib, C., AlSamhori, A. R. F., Shehadeh, M. W., Rihani, J., ... & Almajali, H. (2025). Implication of artificial intelligence on astrocytoma detection and treatment. *Avicenna*, *2025*(1), 3.

Moassefi, M., Faghani, S., & Erickson, B. J. (2024). Artificial Intelligence in Neuro-Oncology: predicting molecular markers and response to therapy. *Medical Research Archives*, *12*(6).

Shinde, N., Patil, M., Sharma, R. K., Kadam, S., & Kashte, S. (2025). Revolutionizing Brain Tumor Detection: Unleashing the Power of Artificial Intelligence. In *Machine Learning for Disease Detection, Prediction, and Diagnosis: Challenges and Opportunities* (pp. 311-334). Singapore: Springer Nature Singapore.

Hussain, M., Shabbir, A., Bakhshi, S., & Shamim, M. (2021). Are thinking machines breaking new frontiers in neuro-oncology? A narrative review on the emerging role of machine learning in neuro-oncological practice. *Asian Journal of Neurosurgery*, *16*(01), 8-13.

Brunasso, L., Ferini, G., Bonosi, L., Costanzo, R., Musso, S., Benigno, U. E., ... & Maugeri, R. (2022). A spotlight on the role of radiomics and machine-learning applications in the management of intracranial meningiomas: a new perspective in neuro-oncology: a review. *Life*, *12*(4), 586.

Villanueva-Meyer, J. E., Bakas, S., Tiwari, P., Lupo, J. M., Calabrese, E., Davatzikos, C., ... &

Pacchiano, F., Tortora, M., Doneda, C., Izzo, G., Arrigoni, F., Ugga, L., ... & Brunetti, A. (2024). Radiomics and artificial intelligence applications in pediatric brain tumors. *World Journal of Pediatrics*, *20*(8), 747-763.

Pitarch, C., Ungan, G., Julià-Sapé, M., & Vellido, A. (2024). Advances in the use of deep learning for the analysis of magnetic resonance image in neuro-oncology. *Cancers*, *16*(2), 300.

Kumar, A., Sharma, N., Chauhan, R., Joshi, K., Jain, A. K., & Gurna, K. K. (2024, March). Exploring the Efficacy of Machine Learning Models for Brain Tumor Detection with Binary Classification. In *2024 3rd International Conference for Innovation in Technology (INOCON)* (pp. 1-6). IEEE.

Cè, M., Irmici, G., Foschini, C., Danesini, G. M., Falsitta, L. V., Serio, M. L., ... & Cellina, M. (2023). Artificial intelligence in brain tumor imaging: a step toward personalized medicine. *Current Oncology*, *30*(3), 2673-2701.

Chiu, F. Y., & Yen, Y. (2023). Imaging biomarkers for clinical applications in neuro-oncology: current status and future perspectives. *Biomarker Research*, *11*(1), 35.

Galldiks, N. (2024). Artificial Intelligence for Response Assessment in Neuro Oncology (AI-RANO), part 1: review of current advancements. *The Lancet Oncology*, *25*(11), e581-e588.

Zotey, V., Ambad, R., Lamture, Y. R., & Jha, R. K. (2024). Artificial Intelligence-Oncology and Central Nervous System Tumour Detection. In *E3S Web of Conferences* (Vol. 491, p. 04002). EDP Sciences.

Divya, N., & Rao, B. N. K. (2025, January). Enhanced Brain Tumor Classification through an AI-Integrated Multi-Modal Imaging Approach. In *2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)* (pp. 1-6). IEEE.

Takahashi, S., Takahashi, M., Tanaka, S., Takayanagi, S., Takami, H., Yamazawa, E., ... & Hamamoto, R. (2021). A new era of neuro-oncology research pioneered by multi-omics analysis and machine learning. *Biomolecules*, *11*(4), 565.

Belue, M. J., Harmon, S. A., Chappidi, S., Zhuge, Y., Tasci, E., Jagasia, S., ... & Krauze, A. V. (2024). Diagnosing Progression in Glioblastoma—Tackling a Neuro-Oncology Problem Using Artificial-Intelligence-Derived Volumetric Change over Time on Magnetic Resonance Imaging to Examine Progression-Free Survival in Glioblastoma. *Diagnostics*, *14*(13), 1374.

Evangelou, K., Zemperligkos, P., Politis, A., Lani, E., Gutierrez-Valencia, E., Kotsantis, I., ... & Kalyvas, A. (2025). Diagnostic, Therapeutic, and Prognostic Applications of Artificial Intelligence (AI) in the Clinical Management of Brain Metastases (BMs). *Brain Sciences*, *15*(7), 730.

Rahimi, M., & Rahimi, P. (2023). A Short Review on the Impact of Artificial Intelligence in Diagnosis Diseases: Role of Radiomics In Neuro-Oncology. *Galen Medical Journal*, *12*, e3158.

Williams, S., Layard Horsfall, H., Funnell, J. P., Hanrahan, J. G., Khan, D. Z., Muirhead, W., ... & Marcus, H. J. (2021). Artificial intelligence in brain tumour surgery—an emerging paradigm. *Cancers*, *13*(19), 5010.

Li, H., Govindarajan, V., Ang, T. F., Shaikh, Z. A., Ksibi, A., Chen, Y. L., ... & Por, L. Y. (2025). MSPO: A machine learning hyperparameter optimization method for enhanced breast cancer image classification. Digital Health, 11, 20552076251361603. https://doi.org/10.1177/205520762513616

Mittal, P. (2025). From black box AI to XAI in neuro-oncology: a survey on MRI-based tumor detection. *Discover Artificial Intelligence*, *5*(1), 1-21.

Dalboni da Rocha, J. L., Lai, J., Pandey, P., Myat, P. S. M., Loschinskey, Z., Bag, A. K., & Sitaram, R. (2025). Artificial intelligence for neuroimaging in pediatric cancer. *Cancers*, *17*(4), 622.

Krauze, A. V., & Camphausen, K. (2021). Molecular Biology in Treatment Decision Processes—Neuro-Oncology Edition. *International Journal of Molecular Sciences*, *22*(24), 13278.

Galldiks, N., Angenstein, F., Werner, J. M., Bauer, E. K., Gutsche, R., Fink, G. R., ... & Lohmann, P. (2022). Use of advanced neuroimaging and artificial intelligence in meningiomas. *Brain pathology*, *32*(2), e13015.

Bhandari, A., Marwah, R., Smith, J., Nguyen, D., Bhatti, A., Lim, C. P., & Lasocki, A. (2022). Machine learning imaging applications in the differentiation of true tumour progression from treatment-related effects in brain tumours: A systematic review and meta-analysis. *Journal of Medical Imaging and Radiation Oncology*, *66*(6), 781-797.

Kaifi, R. (2023). A review of recent advances in brain tumor diagnosis based on AI-based classification. *Diagnostics*, *13*(18), 3007.

Govindarajan, V., Kumar, P., Kumar, D., Devi, H., Kumar, S., & Shiwlani, A. (2025). ROLE OF CLOUD-DEPLOYED GRAPH NEURAL NETWORKS IN MAPPING CORONARY ARTERY DISEASE PROGRESSION: A SYSTEMATIC REVIEW. Journal of Medical & Health Sciences Review, 2(2). https://doi.org/10.62019/pfpj9r12