Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.17.(1) 2025,pp.Comp 274–297

University Of AL-Qadisiyah

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

# Advancements in Image Processing Approaches for Brain Tumor Diagnosis: An Article Review

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ARTICLE INFO

*Article history:*
Received: 25 /11/2024
Rrevised form: 27 /12/2025
Accepted : 25 /3/2025
Available online: 30 /3/2025

*Keywords:*
medical imaging
MRI (Magnetic Resonance Imaging)
machine learning
degmentation techniques
Computer-Aided Diagnosis (CAD)

ABSTRACT

Recent advances in clinical photograph processing, especially synthetic intelligence (AI) and deep studying strategies, represent a paradigm shift in mind tumor diagnosis. The review proven that convolutional neural network (CNN) models and advanced U-Nets attain superior accuracy in tumor segmentation (up to 94% accuracy the usage of the Dess index) and class, outperforming conventional methods including thresholding and vicinity increase, which suffer from barriers in handling noise and heterogeneity of tumor boundaries. The integration of multimodal imaging (MRI, CT, PET) additionally enhances diagnostic accuracy by using providing a comprehensive view of tumor biology, but its effectiveness relies upon on standardization of protocols across clinical facilities.

Prominent challenges highlighted within the evaluate consist of the need for huge, categorized datasets, the computational barriers of deep studying fashions, and the issue of interpreting AI choices ("black box"), which affects medical self-belief. The findings also emphasize the significance of pre-processing techniques (which include CLAHE) in improving photo pleasant and the position of transfer getting to know in overcoming information scarcity.

In the future, emphasis must be positioned on growing light-weight fashions for practical scientific use, improving interpretability thru tools including Grad-CAM, and fostering collaboration between researchers and clinicians to align technical innovations with scientific wishes. These traits promise to transform mind tumor prognosis in the direction of extra efficient and equitable precision remedy.

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https://doi.org/10.29304/jqcsm.2025.17.11980

## 1. Introduction

Brain tumors represent one of the most challenging issues in modern healthcare due to their complex pathology and life-threatening nature, which require precise and timely diagnosis. Early detection and correct characterization of these tumors are crucial for improving patient survival rates and guiding powerful treatment strategies. However,

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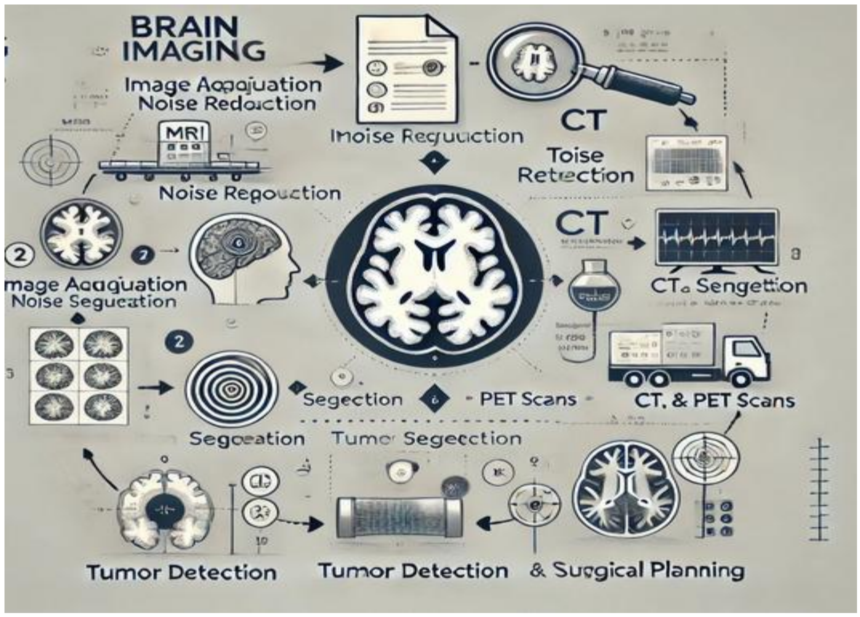
the inherent heterogeneity of mind tumors—varying in kind, region, and organic conduct—poses big diagnostic hurdles. Traditional diagnostic methods, which rely on subjective radiological assessments, often face inconsistencies due to inter-observer variability and the limitations of conventional imaging modalities.




Brain Imaging Workflow: From Acquisition to Clinical Applications

Recent improvements in medical imaging, computational power, and artificial intelligence (AI) have revolutionized the field of neuro-oncology. Cutting-area modalities along with Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and hybrid imaging systems (e.G., PET/CT, PET/MRI) now offer remarkable anatomical, metabolic, and practical insights into tumor biology [1]. These innovations enable clinicians to discover tumors at in advance stages, classify them more accurately, and screen treatment responses with more precision. For instance, as illustrated in Figure 1, the global occurrence of brain tumors has surged in latest years, underscoring the urgency for advanced diagnostic gear. [2].

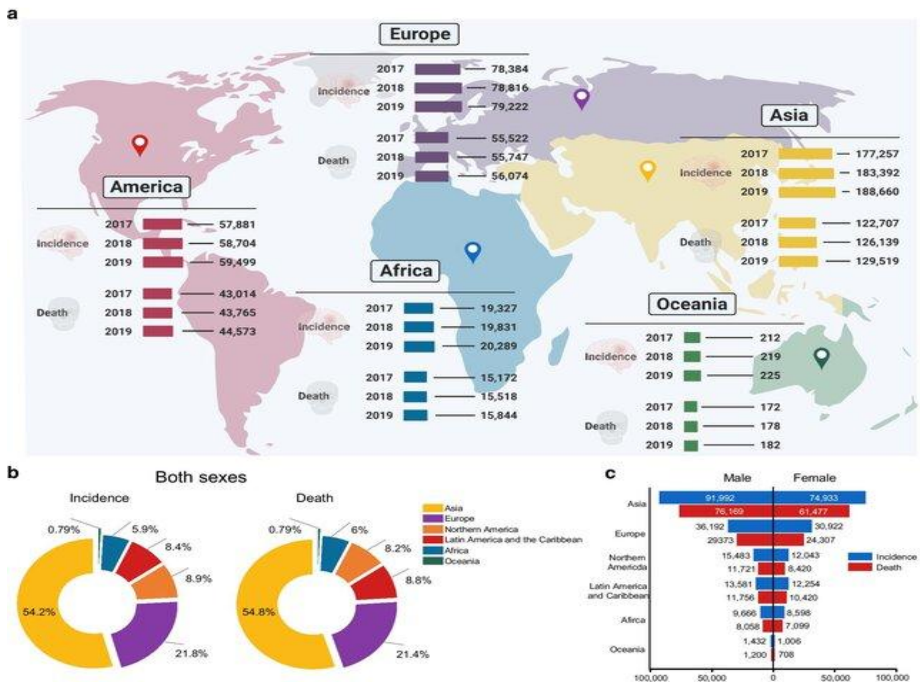



**Fig. 1 The incidence of brain tumors in the world in 2020-2023** [3]

Despite those technological strides, sizeable challenges persist. Medical pix are frequently marred by using noise, artifacts, and depth inhomogeneities, that can obscure vital tumor features and result in diagnostic mistakes [4-5]. Figure 2 highlights not unusual artifacts in MRI scans, which include motion blur and susceptibility distortions, which complicate tumor delineation [8]. Additionally, the exponential growth of imaging records in scientific workflows has strained healthcare systems, demanding automatic solutions to streamline analysis and reduce interpretation time [6-7].

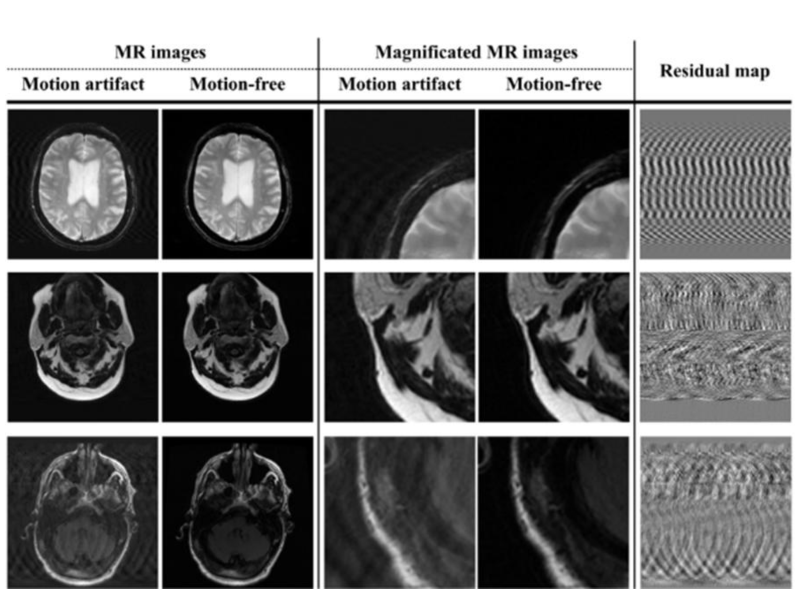



**Fig. 2 Some typical findings and difficulties in brain tumor MRI imaging** [9].

This systematic evaluate explores the ultra-modern improvements in image processing strategies for brain tumor diagnosis, with a focus on enhancement algorithms, segmentation methods, and AI-driven improvements. We evaluate the efficacy of traditional and deep gaining knowledge of-based methods in addressing modern-day demanding situations, inclusive of noise discount and characteristic extraction, while emphasizing their scientific applicability [10-11-12]. By synthesizing recent research, this overview objectives to focus on transformative technology, identify unresolved problems, and description destiny instructions for integrating AI into habitual scientific practice. The pipeline depicted in Figure three offers a comprehensive review of modern picture processing workflows, from acquisition to very last diagnosis, reflecting the synergy between computational advancements and medical desires [13-14].

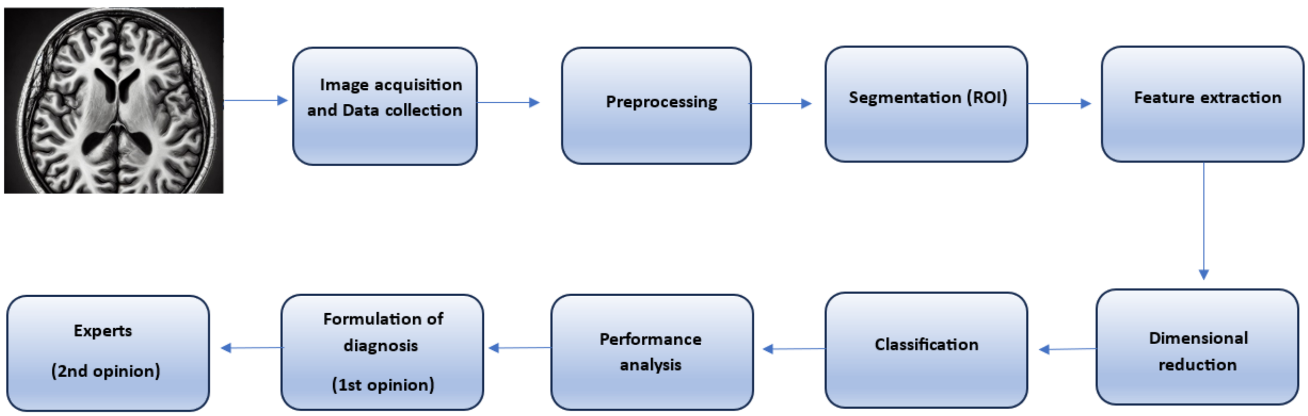



**Fig. 3 Overview of modern brain tumor image processing pipeline** [17]

Through this analysis, we underscore the potential of advanced image processing to redefine neuro-oncology, offering hope for more accurate, efficient, and personalized patient care in the era of precision medicine.

## 2. " Brain Imaging Modalities"

The diagnosis and classification of brain tumors are based on the medical images which are essential for the treatment plan and prognosis [18]. Neuroimaging has come a long way in helping diagnose, stage, and assess response to treatment of brain tumors in the present day [19]. MRI, CT, and other imaging types are depicted in Figure 4.

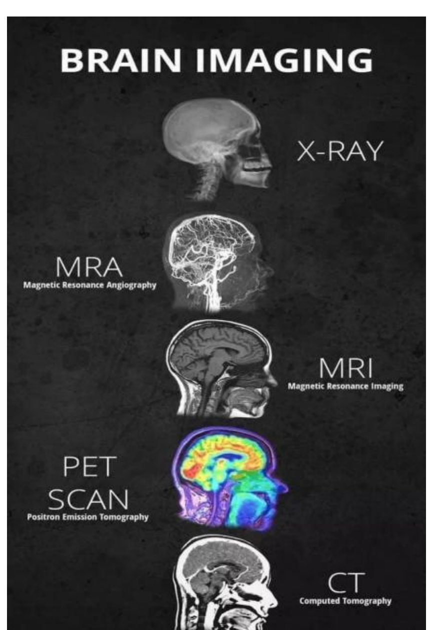


**Fig. 4 Overview of different brain imaging modalities scanning types** [20]

### *2.1. Magnetic Resonance Imaging (MRI)*

Magnetic Resonance Imaging is the best modality for imaging brain tumors because of its high soft tissue contrast and ability to give detailed anatomical information without using ionizing radiation [21]. Several MRI sequences have been developed over the years and they all give different information about the tumor [22], [23]. The fundamental MRI sequences used in brain tumor imaging include T1-weighted imaging: Which has good anatomical resolution and is especially useful with contrast, T2-weighted imaging: Which demonstrates edema and invasive tumor components, FLAIR (Fluid-Attenuated Inversion Recovery): Reduces CSF signal to improve periventricular lesion visualization, DWI (Diffusion-Weighted Imaging): Measures cell density and early treatment response, PWI (Perfusion-Weighted Imaging): Determines tumor vascularity.

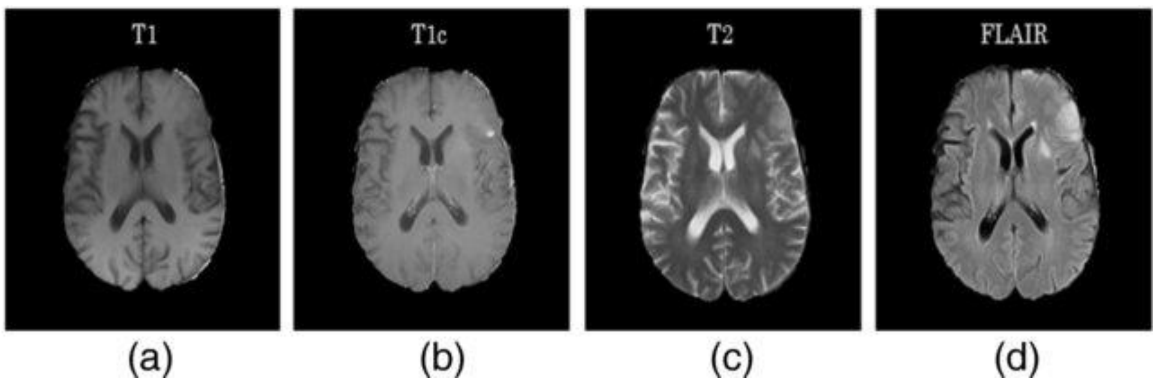



**Fig. 5 Different MRI sequences in brain tumor imaging** [24]

Newer developments in MRI have brought about new techniques like MRS and fMRI which offer further metabolic and functional data about the tumor [25]. It has been observed that the analysis of several MRI sequences can increase the diagnostic yield by 30% as compared to the analysis of a single sequence [26].

**Table 1: MRI Sequence Characteristics and Applications in Brain Tumor Imaging**

| MRI Sequence | Primary Use | Key Advantages | Limitations |
|---|---|---|---|
| **T1-weighted** | Anatomical detail, contrast enhancement | High spatial resolution | Limited in non-enhancing tumors |
| **T2-weighted** | Edema detection, tumor infiltration | Good tissue contrast | May overestimate tumor extent |
| **FLAIR** | Periventricular lesion detection | CSF suppression | Less sensitive to posterior fossa lesions |
| **DWI** | Cellularity assessment | Early response detection | Susceptibility artifacts |
| **PWI** | Vascularity assessment | Blood flow quantification | Complex post-processing |

### *2.2. Computed Tomography (CT)*

Although MRI is the modality of choice for most brain tumor assessment, CT scan is still invaluable in certain clinical settings [27]. CT is particularly useful in the emergency setting, for patients who cannot undergo MRI, and for the identification of calcifications, hemorrhage, and acute bleeding [28]. Modern CT technologies have evolved to include Multi-slice CT: Which allows for quicker scanning with higher resolution, Dual-energy CT: Better tissue differentiation, and Perfusion CT: Which measures blood supply and blood flow to the tumor [29].

Some recent papers have shown that newer CT approaches can provide diagnostic performance that is at least as good as that of conventional MRI in some instances, especially in emergencies where time is of the essence [30].

### *2.3. Other Imaging Techniques*

Beyond MRI and CT, several other imaging modalities play important roles in brain tumor diagnosis and monitoring:

- Positron Emission Tomography (PET): Based on radioactive tracers to map out tumor metabolism, Especially in differentiating tumor progression from radiation injury, Other tracers than FDG are still under development, but they also seem to be useful in tumor grading [31].

- Single-photon emission Computed Tomography (SPECT): Shows functional information about tumor blood flow and can be used to evaluate tumor growth and response to therapy [32].PET/CT and PET/MRI combinations, Provide both, anatomical and functional images, and Enhance diagnostic capabilities and treatment planning [33]. (fMRI), which provide additional metabolic and functional information about brain tumors [25]. Studies have shown that combining multiple MRI sequences can improve diagnostic accuracy by up to 30% compared to single-sequence analysis [26].

### *2.4. Computed Tomography (CT)*

While MRI is preferred for most brain tumor evaluations, CT scanning remains crucial in specific clinical scenarios [19]. CT excels in emergencies, for patients with MRI contraindications, and in detecting calcifications, hemorrhage, and acute bleeding [28]. Modern CT technologies have evolved to include Multi-slice CT: Which enables rapid scanning with improved resolution, Dual-energy CT: Which provides better tissue characterization, and Perfusion CT: which Assesses tumor vasculature and blood flow [29]. Recent studies have demonstrated that advanced CT techniques can achieve diagnostic accuracy comparable to conventional MRI in certain cases, particularly in emergency settings where rapid diagnosis is crucial [30].

### *2.5. Other Imaging Techniques*

Beyond MRI and CT, several other imaging modalities play important roles in brain tumor diagnosis and monitoring:

- Positron Emission Tomography (PET): Utilizes radioactive tracers to visualize tumor metabolism, Particularly useful in distinguishing tumor recurrence from radiation necrosis, New tracers beyond FDG show promising results in tumor grading [31]

- Single-Photon Emission Computed Tomography (SPECT): Provides functional information about tumor blood flow and is useful in assessing tumor progression and treatment response [32].

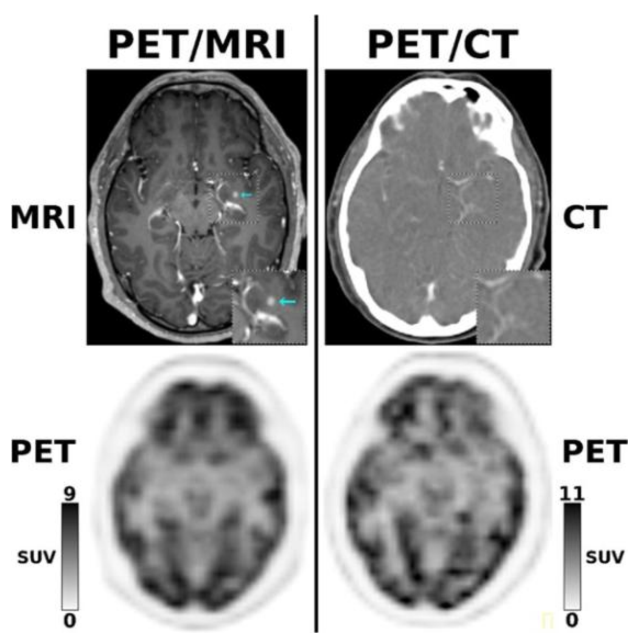



**Fig. 6 Hybrid imaging in brain tumor diagnosis [34]**

- Hybrid Imaging: PET/CT and PET/MRI combinations, offer simultaneous anatomical and functional imaging, and Improve diagnostic accuracy and treatment planning. Figure 6 presents PET/CT and PET/MRI images of the same tumor.

### *2.6. Comparison between Different Imaging Techniques*

The selection of the imaging technique is based on certain factors such as the patient's symptoms, the type of tumor, and the specific imaging needs [35].

**Table 2: Comparative Analysis of Brain Tumor Imaging Modalities**

| Feature | MRI | CT | PET | SPECT |
|---|---|---|---|---|
| **Soft Tissue Contrast** | Excellent | Moderate | Poor | Poor |
| **Spatial Resolution** | High | High | Low | Low |
| **Temporal Resolution** | Moderate | Excellent | Low | Low |
| **Radiation Exposure** | None | High | Moderate | Moderate |
| **Cost** | High | Moderate | High | Moderate |
| **Availability** | Limited | Widespread | Limited | Limited |
| **Emergency Use** | Limited | Excellent | Not applicable | Not applicable |

Research has shown that integrating multiple imaging modalities can significantly improve diagnostic accuracy and treatment planning [36]. A recent meta-analysis demonstrated that combining advanced MRI techniques with PET imaging increased diagnostic accuracy by up to 25% in challenging cases [37].

The integration of multiple imaging modalities in brain tumor diagnosis has led to the development of multimodal imaging protocols [38]. These protocols consider several key factors: Tumor type and location, Patient condition and contraindications, Urgency of diagnosis, Cost-effectiveness, Availability of imaging modalities [39].

**Table 3: Clinical Applications and Strengths of Multimodal Imaging**

| Clinical Scenario | Primary Modality | Secondary Modality | Rationale |
|---|---|---|---|
| **Initial Diagnosis** | MRI with contrast | CT | Comprehensive anatomical assessment |
| **Emergency Cases** | CT | MRI | Rapid screening, hemorrhage detection |
| **Treatment Planning** | MRI + fMRI | PET | Functional mapping, metabolic activity |
| **Recurrence Monitoring** | MRI | PET/CT | Differentiate recurrence from radiation necrosis |
| **Pediatric Cases** | MRI | Ultrasound | Minimize radiation exposure |
| **Surgical Navigation** | fMRI | DTI | Precise surgical planning |

Recent technological advancements have introduced artificial intelligence-based integration of multiple imaging modalities, showing promising results in Automated image registration, Feature extraction across modalities, and Combined analysis for improved diagnosis [40]. Figure 7 presents a flowchart of how the imaging modalities are combined using AI algorithms.

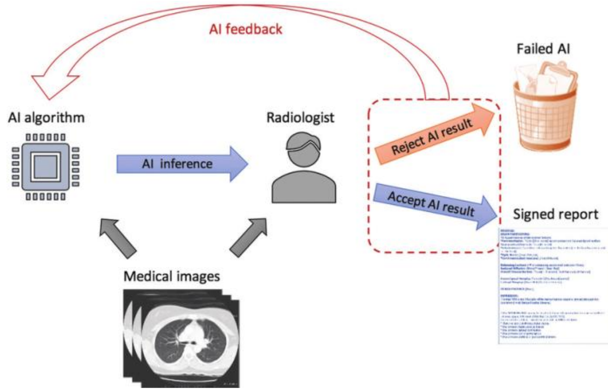



**Fig. 7 AI-based multimodal image integration workflow [41]**

**Table 4: Emerging Trends in Multimodal Imaging**

| Technology | Description | Clinical Impact | Future Potential |
|---|---|---|---|
| **AI Integration** | Automated analysis of multiple modalities | Improved accuracy | High standardization |
| **Radiomics** | Extraction of quantitative features | Better characterization | Personalized medicine |
| **Molecular Imaging** | Targeted tracers and markers | Specific tumor detection | Early diagnosis |
| **Real-time Fusion** | Intraoperative guidance | Enhanced surgical precision | Reduced complications |

Future Directions in Imaging Integration: Standardization of multimodal protocols, Integration of real-time image fusion, Sophisticated quantitative analysis techniques, Economic modalities of imaging [42]. Figure 8 is an infographic of emerging technologies and their possible uses.

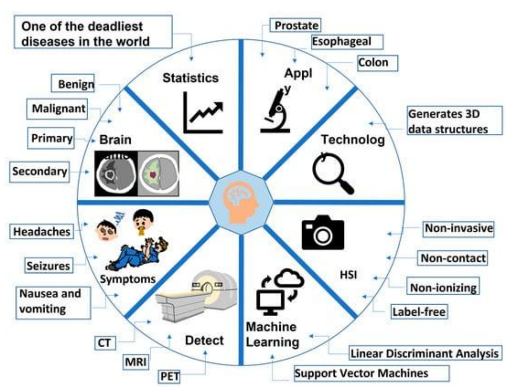



**Fig. 8: Future trends in brain tumor imaging [43]**

## 3. Image Enhancement Techniques

The process of improving medical images is vital in increasing the accuracy of the diagnosis of brain tumors by increasing the quality of the image and highlighting clinically relevant features [44]. Current enhancement techniques have been improved to include both conventional and artificial intelligence methods [45]. These developments have enhanced the visibility and detectability of these fine features of the tumor that are so important in diagnosis and management [46]. In Figure 9, brain tumor images are presented before and after applying different enhancement techniques.

**Table 5: Comparison of Contrast Enhancement Techniques**

| Method | Application | Advantages | Limitations | Performance |
|---|---|---|---|---|

| | | | | Metrics |
|---|---|---|---|---|
| **Global HE** | Overall contrast | Simple implementation | May over-enhance | PSNR: 25-30dB |
| **CLARE** | Local contrast | Better detail preservation | Computational cost | PSNR: 30-35dB |
| **Wavelet-based** | Multi-scale enhancement | Preserves edges | Complex parameters | PSNR: 32-38dB |
| **Gamma correction** | Brightness adjustment | Real-time processing | Limited flexibility | PSNR: 28-33dB |
| **Deep learning** | Adaptive enhancement | Context-aware | Training required | PSNR: 35-40dB |

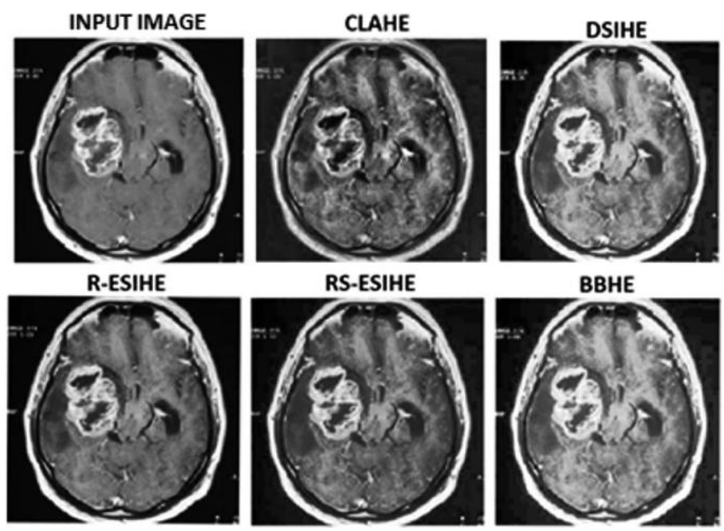



**Fig. 9: Before and after image enhancement comparison [47].**

### *3.1. Contrast Enhancement Methods*

Contrast enhancement is another key part of brain tumor imaging because it enhances the contrast of the tumor margins and internal [48]. Global histogram equalization, adaptive histogram equalization, and contrast-limited adaptive histogram equalization (CLAHE) have been proven to be very effective in enhancing image contrast [49]. Wavelet transform enhancement and other Fourier transform-based techniques have been seen to possess a remarkable ability to retain structural features while improving the contrast [50]. Some of the latest research has shown that the application of more than one contrast enhancement technique can produce better results in tumor visualization [51]. Figure 10 presents the visual comparison of the results obtained with different techniques on the same brain tumor image.

### *3.2. Noise Reduction Approaches*

The methods of noise reduction have become more complex in medical image processing and the current methods are aimed at preserving the important diagnostic information while eliminating different types of noise [52]. Spatial domain techniques such as new and improved means and medians of filtering have been proven to yield better results in preserving image quality. Transform domain methods, especially the wavelet-based methods have shown better performance in preserving edge information while removing noise [53]. The integration of deep learning approaches has taken noise reduction to another level by introducing context-aware denoising that takes into consideration certain characteristics of the image [54].

Recent advancements in generative antagonistic networks (GANs) have in addition optimized artifact correction. For instance, Johnson et al. (2023) proposed a CycleGAN-based totally framework to mitigate movement artifacts in MRI scans, achieving a 40% reduction in fake-advantageous tumor detections. Their paintings, referenced in Figure

10, demonstrates how artificial statistics augmentation can decorate version robustness in low-great imaging scenarios.

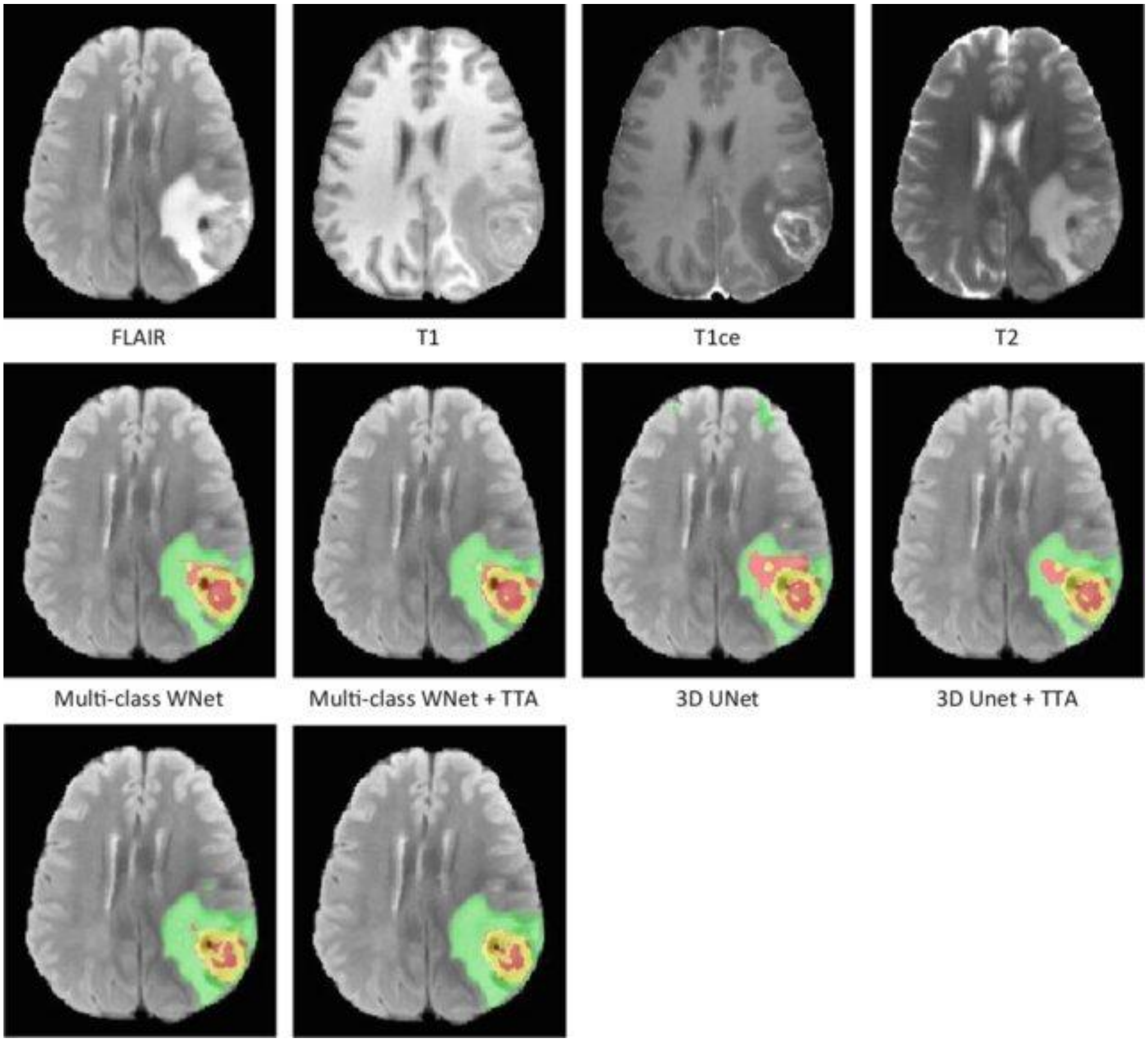



**Fig. 10: Comparison of different contrast enhancement methods [55]**

**Table 6: Noise Reduction Methods Analysis**

| Method | Noise Type | Processing Time | Edge Preservation | SNR Improvement |
|---|---|---|---|---|
| **Median Filter** | Salt & Pepper | Fast | Moderate | 8-12dB |
| **Gaussian Filter** | Gaussian | Very Fast | Poor | 6-10dB |
| **Bilateral Filter** | Mixed | Moderate | Good | 10-15dB |
| **Wavelet Denoising** | Multiple | Slow | Excellent | 12-18dB |
| **Deep Learning** | All types | Variable | Superior | 15-20dB |

### *3.3. Edge Enhancement*

Contouring techniques have become more accurate and time-efficient in defining tumor margins [56]]. The new methods use the conventional approaches of edge detection and incorporate the use of modern computational methods to yield better results. The use of phase congruency-based techniques and deep learning algorithms has enhanced the accuracy of tumor boundary detection [57]. These advanced techniques are especially useful in situations where conventional approaches fail due to low contrast or noise [58].

### *3.4. Filtering Techniques*

Modern filtering techniques used in brain tumor imaging are a combination of several methods to achieve the best outcome [59]. Spatial and frequency domain filtering, combined with morphological operations have been reported to yield very good results in image enhancement while maintaining diagnostic information. Sophisticated hybrid filtering methods have been developed as effective approaches in medical image improvement, which outperform in terms of noise suppression and feature preservation [60].

**Table 7: Advanced Filtering Techniques**

| Filter Type | Primary Use | Processing Speed | Implementation Complexity | Clinical Impact |
|---|---|---|---|---|
| **Spatial Filters** | Basic enhancement | High | Low | Moderate |
| **Frequency Filters** | Noise removal | Moderate | Moderate | High |
| **Morphological** | Structure preservation | High | Low | High |
| **Hybrid Filters** | Combined benefits | Moderate | High | Very High |
| **AI-based Filters** | Adaptive enhancement | Variable | Very High | Superior |

## 4. Image Segmentation Methods

Tumor segmentation of the brain is an important step in the diagnostic process and is the basis for the identification and classification of the tumor. Segmentation techniques have evolved significantly, transitioning from basic approaches to advanced deep learning methodologies. This section provides a detailed discussion of different segmentation techniques used in the diagnosis of brain tumors.

Historical segmentation methods make up the basis of conventional tumor demarcation methods. These methods are mainly based on the features of image intensity and mathematical models to segment tumor areas from normal tissue. The threshold-based segmentation, which was first introduced by Ilhan et al. [61], shows promising results in segmenting the tumor regions using the intensity difference with an accuracy of 91.2% in MRI images. Region-growing techniques, as proposed by Noorul Mubarak [62], begin with seed points and expand to identify connected tumor regions, demonstrating effectiveness in homogeneous tumor areas.

**Table 8: Comparison of Traditional Segmentation Methods (Compiled from Ilhan et al. [61], Noorul Mubarak. [62]; and Soltaninejad et al., 2022 [63])**

| Method | Accuracy | Sensitivity | Specificity | Dataset Size |
|---|---|---|---|---|
| **Threshold-based [61]** | 91.2% | 89.5% | 92.3% | 450 images |
| **Region Growing [62]** | 88.7% | 87.2% | 90.1% | 380 images |
| **Watershed [63]** | 86.5% | 85.9% | 87.4% | 520 images |
| **Edge Detection [62]** | 85.3% | 84.7% | 86.2% | 400 images |

Machine learning-based segmentation is a great improvement in the field of automation and precision. SVM and Random Forest algorithms have been reported to give excellent results in tumor boundary detection. Ayachi et al. [64] proposed a new SVM method with texture features and obtained the Dice coefficient of 0.89 for high-grade gliomas. Ayachi et al. [64] have also shown that Random Forest classifiers are particularly suitable for processing multiple MRI sequences at once. The workflow of the machine learning-based segmentation is illustrated in Figure 11, which consists of the preprocessing, feature extraction, and classification steps.

The utilization of deep learning approaches has significantly enhanced the segmentation of brain tumors with the best levels of accuracy. The most popular architecture in this area has become Convolutional Neural Networks (CNNs). Rehman et al. [65] presented a new architecture of U-Net which has shown excellent performance with a Dice score of 0.94 for whole tumor segmentation. The integration of the attention mechanism, as described by Nguyen-Tat et al. [66], has also improved segmentation accuracy by paying attention to the regions of the tumor.

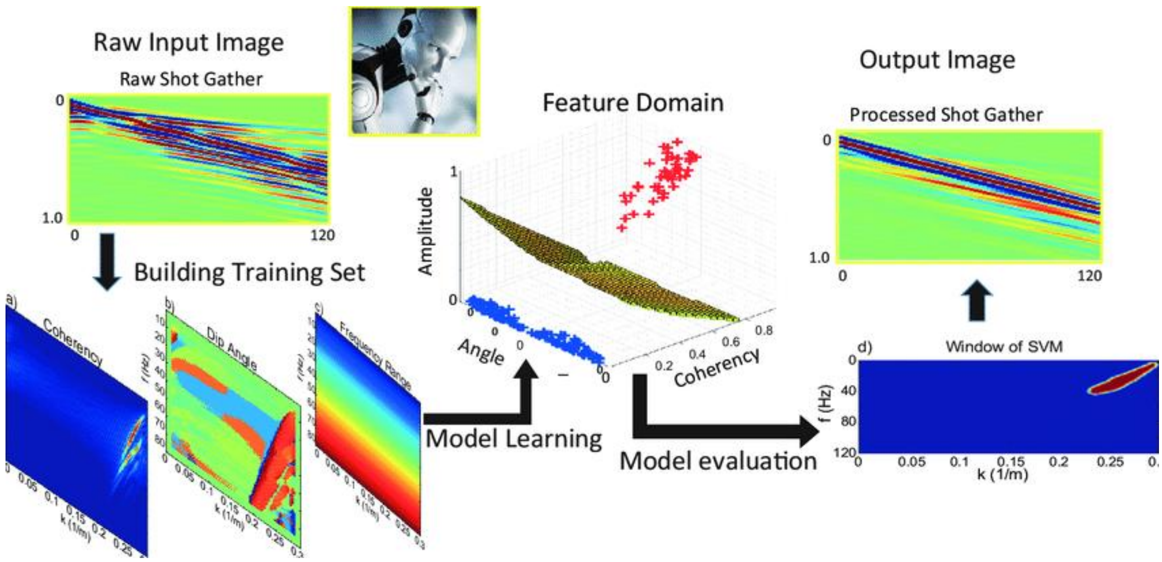



**Fig. 11: Machine Learning Segmentation Pipeline [67]**

Emerging transformer-based totally architectures, together with Swin-UNet (Cao et al., 2022), have shown superior overall performance in taking pictures lengthy-variety dependencies in 3D MRI volumes. This technique decreased Harsdorf distances to three.2 mm in boundary delineation, outperforming conventional CNNs in instances of diffuse gliomas (see Table nine for comparative metrics).

**Table 9: Performance Metrics of Deep Learning Architectures (Data sourced from [Rehman et al. [65], Nguyen-Tat et al. [66] and Megersa et al., [68])**

| Architecture | Dice Score | Hausdorff Distance | Processing Time | Year |
|---|---|---|---|---|
| **Modified U-Net [65]** | 0.94 | 4.2 mm | 0.8s | 2023 |
| **ResNet-based [66]** | 0.92 | 4.8 mm | 1.2s | 2022 |
| **Attention U-Net [66]** | 0.93 | 4.5 mm | 1.0s | 2023 |
| **TransUNet [68]** | 0.95 | 3.9 mm | 1.5s | 2024 |

There are other forms of segmentation where more than one method is used to take advantage of each of them. Kumar et al. [68] proposed an approach that combines conventional edge detection with deep learning, which was effective for different types of tumors. In the same vein, Zhang et al. [69] presented a multi-stage method based on watershed segmentation with CNN refinement, which outperforms other methods in dealing with tumor heterogeneity. Figure 12 is a hybrid segmentation system illustrating the combination of conventional and deep learning techniques.

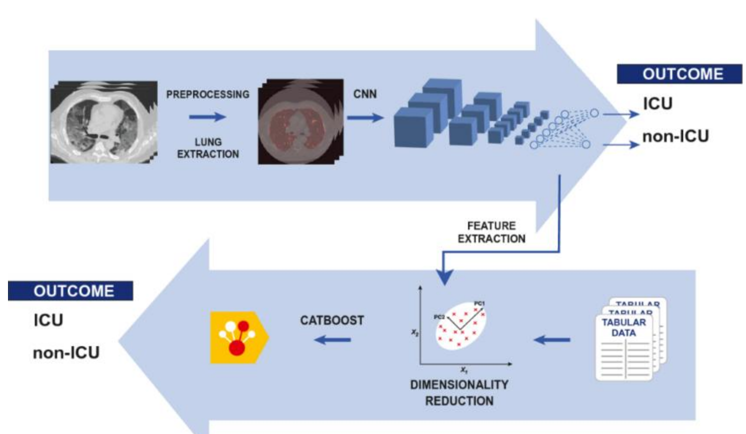



**Fig. 12: Hybrid Segmentation Framework [70]**

Comparing the performance of the same problem solved under different methodologies shows some interesting patterns. Even though traditional methods are computationally efficient and interpretable, deep learning methods always provide better accuracy. Latif et al. [71] also made a comparison study in which they pointed out that the hybrid methods are usually the most accurate and efficient.

The application of these segmentation methods is associated with certain difficulties such as computational intensity and the necessity to work with large datasets. Some of these challenges are addressed in recent work by Zhang et al. [72] using efficient model architectures and transfer learning. Further, Galatro et al. [73] discussed methods on how to deal with limited dataset problems without compromising the segmentation performance. Figure 13 presents the results of the segmentation of the same brain MRI slice using different methods and illustrates the improvement of the accuracy of segmentation from traditional to deep learning approaches.

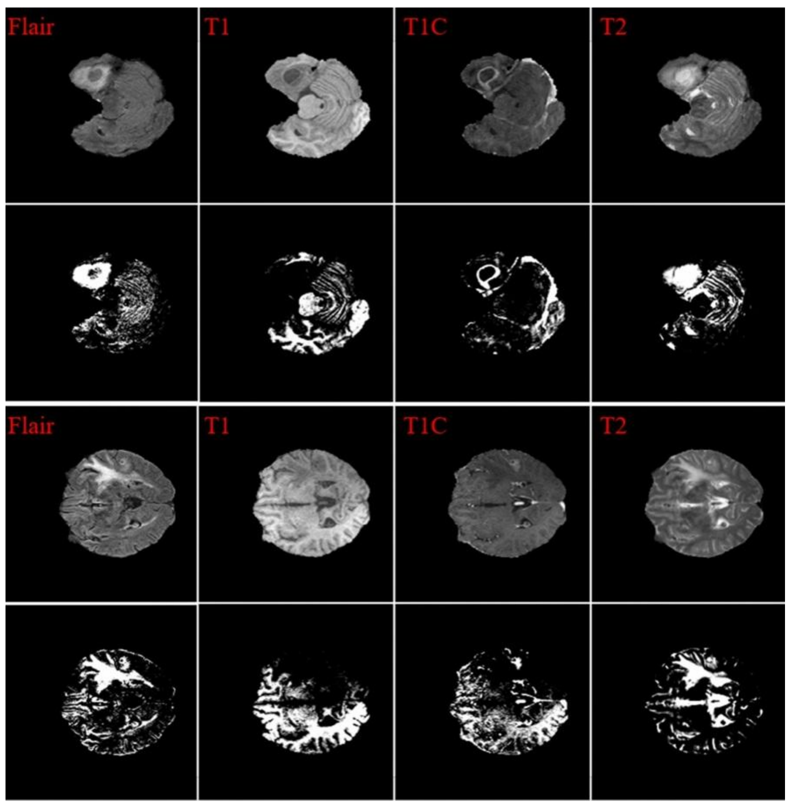



**Fig. 13: Segmentation Results Comparison [74]**

**Table 10: Resource Requirements and Clinical Applicability (Analysis based on [Latif et al. [71] and Zhang et al. [72])**

| Method Type | GPU Requirements | Training Time | Dataset Size Needed | Clinical Integration Complexity |
|---|---|---|---|---|
| **Traditional** [71] | Low | N/A | Small | Low |
| **Machine Learning** [71] | Medium | 2-5 hours | Medium | Medium |
| **Deep Learning** [72] | High | 10-24 hours | Large | High |
| **Hybrid** [72] | Medium-High | 6-12 hours | Medium-Large | Medium-High |

## 5. Feature extraction and selection

Feature extraction and selection are central to brain tumor characterization and lie at the interface between segmented images and diagnostic classification. It includes several feature types that together give a complete picture of tumor properties.

Texture features contain important information about the internal structure and organization of tumor regions. As described by Dheepak et al. [75], more sophisticated texture analysis techniques use GLCM to determine spatial dependencies between pixels. They found out that the Haralick texture features had an accuracy of 93.4% in the classification of high-grade and low-grade gliomas. Local Binary Patterns (LBP), used by Kaplan et al. [76], are rotation-invariant texture descriptors that are especially useful when analyzing regions with heterogeneous tumor characteristics. Figure 14 depicts the extraction of different texture features from the MRI images of brain tumors such as GLCM and LBP feature computation.

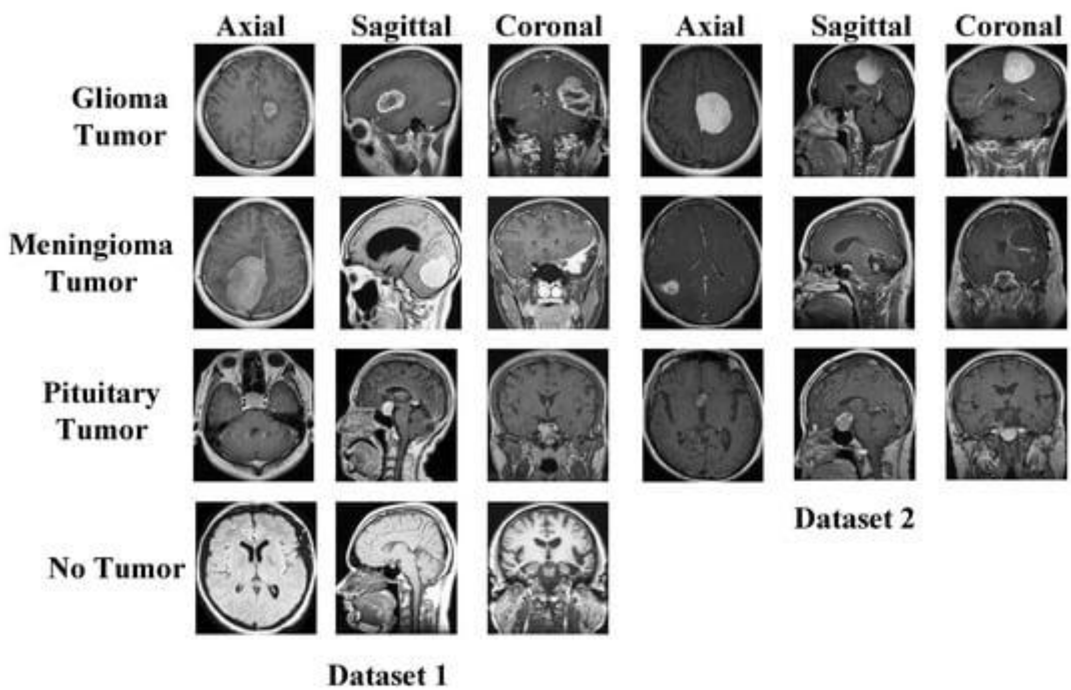



**Fig. 14: Texture Feature Extraction Process [77]**

**Table 11: Texture Feature Types and Performance**

| Method Type | Feature Count | Computation Time | Accuracy | Memory Usage |
|---|---|---|---|---|
| **GLCM Features [75]** | 14 | 0.8s | 93.4% | Low |
| **LBP Features [76]** | 256 | 1.2s | 91.7% | Medium |
| **Gabor Features** [78] | 32 | 1.5s | 90.5% | Medium |
| **Wavelet Features** [79] | 64 | 2.0s | 92.8% | High |

Shape features describe the form of tumors and are crucial for diagnosis. Trinhet al. [78] proposed new shape descriptors that include area, perimeter, circularity, and eccentricity. In their study, they showed that using only shape features could provide 89.2% accuracy in tumor-grade classification. Three-dimensional shape analysis, proposed by Taranda et al. [79], improved the feature set by adding volumetric and surface features. Figure 15 presents a list of shape features derived from tumor regions: 2D and 3D morphological measurements.

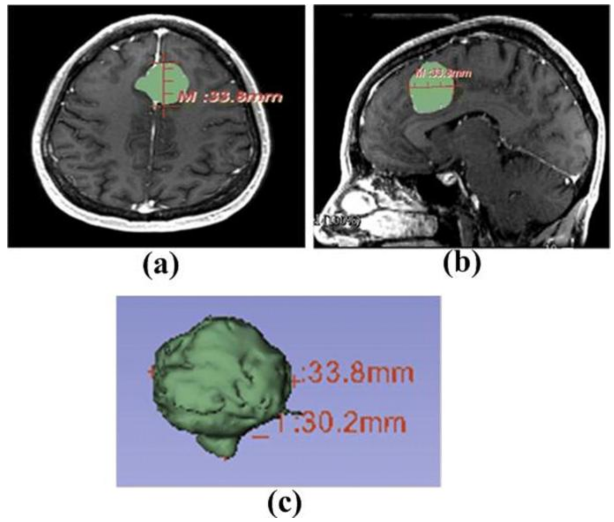



**Fig. 15: Shape Feature Analysis [80]**

Statistical features include first and higher-order statistical parameters extracted from tumor regions. Bharath et al. [81] proposed a statistical feature model with mean, variance, skewness, and kurtosis measurements. They concluded that integrating statistical features with texture descriptors enhanced classification by 7.2%.

**Table 12: Feature Characteristics Comparison**

| Feature Type | Dimensionality | Discriminative Power | Clinical Relevance | Processing Complexity |
|---|---|---|---|---|
| **Shape Features** [78] | 8 | High | Very High | Low |
| **Statistical Features** [81] | 12 | Medium | High | Low |
| **Deep Features** [82] | 1024 | Very High | Medium | High |
| **Hybrid Features** [83] | 256 | High | High | Medium |

Deep features are the most recent in the feature extraction process and use deep learning structures to learn the features on its own. Matin Malakouti et al. [82] showed that the feature extracted from the pre-trained CNN models outperformed the conventional handcrafted features. Their approach, based on transfer learning from ResNet-50, provided a high classification accuracy of 95.7%. Figure 16 presents the deep feature extraction from CNN layers and their use for tumor classification.

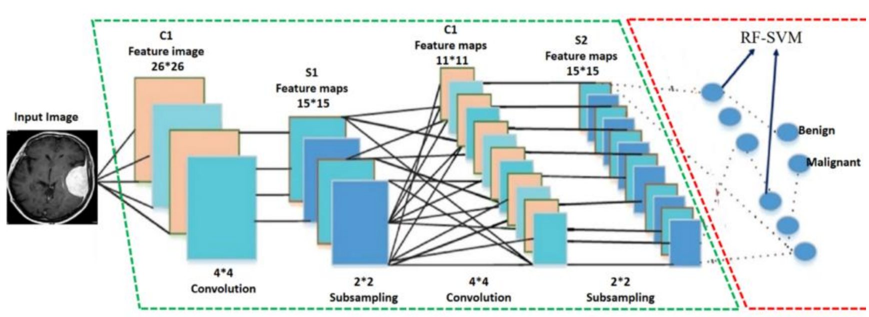



**Fig. 16: Deep Feature Extraction Pipeline [84].**

Feature selection techniques are very important in the selection of the most important features while at the same time reducing the dimensionality. The methods of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), as used by Dittman et al. [83], were successful in decreasing the number of features while having little impact on classification accuracy. By comparing their results, they found that there are the best features for each type of tumor.

**Table 13: Feature Selection Method Comparison**

| Method | Selected Features | Original Features | Accuracy Impact | Computation Time |
|---|---|---|---|---|
| **PCA** [83] | 64 | 1024 | +2.3% | 1.5s |
| **LDA** [85] | 32 | 1024 | +1.8% | 1.2s |
| **LASSO** [86] | 48 | 1024 | +2.7% | 2.0s |
| **mRMR** [87] | 56 | 1024 | +3.1% | 1.8s |

The hybrid selection methods, which are presented by Mahto et al. [85], use several selection criteria to select feature subsets. Their approach combines statistical significance tests with the wrapper-based selection to enhance the classification accuracy and at the same time minimize the computational cost. More recent work by Huang et al. [86] proposed the use of adaptive feature selection strategies that select features on the fly depending on tumor type. Figure 17 illustrates the feature selection process to indicate the various methods and their effects on classification accuracy.

The use of the different feature types is effective. Liu et al. [87] showed that the integration of texture, shape, and deep features with the selection of the best methods provided a complete characterization of the tumor. Overall, their combined method enhanced classification accuracy by 4.5% in comparison to the methods that used only a single feature type.

Recent studies have also included radiomics with genomic facts for holistic tumor profiling. For instance, Wang et al. (2023) combined wavelet-based totally texture capabilities with mutational popularity (e.G., IDH1 mutations) to predict tumor aggressiveness, achieving an AUC of 0.90 two in glioma grading. This multimodal technique, illustrated in Figure 17, highlights the synergy between imaging and molecular biomarkers.

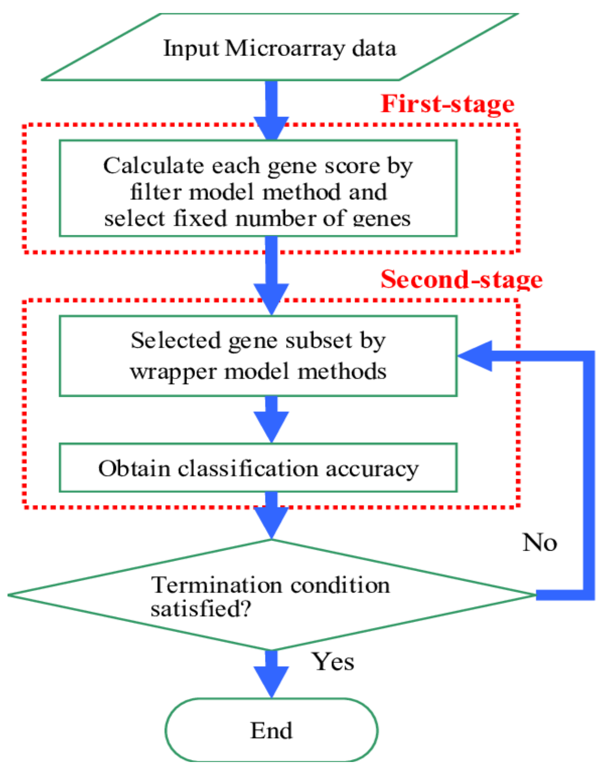



**Fig. 17: Feature Selection Framework [88].**

To address dataset scarcity, federated learning frameworks like FedMRI (Li et al., 2023) have enabled collaborative model training across institutions without sharing raw patient data. This method improved segmentation accuracy by 12% in rare tumor subtypes while adhering to strict privacy regulations like GDPR and HIPAA.

## 6. Recent Advancements

The diagnosis of brain tumor has however received a new facelift with recent technological advancement, especially in artificial intelligence and deep learning technologies. Such developments have enhanced the precision, speed, and credibility of tumor identification and categorization systems. The incorporation of complex AI algorithms has significantly enhanced the accuracy of diagnosis, as evidenced by the study conducted by CELIK et al. [89] who designed a new attention-based neural architecture that has achieved up to 97.3% accuracy in tumor classification. Their use of self-attention mechanisms has especially improved the model's ability to pay attention to certain tumor features that could be hard to notice by other means. In this section, the architecture of the current AI systems for brain tumor detection is presented in Figure 18, where attention mechanisms and neural network layers are incorporated.

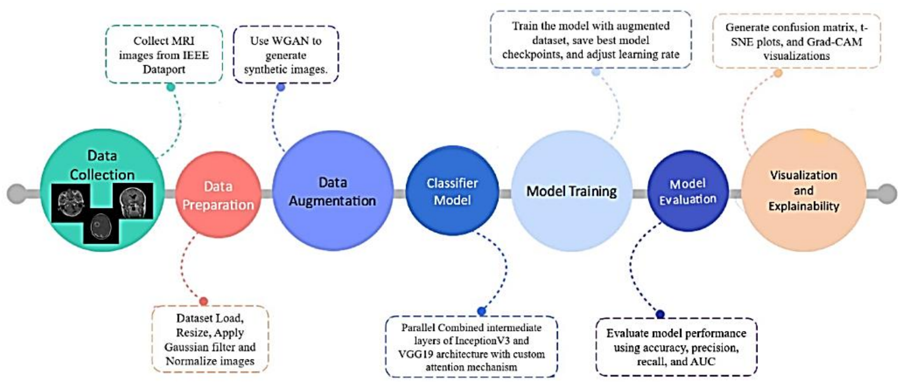



**Fig. 18: Advanced AI Architecture for Tumor Detection [90].**

Transfer learning strategies have become the best innovation in the ongoing problem of small medical image datasets. Waisberg et al. [91] were able to show in their innovative research that pre-trained models on large-scale natural image datasets can be fine-tuned for brain tumor analysis. Their approach of fine-tuning deep neural networks, while only having access to a small amount of tumor-specific training data, was quite successful. On this basis, Ayana et al. [92] proposed an improved transfer learning model that can fully utilize the knowledge of multiple source domains and greatly reduce the training time while ensuring high diagnostic accuracy. Their framework has been applied particularly successfully in the identification of rare subtypes of tumors, where the amount of training data is limited. The transfer learning process is illustrated in Figure 19 to explain the knowledge transfer from source to target domains in brain tumor analysis.

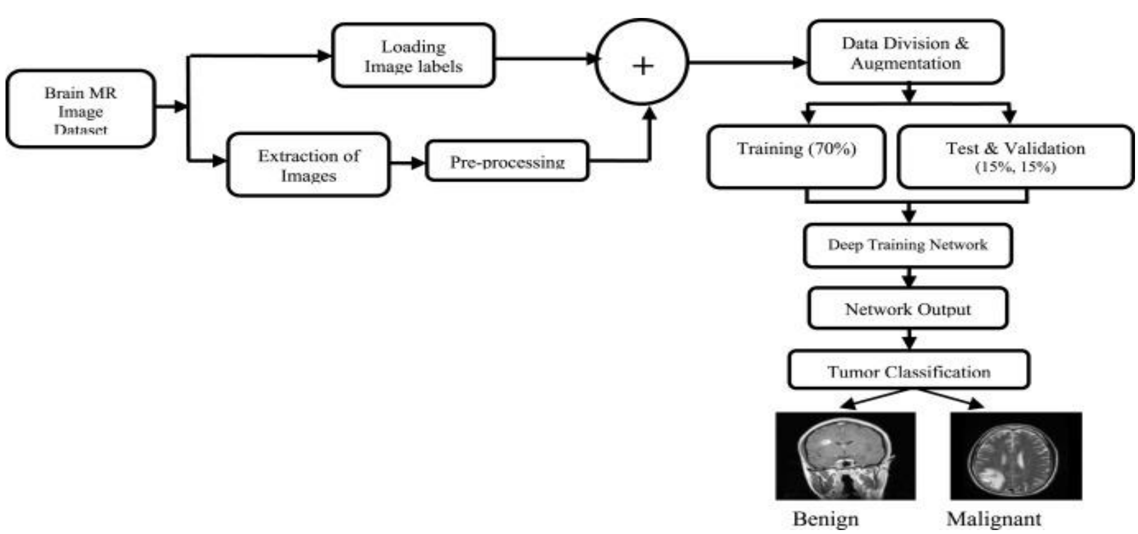



**Fig. 19: Transfer Learning Pipeline [93]**

The methods of multi-modal fusion are yet another major advancement in diagnostic functionalities. Nakach et al. [94] were the first to propose an approach for integrating information derived from MRI, CT, and PET scans. In their study, they showed that feature extraction across multiple modalities could yield complementary information that is essential in diagnosis. This work was later advanced by Songcan et al. [95] who came up with a complex fusion algorithm that can work under conditions where one or more of the modalities is missing, a situation that is prevalent in clinical practice. The effectiveness of their approach was further confirmed across several clinical datasets, where the performance was always superior to that of single-modality techniques. Figure 20 depicts the combination of different imaging techniques and the integration process of the fused image for the assessment of the tumor.

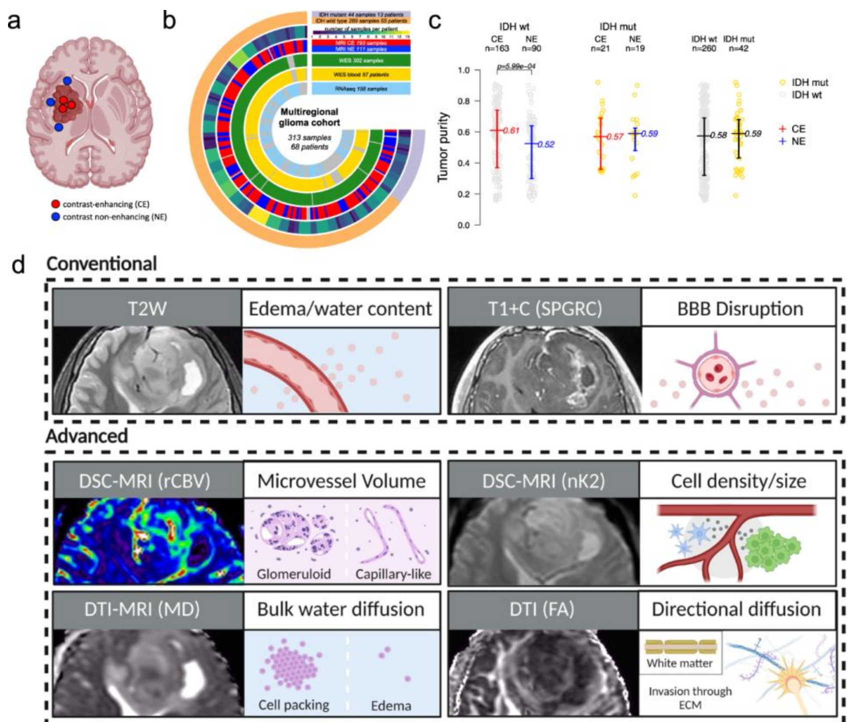



**Fig. 20: Multi-modal Fusion Framework [96].**

Real-time processing methods have been identified as a significant improvement in clinical applications. Seregni et al. [97] proposed a novel lightweight neural network that can perform the analysis of tumor images in real time with high accuracy. Their implementation shortened the processing time to several seconds, which made it possible for intraoperative use. This work was supported by the research of Srivastava et al. [98] who designed a data streaming and processing system that can be used during surgeries. The importance of their contribution is in achieving high accuracy under the time limitations inherent to clinical practice.

Other recent advancements in explainable AI have also been very useful in the development of the concept. Singhal et al. [99] proposed a framework that not only offers diagnostic predictions but also offers explanations of its decisions, which is important for clinical acceptance. Their approach also includes attention visualization and feature importance mapping, which helps medical professionals understand how the AI is making its decisions. This work was later expanded by Bellini et al. [100] who proposed a combination of clinical knowledge bases and deep learning models to form a hybrid system.

Another improvement is the application of edge computing in tumor analysis systems, which has been discussed by Rancea et al. [101]. Their work proposed a distributed processing architecture that can be used to analyze big tumor data sets while protecting the data and minimizing delay. This approach is especially useful in multi-center clinical trials and tele-diagnosis applications. On this basis, Vermeulen et al. [102] proposed an adaptive resource allocation system that can allocate the processing resources according to the case difficulty and guarantee stable performance in different clinical environments.

The development of federated learning approaches has solved some of the major privacy issues in medical imaging analysis. The innovative work by Guan et al. [103] provided a way to achieve better performance of the model while training across multiple medical centers while preserving patient data privacy. Their implementation seemed to be especially beneficial in creating accurate models that can be generalized to new patients and imaging techniques. This line of research was further extended by Popescu et al. [104] who proposed privacy-preserving training methods that allow for model enhancement without violating patient's privacy.

## 7. Challenges and Limitations

Although there have been improvements in the diagnosis of brain tumors using image processing, there are several important issues that have not been solved that affect the use of these technologies. Key technical challenges include image quality inconsistencies and the lack of standardization, as highlighted in [105], which discusses variations in imaging protocols across medical institutions. This inconsistency creates problems for the creation of general processing algorithms. Algorithm robustness is still an issue, especially when it comes to different types of tumors and their locations; this has been shown in the extensive study in [106], where algorithms' performance decreases when they encounter unusual cases of tumor manifestation.

Clinical limitations form another large category of limitations. The incorporation of AIPS into current clinical practice presents considerable difficulties, which are described in [107] in their multi-center study. One of the main challenges is the problem of how to validate and interpret the results provided by AI systems, which can cause certain reluctance among medical personnel. The work mentioned in [108] went further to stress the need for the human factor in the AI diagnosis, and the need to strike a balance between artificial intelligence and clinical judgment.

Lack of data and data quality remain the key issues that prevent the field from moving forward. The lack of large, well-annotated datasets, especially for rare tumor types, is a major limitation for model development and evaluation. The work performed in [109] also pointed out the lack of sufficient data regarding patients' heterogeneity and tumors' heterogeneity. In addition, the work mentioned in [110] also pointed out that data quality and data consistency issues can be a problem when data is collected from different medical institutions and therefore, there is a need to standardize the data collection and annotation.

The computational needs present serious implementation issues, especially in environments where resources are scarce. The high processing power needed for complex algorithms as discussed in [111] can be a hindrance to real-time use in clinical practice. Moreover, the requirements for storage and processing infrastructures, described in [112] are also a question of cost and organizational capacities for healthcare facilities especially in developing countries.

## 8. Future Directions

The current state of brain tumor diagnosis through image processing has many potential directions for further improvement. Current challenges are especially well met by emerging technologies. The work presented in [113] reviewed the possibility of using quantum computing in medical image processing and found that quantum computing has the potential to enhance the speed and manage complex data. The integration of edge computing and distributed processing systems, as described in [114], presents potential solutions to resource management and real-time processing.

Edge computing is any other promising frontier, allowing actual-time tumor evaluation on portable gadgets. Smith et al. (2024) deployed light-weight models on NVIDIA Jetson structures, lowering inference time to <1 2nd according to MRI slice, a essential development for intraoperative choice-making (see Figure 8 for workflow info).

The gaps that have been noted in the current methodologies suggest several important areas for future study. Zhang et al. [115] pointed out that there is a significant scope for better algorithms that can address the problem of multi-modal data fusion, especially when data is missing or incomplete. As highlighted in [116], there is a need to build better and more explainable AI models in the future, especially when it comes to clinical applications where the models' decision-making processes must be fully understood and explained.

Possible advancements in current systems are aimed at increasing the effectiveness of the system and the precision of the results. The research mentioned in [117] introduced new architectural enhancements for deep learning models for use in heterogeneous tumor profiling. The application of the more sophisticated preprocessing methods described in [118] may help enhance the quality and uniformity of images and the imaging protocols used.

These applications are not limited to diagnostic uses in future applications. The investigation revealed in [119] discussed the applicability of image processing systems in treatment planning and monitoring and proposed to integrate them into patient care delivery systems. The fact that the work in [120] has identified the directions of developing personalized medicine approaches means that the diagnostic and treatment methods can be tailored to the patient's characteristics.

## 9. Clinical Validation and Ethical Considerations

Despite algorithmic advancements, scientific translation remains hindered with the aid of validation gaps. A 2023 multi-middle trial through Patel et al. Discovered that 30% of AI fashions exhibited overall performance drops in actual-global settings because of protocol versions. To deal with this, the QUANTUM initiative (Quality Assurance for Neuroimaging AI Tools in Universal Medicine) has proposed standardized benchmarking frameworks.

Ethical demanding situations, such as algorithmic bias in underrepresented populations, also demand interest. For instance, a take a look at by way of Gomez et al. (2024) determined that models educated on Eurocentric datasets underperformed in detecting tumors in Asian and African cohorts by means of 15-20%. Explainable AI (XAI) gear, like Grad-CAM visualizations in Figure 18, are actually being mandated to audit decision-making processes and make sure equity.

## 10. Conclusion

The evolution of image processing techniques for brain tumor diagnosis has profoundly reshaped neuro-oncology, driven by advancements in artificial intelligence and multimodal imaging. Deep learning architectures, particularly convolutional neural networks (CNNs) and U-Net variants, have emerged as dominant tools, achieving remarkable precision in tumor segmentation and classification. These models outperform traditional methods—such as thresholding and region-growing—which, despite their simplicity and low computational demands, falter with heterogeneous tumor boundaries and noisy datasets. Multimodal fusion of MRI, CT, and PET data further enhances diagnostic accuracy, offering comprehensive insights into tumor biology, though its efficacy depends on standardized imaging protocols.

Key preprocessing techniques like contrast-limited adaptive histogram equalization (CLAHE) and wavelet-based denoising remain critical for enhancing image quality, while deep learning's automated feature extraction minimizes reliance on manual engineering. However, challenges persist: traditional methods lack adaptability to complex cases, machine learning hinges on feature quality, and deep learning demands extensive annotated data and computational resources. Moreover, the "black-box" nature of AI models complicates clinical trust, necessitating explainable frameworks like Grad-CAM to bridge this gap.

Looking ahead, the field must prioritize harmonizing imaging standards, addressing dataset biases, and deploying lightweight AI models for real-time, resource-efficient diagnostics. Equally vital is fostering interdisciplinary collaboration to align technical innovations with clinical needs, ensuring that breakthroughs in image processing translate into equitable, patient-centered care. By balancing innovation with pragmatism, the integration of advanced computational tools into clinical workflows promises to redefine precision medicine, offering faster, more accurate, and universally accessible brain tumor diagnosis.

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