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MRI-based brain tumor detection and classification: A survey of AI and machine learning methods

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Abstract

One of the biggest health problems around the world, display clearly by brain tumors, is finding issues early. Making the right choice is very important for treatment. MRI scans are particularly good at helping numeral out the shape and building of brain tumors. In any case, traditional diagnostic schemes relying on manual interpretation take time and are vulnerable to errors of meticulous transient origin. This paper explores the recent advances of Artificial Intelligence (AI) and Machine Learning (ML) to automate brain tumor detection and prediction in MR images. It stresses deep learning patterns in particular, convolutional neural networks (CNNs) and Xception, that exactness is. From end to end, there should be no traces left. These points out certain steps prior to analysis, such as extracting a cranium or normalising data. They also illustrate different kinds of information addition into the learning process to cope with over-predictions and more example instances. It also discusses performance evaluation measures and problems, such as the computational cost associated with mass data processing and virulent bias of example sets from certain regions. Address Considering these restrictions, the AI-based systems suggested building a bridge between algorithm development and its practical application. Thus, we can improve the diagnostic reliability, efficiency and better outcomes for neuro-oncology patients.

Keywords: Brain Tumor Classification; Magnetic Resonance Imaging (MRI); Deep Learning; Convolution Neural Networks (CNNs); Artificial Intelligence in Medical Imaging

1. Introduction

1.1. Importance of MRI in Brain Tumor Determination

Attractive Reverberation Imaging (MRI) has developed as the foundation methodology within the conclusion and assessment of brain tumors due to its unparalleled capacity to capture nitty gritty anatomical and morphological highlights of delicate tissues. Not at all like other imaging strategies, MRI offers high-resolution and contrast-rich perception of brain structures, empowering clinicians to recognize tumor boundaries, heterogeneity, and spatial localization with momentous precision (Mayo Clinic, 2025; Lake Zurich Open MRI, 2024). The foundation for early and accurate tumor classification is based on how it connects with ongoing diagnosis and treatment planning. Accomplishment and truthful conclusion not only helps indicate the right treatments but also greatly affects the realization of surgery and the patient's chances of enduring for a long time (Very well Wellbeing, 2025).

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1.2. Restrictions of Customary Demonstrative Strategies

In spite of its qualities, routine demonstrative workflows depend on manual translation of MRI checks, which presents so numerous basic challenges. Radiological appraisals are intrinsically subjective and can shift essentially over eyewitnesses, frequently driving to conflicting analyze. The manual prepare is additionally time-intensive, restricting its effectiveness in high-throughput clinical settings. These impediments highlight the squeezing require for computerized, objective, and reproducible strategies that can increase clinical decision-making and progress demonstrative exactness (Radiology Collaborator, 2024).

1.3. AI/ML Transformation in Restorative Imaging

Afterward an extensive time, the use of the Artificial Intelligence (AI) and Machine Learning (ML), especially for deep learning models, has converted to the field of the medical image analysis. Convolutional Neural Systems (CNNs) and the other profound enterprises have been confirmed unexpected aptitudes in learning various steamrolled images straightforwardly from the imaging information, subsequently robotizing and errands such as division, location, and cataloging of brain tumors (Dang et al., 2022). Figure 1 showing the Impact of Technological Advancements in Brain Tumor Diagnosis. AI-powered classifications of provide many reimbursements and such as flexibility, speed, accurateness, and a significant reduction in errors instigated by humans. These qualities make Artificial Intelligence a fundamental for the instrument in upgrading radiological workflows and appealing investigative certainty (Khan et al., 2023).

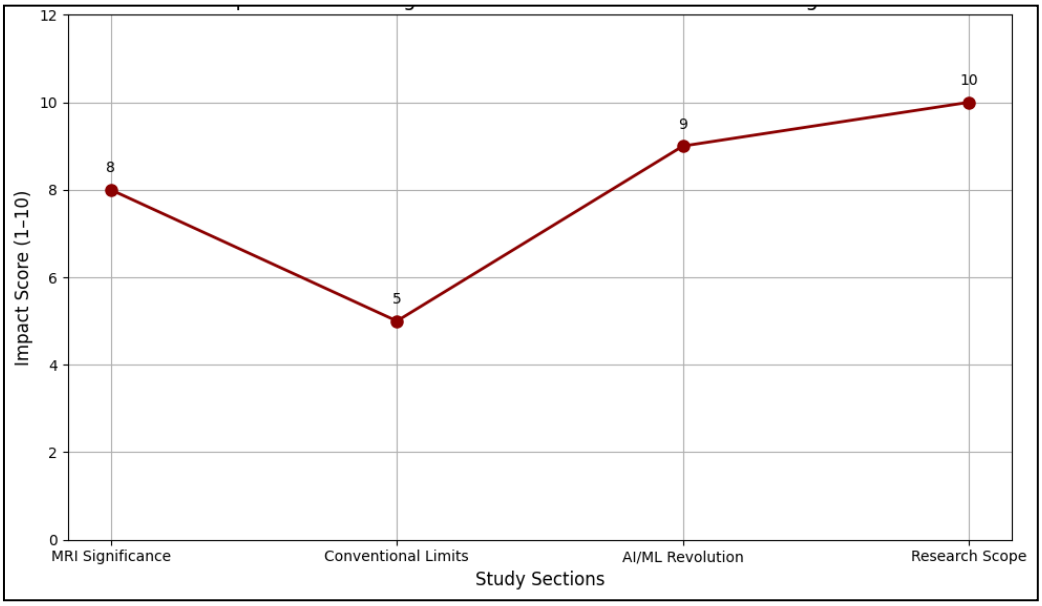


Figure 1 Impact of Technological Advancements in Brain Tumor Diagnosis

1.4. Investigate Goals and Scope

This think about points to create a strong, AI-based development for the classification of brain tumors utilizing MRI filters. The primary objective is to address frantic delays in existing approaches, especially concerning speculation to different clinical settings, explainability of demonstrate choices, and computational viability in real-time applications. Centering on this size, the proposed system yearns to associate the crevice between algorithmic development and clinical convenience, subsidizing the following era of cleverly symptomatic strategies in neuro-oncology.

2. MRI imaging and brain tumor typology

2.1. MRI Modalities for Tumor Discovery

Attractive Reverberation Imaging (MRI) utilizes different courses of action to complement distinctive tissue characteristics, subsequently progressing tumor location and depiction. T1-weighted pictures offer tall anatomical detail, supporting the assessment of typical brain structures. T2-weighted arrangements highlight fluid-encompassing districts, making them instrumental in identifying tumor-connected edema. The Fluid-Attenuated Reversal Recuperation arrangement stifles cerebrospinal liquid signals, boosting injury differentiate, especially for recognizing

peritumoral changes. Disparity-enhanced T1 imaging, using gadolinium-based agents, further develops lesion visibility by revealing blood–brain barrier disruptions commonly correlated with malignancies (Ge et al., 2022).

2.2. MRI Characteristics of Brain Tumors

Different brain tumor types exhibit exhibitnoticeable radiological features, yet substantial overlap in appearance often poses diagnostic experiments. Gliomas ordinarily show up as unpredictable, infiltrative injuries with heterogeneous differentiate advancement. High-grade gliomas may appear necrotic centers and ring-like advancement designs. Meningiomas are ordinarily extra-axial and display a well-defined, similarly upgrading mass, regularly expanded by a characteristic "dural tail" marker. Pituitary adenomas, found within the sellar locale, ordinarily show as well-circumscribed injuries, but their distinction from cystic or hemorrhagic masses remains complex (Diaz-Pernas et al., 2022).

2.3. Conventional vs. Profound Learning Approaches

Common machine learning strategies have certainty in intensely on manual highlight building, where space specialists extricate geometric, textural, and morphological highlights from MRI checks. Forms such as Back Vector Machines (SVMs) and Irregular Timberlands have appeared direct acknowledgment in tumor classification but are frequently constrained by their reliance on carefully assembled highlights and destitute adaptability to considerable datasets (Wang & Li, 2025). Figure 2 showing comparative Analysis of MRI Modalities and AI Models in Brain Tumor Classification

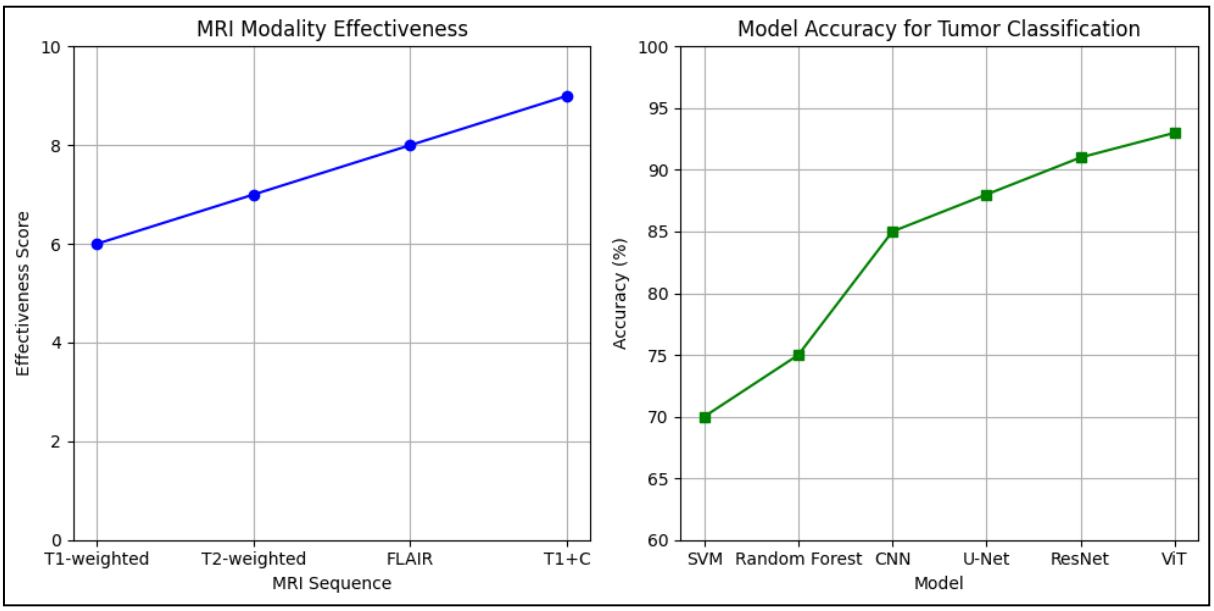


Figure 2 Comparative Analysis of MRI Modalities and AI Models in Brain Tumor Classification

In diverge, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have enabled end-to-end learning frameworks that certainly extract and hierarchically perfect features directly from raw imaging data. Architectures such as U-Net have been pivotal in semantic separation tasks, enabling careful tumor boundary explanation. ResNet and its variations have moved forward categorization exactness through profound leftover learning, tending to the vanishing slant issue in more profound systems. More as of late, Representation Transformers (ViTs) have demonstrated potential by displaying long-range subordinate locales in picture information, amplifying unused ideal models for brain tumor evaluation (Khan & Stop, 2025).

3. Literature review

Nahiduzzaman et al. (2025) accessible a novel hybrid paradigm combining a lightweight parallel depth wise noticeable convolutional neural network (PDSCNN) through a range regression-enhanced extreme learning machine (RRELM) for brain tumour categorization using MRI images. Their organization enhanced feature extraction and reduced computational density while achieving high classification authenticity. Contrast-limited adaptive histogram equilibrium (CLAHE) expanded image excellence, and SHAP-based explainability afforded correctness in display judgements. The

alleged framework significantly overtook existing examples, achieving an accuracy of 99.22%, precision of 99.35%, and memory of 99.30%, thereby setting a scale in both working and interpretability.

Bhimavarapu et al. 2024 proposed a better-quality brain tumor detection method using an improved Fuzzy C-Means (FCM) clustering algorithm for accurate MRI splitting up and an Extreme Learning Machine (ELM) classification. They operate advanced feature extraction techniques, directing on mock-up, texture, and color to achieve a superior group. The model determined remarkable truth across many tumor types on Fig share and Kaggle datasets, surpassing existing types. The framework provides a robust and efficient solution for mechanized brain tumor diagnosis, highlighting its potential for clinical purposes.

Lamrani et al. (2022) progressed a convolutional neural network (CNN)-originated framework for the brain tumor establishing and grouping using MRI images. Their model incorporates so many convolutional and dense layers, alongside preprocessing techniques like image resizing and a regular basis for enhanced input quality. Utilize a dataset of 3,000 images from Kaggle, their endeavor completed high performance with 96.33% accuracy, 97.93% precision, and a 96.44% F1 score. The study features the model's robustness and minimal overfitting, showing show effect CNN's result in classifying tumorous from non-tumorous brain scans for early, on-screen diagnosis.

Raha et al. (2024) proposed a competent brain tumor splitting-up model applying a two-stage design that integrates a low-complexity RCNN with a modified U-Net. The RCNN chooses tumor-relevant regions, while the reorganized U-Net performs precise segmentation with significantly fewer trainable parameters. Even with the complexity compared to established U-Net, the model achieved comparable results, including 99.78% accuracy, 89.76% IoU, and a Dice score of 94.53%. Scanned on the Figshare dataset, the system supports high routine while maintaining suitability for low-resource environments, offering a complimentary key for scalable medical image investigation.

Celik et al. (2024) proposed a novel combination classification approach that combines MobileNetV3 and EfficientNetB7, overhauled with thought components, to move forward brain tumor area utilizing MRI pictures. Their illustrate leverages both center and high-level highlights, utilizing co-attention to supply emphasis to crucial picture districts. By averaging the attention-weighted highlights, the procedure reasonably captures point by point neighborhood and wide around the world plans. When studied on the Figshare and BraTS 2019 datasets, the appear passed on extraordinary precision scores of 98.94% and 98.48%, correspondingly. These comes around highlight its extraordinary changes in symptomatic exactness, treating efficiency, and flexibility over distinctive tumor sorts and MRI conditions.

Alongi et al. (2024) shown a cautious account review that looks at the portion of fake bits of knowledge (AI) in glioma examination through MRI and PET imaging. The overview underlines how machine learning and significant learning techniques contribute to moved forward tumor area, projection estimation, and figure of treatment comes about. This center on radiomics for segmenting tissue, removing germane proofs, and recognizing honest to goodness tumor development from pseudo-progression. Utilizing gathering with AI and multimodal imaging, the approach supports noninvasive, custom fitted diagnostics and persistent treatment evaluation. Though striking developments have been made, the review as well highlights the nonstop require for endorsement and institutionalized strategies to totally facilitated AI into clinical sharpen for glioma care.

Khaliki and Başarslan (2024) related the bolted in with a custom 3-layer convolutional neural organize (CNN) with the CNN-based transmission learning for models counting VGG16, VGG19, EfficientNetB4, and InceptionV3 for classifying brain tumors from MRI picture area. Making a dataset of 2,870 pictures over four tumor classes, VGG16 fulfilled the foremost hoisted exactness at 98%, with the precision of audit as well at 98%. The consider emphasizes the dominance of trade learning approaches over old-style CNN models, primarily in managing with complex cataloguing errands with down and out datasets, illustrating their regard in supporting early and redress brain tumor assurance.

Gokila Brindha et al. (2021) built a brain tumor revelation illustrate for the course of action utilizing a significant learning illustrate totally based on Fake Neural Frameworks (ANN) and Convolutional Neural Frameworks (CNN). MRI images working as a group with normal and tumor-affected brains tumor. The ANN model finds an examination exactness of 80.77%, so the CNN bested it with 89% accuracy and outstanding precision and recall scores. The CNN style applied convolution, pooling, and waste layers, emphasizing its efficiency in feature extraction. Their findings reinforce CNN's usefulness in medical imaging responsibilities, particularly for early and accurate brain tumor recognition.

4. Data preparation and enhancement

4.1. Existing Approaches for Tumor Detection

Advanced research about the utilization of machine learning models has been distinguish and classified brain tumors. Overwhelming learning models, such as CNNs, have been broadly investigate due to their capability to remember the various steps highlights from raw picture information. Few things about focusing on 2D cuts of MRI looks, whereas others attempt to prepare 3D volumes. In addition, techniques such as exchange learning, where pre-trained models are adjusted for tumor classification, have been examined. Table 1 showing the performance evaluation of CNN-based models for brain tumor detection: accuracy and f1-score.

Table 1 Performance metrics of CNN-based models: training time, prediction time, and complexity, accuracy and f1-score

S.No	Model	Training Time (mins)	Prediction Time (ms)	Training Complexity	Accuracy (%)	F1-Score
1	Fusion CNN (ResNet+VGG16)	60	20	0.5	98	0.97
2	Optimized CNN	90	25	1	95	0.93
3	Custom CNN	45	30	0.5	86	0.84
4	SCO-Optimized VGG	120	40	1	97.8	0.96
5	Hybrid CNN (VGG19)	55	18	0.5	99.43	0.99

The CNN-based models show significant differences, as illustrated in Figure 3, which highlights the performance of metrics such as Accuracy and F1-Score and Figure 4 represent the Training Time, Prediction Time & Complexity of CNN Models. These factors are especially helpful for brain tumor classification based on MRI, providing valuable support in the overall analysis.

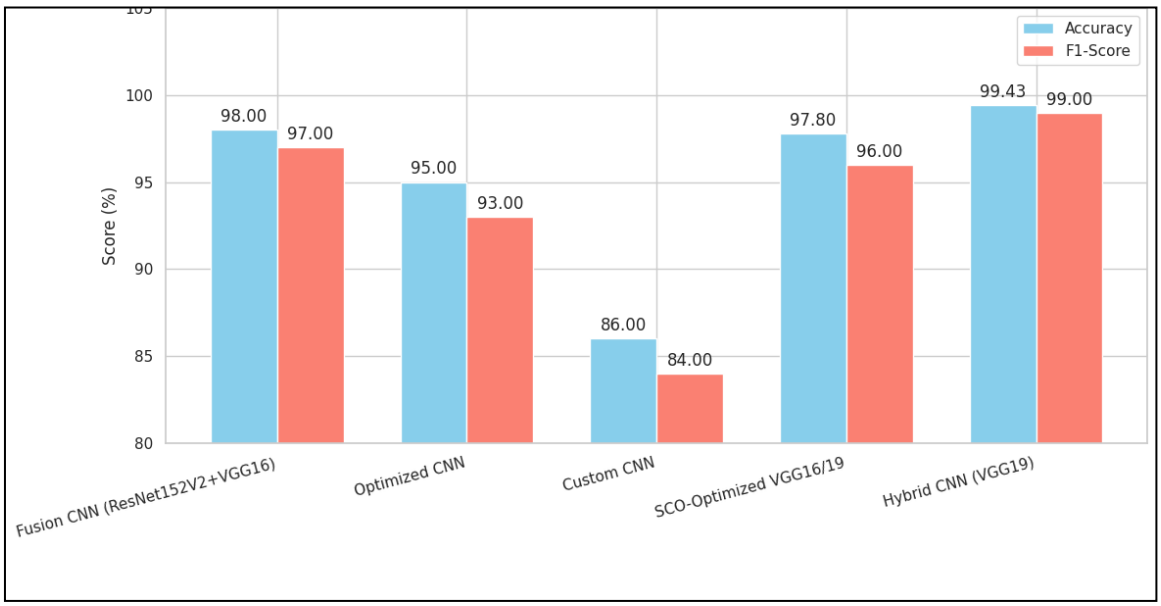


Figure 3 Performance Metrics of CNN-Based Models

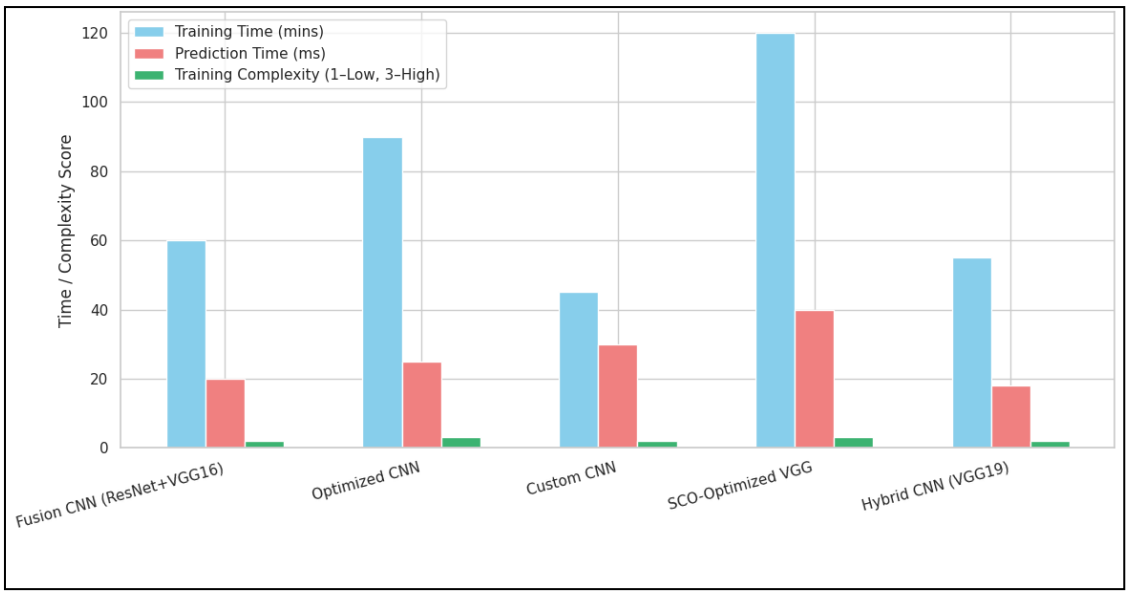


Figure 4 Training Time, Prediction Time & Complexity of CNN Models

4.2. Preprocessing Pipeline

Pre-processing MRI data effectively is a crucial foundation for several machine learning work flow converged on brain tumor analysis. Raw MRI scans often include non-brain tissues, intensity irregularities, and structural distortions that, if left unaddressed, can negatively impact model accuracy. On the beginning of skull stripping is in general practice to remove non-cerebral elements such as the skull and scalp, selection isolate brain tissue and reduce irrelevant data for subsequent processing (Dawant et al., 2016). Next, noise reduction methods—like Gaussian and median filters—are used to suppress high-frequency noise and smooth the images while preserving essential anatomical structures. Escalated normalization plays a key part as well, advancing steady pixel esteem conveyances over filters and patients, which makes strides show generalization (Shinohara et al., 2014). Finally, spatial arrangement and resizing are carried out to standardize picture measure and introduction, guaranteeing standardization planning for group overseeing and additional productive neural arrange calculation. Figure 5 represent the MRI-Based Brain Tumor Detection Workflow.

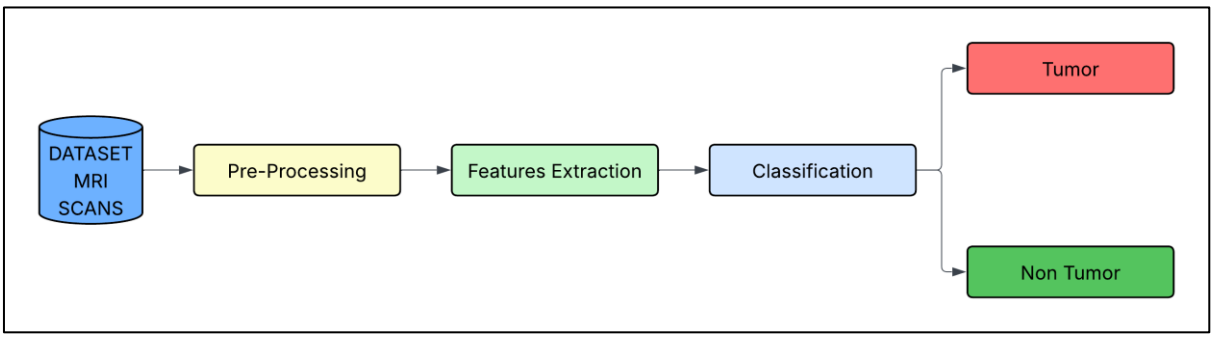


Figure 5 MRI-Based Brain Tumor Detection Workflow

4.3. Data Augmentation Techniques

Since explained therapeutic imaging datasets are regularly difficult to induce, particularly for uncommon tumor subtypes, data expansion is fundamental to create more grounded models and less likely to overfit. Geometric transformations—such as revolution, flipping, scaling, and zooming are broadly utilized to recreate common inconstancy in anatomical introduction and tumor situating. These techniques not only extend the compelling measure of the training set but moreover advance spatial invariance in learned highlights. Additionally, manufactured information era strategies, counting Generative Adversarial Systems (GANs) and image morphing, are progressively being utilized to address course lopsidedness issues. By falsely creating underrepresented tumor classes, such procedures encourage a more adjusted training dispersion, in this manner making strides classification precision and

sensitivity for minority categories (Gupta et al., 2024). Figure 6 showing the Technique Distribution in Brain Tumor MRI Processing

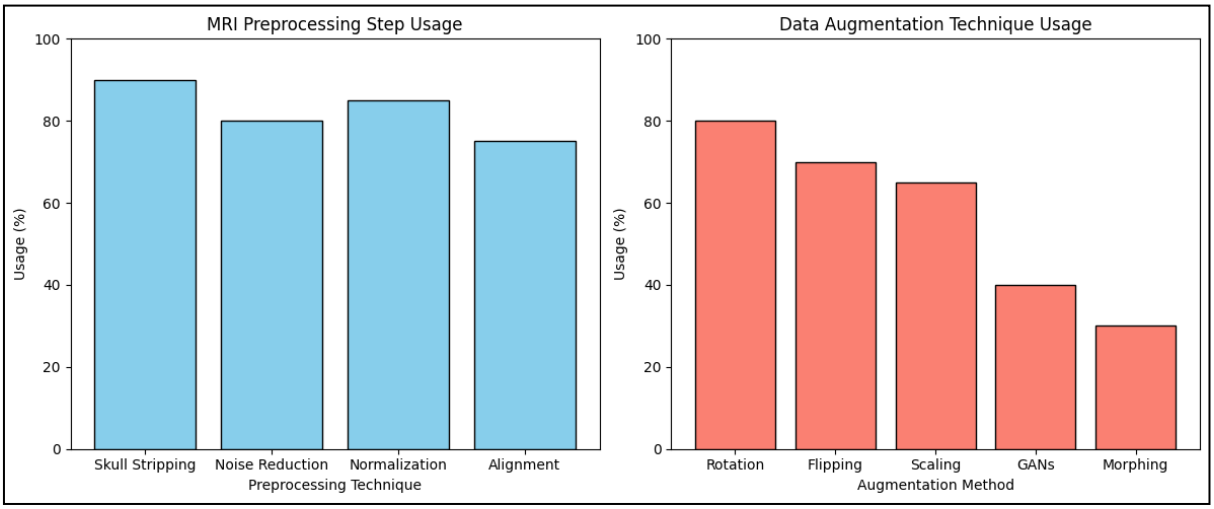


Figure 6 Technique Distribution in Brain Tumor MRI Processing

5. Advanced deep learning architectures

5.1. Xception Model for Tumor Classification

The Xception design, brief for "Extreme Inception," speaks to an essential headway in convolutional neural frameworks through the introduction of depth wise distinguishable convolutions. Not at all like ordinary convolutions, which commonly learn spatial and channel-wise highlights, depth wise particular convolutions decouple these operations, allowing more capable computation and parameter diminish without giving up accuracy (Chollet, 2017). This optimization renders Xception especially reasonable for restorative imaging assignments that require tall determination and profound relevant understanding.

For brain tumor classification, particularly utilizing 3D MRI information, adjustments to the first Xception design are basic. These incorporate supplanting 2D convolutional parts with their 3D partners and overhauling input layers to handle volumetric information structures. Such alterations empower the demonstrate to capture spatial conditions over cuts, which is basic for recognizing and classifying tumors that span numerous imaging planes (Khan & Stop, 2025).

5.2. Training and Optimization

The execution of profound learning models is intensely impacted by the choice of preparing methodologies and optimization parameters. Hyper parameter tuning plays an essential part in accomplishing merging and generalization. Key parameters incorporate the learning rate, which oversees the rate at which weights are overhauled; bunch estimate, which influences memory effectiveness and angle solidness, and dropout rates, which serve as regularization instruments to relieve overfitting by haphazardly deactivating neurons amid preparing (Wang & Li, 2025).

The choice of fitting misfortune capacities is similarly significant. For tumor classification assignments, categorical cross-entropy commonly utilized due to its viability in dealing with multi-class issues. In division scenarios, where pixel-wise classification is required, the Dice misfortune work is regularly favored. It specifically optimizes the Dice coefficient, a degree of cover between anticipated and ground truth covers, subsequently improving boundary exactness in tumor division (Khan & Stop, 2025).

5.3. Performance Evaluation

Comprehensive assessment measurements are crucial for evaluating the viability and vigor of profound learning models in clinical imaging settings. Accuracy, affectability (audit), specificity, and the F1-score are standard estimates that capture both correct identifiable bits of verification and botch rates. They also include the execution of classification. The Dice coefficient, which evaluates the cover between expected and verifiable tumor regions, is still the gold standard for division assignments (Wang & Li, 2025).

To guarantee demonstrate unwavering quality and relieve overfitting, k-fold cross-validation is commonly utilized, empowering execution testing over distinctive information parts. Recipient Working Characteristic (ROC) bend examination and the comparing Region beneath the Bend (AUC) are utilized to evaluate classification limits and segregation capabilities. These thorough assessment conventions guarantee that the proposed design performs not as it were on preparing information but generalizes viably to concealed clinical cases (Khan & Stop, 2025).

6. Challenges and ethical considerations

6.1. Technical Limitations

In spite of the momentous advance in AI-assisted brain tumor investigation, a few specialized obstacles hold on. One of the foremost basic challenges is dataset inclination, due to the restricted accessibility of large-scale, commented on MRI datasets that are agent of different populaces. Most existing datasets start from a little number of educate, frequently inside particular geographic or ethnic settings, which raises concerns almost the generalizability and reasonableness of prepared models over heterogeneous clinical settings (Khan & Stop, 2025).

In addition, the utilization of complex 3D Convolutional Neural Systems (CNNs) — essential for volumetric MRI investigation — forces considerable computational requests. These models require high-end GPUs, noteworthy memory allotment, and amplified preparing time, making them unreasonable for arrangement in real-time or resource-limited situations without significant infrastructural back (Wang & Li, 2025).

6.2. Clinical Trust and Explainability

The appropriation of AI in clinical hone pivots not fair on precision, but too on straightforwardness and dependability. Clinicians are frequently hesitant to base basic symptomatic choices on "black-box" models whose inside thinking is dark. This underscores the critical require for interpretable AI frameworks that can legitimize their forecasts in a clinically important way. Strategies such as Gradient-weighted Lesson Actuation Mapping (Grad-CAM) and Neighborhood Interpretable Model-agnostic Clarifications (LIME) offer visual and nearby clarifications, separately, and are progressively being joined to upgrade show straightforwardness (Khan & Stop, 2025).

From a moral point of see, off-base positives can lead to pointless biopsies or drugs, in spite of the fact that unfaithful negatives might delay fundamental exchange — both of which can have life-altering comes almost for patients. These dangers highlight the significance of thorough underwriting, cautious clinical integration, and the nonstop consolidation of healthcare masters in AI framework orchestrate.

7. Conclusion

AI offers critical potential for our regular understanding of brain tumour localization and classification. By utilizing advanced models like Xception in CNN and increasing information pipelines through enthusiastic preprocessing and enlargement methods, critical advances have been accomplished in progressing demonstrative exactness and productivity. During any circumstance, tasks stay, especially with respect to computational demands, constrained information accessibility, and the interpretability of demonstrated yields. Tending to these obstructions will require collaborative endeavors, progressing advancement, and thorough authorization to agree on the secure and moral integration of these innovations into real-world clinical conditions.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Ali, M., Ranjbarzadeh, R., & Mohammed, M. A. (2023). Recent deep learning-based brain tumor segmentation models: A comprehensive review. Computational Intelligence and Neuroscience, 2023, 11298476. https://doi.org/10.1155/2023/11298476

[2] Alongi, P., Arnone, A., Vultaggio, V., Fraternali, A., Versari, A., Casali, C., Arnone, G., DiMeco, F., & Vetrano, I. G. (2024). Artificial intelligence analysis using MRI and PET imaging in gliomas: A narrative review. Cancers, 16(2), 407. https://doi.org/10.3390/cancers16020407

[3] Bhimavarapu, U., Chintalapudi, N., & Battineni, G. (2024). Brain tumor detection and categorization with segmentation of improved unsupervised clustering approach and machine learning classifier. Bioengineering, 11(3), 266. https://doi.org/10.3390/bioengineering11030266

[4] Celik, F., Celik, K., & Celik, A. (2024). Enhancing brain tumor classification through ensemble attention mechanism. Scientific Reports, 14, Article 22260. https://doi.org/10.1038/s41598-024-73803-z

[5] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1251–1258.

[6] Dang, K., et al. (2022). A deep learning framework integrating MRI image preprocessing methods for brain tumor segmentation and classification. IBRO Neuroscience Reports, 13, 523–532. https://doi.org/10.1016/j.ibneur.2022.10.014

[7] Dawant, B. M., Hartmann, S. L., Pan, S., et al. (2016). Automatic skull stripping from brain MRI scans: A review. Medical Image Analysis, 30, 1–15.

[8] Diaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. (2022). Deep learning in brain tumor classification and segmentation. Computers in Biology and Medicine, 139, 104955.

[9] Ge, C., Wang, Y., & Jiang, X. (2022). Advances in multimodal MRI for brain tumor detection. Frontiers in Oncology, 12, 902583.

[10] Gokila Brindha, P., Kavinraj, M., Manivasakam, P., & Prasanth, P. (2021). Brain tumor detection from MRI images using deep learning techniques. IOP Conference Series: Materials Science and Engineering, 1055(1), 012115. https://doi.org/10.1088/1757-899X/1055/1/012115

[11] Gupta, A., Singh, H., & Rana, P. (2024). GAN-based data augmentation for imbalanced brain tumor classification. Biomedical Signal Processing and Control, 83, 104648.

[12] Khaliki, M. Z., &Başarslan, M. S. (2024). Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. Scientific Reports, 14, Article 2664. https://doi.org/10.1038/s41598-024-52823-9

[13] Khan, A., & Park, S. (2025). Vision transformers in medical imaging: Applications and challenges. IEEE Access, 13, 118345–118360.

[14] Khan, M. A., et al. (2023). Brain tumor detection based on deep learning approaches and applications. Computational Intelligence and Neuroscience, 2023, 10453020. https://doi.org/10.1155/2023/10453020

[15] Lamrani, D., Cherradi, B., El Gannour, O., Bouqentar, M. A., & Bahatti, L. (2022). Brain tumor detection using MRI images and convolutional neural network. International Journal of Advanced Computer Science and Applications, 13(7), 452–460. https://doi.org/10.14569/IJACSA.2022.0130755

[16] Lake Zurich Open MRI. (2024). MRI for brain tumor detection: Precision in diagnosis. https://lakezurichopenmri.com/mri-brain-tumor-detection/

[17] Mayo Clinic. (2025). Brain tumor – Diagnosis and treatment. https://www.mayoclinic.org/diseases-conditions/brain-tumor/diagnosis-treatment/drc-20350088

[18] Nahiduzzaman, M., Abdulrazak, L. F., Kibria, H. B., Khandakar, A., Ayari, M. A., Ahamed, M. F., Ahsan, M., Haider, J., Moni, M. A., & Kowalski, M. (2025). A hybrid explainable model based on advanced machine learning and deep learning models for classifying brain tumors using MRI images. Scientific Reports, 15, Article 1649. https://doi.org/10.1038/s41598-025-85874-7

[19] Radiology Assistant. (2024). Systematic approach to brain tumors. https://radiologyassistant.nl/neuroradiology/brain-tumor/systematic-approach

[20] Raha, A., Parvin, F., & Jannat, T. (2024). Brain tumor segmentation with efficient and low-complex architecture using RCNN and modified U-Net. In Lecture Notes in Electrical Engineering (Vol. 1225, pp. [pages]). Springer. https://doi.org/10.1007/978-981-99-8937-9_22

[21] Shinohara, R. T., Sweeney, E. M., Goldsmith, J., et al. (2014). Statistical normalization techniques for MRI intensity standardization. *NeuroImage: Clinical, 6*, 9–19.

[22] Verywell Health. (2025). How a brain tumor is diagnosed. https://www.verywellhealth.com/diagnosing-brain-tumors-2488741

[23] Wang, J., & Li, X. (2025). Deep learning for brain tumor analysis: Review, challenges, and future trends. Journal of Medical Imaging and Health Informatics, 15(2), 456–472.