A Comprehensive Review on Brain Tumor Classification Using Machine Learning and Deep Learning Techniques

Ashish Cha nd[1], Raj Kumar[2]

[1]*Assistant Professor, Dept. of Electrical, Electronics & Communication Engineering, RIMT University, Punjab, India*
[2]*Assistant Professor, Dept. of Civil Engineering, RIMT University, Punjab, India*

***

Abstract - *Brain tumor classification plays a crucial role in early diagnosis, treatment planning, and patient prognosis. Magnetic Resonance Imaging (MRI) is the most widely used non-invasive imaging modality for detecting and analyzing brain tumors due to its high soft-tissue contrast. However, manual interpretation of MRI scans is time-consuming, subjective, and prone to inter-observer variability. To overcome these challenges, automated brain tumor classification systems based on Machine Learning (ML) and Deep Learning (DL) techniques have gained significant attention. This review paper presents a comprehensive analysis of traditional image processing methods, machine learning algorithms, and state-of-the-art deep learning models used for brain tumor classification. The paper discusses commonly used datasets, preprocessing techniques, feature extraction methods, classification strategies, evaluation metrics, and current challenges. Finally, future research directions and emerging trends in intelligent brain tumor diagnosis systems are highlighted.*

***Key Words*: Brain Tumor Classification, MRI, Machine Learning, Deep Learning, CNN, Medical Image Analysis**

1. INTRODUCTION

Brain tumors are among the most life-threatening neurological disorders, characterized by abnormal and uncontrolled cell proliferation within the brain. According to the World Health Organization (WHO), brain tumors are broadly classified into benign and malignant categories, with gliomas, meningiomas, and pituitary tumors representing the most frequently occurring types [1], [14], [17]. Early and accurate classification of these tumors is critical for effective clinical decision-making, treatment planning, and improving patient survival rates [2], [15]. Magnetic Resonance Imaging (MRI) has become the imaging modality of choice for brain tumor diagnosis due to its superior soft-tissue contrast and absence of ionizing radiation. However, despite significant advancements in MRI technology, manual interpretation of brain MRI scans remains a challenging task for radiologists. Tumor heterogeneity, variations in size and shape, and overlapping intensity patterns between normal and abnormal tissues often lead to diagnostic uncertainty and inter-observer variability [1], [3], [18].To overcome these limitations, researchers have increasingly focused on automated brain tumor classification systems. In recent years, Machine Learning (ML) and Deep Learning (DL) techniques—particularly Convolutional Neural Networks (CNNs), residual networks, hybrid models, and transfer learning approaches—have demonstrated remarkable success in medical image analysis by enabling robust feature extraction and accurate classification [2], [4], [6], [9], [10], [11]. Several studies have reported improved classification performance using data augmentation techniques, hybrid deep learning architectures, and large-scale public MRI datasets such as TCIA and Kaggle repositories [4], [16], [19], [21]. Consequently, this review systematically examines existing ML- and DL-based approaches for brain tumor classification, highlighting their methodologies, strengths, limitations, and emerging research trends [1], [14], [17].

2. BRAIN TUMOR TYPES AND MRI MODALITIES

2.1 Brain Tumor Types

Brain tumors are characterized by abnormal cell growth within the brain and are broadly classified based on their origin, growth behavior, and degree of malignancy. In MRI-based brain tumor classification research, certain tumor types are more frequently studied due to their clinical prevalence, distinct radiological features, and availability in public datasets. Among these, gliomas, meningiomas, pituitary tumors, and healthy (no tumor) cases are the most commonly investigated categories [1], [14], [17].

2.1.1 Glioma

Gliomas are malignant brain tumors that originate from glial cells, including astrocytes, oligodendrocytes, and ependymal cells. They represent the most aggressive and frequently occurring primary brain tumors in adults. Gliomas exhibit highly infiltrative growth patterns, making clear delineation from surrounding healthy tissue particularly challenging. On MRI scans, gliomas often display heterogeneous intensity patterns, irregular tumor boundaries, edema, and necrotic regions, especially in high-grade cases. These complex characteristics make glioma detection and classification a critical yet challenging task for automated machine learning and deep learning systems [2], [11], [15], [21].

2.1.2 Meningioma

Meningiomas are generally benign tumors that arise from the meninges, the protective membranes covering the brain and spinal cord. They are typically slow-growing and well-circumscribed, which facilitates their detection and classification compared to malignant tumors. On MRI images, meningiomas often appear as well-defined, extra-axial masses with homogeneous signal intensity and strong contrast enhancement. Due to their relatively uniform structure and distinct appearance, meningiomas have been widely used in early and contemporary machine learning- and deep learning-based brain tumor classification studies [1], [4], [10], [14].

2.1.3 Pituitary Tumor

Pituitary tumors develop in the pituitary gland, a small but vital endocrine organ located at the base of the brain. Although most pituitary tumors are benign, they can significantly disrupt hormonal regulation and neurological function. In MRI scans, pituitary tumors are typically observed in the sellar and suprasellar regions and may cause compression or displacement of adjacent anatomical structures. Their relatively small size, central location, and subtle intensity variations necessitate high-resolution MRI imaging and robust feature extraction techniques for accurate classification [6], [8], [9], [19].

2.1.4 No Tumor (Healthy Brain)

The “No Tumor” or healthy brain category consists of MRI scans that do not exhibit any pathological abnormalities. This class serves as an essential reference in both binary and multi-class brain tumor classification frameworks. Healthy brain MR images generally demonstrate symmetrical anatomical structures and consistent tissue intensity distributions. Inclusion of this category enhances model generalization, improves robustness, and helps reduce false-positive tumor detections in automated diagnostic systems [1], [5], [16], [19].

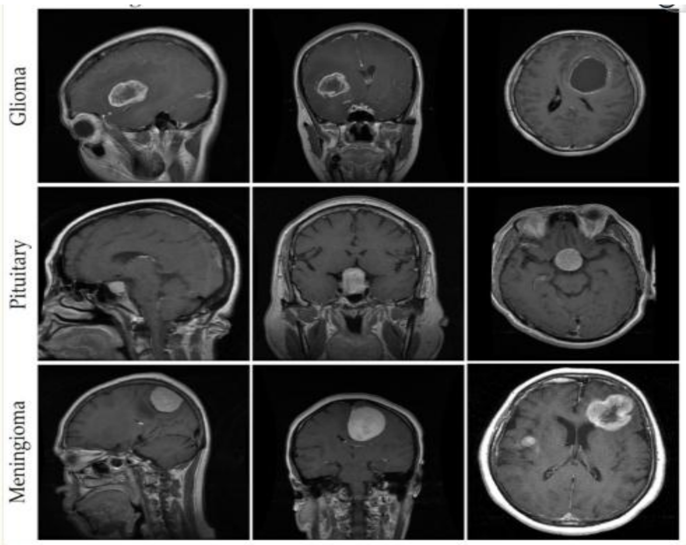

Fig -1: A sample of MRI images from the brain tumor dataset.

2.2 MRI Modalities

Magnetic Resonance Imaging (MRI) is the most widely used imaging modality for brain tumor diagnosis and analysis due to its superior soft-tissue contrast, multiplanar capability, and non-invasive nature. Different MRI sequences emphasize distinct tissue characteristics, and their combined use provides complementary diagnostic information that is essential for accurate tumor detection, segmentation, and classification in automated systems [1], [14], [17].

2.2.1 T1-Weighted (T1)

T1-weighted MRI images provide high anatomical detail and clear visualization of normal brain structures. In T1 images, cerebrospinal fluid (CSF) appears dark, while white matter appears brighter than gray matter. Although tumor regions may not always be distinctly visible in T1 images alone, these scans are crucial for anatomical reference, structural integrity assessment, and initial tumor localization. Consequently, T1-weighted images are frequently used as baseline inputs in multi-modal brain tumor classification frameworks [1], [10], [18].

2.2.2 T1-Weighted with Contrast Enhancement (T1c)

T1-weighted contrast-enhanced images are acquired following the administration of contrast agents such as gadolinium, which accentuate areas with a disrupted blood–brain barrier. Tumorous regions often exhibit strong enhancement in T1c images, enabling improved visualization of tumor boundaries, vascularization, and active tumor regions. Due to their ability to highlight malignant tissue, T1c images are extensively used in both tumor segmentation and classification tasks, particularly in deep learning-based approaches [2], [6], [11], [16].

2.2.3 T2-Weighted (T2)

T2-weighted MRI images are highly sensitive to variations in water content and are effective in visualizing edema and fluid-rich regions surrounding tumors. In T2 images, fluids appear bright, making this modality valuable for identifying tumor-associated swelling and peritumoral edema. T2-weighted scans provide complementary information to T1 and T1c images and are commonly integrated into multi-modal classification systems to improve diagnostic performance [4], [9], [15], [21].

2.2.4 Fluid-Attenuated Inversion Recovery (FLAIR)

FLAIR images suppress cerebrospinal fluid signals while maintaining sensitivity to pathological tissues, thereby enhancing the visibility of lesions adjacent to fluid-filled regions. This property makes FLAIR particularly effective for detecting infiltrative tumor regions and edema that may be obscured in T1 or T2 images. FLAIR sequences are extensively used in glioma analysis and classification studies, as they provide clear delineation of tumor infiltration zones critical for accurate diagnosis and treatment planning [1], [11], [17].

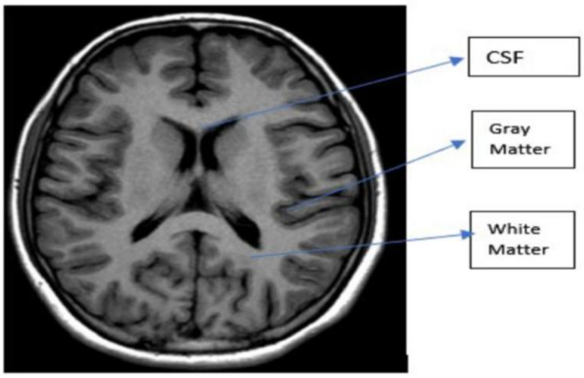

Fig -1: Properties of various MRI sequences.

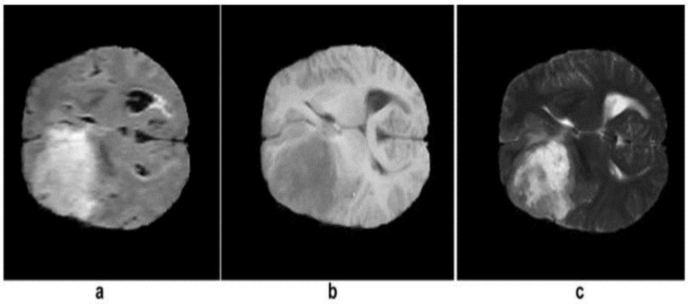

Fig -1: MRI brain tumor: (**a**) FLAIR image, (**b**) T1 image, and (**c**) T2 image

3.DATASETS USED FOR BRAIN TUMOR CLASSIFICATION

Publicly available datasets have played a crucial role in advancing brain tumor classification research by enabling standardized training and evaluation of machine learning and deep learning models. The Brain Tumor Segmentation (BraTS) dataset is one of the most widely used resources, offering multimodal MRI scans such as T1, T1-contrast, T2, and FLAIR images along with expert annotations. The availability of multiple MRI modalities allows models to learn comprehensive tumor characteristics; however, models trained solely on BraTS may show limited generalization when applied to simpler or single-modality datasets [1], [11], [17]. The Figshare brain tumor dataset primarily contains T1-weighted contrast-enhanced MRI images and is commonly employed for multi-class classification of glioma, meningioma, and pituitary tumors. While this dataset is easy to use and often produces high classification accuracy, its reliance on a single MRI modality restricts its ability to capture real-world imaging variability [4], [10], [20]. The Br35H (Brain Tumor Detection 2020) dataset is mainly designed for binary classification and includes MRI scans labeled as tumor or no tumor. Although useful for benchmarking tumor detection models, it does not support detailed tumor subtype classification [12], [19]. TCIA provides large, heterogeneous MRI datasets collected from multiple institutions, making it valuable for developing models with improved clinical generalization, though extensive preprocessing is often required [16], [17]. Kaggle MRI datasets are widely used due to easy accessibility but may lack sufficient diversity to fully represent clinical scenarios [5], [19]. Overall, dataset size, modality diversity, and labeling strategy significantly influence model accuracy and generalization performance [1], [14], [21].

Dataset	Modalities	Task Type	Clinical Diversity	Generalization
BraTS	Multi-modal	Segmentation & Classification	Moderate	Medium
Figshare	Single-modal	Multi-class Classification	Low	Low–Medium
Br35H	Single-modal	Binary Classification	Low	Low
TCIA	Multi-modal	Detection & Prognosis	High	High
Kaggle MRI	Single-modal	Multi-class Classification	Low	Low–Medium

Table -1: Comparative Analysis and Generalization Challenges

Datasets such as BraTS, Figshare, Br35H, TCIA, and Kaggle MRI collections have significantly advanced brain tumor classification research. However, variations in dataset size, modality, labeling strategy, and clinical diversity strongly influence model performance.

4. PREPROCESSING TECHNIQUES

Preprocessing is a critical stage in brain tumor classification pipelines, as it enhances image quality and enables learning of discriminative features by machine learning and deep learning models. Noise removal techniques such as Gaussian and median filtering are widely employed to suppress unwanted distortions while preserving essential structural information in MRI images [1], [14]. Skull stripping is performed to eliminate non-brain tissues, including the skull and scalp, ensuring that models focus exclusively on relevant brain regions where tumors occur [11], [18].

Intensity normalization is applied to minimize variations in brightness and contrast caused by different MRI scanners and acquisition protocols, thereby improving dataset consistency and model generalization [1], [17]. Image resizing and spatial normalization are commonly used to standardize input dimensions, allowing compatibility with convolutional neural network architectures [10], [15].

To address data scarcity and class imbalance, data augmentation techniques such as rotation, flipping, scaling, and translation are extensively used to increase training data diversity and reduce overfitting [4], [9], [21]. Additionally, contrast enhancement techniques improve tumor visibility by amplifying intensity differences between normal and abnormal tissues, facilitating more accurate tumor discrimination [3], [18]. Overall, effective preprocessing significantly improves classification accuracy, robustness, and generalization across diverse MRI datasets [1], [14], [21].

5. TRADITIONAL MACHINE LEARNING–BASED CLASSIFICATION

Traditional machine learning–based brain tumor classification approaches rely on handcrafted feature extraction from MRI images, followed by conventional classifiers for tumor identification. Texture-based feature extraction techniques such as the Gray Level Co-occurrence Matrix (GLCM) are widely used to quantify spatial relationships between pixel intensities, enabling effective characterization of tumor texture patterns [1], [18], [20]. Local Binary Patterns (LBP) capture local texture variations by comparing each pixel with its neighboring pixels and are effective in highlighting fine-grained tumor details [18]. Histogram of Oriented Gradients (HOG) focuses on edge orientations and structural information, making it useful for capturing tumor boundaries and shape characteristics [20].

Wavelet Transform–based features decompose MRI images into multiple frequency sub-bands, allowing simultaneous analysis of spatial and frequency information relevant to tumor characterization [1], [21]. In addition, shape and statistical texture features—such as area, perimeter, smoothness, contrast, and entropy—provide valuable information about tumor morphology and appearance [14], [20].

Following feature extraction, machine learning classifiers are employed for decision-making. Support Vector Machines (SVMs) are among the most widely used classifiers due to their effectiveness in handling high-dimensional feature spaces and achieving robust classification performance [5], [15]. K-Nearest Neighbors (KNN) classifies tumors based on similarity measures and is simple to implement, particularly for small datasets [14]. Random Forest (RF) classifiers combine multiple decision trees to enhance robustness and reduce overfitting [21]. Naïve Bayes classifiers leverage probabilistic learning and perform well on limited data, while Decision Trees offer interpretable classification rules [1], [14]. Although these traditional methods are computationally efficient and effective for smaller datasets, their performance is highly dependent on the quality of handcrafted features and lacks scalability for complex tumor heterogeneity [1], [17].

6. DEEP LEARNING–BASED BRAIN TUMOR CLASSIFICATION

Deep learning–based approaches have gained significant attention in brain tumor classification due to their ability to automatically learn hierarchical and discriminative features directly from MRI images, thereby eliminating the need for manual feature engineering. Among these approaches, Convolutional Neural Networks (CNNs) are the most widely adopted because of their strong capability to capture spatial and structural patterns in medical images [1], [14], [17].

Early CNN architectures such as AlexNet demonstrated the effectiveness of deep learning for image classification by employing multiple convolutional and pooling layers to extract low- and high-level features [10], [15]. VGG16 and VGG19 introduced deeper yet uniform network architectures using small convolutional filters, enabling the extraction of fine-grained tumor features from MRI scans [2], [9]. ResNet addressed the vanishing gradient problem through residual or skip connections, allowing very deep networks to be trained efficiently and resulting in improved classification accuracy for complex tumor patterns [2], [11]. DenseNet further enhanced feature reuse by connecting each layer to every other layer, promoting efficient information flow and reducing overfitting in limited medical datasets [12], [21]. Inception-based architectures employed parallel convolutional filters of varying sizes within the same layer, allowing multi-scale feature extraction that is particularly beneficial for tumors with heterogeneous structures [10], [15]. Collectively, these CNN-based architectures have significantly improved the accuracy, robustness, and reliability of automated brain tumor classification systems [1], [17], [21].

7. PERFORMANCE EVALUATION METRICS

Performance evaluation metrics play a critical role in assessing the effectiveness of brain tumor classification models. Accuracy measures the overall proportion of correctly classified MRI images and provides a general assessment of model performance [14], [15]. Precision quantifies the proportion of correctly predicted tumor cases among all predicted tumor cases, helping to reduce false-positive diagnoses [1]. Recall, also known as sensitivity, evaluates the model's ability to correctly identify tumor cases and is particularly important in medical diagnosis, where missed detections can have severe consequences [2], [9]. Specificity measures the ability of the model to correctly classify non-tumor cases, minimizing unnecessary medical interventions [14], [17]. The F1-score combines precision and recall into a single metric, offering a balanced evaluation when class distributions are imbalanced [15], [21]. Additionally, the Area Under the Receiver Operating

Characteristic Curve (AUC) assesses the model's discriminative capability across different decision thresholds, with higher AUC values indicating superior classification performance [10], [17].

8. CHALLENGES AND LIMITATIONS

Despite significant progress in brain tumor classification, several challenges and limitations still exist. One major issue is the limited availability of annotated medical datasets, as expert labeling by radiologists is time-consuming and expensive, resulting in small training datasets. Another challenge is class imbalance, where certain tumor types have far fewer samples than others, causing models to be biased toward majority classes and reducing accuracy for rare cases. Deep learning models also suffer from overfitting, especially when trained on limited or repetitive data, leading to poor performance on unseen images. In addition, the high computational cost required for training and deploying deep models demands powerful hardware and long processing times, which may not be feasible in all healthcare settings. The lack of model interpretability is another concern, as many deep learning systems function as black boxes, making it difficult for clinicians to understand and trust their predictions. Finally, clinical validation and deployment remain challenging because models trained on public datasets may not perform consistently in real hospital environments due to variations in scanners, imaging protocols, and patient populations.

9. FUTURE RESEARCH DIRECTIONS

Future research in brain tumor classification is expected to focus on several promising directions to improve accuracy, reliability, and clinical usability. One important area is Explainable AI (XAI), which aims to make model decisions transparent and understandable for doctors, thereby increasing trust in AI-assisted diagnosis. Multimodal MRI fusion is another key direction, where information from different MRI sequences is combined to capture complementary tumor features and enhance classification performance. Developing lightweight and efficient models will support real-time diagnosis and make AI systems suitable for deployment in resource-constrained clinical settings. Federated learning is gaining attention as it enables collaborative model training across multiple hospitals without sharing patient data, thus ensuring data privacy and security. Integration of AI models with clinical decision support systems will help doctors by providing timely and accurate diagnostic assistance within existing healthcare workflows. Additionally, self-supervised and semi-supervised learning methods are expected to reduce dependency on large labeled datasets by effectively learning from unlabeled or partially labeled medical images.

10. CONCLUSION

This review presented a comprehensive overview of brain tumor classification techniques using machine learning and deep learning approaches. While traditional ML methods laid the foundation, deep learning models—particularly CNNs—have achieved remarkable performance improvements. However, challenges related to data availability, interpretability, and clinical applicability persist. Addressing these issues will be key to developing reliable and deployable automated brain tumor diagnosis systems in the future.

REFERENCES

[1] Zine-dine, I., Riffi, J., El Fazazy, K., El Batteoui, I., Mahraz, M. A., & Tairi, H. A review: Machine learning techniques of brain tumor classification and segmentation. Machine Graphics & Vision, 34(3), 31–55, 2025.

[2] Zahoor, M. M., Khan, S. H., Alahmadi, T. J., et al. Brain Tumor MRI Classification Using a Novel Deep Residual and Regional CNN. Biomedicines, 12(7):1395, 2024.

[3] Refining neural network algorithms for accurate brain tumor classification in MRI imagery. BMC Medical Imaging, 24:118, 2024.

[4] Classification of Brain MRI Tumor Images Based on Deep Learning PGGAN Augmentation. PubMed (2021).

[5] Brain tumor magnetic resonance images classification based machine learning paradigms. PubMed, 2022.

[6] Brain Tumor/Mass Classification Framework Using MRI-Based Transfer Deep-Learning Model. PubMed.

[7] Brain tumor classification using MRI images and deep learning techniques. PubMed (2025).

[8] T1-weighted MRI-based brain tumor classification using hybrid deep learning models. PubMed (2025).

[9] Brain Tumor Classification from MRI Using Image Enhancement and CNN Techniques. PubMed (2024).

[10] Brain Tumor Classification From MRI Using Deep Learning and CNN Techniques. MDPI article (2023).

[11] Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale CNN. arXiv, 2024.

[12] Shah, M. A., Alam, M. M., & Khan, S. H. Tumor Aware DenseNet Swin Hybrid Learning for Large-Scale Brain MRI Classification. arXiv, 2026.

[13] Filvantorkaman, M., Piri, M., & Filvan Torkaman, M. Fusion-Based Brain Tumor Classification Using Deep Learning and Explainable AI. arXiv(2025).

[14] Toufiq, D. M., Sagheer, A. M., & Veisi, H. A Review on Brain Tumor Classification in MRI Images. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 2021.

[15] Raza, M. U., et al. Classifying Brain Tumors on MRI Using CNNs. Electronics, 12(4), 2023.

[16] The Cancer Imaging Archive (TCIA). Public MRI tumor imaging repository — widely used in classification and segmentation research.

[17] Investigating brain tumor classification using MRI: scientometric analysis (2015–2024). Springer Nature publication.

[18] Abbasi, S., & Tajeripour, F. Detection of brain tumor in 3D MRI images using local binary patterns and histogram orientation gradient. Neurocomputing 219:526-535, 2017 (reviewed in broader survey).

[19] Brain Tumor MRI Dataset on Kaggle — widely referenced public dataset used in numerous classification studies.

[20] Cheng, J., et al. Classification of Brain Tumors from MRI Using Handcrafted and Deep Features. MDPI/Applied Sciences (earlier database users).

[21] Gumaei, A., et al. Hybrid feature extraction and classification for brain tumor MRI images. Brain Sciences article (2024).