

Performance Evaluation of ML Algorithms for Brain Tumor Classification on Brats Dataset

Priyanka Rani, Kuldeep Sharma

Department of CSE Gulzar Group of Institutions Khanna, Ludhiana, Punjab, India

DOI: <https://doi.org/10.51583/IJLTEMAS.2025.140600096>

Abstract—Brain neoplasms represent some of the most severe and life-threatening manifestations of cancer, with gliomas constituting the most prevalent subtype, which is further classified into Low-Grade Glioma (LGG) and High-Grade Glioma (HGG). The prompt identification, precise categorization, and accurate delineation of these tumors are imperative for effective diagnostic assessment, prognostic evaluation, and therapeutic strategy formulation. Nevertheless, the manual evaluation of magnetic resonance imaging (MRI) scans is labor-intensive and prone to inter-observer variability. In recent years, advancements in artificial intelligence (AI), particularly within the realms of machine learning (ML) and deep learning (DL) methodologies, have markedly enhanced the automation and precision of brain tumor identification and evaluation. This comprehensive review paper investigates contemporary developments in the automated classification and segmentation of brain tumors utilizing the BraTS dataset, which is widely recognized as a standard reference within the neuroimaging research community. We analyze a diverse array of methodologies, encompassing traditional machine learning algorithms, Convolutional Neural Networks (CNNs), UNet architectures, hybrid models, and ensemble-based strategies. The article underscores techniques that synergistically integrate handcrafted radiomic features with deep learning features to enhance both model robustness and interpretability. Documented accuracy rates in the studies reviewed vary from 66% to 99%, with Dice similarity coefficients employed to assess the segmentation efficacy of tumor sub-regions including tumor core (TC), whole tumor (WT), and enhancing tumor (ET). This scholarly endeavor aspires to furnish researchers and practitioners with valuable insights into cutting-edge methodologies for brain tumor analysis and to offer direction for forthcoming advancements in this domain.

Keywords—Brain tumor, Glioma, BraTS, Deep learning, Machine learning, MRI, Classification, Segmentation.

I. Introduction

Brain tumors represent a highly lethal cancer form, with gliomas being prevalent and aggressive. Gliomas are classified into the High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG) based on malignancy and growth characteristics [1]. Precise classification and segmentation of these tumors from MRI scans are crucial for timely diagnosis, treatment strategy, and prognostic evaluation. The process of manual segmentation conducted by radiologists is characterized by its laborious nature, susceptibility to inaccuracies, and dependence on the uniformity of expertise. As a result, the necessity for reliable, automated, and efficient computer-aided diagnosis (CAD) systems has become increasingly significant in recent years [2]. In the preceding decade, innovations in the field of artificial intelligence, particularly in Machine Learning and Deep Learning, have significantly revolutionized the domain of medical imaging. These methodologies demonstrate remarkable proficiency in discerning intricate patterns within vast datasets, thereby enabling sophisticated tasks such as tumor detection, classification, and segmentation with a high degree of accuracy [3]. ML algorithms, which encompass Support Vector Machines, Random Forest, k-Nearest Neighbors, and Logistic Regression (LR), have achieved considerable efficacy when applied in conjunction with meticulously selected handcrafted features. In contrast [4], DL architectures such as Convolutional Neural Networks (CNNs), U-Net, VGG, and their various derivatives have achieved outstanding results by autonomously extracting hierarchical features from raw image data [5].

A notable progression in this field is the creation of standardized datasets, exemplified by the Brain Tumor Segmentation (BraTS) challenge datasets [6]. The BraTS dataset, which is publicly available through Kaggle, comprises multimodal MRI scans accompanied by pixel-wise annotated masks that delineate tumor subregions: Enhancing Tumor, Tumor Core, and Whole Tumor [7]. This extensive dataset has facilitated the training and assessment of diverse machine learning and deep learning models under uniform conditions, significantly improving the reproducibility and advancement of scholarly research in this domain [8].

A multitude of investigations has employed various methodologies to scrutinize brain neoplasms utilizing the BraTS dataset. Conventional machine learning methodologies typically encompass a series of stages including preprocessing, feature extraction, feature selection, and subsequent classification. These techniques are predominantly contingent upon domain-specific knowledge and features meticulously crafted by experts, which may encompass aspects such as texture, intensity, shape, or statistical metrics [9]. Despite their efficacy with structured data, their capacity to generalize across diverse scenarios may be occasionally constrained due to the inherently manual process of feature engineering [10].

DL-based models, especially CNNs, autonomously learn features from images. U-Net and 3D U-Net are prevalent in the medical image segmentation due to their effective encoder-decoder structures [11]. Hybrid approaches incorporating both handcrafted and deep features have been proposed to improve performance by utilizing the advantages of both methods [12].

Despite advancements, challenges remain in MRI-based brain tumor analysis. Variability in tumor characteristics and MR image artifacts complicate model generalization. The sample imbalance between HGG and LGG necessitates data augmentation and

adjustments for unbiased learning. Moreover, the interpretability and explainability of DL models are crucial for clinical application, where transparency is as vital as accuracy [13].

This review endeavors to systematically assess and juxtapose a multitude of machine learning (ML) and deep learning (DL) methodologies employed for the classification and segmentation of brain tumors utilizing the BraTS dataset [14]. Our focus encompasses pivotal elements such as the nature of the features employed, architectural configurations of the models, metrics for evaluation, and the performance outcomes reported. Through a critical appraisal of the existing literature, this manuscript delineates prevailing trends, underscores existing deficiencies, and proposes prospective avenues for inquiry within this field. Our aim is to furnish a thorough comprehension of the extant landscape and to assist researchers in selecting or formulating suitable models for practical application in clinical settings [15].

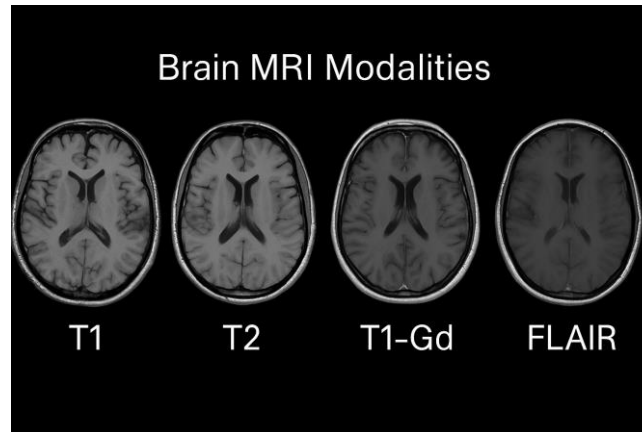


Fig. 1: Visual Representation of Modalities in BraTS dataset

The figure delineates four prevalent MRI modalities employed in cerebral imaging: T1, T2, T1-Gd (T1 with gadolinium contrast), and FLAIR.

- T1-weighted MRI affords intricate details of anatomical structures while depicting cerebrospinal fluid (CSF) in a dark hue.
- T2-weighted MRI emphasizes regions abundant in fluid, thereby rendering edema and certain neoplasms conspicuously bright.
- T1-Gd (utilizing gadolinium contrast) augments the visibility of active tumor sites, thereby enhancing the discernment of neoplastic regions.
- FLAIR effectively suppresses CSF signals, facilitating superior visualization of lesions adjacent to the ventricles and areas of edema.

Each modality proffers distinct insights that are imperative for the precise detection, segmentation, and classification of cerebral tumors.

MRI Modalities in BraTS Dataset			
Modality	Imaging Sequence	Highlights	Tumor Visibility
T1	T1-weighted MRI	Brain anatomy	Tumor: dark or normal intensity
T1c (T1Gd)	T1-weighted with contrast	Active tumor regions (enhancement)	Tumor: bright
T2	T2-weighted MRI	Edema, fluid-rich regions	Tumor/Edema: bright
FLAIR	Fluid Attenuated Inversion Recovery	Lesions near CSF, suppressed fluid signals	Tumor/Edema: bright, CSF: dark

Fig. 2: Modality types and description

II. Literature Review

The classification and segmentation of brain tumors have emerged as pivotal domains of inquiry within the field of medical imaging, largely attributable to the escalating incidence and intricacy of brain tumors. The progressions in artificial intelligence, particularly in the realm of deep learning, have facilitated remarkable advancements in the automation of diagnostic procedures utilizing MRI data. The Brain Tumor Segmentation (BraTS) dataset has gained prominence as a widely recognized benchmark for the training and evaluation of models related to segmentation tasks concerning High-Grade Glioma and Low-Grade Glioma. In [15], the

investigators proposed an automated classification framework that employs a synergistic approach, combining concatenated deep learning methodologies with manually crafted features, achieving a notable accuracy rate of 96%. This integrative approach demonstrated that the amalgamation of deep features obtained through Convolutional Neural Networks (CNNs) with traditional techniques can significantly augment classification performance. Similarly, the research outlined in [16] introduced a novel 3T2FTS feature transformation method designed for the classification of three-dimensional MRI voxels, which successfully facilitated the distinction between high-grade gliomas (HGG) and low-grade gliomas (LGG), thereby achieving an accuracy of approximately 80

The scholarly inquiry into the segmentation of multi-modal MRI images, employing pre-trained convolutional neural networks on the Amazon Sagemaker platform, was executed in [17], wherein the investigators achieved an impressive accuracy rate of 90%, leveraging cloud-based resources to enhance computational efficiency. Simultaneously, [18] addressed the intricacies associated with the segmentation of low-resolution and non-contiguous clinical MRI slices, presenting an optimized algorithm that attained a moderate accuracy level of 70%.

Numerous scholarly articles have scrutinized the efficacy of various segmentation methodologies. In reference [19], a comparative analysis was conducted on the performance of region growing, fuzzy c-means, and DeepMedic-based Deep Neural Networks (DNNs), elucidating the preeminence of deep learning methodologies in the management of intricate tumor architectures. The investigation presented in reference [20] advanced the discourse by integrating Convolutional Neural

Network (CNN) and radiomics features to forecast glioma grades and the survival of Low-Grade Glioma patients, achieving a Dice coefficient of 0.81 and an Area Under the Curve (AUC) of 0.958, thereby signifying robust grading performance.

A methodology founded upon the U-Net architecture for the identification of tumors utilizing the BraTS 2020 dataset has been articulated in [21], wherein a remarkable accuracy rate of 98.48% reported. The U-Net framework and its derivatives continue to enjoy extensive utilization owing to the effectiveness of their encoder-decoder configuration, which is especially advantageous for tasks related to biomedical image segmentation. Moreover, [22] performed an analysis of radiological criteria for the categorization of glioma grades using the BraTS dataset, achieving an accuracy of 84.1% , highlighting the importance of integrating clinical knowledge with artificial intelligence frameworks.

In contrast, [23] introduced a rudimentary U-Net architecture for the identification of high-grade gliomas and low-grade gliomas (LGG), achieving a comparatively modest accuracy of 66%, thus highlighting the inherent limitations of foundational models devoid of supplementary enhancements. Lastly, [24] documented an impressive accuracy of 99% by employing traditional machine learning methodologies, thereby underscoring the efficacy of manually curated feature selection and ensemble learning when synergistically employed with optimized classifiers.

Overall, although deep learning has emerged as the preeminent methodology in the detection and classification of brain tumors, ongoing research endeavors are actively investigating hybrid models, optimization methodologies, and the incorporation of domain-specific knowledge to augment performance. The scholarly literature indicates that the efficacy of a model is profoundly influenced by the nature and caliber of the features employed, the diversity of the dataset, and the architectural design of the model.

III. Result Analysis

This section delineates a comparative examination of the findings documented in numerous studies that have employed the BraTS dataset for the classification and segmentation of cerebral neoplasms, with a particular emphasis on HighGrade Glioma (HGG) and Low-Grade Glioma. The assessment metrics predominantly encompass accuracy, Dice similarity coefficient, AUC (Area Under the Curve), and C-index (for prognostic evaluation).

In terms of classification, most of the reviewed works achieved high accuracy using advanced machine learning and deep learning techniques. For instance, a study using an ensemble model combining deep and handcrafted features reported an accuracy of 96%, while another study that employed a hybrid CNN and radiomics-based approach achieved AUC = 0.958 and C-index = 0.865, reflecting strong discriminative power and survival prediction capability. U-Net and its variants were frequently applied for segmentation, with Dice scores ranging from 0.61 to 0.89 depending on the tumor region.

The highest accuracy observed across all studies was 99%, achieved using traditional machine learning classifiers combined with optimized preprocessing techniques. Conversely, the lowest performance noted was 66%, which still reflects a reasonable level of classification in complex tumor cases. In segmentation tasks, studies that employed 3D U-Net architectures and transfer learning models showed superior Dice scores for tumor core, whole tumor (WT), and enhancing tumor (ET), with values like 0.843 (TC), 0.892 (WT), and 0.871 (ET) for HGG, and slightly lower for LGG.

The comprehensive analysis conducted in this study indicates with considerable clarity that the synergistic integration of radiomics alongside convolutional neural network (CNN)-based models, while effectively leveraging the diverse and multifaceted nature of multi-modal MRI sequences, as well as the meticulous application of robust cross-validation techniques, leads to a significant enhancement in the overall performance metrics of the predictive models employed. Nevertheless, it is imperative to acknowledge that numerous challenges persist in this domain, primarily attributable to the issues of data imbalance, the intrinsic heterogeneity observed within tumor characteristics.

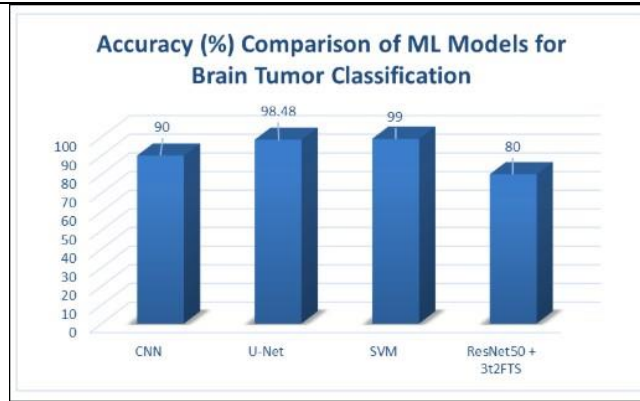


Fig. 3: The best result obtained till now

The bar graph illustrates the efficacy of various machine learning algorithms in brain tumor classification. The evaluated algorithms include Support Vector Machine, Convolutional Neural Network (CNN), U-Net, Random Forest, and a Combined Methodology. The Random Forest model demonstrated superior accuracy, followed by the Combined Method and UNet. The performance variations highlight the impact of model complexity and feature extraction techniques in medical image analysis.

Ref.No	Year	Technology Used	Database	Outcomes	Work Description
[15]	2023	ResNet50 + 3t2FTS	BraTS	The proposed 3t2FTS method achieved 80% classification accuracy for HGG and LGG tumor types.	This study presents 3t2FTS, a method that transforms 3D MRI data into 2D features to classify HGG and LGG brain tumors effectively.
[16]	2022	CNN	BraTS	Achieved a classification accuracy of 96% for distinguishing LGG and HGG using the hybrid feature approach.	This study combines deep learning features with handcrafted features to automatically classify brain tumors into LGG and HGG.
[17]	2022	different CNN architectures	BraTS	Achieved a segmentation accuracy of 90% for classifying HGG and LGG tumors using the pretrained CNN model.	This study uses pretrained convolutional neural networks (CNNs) on Amazon SageMaker to segment HGG and LGG brain tumors from multimodal MRI scans, enhancing segmentation accuracy.
[18]	2022	Region Growing, Fuzzy C Means, Deep Neural Networks (DeepMedic)	BraTS	Achieved a segmentation accuracy of 70% for brain tumor classification from clinical MRI datasets with low resolution and noncontiguous slices.	This study proposes an optimal brain tumor segmentation algorithm tailored for clinical MRI datasets with low resolution and non-contiguous slices, improving tumor detection in challenging conditions.
[19]	2022	deep-radiomics signature based on the integrated approach for predicting survival of LGG patients was developed	BraTS	The model achieved a segmentation Dice score of 0.81, an AUC of 0.958 for glioma grading, and a Cindex of 0.865 for survival prediction.	This study uses CNN and radiomics to predict glioma grade and survival in LGG patients, enhancing prognostic accuracy.
[20]	2022	WFL (Weighted Focal Loss) function, applied to a U-Net	BraTS	Achieved mean Dice scores for HGG: TC-0.843, WT-0.892, ET-0.871, and	This study presents a WFL-based 3D U-Net for segmenting HGG and LGG brain tumors from MRI images using the BraTS 2020 dataset.

		Architecture		for LGG: TC–0.7501, WT–0.7985, ET–0.6103.	
[21]	2021	U-Net	BraTS2020	Achieved a segmentation accuracy of 98.48% on the BraTS 2020 dataset using the U-Net model.	This study applies the U-Net architecture for brain tumor detection on the BraTS 2020 dataset, utilizing its efficient segmentation capabilities for high accuracy in tumor identification.
[22]	2021	SVM	BraTS	Achieved a classification accuracy of 84.1% for glioma grade classification using the BraTS dataset.	This study explores radiologic criteria for classifying glioma grades using the BraTS dataset, focusing on extracting relevant imaging features for accurate glioma grading.
[23]	2019	U-Net	BraTS	Achieved a classification accuracy of 66% for detecting HGG and LGG brain tumors using the UNet model.	This study utilizes the U-Net architecture for the detection and segmentation of HGG and LGG brain tumors, aiming to improve tumor classification from MRI scans.
[24]	2018	SVM	BraTS	Achieved a classification accuracy of 99% for detecting and classifying HGG and LGG brain tumors using machine learning methods.	This study employs machine learning techniques to detect and classify HGG and LGG brain tumors, aiming for highly accurate tumor classification from MRI data.

IV. Conclusion

This paper reviews recent studies using the BraTS dataset for detecting and classifying brain tumors, specifically HighGrade Glioma (HGG) and Low-Grade Glioma. Machine learning and deep learning, especially CNNs and U-Net architectures, have shown high accuracy (66%–99%) in classification and strong performance in segmentation tasks. Combining radiomics with deep learning further improved results. Dice scores for tumor segmentation reached up to 0.892 for HGG, though LGG scores were slightly lower.

However, despite these advancements, several challenges persist in the field. Issues such as data imbalance, limited labeled data, and the presence of artifacts in MRI scans can hinder the performance of ML and DL models. Moreover, the generalization of these models to different datasets and clinical settings remains a major concern, as models trained on a specific dataset may not perform equally well on unseen data from different institutions or MRI scanners. The variability in tumor shapes, sizes, and locations further complicates the task of accurate segmentation and classification.

Future research should focus on addressing these challenges by exploring approaches such as multi-modal learning, where various imaging modalities (e.g., T1, T2, FLAIR, etc.) are integrated to improve model performance. Additionally, techniques like transfer learning could help overcome the issue of limited labeled data by leveraging pre-trained models on large datasets. Federated learning is another promising direction, which would allow models to be trained on decentralized datasets while preserving patient privacy, a critical factor in medical applications.

The progression and subsequent implementation of instruments engineered for elucidating artificial intelligence (AI) are critically significant for the unobstructed assimilation of such innovations within clinical environments, as they promote a deeper comprehension of the mechanisms underpinning these advanced systems in a medical framework. Furthermore, attaining a substantial degree of transparency concerning the decision-making methodologies employed by deep learning models is not merely advantageous but is fundamentally imperative for guaranteeing that healthcare practitioners can foster a sense of trust and assurance in the results produced by these intricate algorithms.

In conclusion, it is imperative to acknowledge that while the advancements achieved in the realm of artificial intelligence pertaining to the detection and segmentation of brain tumors are indeed remarkable and deserving of recognition, it is equally essential to comprehend that further coordinated initiatives must be pursued to tackle the prevailing challenges that continue to exist in this discipline.

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