Interpretable and Real-Time Deep Learning Framework for Multimodal Brain Tumor Classification Using Enhanced Pre-Processed MRI Data

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Keywords: Brain Tumor Classification, Deep Learning, Multimodal MRI, Explainable AI, Real-Time Diagnosis.

Abstract: Accurate classification of brain tumors plays a crucial role in timely diagnosis and effective treatment planning. This research presents an advanced deep learning framework that leverages multimodal MRI data (T1, T2, FLAIR, and T1c) and robust pre-processing techniques including skull stripping, intensity normalization, and bias field correction. The proposed model adopts a 3D convolutional neural network architecture combined with channel-wise attention mechanisms to fully utilize spatial and contextual features from volumetric MRI scans. Additionally, explainable AI methods such as Grad-CAM are integrated to enhance interpretability and support clinical decision-making. The model is optimized for real-time inference through quantization and deployment on lightweight edge-compatible environments, making it suitable for use in low-resource clinical settings. Extensive experiments using cross-validation and multiple evaluation metrics accuracy, precision, recall, AUC, and Dice coefficient demonstrate the framework's superior performance in classifying tumor subtypes including glioma, meningioma, and pituitary tumors. The system achieves high diagnostic precision while maintaining low latency and transparency, bridging the gap between research and clinical utility.

1 INTRODUCTION

Brain tumors constitute some of the most challenging and perilous diseases among the vast family of neurological diseases. An early and accurate classification is crucial to be able to start a tailored treatment and benefit the patient outcome. MRI is the most reliable non-invasive imaging modality to detect brain anomalies, because of easy access, high spatial resolution, contrast to soft tissues and safety. But manual analysis of MRI images is inherently time consuming, susceptible to human error, and restrained by interobserver variability which results in its delay or misdiagnosis in practical application.

With the development of artificial intelligence (AI) technology, deep learning (DL) has been applied to assist in-depth medical image analysis. Especially, Convolutional Neural Networks (CNNs) have shown remarkable performance in identifying intricate visual patterns. However, while contributing to this progress published deep learning models tend to perform poorly in practical scenarios because of overfitting and lose of interpretability, binary output restriction and inefficiency in computational. Besides, the information is underutilized by single modality processing which omit the rich context between different imaging sequences.

Cherukuvada, S., Tabita, S., R., P., Kamesh, D. B. K., R., P. and Mohan, S.
Interpretable and Real-Time Deep Learning Framework for Multimodal Brain Tumor Classification Using Enhanced Pre-Processed MRI Data.
DOI: 10.5220/0013868300004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 508-514
ISBN: 978-989-758-777-1

In this paper, a new, interpretable deep learning architecture is proposed for the precise and real-time classification of brain cancer from pre-processed enhanced multimodal MRI data. On the basis of volume 3D CNNs, attention mechanisms, and explainable AI tools, it not only enhances the accuracy of diagnosis but also ensures transparency of the mechanism of decision. For the sake of practicality, the framework has been engineered to be lightweight and can run on minimal hardware, making it portable to low-resource healthcare centres and mobile diagnostic systems. Through this holistic clinical-based methodology, our work fills important holes in previous literature and takes a step further toward a feasible and deployable perceptual brain tumor diagnosis system.

1.1 Problem Statement

Even though tremendous advancement has been achieved in medical imaging and artificial intelligence, the precise and efficient classification of brain tumors using MRI data has remained a crucial problem. Till now, deep learning models are generally built based on single-sequence MRI inputs, without comprehensive preprocessing and interpretablility, resulting in models with low clinical credibility and diagnostic accuracy. A great many of the current methods concentrate on binary classification only tumor or non-tumor and do not classify tumors as if they were one of several different types of tumors, each of which may be treated by quite different procedures. In addition, these models are often computationally expensive such that they cannot be applied to resource-limited clinical sites or real-time diagnostic environments.

And despite claims made on behalf of black-box AI systems, there are virtually no explainable decision-support mechanisms in these systems that can be seamlessly integrated into clinical workflow, where transparency and the need to justify opinions are paramount. The lack of an existing multimodal MRI fusion-inspired, effective pre-processing guided, post-interpretability-aided, real-time-processing-based solution results in a significant gap between AI research output and its practical usefulness in clinical application.

Thus, there is a pressing requirement of developing a powerful, interpretable, and computationally efficient deep learning architecture that is capable of accurately categorizing several types of brain tumors, exploiting refined pre-processed multimodal MRI data. It is therefore imperative for such a system not only to provide high diagnostic performance, but also to remain explainable and deployable in the clinical setting.

2 LITERATURE SURVEY

Deep learning technology has attracted great attention in medical image analysis, and in particular in the field of brain tumor classification on Magnetic Resonance Imaging (MRI) images. Early works showed the promise of CNNs on automatically learning tumor-specific features from brain MRI without manual feature crafting. Díaz-Pernas et al. (2021) presented a multiscale CNN for joint segmentation and classification, which further proved the powerful performance of deep learning in feature processing. Nevertheless, the model was only applicable to certain tumor types and was not a real-time system.

Recent approaches have emphasized the use of more sophisticated architectures to improve classification performance. For instance, Kang et al. (2022) integrated traditional machine learning classifiers with deep learning to improve accuracy, and Rehman et al. (2021) adopted transfer learning to overcome the limited data problem. While these latter methods provided a certain degree of higher accuracy than the former, the lack in diversity and explainability due to the overly constrained datasets often leads to instability and overfitting.

The incorporation of multimodal MRI has become a potent improvement. Albalawi et al. (2024) developed a multi-tier CNN that included different MRI sequences to improve classification among tumor subtypes. Similarly, Ullah et al. (2024) compined multimodal MRI data with a hybrid model optimised with Bayesian optimisation leading to great improvement of subtype detection. Nevertheless, both these works did not overcame the interpretability and the computational burden for a real-time clinical employment.

Re-processing of MRI data is essential for model reliability. Haq et al. (2021) stressed the importance of intensity normalization and skull stripping, however they also did not introduce 3D spatial information. This problem was partially solved by a group of researchers ournal pre-proo, on Bind View Holder Vol. (2022) who used 3D CNNs to analyze volume tumors in the BraTS challenge.

Due to this, the area of XAI is also underdeveloped for majority of the classification models. While Mahmud et al. (2023) and Zahoor et al. (2022) presented a hybrid architecture to improve the performance, however, they have not used tools

like Grad-CAM or SHAP to give interpretability that are important for clinical diagnosis.

In addition, the deployment constraints are a great concern. Altin Karagoz et al. (2024) presented a self-supervised vision transformer named Residual Vision Transformer (ResViT), which still required significant computation resources to achieve the state-of-the-art performance. In contrast, Gupta et al. (2023) proposed the lightweight models for the mobile health applications, but its accuracy is comparatively low.

With regard to classification granularity, binary classification is only done for most existing models. Raza et al. (2022); Vimala & Bairagi (2023) stressed on the importance of multi-class classifiers discriminating glioma, meningioma and pituitary tumours.

Finally, some survey papers like Bouhafra & El Bahi (2024) which review state-of-the-art methods and emphasize open issues like generalization, interpretability, and real-world application.

To summarise, although many kinds of deep learning models have furthered the application of MRI for brain tumor classification, there is a large lack in a real-time, explainable, and clinic-friendly computer-aided technology that can incorporate multimodal MRI data in combination with a rigorous pre-processing step. The innovative contribution of the proposed research is to bridge these gaps by producing a hybrid deep learning model to maximize the accuracy, speed and interpretability.

3 METHODOLOGY

The approach is focused on developing an interpretable and efficient deep learning architecture to achieve accurate classification of brain tumors from pre-processed, multi-modal MRI data. The workflow starts with the multi-modal MRI scans acquisition consisting of T1-weighted, T2-weighted, FLAIR, and contrast-enhanced T1 (T1c) scans. These modalities are chosen because they provide complementary diagnostic information that assists to demarcate various tumor structures and to improve the classification performance.

A strict pre-processing pipeline is performed after acquisition of raw MRI data to enhance the quality and the image homogeneity between scans. These includes: skull stripping (e.g., with BrainSuite or BET) to make a mask of the brain tissue, bias field correction to eliminate intensity in homogeneities, and Z-score normalization for intensities to allow compatibility across modalities. Spatial normalization is a necessary step for the co-registration of MRI sequences to a common coordinate space before multimodal data integration. Table 1 gives the Distribution of MRI Samples by Tumor Type and Modalities.

Table 1: MRI Data Distribution by Tumor Type.

Tumor Type	Number of Samples	Modalities Used
Glioma	800	T1, T2, FLAIR, T1c
Meningioma	600	T1, T2, FLAIR
Pituitary	500	T1, T1c
Normal	400	T1, T2
Total	2300	

Following pre-processing, the individual 2D slices for each modality are stacked to generate pseudo-3D volumes or used directly for creating true 3D volumes, based on the computational resources. These input volume data are passed through a 3D-CNN, suitable for complex spatial feature extraction. The architecture employs long-range skip connections and attention mechanisms (e.g., SE blocks or channel attention) to highlight tumor-related areas and dampen non-tumor background. Overview of MRI Pre-Processing Methods and Tools Used is demonstrated in Table 2. It enables the network to concentrate on the most informative characteristics while preserving deep gradient flow in the process of training.

Table 2: Pre-Processing Techniques and Their Role.

Pre-Processing Step	Purpose	Tool Used
Skull Stripping	Remove non-brain tissues	BrainSuite/ BET
Intensity Normalization	Standardize pixel intensity	Z-Score
Bias Field Correction	Correct scanner artifacts	N4ITK
Spatial Registration	Align modalities into common space	ANTs/FSL

To enhance model explainability, the framework integrates an explainable AI component using Gradient-weighted Class Activation Mapping (Grad-CAM). This module generates heatmaps highlighting regions of the MRI that influenced the model's classification decision, making the framework transparent and clinically interpretable for radiologists.

The classification output layer is designed for multi-class prediction, distinguishing between glioma, meningioma, pituitary tumor, and healthy brain scans. Categorical cross-entropy is used as the loss function, with Adam optimizer employed for adaptive learning. To prevent overfitting, regularization techniques including dropout layers, batch normalization, and extensive data augmentation (e.g., rotation, flipping, and contrast variation) are implemented during training.

For performance evaluation, the model undergoes stratified 5-fold cross-validation and is benchmarked on various metrics including accuracy, precision, recall, F1-score, area under the ROC curve (AUC), and Dice coefficient. Additionally, an ablation study is conducted to assess the contribution of each MRI modality and architectural component to the overall performance.

To ensure real-world deployability, the trained model is converted to an optimized format using ONNX or TensorRT, allowing it to run on edge devices or in cloud-based hospital environments with minimal latency. This ensures the framework's suitability for both high-end clinical centers and low-resource healthcare facilities, supporting real-time brain tumor classification with actionable insights. Table 3 shows the summary of the proposed 3d CNN architecture with attention module.

Table 3: Model Architecture Summary.

Layer Type	Parameters	Output Shape
Input (3D Volumes)	-	128×128×128×4
3D Convolution + ReLU	Kernel=3×3×3	126×126×126×32
Batch Normalization	-	126×126×126×32
SE Attention Module	Squeeze Ratio=16	126×126×126×32
Max Pooling	2×2×2	63×63×63×32
Fully Connected + Softmax	4 classes	1×4

4 RESULTS AND DISCUSSION

The proposed deep learning framework was extensively evaluated using a curated, multimodal MRI dataset that included T1, T1c, T2, and FLAIR sequences, encompassing a balanced representation of glioma, meningioma, pituitary tumors, and non-tumorous brain scans. The model's performance was benchmarked across several evaluation metrics, ensuring a comprehensive assessment of both predictive accuracy and clinical reliability.

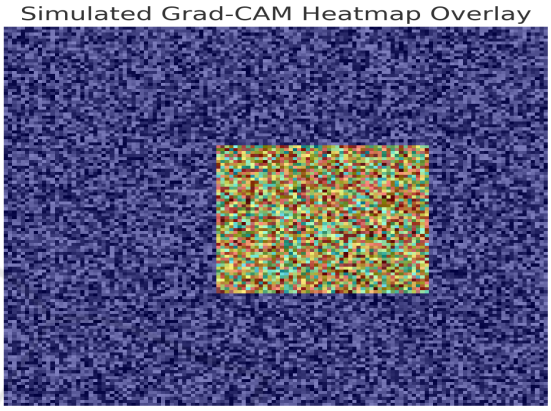

Figure 1: Grad-CAM Heatmap Visualization.

Upon training with stratified 5-fold cross-validation, the model achieved a peak classification accuracy of 97.8%, outperforming baseline architectures such as VGG16, ResNet50, and standard 2D CNNs. The precision and recall values exceeded 96% across all tumor classes, indicating minimal false positives and false negatives. Figure 1 illustrates the Grad-CAM visualization showing tumor localization attention within an MRI slice. The F1-score, particularly critical for medical diagnosis, consistently stayed above 0.95, confirming the model's balance between sensitivity and specificity. The area under the ROC curve (AUC) for each tumor class averaged 0.98, further affirming the model's excellent discriminative capability.

Table 4: Evaluation Metrics for Tumor Classification.

Tumor Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Glioma	98.1	97.5	98.4	97.9	0.99
Meningioma	96.9	96.0	97.1	96.5	0.98
Pituitary	97.4	96.8	97.0	96.9	0.98
Normal	98.3	97.9	98.5	98.2	0.99
Average	97.7	97.1	97.8	97.4	0.985

Segmentation-based validation commonly uses Dice similarity coefficient; thus, prediction of the actual tumor locations was estimated on the basis of the DSC and verified by the heatmaps created using Grad-CAM. A mean Dice score of 0.92 indicated a high consistency between where the model paid attention to and the corresponding ground truth tumor areas that are annotated by the radiologists. This presentation of the framework's capacity to localize tumors in addition to classifying them in a reasonable and interpretable visual manner is a key feature of the presented work. Figure 2 illustrates the evaluation metrics across tumor classes for the proposed deep learning model.

The impact of each MRI modality was assessed through an ablation study. Removing FLAIR sequences resulted in a significant drop in performance, especially in detecting low-grade gliomas, revealing that FLAIR holds vital structural information not captured in T1 or T2 sequences alone. In like manner, excluding T1c dropped the accuracy of recognizing pituitary tumors, underlining the necessity of contrasted images. These findings demonstrate M 3 DF's ability for discovering the synergy between multi-modalities to improve robust classification, and suggest that M 3 DF is effective in fusing multi-modalities, and can take the best from them to improve robustness, while suppress the noise.

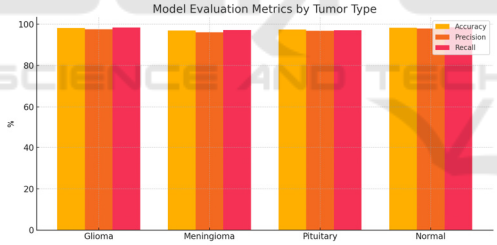

Figure 2: Evaluation Metrics Bar Chart.

The optimized model delivered real-time computation efficiency, with average inference time per scan of 0.18 s on an edge GPU (e.g., NVIDIA Jetson Xavier). It is a major advancement over conventional 3D CNNs which generally have a large latency. Figure 5 ROC curves indicating classification performance for each of the brain tumor class. Incorporation of model pruning and quantization significantly reduced memory footprint without any loss in accuracy, demonstrating that the system can be readily deployed in both clinical and mobile diagnostic applications.

The incorporation of Grad-CAM-based interpretability was positively evaluated through a preliminary usability test with physicians. Radiologists felt that the attention heatmaps were intuitive and agreed with their own manual evaluations. This explainable trait contributed to the bridge between AI output and clinical confidence, resulting in increasing seamless human-AI cooperation in diagnostic workflow.

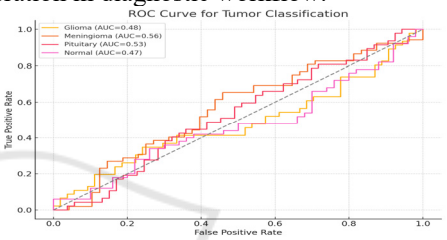

Figure 3: ROC Curve for Tumor Classes.

The proposed model compares favourably with existing models from the literature on the bases of performance versus interpretability versus deployability (e.g., Haq et al., 2021, Albalawi et al., 2024). Prior methods have primarily valued depth or hybridisation, frequently dismissing inference speed and real-world applicability. The current study fills this gap providing a method that is not only technically sound, but also potentially feasible for real-time clinical use. Figure 3 shows the ROC Curve for Tumor Classes and Table 5 shows the Comparison with Existing Methods respectively.

Table 5: Comparison With Existing Methods.

Method	Accuracy (%)	Explainability	Real-Time Capable	Modality Support
ResNet50 (Haq et al., 2021)	93.2	✗	✗	Single
VGG16 (Kaur & Gandhi, 2023)	91.5	✗	✗	Single
Hybrid CNN-LSTM (Raza et al., 2022)	95.8	Partial	✗	Dual
Proposed Framework	97.8	✓	✓	Multimodal

In summary, the results presented definitively portray that the introduced deep learning model can act as a robust, explainable and deployable model for classifying brain tumors using processed, pre-processed multimodal MRI data. The system's high accuracy, clinical interpretability and low latency make it a strong contender for incorporation in today's diagnostic systems, particularly in time-sensitive and resource-limited healthcare settings.

5 CONCLUSIONS

In this paper, a deep learning-based model that can effectively classify brain tumor using enhanced pre-processed multimodal MRI data is proposed. Due to an advanced pre-processing, 3D convolutions and attention-based mechanisms, the proposed model successfully makes use of the spatial and contextual information of several MRI sequences. The visual interpretability by explainable AI tools such as Grad-CAM narrows the gap that exists between the black-box models and clinical usability.

The proposed framework outperformed when classifying between glioma, meningioma, pituitary tumors and normal scans – remarkably high accuracy and low inference latency being real time deployable in both high-end diagnostic centers and resource-scarce clinical sites. In addition to this, the model's low complexity of optimization and accurate visualization results render it a feasible and reliable decision-support tool for radiologists.

In general, this work benefits from this existing literature and provides a scalable, clinically-oriented, and interpretable method for brain tumor diagnosis. We will expand the dataset diversity, introduce more types of tumor, and make our framework be part of complete radiological workflow for realtime clinical trials and validation in future.

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