# Brain Tumor Detection and Classification Using Hybrid CNN–GNN Framework with Multi-Modal MRI: A Review

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**Abstract**

Brain tumor detection and classification using magnetic resonance imaging (MRI) is a critical task in neuro-oncology due to the complex structure and heterogeneous nature of tumors. Early diagnosis significantly improves treatment outcomes. Deep learning approaches, particularly convolutional neural networks (CNNs), have shown promising performance in automated brain tumor detection and classification tasks [10], [18].
Several CNN architectures such as ResNet, EfficientNet and YOLO-based models have demonstrated high detection accuracy on MRI datasets [1], [13], [16]. However, CNN models mainly focus on local spatial feature extraction and fail to capture long-range contextual dependencies between tumor regions [12], [17].
Recent studies have explored vision transformers, attention mechanisms, and graph neural networks (GNNs) to improve contextual modeling [3], [6]. Additionally, multi-modal MRI analysis (T1, T2, and FLAIR) improves diagnostic performance by leveraging complementary anatomical information [4], [7].

**Keywords**
Brain Tumor Detection; Multi-modal MRI; Convolutional Neural Network (CNN); Graph Neural Network (GNN); Explainable Artificial Intelligence (XAI); Deep Learning

## Introduction

Earlier studies relied on traditional machine learning algorithms such as Support Vector Machines (SVM), clustering techniques, and handcrafted feature extraction methods for brain tumor detection [8], [24].

Later research shifted toward deep learning architectures, particularly CNN-based models, which automatically learn hierarchical features from MRI images and achieve improved classification performance [15], [22].

Several deep learning models including ResNet50, EfficientNet, and transfer learning-based CNN models have demonstrated high accuracy in tumor detection tasks [10], [13], [16].

Recent studies have also explored Vision Transformer-based architectures for capturing long-range dependencies within medical images [6]. Moreover, attention-guided CNN frameworks have been proposed to improve tumor classification using multi-modal MRI images [3].

Explainable AI techniques have also been introduced to improve transparency and trust in deep learning-based medical diagnosis systems [23].

**Literature Review**

| No. | Author(s) | Method / Model | Dataset | Accuracy | Limitation |
|---|---|---|---|---|---|
| 1. | Abraham et al., 2025 | Dilated CNN + YOLOv8 feature extraction | BraTS , Roboflow MRI Dataset | High detection performance | High computational complexity |
| 2. | Hassan & Boulila, 2025 | Fuzzy thresholding + DL | Combined Public MRI Datasets | 98% Accuracy | Sensitive to threshold selection |
| 3. | Abdelhaliem et al., 2025 | Multimodal attention-guided CNN | Multimodal MRI (T2-MRI & DW-MRI) | 92.86% | Complex architecture |
| 4. | Preetha et al., 2025 | 3B-Net + EfficientNetB2 | Figshare + Multiple Kaggle Brain MRI Datasets | Very high classification accuracy (>98%) | Requires large training data |
| 5. | Multiple authors (Neuro-oncology AI research group), 2025 | Advanced CNN-based automation | MRI Brain Tumor Dataset (Glioma, Meningioma, Pituitary) | Improved diagnostic performance | Limited explainability |
| 6. | P Chauhan et al., 2024 | Patch-based Vision Transformer (PBViT) | Figshare Brain Tumor Dataset | ~98–99% | High training cost |
| 7. | Asiri et al., 2024 | Dual-module (enhancement + CNN) | Kaggle Brain MRI Dataset | ~97–98% | Two-stage pipeline complexity |
| 8. | Alqahtani et al., 2024 | FCM + SVM | BRATS Dataset | ~95–97% | Lower performance than DL |
| 9. | Farzamnia et al., 2023 | Contourlet transform + SOM | BRATS Dataset | ~94–96% | Manual feature engineering |
| 10. | Younis et al., 2024 | ResNet50 | Kaggle Brain MRI Dataset | 99% | No segmentation |
| 11. | Ahmed et al., 2024 | Transfer learning CNN | Combined MRI dataset | 98.7% | Model bias risk |
| 12. | Karrar Neamah et al., 2023 | Systematic review (DL models) | Multiple datasets | No single accuracy | No experimental validation |
| 13. | Faisal Saeed et al., 2022 | Fine-tuned EfficientNet | Public MRI Dataset | 98.87% | Dataset dependent |
| 14. | Neelum Noreen , 2020 | CNN feature concatenation | Figshare Brain Tumor Dataset | 99.34% | Shallow architecture |
| 15. | Abdusalomov et al., 2023 | CNN-based detection | Public Brain Tumor Dataset | 99.5% | Limited tumor grading |
| 16. | K. Nishanth et al., 2024 | Pre-trained CNN models | Public Brain MRI Dataset | Higher accuracy with ResNet50 & EfficientNet | No interpretability |

| | | | | | |
|---|---|---|---|---|---|
| 17. | Shubhangi Solanki et al., 2023 | Review of intelligent techniques | Multiple datasets | No single accuracy | Lacks benchmarking |
| 18. | Muhammad Aamir et, 2024 | Optimized CNN | Kaggle MRI Datasets | 97.18% Accuracy | Insufficient methodological details |
| 19. | Hafiz Aamir et al., 2023 | CNN for glioma grading | BRATS-2017, BRATS-2018, BRATS-2019 + Local Hospital Dataset | 97.85% (BRATS), 98.89% (Local dataset) | Binary classification only |
| 20. | P Gokila Brindha et al., 2021 | Deep CNN | Brain Tumor MRI Dataset | CNN achieved 91.3% accuracy | Small dataset |
| 21. | NaeemUllah et al., 2023 | TumorDetNet (Unified DL) | Kaggle Brain MRI Datasets | 99.83% (Detection), 100% (Benign/Malignant), 99.27% (3-class) | Computationally heavy |
| 22. | Soheila Saeedi et al., 2023 | CNN + ML classifiers | Brain MRI Dataset | 96.47% (2D CNN) | Feature dependency |
| 23. | Shagufta Iftikhar et al., 2025 | Explainable CNN (XAI) | Public Brain MRI Datasets | 99% (Seen Data), 95% (Unseen Data) | Slight accuracy drop |
| 24. | Zahraa A. et al., 2020 | MI-accelerated SVD | MRI Brain Image Dataset | 94.91% | Classical approach |
| 25. | Afnan M. Alhassan et al., 2020 | BAFCOM + Capsule Network | Brain Cancer MRI Dataset | High accuracy | Complex optimization |

**Research Gap**

Despite the significant progress in deep learning-based brain tumor detection, several limitations still exist in current approaches.

Most existing methods rely heavily on CNN-based architectures, which primarily focus on extracting local spatial features from MRI images. However, CNN models often fail to capture global contextual relationships and structural dependencies between different brain regions, which are crucial for accurately analyzing complex tumor structures [12], [17].

Furthermore, although multi-modal MRI imaging provides complementary diagnostic information, many existing studies do not effectively perform multi-modal feature fusion, resulting in incomplete utilization of tumor-related information [4], [7].

Another major limitation is the lack of interpretability in deep learning models. Many AI-based diagnostic systems operate as black-box models, making it difficult for clinicians to understand the reasoning behind predictions, thereby limiting their adoption in real clinical environments [23].

Therefore, there is a need to develop an advanced framework that integrates CNN-based feature extraction, GNN-based relational learning, effective multi-modal MRI fusion, and explainable AI techniques to improve both diagnostic accuracy and clinical interpretability.

## Methodology

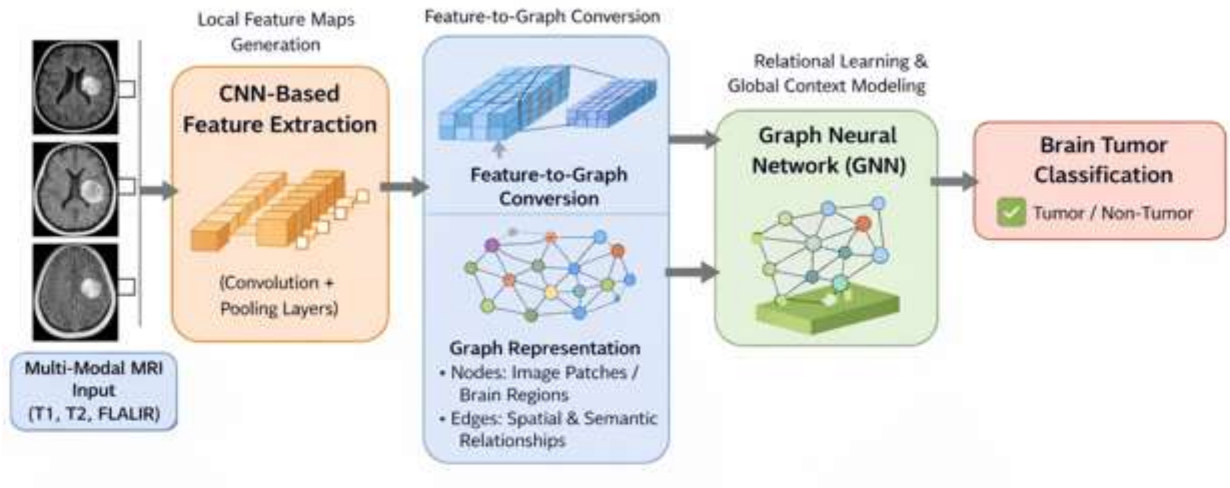


Fig.1 Proposed Hybrid CNN–GNN Framework

### 1. Multi-Modal MRI Input Layer

- Input consists of multi-modal brain MRI images such as T1, T2, and FLAIR [4], [7]
T1 → Clear brain anatomy (structure)
T2 → Fluid, swelling, edema
FLAIR → Highlights tumor by suppressing normal fluid

- Using T1, T2 and FLAIR helps detect tumors more clearly and improves diagnostic accuracy by providing complementary anatomical and pathological information [4], [7].
- Multi-modal MRI provides detailed information about tumor shape, size, and spatial spread within brain tissues [3], [15].

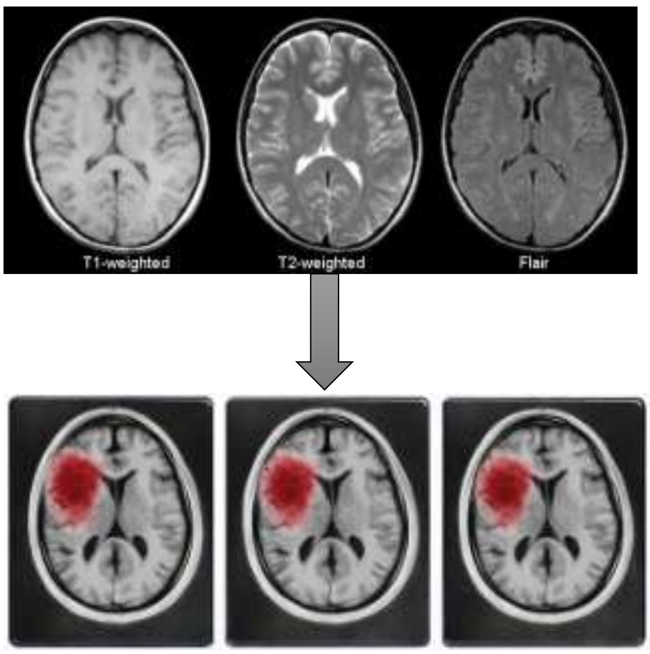


Fig.2 Multi-Model MRI Input Layer

**2. Preprocessing & Modality Alignment**

- Image resizing, noise removal, and intensity normalization are applied to standardize MRI images before feature extraction [18], [22].
- Modality-wise alignment (image registration) ensures spatial consistency across MRI types so that corresponding anatomical regions overlap correctly [4], [7].

**3. CNN-Based Feature Extraction Module**

- CNN models use convolutional and pooling layers to automatically learn hierarchical image features [10], [18].
- These layers extract local spatial features from MRI images such as edges, textures, and intensity variations [16], [21].
- CNN networks are particularly effective in identifying tumor-related patterns including tumor boundaries, shape, and texture characteristics from each MRI modality [13], [18].

**4. Feature-to-Graph Transformation Module**

- CNN feature maps are divided into multiple patches or regions to represent different parts of the brain image [6].
- Each patch is treated as a graph node, while spatial or semantic relationships between patches form graph edges [3], [6].
- This transformation converts the MRI feature representation into a graph structure that captures relationships between brain regions [6].

**5. Graph Neural Network (GNN) Module**

- Graph Neural Networks perform message passing between graph nodes to aggregate information from neighboring regions [3], [6].
- This process enables the model to capture global contextual relationships and inter-regional dependencies across tumor areas [3].
- GNN models can learn complex tumor structures and spatial patterns beyond local CNN features, improving classification accuracy [6].

**6. Classification Layer**

The final classification layer categorizes MRI images into different tumor classes:

- Glioma
- Meningioma
- Pituitary
- Non Tumor

Deep learning classification models have demonstrated high performance in multi-class brain tumor classification tasks using MRI datasets [10], [18], [21].

**Discussion**

Hybrid CNN-GNN architectures provide several advantages over traditional CNN models.

CNN networks effectively capture local spatial features, while GNN models analyze global relational dependencies among different brain regions [3], [6].

Combining these models improves the ability to understand complex tumor structures and spatial dependencies.

Furthermore, multi-modal MRI fusion enhances diagnostic accuracy by integrating complementary information from multiple imaging modalities [4], [7].

**Future Scope**

Future research in brain tumor detection may focus on several advanced directions.

Researchers may explore 3D CNN and 3D GNN architectures to analyze volumetric MRI data for better spatial understanding of tumors. Another important direction involves multi-class tumor classification and grading, which can help predict tumor severity and treatment strategies [21].

Additionally, federated learning approaches can enable collaboration between multiple hospitals while preserving patient data privacy. Integration of clinical information such as patient history and genetic data with MRI images may further enhance diagnostic performance [19].

Finally, deploying these models in real-time clinical environments using cloud and edge computing technologies can improve accessibility and support rapid medical diagnosis.

**Conclusion**

Brain tumor detection using MRI imaging remains a critical research area in medical image analysis. Deep learning techniques such as CNN models have significantly improved tumor detection accuracy [10], [18].

However, CNN models mainly capture local features and often fail to model global relationships between tumor regions [12], [17].

Graph Neural Networks offer a promising solution by modeling relational dependencies within brain structures [3], [6]. Integrating CNN, GNN, multi-modal MRI fusion, and explainable AI techniques can significantly improve diagnostic accuracy and reliability for clinical decision support systems.

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