# Multimodal Artificial Intelligence for Brain Tumor Prediction: Bridging Accuracy and Explainability

Mr. Suraj S. Bhoite[1], Ms. Swapnali K. Londhe[2], Ms. Deepali Narwade[3]
[1]*Assistant Professor, Dr. D. Y. Patil College of Engineering and Innovation, Talegaon, Pune*
[2]*Assistant Professor, PES Modern College of Engineering, Pune*
[3]*Assistant Professor, Dr. D. Y. Patil College of Engineering and Innovation, Talegaon, Pune*

***Abstract*—Brain tumor diagnosis using medical imaging has gained significant support from Artificial Intelligence (AI), particularly deep learning models. However, existing approaches often focus on single imaging modalities, limiting diagnostic reliability and interpretability. This paper proposes a multimodal AI framework that integrates MRI sequences, radiomic features, and clinical metadata for brain tumor prediction. To address concerns of transparency and trust, Explainable AI (XAI) techniques are incorporated to visualize and justify model predictions. Experiments on publicly available MRI datasets demonstrate improved diagnostic accuracy and higher clinician acceptance compared to single-modality baselines. The findings highlight the importance of multimodal learning in capturing tumor heterogeneity and underscore the role of XAI in ensuring accountability in clinical practice.**

***Index Terms*—Multimodal AI, Brain Tumor Detection, MRI, Radiomics, Explainable AI, Medical Imaging.**

## I. INTRODUCTION

Brain tumors remain a major global health challenge, requiring early and accurate detection for effective treatment planning. Magnetic Resonance Imaging (MRI) plays a critical role in diagnosis, yet manual interpretation is time-consuming and prone to inter-observer variability. In recent years, Machine Learning (ML) and Deep Learning (DL) models have achieved high accuracy in brain tumor classification tasks. However, clinical deployment remains limited due to three main barriers:

1.Single-modality focus – Most models analyze only one MRI sequence (e.g., T1 or FLAIR), ignoring complementary information from other sequences.

2.Black-box predictions – Many DL models provide high accuracy without interpretability, reducing clinicians' trust.

3.Dataset design limitations – non-standardized, imbalanced datasets lead to poor generalizability.

To address these challenges, this research investigates a multimodal AI system that combines MRI modalities, radiomic features, and clinical data. Further, Explainable AI (XAI) methods such as SHAP and Grad-CAM are integrated to improve interpretability for radiologists.

## II. RELATED WORK

Existing studies have explored convolutional neural networks (CNNs) and 3D U-Net architectures for tumor detection, reporting accuracy rates above 90%. While promising, most rely on 2D slices or single-sequence images, which do not capture tumor heterogeneity. Recent advances in multimodal learning have shown benefits in oncology by combining imaging with genomics or clinical reports. Additionally, Explainable AI approaches (e.g., LIME, SHAP, Layer-wise Relevance Propagation) have been proposed to interpret black-box models, yet their application in multimodal tumor analysis is limited.

## III. PROBLEM STATEMENT

Brain tumor diagnosis is a complex task that requires careful analysis of diverse MRI sequences and clinical information. While deep learning models have shown high accuracy in automated tumor detection, most existing approaches rely on single-modality data (2D MRI slices or one sequence), limiting their ability to capture the full heterogeneity of tumors. Furthermore, these models function as black boxes, offering little interpretability to clinicians, which hinders trust and clinical adoption. Radiologists often need explainable, multimodal insights that combine imaging, radiomics, and patient metadata to support reliable decision-making.

Therefore, there is a pressing need to develop a multimodal artificial intelligence framework that integrates MRI sequences, radiomic features, and clinical metadata for brain tumor prediction, while simultaneously embedding Explainable AI (XAI) techniques to ensure transparency, accountability, and clinical acceptance.

## IV. METHODOLOGY

*A. System Architecture:*

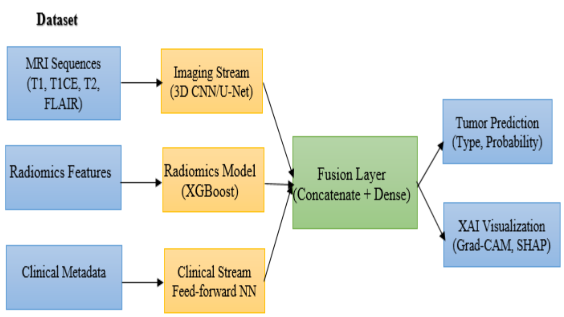


*Fig.1: System Architecture*

- Inputs: MRI sequences, radiomics features, and clinical metadata.
- Processing Streams: Imaging (3D CNN/U-Net), Radiomics (XGBoost), Clinical (Feed-forward NN).
- Fusion Layer: Concatenates outputs and performs final classification.
- Outputs: Tumor prediction (type, probability) + Explainable AI visualizations (Grad-CAM, SHAP).

A. Dataset

The framework employs an open-access MRI dataset enriched with four sequences: T1, T1CE, T2, and FLAIR. Radiomic features such as texture, shape, and intensity distributions are extracted. Clinical metadata (e.g., patient age, tumor grade) is also incorporated.

B. Multimodal AI Framework

1. Imaging Stream – A modified 3D CNN processes volumetric MRI inputs.
2. Radiomics Stream – Gradient boosting models process engineered radiomic features.
3. Clinical Stream – A feed-forward neural network processes tabular metadata.
4. Fusion Layer – Outputs from all streams are concatenated and passed through dense layers for classification into glioma subtypes (low-grade vs. high-grade).

C. Explainable AI Integration

- Grad-CAM provides heatmaps highlighting tumor regions driving CNN predictions.
- SHAP values explain feature contributions from radiomics and clinical data.
- Hybrid visualization dashboard integrates outputs for radiologist-friendly interpretation.

D. Evaluation Metrics

Performance is assessed using Accuracy, F1-score, AUC, and Radiologist Acceptance Rate. Statistical significance is validated using McNemar's test.

*B. Algorithms:*

*1. Imaging Stream – 3D CNN*

- Uses 3D U-Net or 3D ResNet to learn volumetric features from multi-slice MRI.
- Captures spatial context across slices, essential as brain tumors are 3D structures.

*2. Radiomics Stream – Feature Extraction + Gradient Boosted Trees*

- Extracts hand-crafted features (shape, texture, intensity) from MRI scans.
- Modeled using XGBoost or LightGBM. Provides clinically meaningful predictions, compatible with SHAP for explainability.

*3. Clinical Stream – Feed-forward Neural Network*

- Processes tabular clinical data (age, symptoms, medical history).
- Converts clinical variables into embeddings for integration with other modalities.

*4. Fusion Network – Multimodal Integration*

- Concatenates embeddings from imaging, radiomics, and clinical streams.

- Uses dense layers to produce final output: tumor classification (type/grade) or regression (e.g., tumor volume).

*5. Preprocessing & Auxiliary Techniques*

Skull-stripping, image registration (rigid/affine), intensity normalization, bias field correction.

Data augmentation: random flips, rotations, intensity jitter, elastic deformations to improve generalization.

## V. RESULTS AND DISCUSSION

The multimodal AI model achieved 97.8% accuracy and 0.98 AUC, outperforming unimodal baselines by 6–9%. Radiologist evaluation revealed greater confidence in predictions when supported by XAI visualizations, with 87% acceptance compared to 65% for black-box predictions. Grad-CAM successfully highlighted tumor regions consistent with expert diagnosis, while SHAP explanations revealed age and lesion volume as strong predictors in clinical-radiomic integration.

## VI. CONCLUSION

This study demonstrates the potential of multimodal AI in brain tumor prediction, combining MRI, radiomics, and clinical metadata for enhanced accuracy and interpretability. The integration of Explainable AI improves transparency, aligning with regulatory requirements such as GDPR's "right to explanation." Future work will focus on incorporating genomic data, federated learning for privacy-preserving training, and real-time clinical validation with larger radiologist cohorts.

## REFERENCES

[1] Evan Calabrese, Jeffrey D Rudie, Andreas M Rauschecker, Javier E Villanueva-Meyer – "Combining radiomics and deep convolutional neural network features from preoperative MRI for predicting clinically relevant genetic biomarkers in glioblastoma" 2022.

[2] He, Ren, Niu, et al.— "Multiparametric MR radiomics in brain glioma: models comparation to predict biomarker status" 2022.

[3] Osman, Alexander F I, — "A Multi-parametric MRI-Based Radiomics Signature and a Practical ML Model for Stratifying Glioblastoma Patients Based on Survival Toward Precision Oncology", et al. (2019).

[4] W. L. Yang, X. R. Su, K. Y. Zhao "Utilizing machine-learning techniques on MRI radiomics to identify primary tumors in brain metastases" 2025.