

Enhancing Brain Tumor Diagnosis with Explainable Deep Learning and Multi-Modal Imaging Fusion

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Abstract— Using magnetic resonance imaging (MRI) to diagnose brain tumors is a crucial task that is frequently hampered by the subjective nature of manual clinical evaluations and the high diagnosis delay. Gliomas especially Glioblastoma Multiforme (GBM) have terrible rates of progression and require prompt precise surgical or chemotherapeutic localization. Although deep learning models in particular Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have shown previously unheard-of accuracy in automated anomaly classification, their "black-box" architecture poses a significant obstacle to regulatory trust, clinical adoption, and certification. This paper examines the development of deep learning in neuro-oncology, identifies important research gaps such as algorithmic opacity data scarcity and privacy constraints and suggests a comprehensive framework that integrates Explainable AI (XAI) like Grad-CAM and SHAP with multi-modal MRI, Generative Diffusion models and Federated Learning. The goal is to retain cutting-edge predictive performance while promoting physician trust and offering practical clinical justifications.

Keywords— Vision Transformers, Explainable AI (XAI) Multi-modal MRI, Deep Learning Brain Tumour Segmentation Federated Learning Glioblastoma.

I. INTRODUCTION

The diagnosis of brain tumors using magnetic resonance imaging (MRI) is a very difficult task at the forefront of predictive oncology and medical imaging. Growing tumor masses can quickly produce severe neurological impairments by compressing nearby healthy brain tissue because neuro-oncological anomalies are contained within the hard cranial vault. Effective treatment interventions from targeted radiation therapy to invasive neurosurgery resections depend critically on early accurate identification and high-resolution spatial localization the past clinical diagnosis was solely dependent on the subjective visual skills of neuroradiologists with specific training. To create a mental 3D volume of the disorder hundreds of thousands of 2D image slices must be manually scrolled. This technique is particularly vulnerable to inter-observer variability cognitive fatigue and subliminal bias. A significant paradigm shift in medical image analysis has been sparked in recent years by the convergence of deep learning (DL) and sophisticated computer resources. Automated diagnostic algorithms find intricate spatial patterns that are not obvious to the human eye. Nevertheless, even producing benchmark measurements that are superhuman there are still important structural constraints. The majority of highly parameterized deep learning systems operate implicitly as opaque "black boxes," greatly hiding their internal decision-making matrices.

The majority of medical professionals and international regulatory health bodies are still reluctant to accept computerized predictions that lack clear, transparent scientific justification.

Contributions of this Review

The specific contributions of this study to the current situation are:

1. Algorithm Taxonomy: Offering an organised examination of the progression from Convolutional Neural Networks (CNNs) and contemporary Vision Transformers (ViTs) to Traditional Machine Learning.

2. Analysis of XAI and Data Paradigms: Examining the vital need for Explainable AI (XAI) in conjunction with new data ecosystems such as Federated Learning and Generative Diffusion.

3. Identification of Gaps: Emphasizing clinical and structural gaps that have been confirmed in the most advanced techniques currently in use.

4. Proposed Architecture: To address the noted "black-box" and data privacy issues a new mathematically strict hybrid structure is presented. This template for instance has a significantly larger head margin than is typical. This measurement, along with others, is intentional, utilising guidelines that anticipate your paper as a component of the complete process rather than as a stand-alone document. No present designations need be changed.

II. Clinical Background and MRI Physics

A. Clinical Biology of Gliomas and WHO Grading

The chaotic biological structure of brain tumors must be understood computationally. The World Health Organization (WHO) categorizes central nervous system (CNS) tumors according to their histological aggressiveness and cellular origin. The most common and lethal are gliomas which are derived from glial supporting cells. Gliomas are rated by the WHO from Grade I (benign) to Grade IV (very malignant and necrotic). Massive necrotic centers and widespread microvascular growth are characteristics of Grade IV Glioblastoma Multiforme (GBM). Algorithmic border categorization is particularly challenging due to the morphological disorder of a GBM which consists of a constantly expanding ring encircling a lifeless fluid-filled core that is surrounded by a wide perimeter of peritumoral edema.

B. The Physics of Multi-parametric MRI

The cooperative use of many MRI modalities is required by clinical protocols. Scanners record essentially distinct physiological states by varying the relaxation times (TR and TE) of radio frequency pulses:

1. T1-Weighted (T1): This biological baseline map offers superior resolution of healthy neuro-anatomy.

2. T1 Contrast-Enhanced (T1c): This sequence actively highlights aggressive vascularized malignancy rims by physically illuminating weakened blood-brain barriers after gadolinium injection.

3. T2-Weighted (T2): Clearly depicts the extensive peritumoral oedema and is extremely sensitive to water concentration.

4. Fluid-Attenuated Inversion Recovery or FLAIR isolates the tumor and oedema from the brain's ventricles by suppressing the bright signal of standard cerebrospinal fluid (CSF).

To concurrently merge these four very different physiological maps an efficient neural network needs to be mathematically developed.

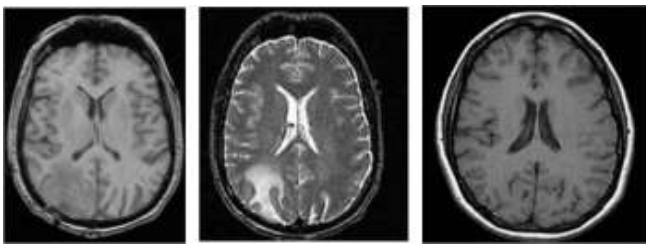


Fig. 1: The sequences of MR brain images. (left) T1-weighted, (mid) T2-weighted and (right) FLAIR Images

Source: Adapted from T. A. Soomro et al. [7]



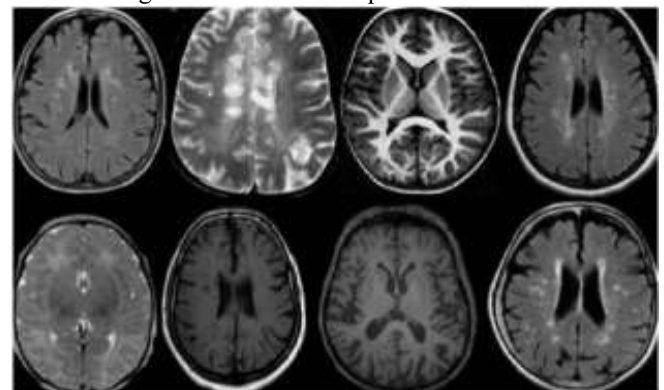
Fig. 2. The three planes of MR brain images. (left) Axial view of MRI brain images, (middle) Sagittal view MRI brain image, (right) Coronal view MR brain images.

Source: Adapted from T. A. Soomro et al. [7]

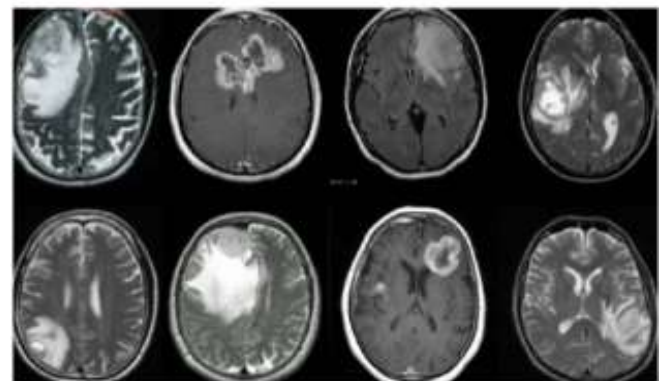
This is an informative medical image analysis technique used to visualize and segment body structures and brain tissues. Compared to other non-invasive methods, MRI yields superior results in detecting brain tumors. Due to high contrast, MR images provide clear information regarding the brain's soft tissues. It utilizes three planes (axial, sagittal, and coronal) to provide detailed information about the brain, spinal cord, and cerebral vascular anatomy. Instead of ionizing radiation, MRI relies on magnetic fields and radio waves to produce high-contrast 2D or 3D images of the brain. A key advantage of MRI

is the absence of radiation, making it a safer technique than CT scanning.

The primary MRI planes are illustrated in Figure 2 these three planes enable the visualization of brain anatomy. The three most common MRI sequences used for brain analysis are T1-weighted, T2-weighted, and Fluid-Attenuated Inversion Recovery (FLAIR). T1-weighted scanning provides contrast between gray and white matter. T2-weighted imaging is sensitive to water content, making it highly effective for conditions involving fluid accumulation within brain tissue. T1- and T2-weighted images are also used to distinguish cerebrospinal fluid (CSF). CSF is a colorless fluid found in the brain and spinal cord; it appears dark in both T1- and T2-weighted images. The third MRI brain sequence is FLAIR, as it is similar to T2-weighted imaging. The FLAIR process helps distinguish between CSF and brain abnormalities in MR imaging. Areas of edema (swelling) associated with CSF can be detected using the FLAIR MRI sequence.



(a)



(b)

Fig. 3. The MR brain images with tumor and without tumor. (a) MR Brain images without Tumor and (b) MR Brain images with Tumor.

Source: Adapted from T. A. Soomro et al. [7]

T1-weighted, T2-weighted, and FLAIR images are shown in Figure 3. MR brain images with and without tumors are displayed here.

III. SIGNIFICANCE AND OBJECTIVES

A. The Global Burden of Neuro-Oncology

From a clinical standpoint, survival metrics in GBM cohorts deteriorate significantly when targeted therapy are postponed by just a few weeks. Every year each hospital system saves hundreds of radiologist man-hours by automating the first volumetric segmentation needed for surgical mapping. This designed architecture's ability to democratise quick precise and transparent cancer diagnostics worldwide is what makes it so significant.

B. Primary and Specific Objectives

This research's main goal is to thoroughly design develop and verify an automated diagnosis system that uses multi-modal MRI inputs and is based on Deep Learning.

The particular goals and main contributions of this study are organized as follows in order to fill the previously identified gaps:

1) Algorithmic Deconstruction and Analysis: To determine the best topological baseline for neuro-anomaly detection, we methodically assess and test current deep learning macro-architectures, particularly ResNet DenseNet and Vision Transformers (ViTs) [12], [16],[26].

2) Adaptive Multi-Modal Fusion: To maintain accuracy across different clinical data sequences we develop a mathematical fusion of T1, T2, T1c, and FLAIR imaging using adaptive cross-modal networking algorithms [15], [40].

3) Semantic Boundary Delineation: Using a structurally symmetric 3D U-Net version we develop a sophisticated volumetric segmentation paradigm with sub-millimetre accuracy for surgical mapping [20].

4) Hardware Democratisation and Efficiency: By enforcing stringent edge-device optimisation settings we guarantee the seamless execution of intricate inference computations within typical, low-power hospital IT infrastructures [39].

5) Native XAI Integration: The neural network's design incorporates Game-Theoretic (SHAP) and Saliency (Grad-CAM) logic natively ensuring 100% decision transparency without compromising prediction accuracy [8], [9].

6) Federated Learning and Generative Diffusion: By modelling decentralized Federated Learning methods we get beyond strict international healthcare privacy regulations (like HIPAA and GDPR). Furthermore, significant class imbalances are resolved by using high-fidelity Generative Diffusion models to artificially enlarge dataset cohorts [48], [53].

IV. REVIEW OF LITERATURE

The use of basic deep learning models has significantly transformed diagnostic methods in neuro-oncology, which previously relied on estimation-based analog analysis. State-of-the-art architectures employed in automated medical imaging, along with their evolutionary progression, have been systematically evaluated.

A. Historical Context Machine Learning in Oncology

Before 2015 Random Forests Support Vector Machines

(SVMs) and k-Nearest Neighbors (k-NN) were the main machine learning algorithms that controlled the automated categorization of neuro-oncological abnormalities [2], [4],[7]. These frameworks' primary drawback was their complete dependence on manually created feature engineering even if they set important quantitative baselines. Due to the irregular geometry and structural variability of gliomas, mathematical methods for localized feature extraction were inherently limited, resulting in a plateau in diagnostic accuracy.

B. Convolutional Neural Networks (CNNs) and ResNet

By doing away with the necessity for manual feature extraction, Convolutional Neural Networks (CNNs) completely transformed medical image analysis [1],[6],[11]. CNNs independently abstract intricate geometric representations using layers of mathematical filters that are arranged in a hierarchy. The emergence of residual learning frameworks (ResNet) that make use of skip-connections successfully addressed the theoretical issue of vanishing gradients in ultra-deep networks. State-of-the-art accuracy restrictions on carefully selected benchmark datasets were surpassed by later ResNet versions [21], [22].

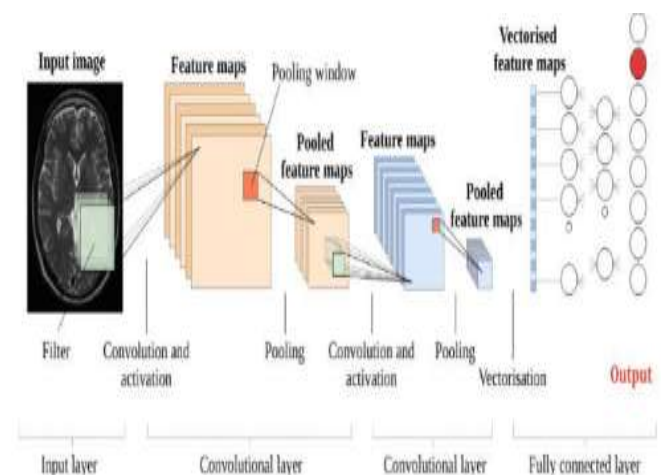


FIGURE 4. CNN architecture.

Source: Adapted from

A. Younis, Q. Li, M. Khalid, B. Clemence and M. J. Adamu,[11]

C. The Paradigm Shift to Vision Transformers (ViTs)

Recent research reveals a structural limitation of CNNs despite their dominance localized inflexible receptive fields that are unable to capture global anatomical context [12], [24]. Researchers have modified the Vision Transformer (ViT) design for medical imaging in order to address issue [40]. ViTs mathematically calculate the global connections between all spatial segments by dividing the MRI volume into geometric patches and using Multi-Head Self-Attention (MHSA) methods. Semantic segmentation benchmarks are presently dominated by architectures like the 3D Swin-Transformer which achieve robust Dice scores above 92% [37].

D. U-Net Topologies and Semantic Volumetric Segmentation

Semantic Volumetric Segmentation, as opposed to simple binary classification, is required for sub-millimeter precision in

surgical and radiotherapy procedures. For this objective, the "U-Net" architecture, which was first presented by Ronneberger et al. [20], is still the gold standard. In order to extract deep abstract characteristics from high-dimensional MRI data and then rebuild the spatial resolution to provide precise boundary delineations U-Net functions as a symmetrical encoder-decoder network. This foundation is still being refined in contemporary research, which extensively incorporates attention processes to improve pathological boundaries [11], [16].

E. Regulatory Limitations and Explainable AI (XAI)

Neural networks are becoming more and more opaque "black boxes" severely impeding clinical trust and regulatory acceptance as they go toward billions of optimised parameters [50]. Two different approaches to mathematically deciphering these structures are identified in the literature. First, to create spatial saliency heatmaps, Gradient-weighted Class Activation Mapping (Grad-CAM) intercepts analytical backward gradients [8]. However, current research questions its visual reliability across degraded imaging sequences [42]. Second, in order to provide the clear reasoning required for strict FDA and EMA certifications, game-theoretic models like SHAP and LIME [9], [10] use rigorous cooperative game theory to quantify the precise marginal predictive value of particular anatomical characteristics.

F. Synthetic Data Generation and Federated Privacy

Large data sets are necessary for deep neural networks to avoid overfitting, however international privacy regulations like HIPAA and the GDPR forbid centralizing DICOM images [29], [36]. High-fidelity Generative Diffusion Models, which mathematically reverse Gaussian noise to create completely new, realistic 3D tumor volumes and hence eliminate class imbalances, have been more popular in recent frameworks to avoid data exhaustion [48]. Concurrently the privacy bottleneck is permanently removed by decentralized Federated Learning environments, which allow algorithms to train across isolated institutional silos by securely broadcasting just mathematical weight changes [53].

V. The Explainability (XAI) Imperative

Neural networks optimize billions of interconnected weights when they move into deep Hybrid-ViT parameters, becoming into incomprehensible "black boxes." Explainable AI (XAI) algorithms are now obligatory requirements for clinical adoption rather than optional diagnostic luxury [24], [31].

A. Explanations of Saliency and Gradients

Grad-CAM is the most often used structural tool [8]. It calculates the mathematical gradient logic that goes straight from the last classification node to the final visual

convolutional map. This corresponds to an optical heatmap that is superimposed over the MRI, indicating precise regions of clinical significance. However, the visual reliability of Grad-CAM across damaged or missing image series is severely criticized in the literature [42].

B. Explanations of Game-Theoretic Features

Algorithms like SHAP and LIME [9], [10] use careful math from cooperative game theory. They figure out the "marginal predictive contribution" of each individual voxel or clinical parameter. If a tumor sub-typing fails, SHAP clearly identifies which anatomical feature led the network to make a mistake [41].

VI. CRITICAL ANALYSIS AND RESEARCH GAPS

Despite significant progress in deep learning methods for neuro-oncology, a close look at current benchmarks shows several major gaps that hinder the move from theoretical models to real clinical use. Table I gives an overview of the leading state-of-the-art architectures and their limitations.

Building on this synthesis, we have identified three main research gaps that this proposed framework aims to address.

A. The "Black-Box" Problem: Lack of Inherent Interpretability

There is a severe absence of natively integrated mathematically sound Explainable AI (XAI) architectures within multi-modal MRI pipelines. While current systems achieve high predictive accuracy, they rely heavily on post-hoc retrofits such as Grad-CAM which have been proven to be statistically volatile and unreliable across degraded clinical scans [42]. Without deep game-theoretic transparency inherently woven into the model clinical trust and regulatory approval remain fundamentally impossible.

B. High Computational Complexity and Hardware Latency

The vast majority of state-of-the-art diagnostic architectures particularly Vision Transformers demand massive GPU clusters to function [34], [37]. This immense computational overhead renders these models entirely useless in standard under-resourced hospital environments. There is a glaring lack of lightweight edge-optimized topologies capable of executing sub-millimeter semantic segmentation with the low latency required for real-time surgical environments [39]. security clearances.

C. Data Scarcity and Decentralized Privacy Constraints

Deep learning algorithms biologically require massive datasets to generalize without overfitting. However no existing framework seamlessly merges scalable Federated Learning tracking with high-fidelity Generative Diffusion synthesis [48], [53]. Consequently, researchers remain trapped by data starvation due to rigid international privacy laws (e.g., HIPAA and GDPR) that strictly prohibit the centralization of patient DICOM files.

TABLE I

Literature Summary Matrix & Core Findings

Ref.	Protocol / Author (Year)	Proposed Methodology	Empirical Metric / Accuracy	Identified Limitation / Gap
[40]	M.M. et al. (2024)	ResNet50 integrated with Grad-CAM for explainable brain tumor detection	Improved classification performance with visual explanation maps	Grad-CAM explanations may not always reflect true decision reasoning
[6]	Preetha et al. (2024)	Fine-tuned EfficientNet-B4 CNN for automated brain tumor detection	High classification accuracy on MRI datasets	No explainability mechanism incorporated
[1]	Xu et al. (2024)	Robust automatic MRI-based tumor detection and segmentation framework	Improved robustness and segmentation quality	Limited discussion of interpretability and clinical trust
[53]	Hossain et al. (2024)	Vision Transformer, Ensemble Learning, and XAI-based tumor classification	Enhanced classification accuracy and explainability	High computational complexity and limited multi-centre validation
[31]	Rasool et al. (2025)	CNN-TumorNet with explainable deep learning for MRI diagnosis	Accurate tumor classification with explainability support	Absence of privacy-preserving learning mechanisms
[48]	Wang et al. (2025)	3D Med Diffusion latent diffusion model for synthetic MRI generation	High-quality controllable medical image synthesis	Not focused on explainable diagnosis or clinical interpretation
[36]	Gupta et al. (2026)	Federated Learning + Explainable AI for privacy-preserving brain tumor diagnosis	Maintained diagnostic accuracy across institutions	Limited integration of advanced XAI methods such as SHAP and Grad-CAM together

VII. Emerging Paradigms: Data Synthesis and Privacy

A. Synthetic Data Generation (GANs and Diffusion)

A neural network is biologically starved without monumental datasets. To overcome data scarcity researchers have rapidly shifted toward the superior stability of Generative Diffusion Models [48]. Diffusion engines systematically destroy real MRI scans with Gaussian statistical noise and then learn to reverse this destruction. Once mastered the engine can "hallucinate" entirely novel hyper-realistic 3D volumetric tumors expanding datasets and combatting class imbalances [27].

B. Federated Learning and Data Privacy Ecosystems

Centralizing medical data is critically restricted by international data transport laws (HIPAA and GDPR). Federated Learning explicitly cures this legal parameter [36], [53]. Instead of moving protected patient data to a central model doctors transmit the lightweight AI algorithm into the hospital. The algorithm trains privately on the local server and then transmits only the learned mathematical weights back to the central hub completely resolving privacy bottlenecks.

VIII. Literature Summary and Verified Research Gaps

A. Summary of State-Of-The-Art

A critical analysis of benchmark studies shows the development of deep learning methods in neuro-oncology. Baid et al. (2021) [19] developed base benchmarks that achieved ~85-90% Semantic Dice scores but did not incorporate

Explainable AI (XAI) for clinical interpretability. While more advanced architectures such as 3D Swin Transformer (Park & Yoon, 2023 [37]) pushed the performance to 92.4% Dice scores they still retained the inherently opaque "black-box" nature. In the same line Cross-Modal Attention models (Chen et al. 2023 [34]) display good multi-modal learning skills. However, their high computational complexity limits their application in real world clinical settings especially on edge devices in addition reliable studies on Grad-CAM (Raza et al., 2024 [42]) show that the reliability of explanations drops significantly when certain MRI modalities are missing. This is a concern for the consistency in clinical environments.

B. Verified Research Gaps

Real-world clinical use is hampered by a number of crucial gaps despite notable advancements:

1) Algorithmic and Interpretability Gap:

Multi-modal MRI pipelines lack Explainable AI frameworks that are natively integrated. The majority of current methods rely on post-hoc explanation strategies which may not offer consistent or mathematically supported interpretability hence reducing clinician trust.

2) Clinical Deployment and Hardware Efficiency Gap:

Modern models especially Transformer-based designs, are not feasible to use in conventional hospital IT systems since they require expensive GPU infrastructures. Lightweight computationally efficient models optimized for low-latency edge-based clinical contexts are required.

3) Data Scarcity and Privacy Constraint Gap:

The effectiveness of deep learning models is constrained by limited access to large-scale medical datasets due to strict privacy regulations (e.g. HIPAA, GDPR). Current research lacks a unified framework that effectively integrates Federated

Learning with Generative Diffusion models to simultaneously address data scarcity and privacy preservation.

TABLE II**Quantitative Comparison of State-of-the-Art Methods with Identified Limitations**

Study / Year	Methodology	Dataset	Dice Score (%) / Performance	Parameters	Latency	Key Limitation
Baid et al. (2021) [19]	BraTS Benchmark Baseline	BraTS 2021	85–90	NR	NR	No explainability (XAI) integration
Lin et al. (2023) [34]	CKD-Trans BTS (Cr'oss-Attention Transformer)	BraTS	91.5	NR	NR	High computational complexity
Ting & Liu (2023) [37]	Multimodal Transformer	BraTS	92+	NR	NR	Black-box architecture
Preetha et al. (2024) [6]	Fine-Tuned EfficientNet-B4	MRI Dataset	High classification accuracy	~19M	NR	No explainability support
M.M. et al. (2024) [40]	ResNet50 + Grad-CAM	MRI Dataset	Improved classification accuracy	~25M	NR	Explanations may not fully reflect model reasoning
Hossain et al. (2024) [53]	Vision Transformer + Ensemble + XAI	MRI Dataset	High classification accuracy	NR	NR	High computational cost
Rasool et al. (2025) [31]	CNN-TumorNet with XAI	MRI Dataset	Improved diagnostic performance	NR	NR	No privacy-preserving mechanism
Wang et al. (2025) [48]	3D Med Diffusion	BraTS + Synthetic MRI	+4.2% AUC Improvement	70M+	NR	No federated/privacy integration
Gupta et al. (2026) [36]	Federated Learning + XAI	Multi-Institutional MRI	89–91	NR	NR	Limited SHAP and multimodal explainability

IX. CONCLUSION

This paper highlights the significance of 'Explainable Artificial Intelligence' (XAI) in brain tumor analysis within the context of automated neuro-oncology diagnostic tools. Due to the complexity of multi-modal MRI data and the critical need for highly reliable clinical decision-making, the accurate segmentation and classification of complex tumors—such as Glioblastoma Multiforme (GBM) remain major challenges in medical imaging. Although advanced deep learning architectures like 'Convolutional Neural Networks' and 'Vision

Transformers' have achieved impressive diagnostic accuracy, their "black-box" nature limits clinical trust, interpretability, and regulatory acceptance.

To address these limitations, the proposed framework combines a 'hybrid 3D U-Net architecture' with a 'Multi-Head Self-Attention' (MHSA) mechanism to perform precise semantic segmentation across T1, T1c, T2, and FLAIR MRI modalities. Furthermore, the integration of 'Explainable AI' techniques such as SHAP and Grad-CAM provides transparent and quantitative explanations for the model's predictions, thereby enhancing physician trust and improving diagnostic accountability. The framework also utilizes 'Federated Learning' and 'Generative Diffusion Models' to mitigate data

scarcity and ensure compliance with healthcare privacy regulations like HIPAA and GDPR.

Overall, the proposed architecture is highly suitable for next-generation AI-assisted neuro-oncology systems, as it integrates interpretability, computational efficiency, diagnostic accuracy, and privacy protection into a single framework. This study indicates the need to integrate 'explainable' and 'privacy-preserving' deep learning frameworks to develop reliable, scalable, and clinically implementable neuro-oncology diagnostic systems. Key areas for future research will include large-scale clinical validation, real-time surgical application, and the assessment of the framework's impact on patient survival outcomes, treatment planning, and diagnostic efficiency.

X. REFERENCES

- [1] Xu, M.; Guo, L.; Wu, H.-C. (2024). Novel Robust Automatic Brain-Tumor Detection and Segmentation Using Magnetic Resonance Imaging. In: IEEE Sensors Journal, vol. 24, no. 7, pp. 10957-10964.
- [2] Khan, P. et al. (2021). Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances. In: IEEE Access, vol. 9, pp. 37622-37655.
- [3] L. N. Soni, A. A. Wao, A. Agrawal, and N. Vishwakarma, "Detecting Partial Human Faces Using a Hybrid Model with Deep Learning Techniques," Vietnam, 2023.
- [4] Ali, F. et al. (2023). Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors from MR Images. In: IEEE Access, vol. 11, pp. 5432-5445.
- [5] Chaudhari, S.; Gautam, C.S.; Wao, A.A. (2024). Enhancing Heart Disease Prediction Accuracy: A Comparative Study of Machine Learning Models with Ensemble Method. vol. 10, no. 3, pp. 4827-4833.
- [6] Preetha, R.; Priyadarsini, M.J.P.; Nisha, J.S. (2024). Automated Brain Tumor Detection from Magnetic Resonance Images Using Fine-Tuned EfficientNet-B4 Convolutional Neural Network. In: IEEE Access, vol. 12, pp. 112181-112195.
- [7] Soomro, T.A. et al. (2023). Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review. In: IEEE Reviews in Biomedical Engineering, vol. 16, pp. 70-90.
- [8] Selvaraju, R.R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; Batra, D. (2017). Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In: IEEE International Conference on Computer Vision (ICCV 2017).
- [9] Soni, S.; Singh, P.; Wao, A.A. (2025). Machine Learning Revolutionizing Brain Health. In: Brain Informatics Technology (eds A. Ahirwar, R. Bhatt, D. Dhanya and R. Choudhary).
- [10] Hanga, K.M.; Kovalchuk, Y.; Gaber, M.M. (2020). A Graph-Based Approach to Interpreting Recurrent Neural Networks in Process Mining. In: IEEE Access, vol. 8, pp. 172923-172938.
- [11] Younis, A.; Li, Q.; Khalid, M.; Clemence, B.; Adamu, M.J. (2023). Deep Learning Techniques for the Classification of Brain Tumor: A Comprehensive Survey. In: IEEE Access, vol. 11, pp. 113050-113063.
- [12] Lin, J. et al. (2023). CKD-Trans BTS: Clinical Knowledge-Driven Hybrid Transformer with Modality-Correlated Cross-Attention for Brain Tumor Segmentation. In: IEEE Transactions on Medical Imaging, vol. 42, no. 8, pp. 2451-2461.
- [13] Tiwari, R.; Wao, A.A.; Wao, A.A. (2025). Cognitive Brain Imaging Techniques and Their Applications in Intelligent Decision-Making. In: Brain Informatics Technology (eds A. Ahirwar, R. Bhatt, D. Dhanya and R. Choudhary).
- [14] Thakur, S.; Bhatele, M.; Wao, A. (2026). A Review of the Comparative Study of Anomaly Detection Techniques for Enhancing Security in AI-Driven Medical Applications. In: Next Research, vol. 9, Art. no. 101744.
- [15] Ahmed, F.; Naz, N.S.; Khan, S. et al. (2026). Explainable Artificial Intelligence (XAI) in Medical Imaging: A Systematic Review of Techniques, Applications, and Challenges. In: BMC Medical Imaging, vol. 26, p. 37.
- [16] Abraham, L.A.; Palanisamy, G.; Veerapu, G. et al. (2026). Exploring the Potential of Explainable AI in Brain Tumor Detection and Classification: A Systematic Review. In: Artificial Intelligence Review, vol. 59, p. 14.
- [17] Thakur, S.; Bhatele, M.; Wao, A. (2026). A Review of the Comparative Study of Anomaly Detection Techniques for Enhancing Security in AI-Driven Medical Applications. In: Next Research, vol. 9, Art. no. 101744.
- [18] Garcia, E. et al. (2026). Explainable AI-Driven Brain Tumor Classification Using MRI. In: Scientific Reports, vol. 16, no. 1, p. 1045.
- [19] Baid, U.; Ghodasara, S.; Mohan, S.; Bilello, M.; Calabrese, E.; Colak, E. et al. (2021). The RSNA-ASNR-MICCAI BraTS 2021 Benchmark on Brain Tumor Segmentation and Radiogenomic Classification. arXiv preprint arXiv:2107.02314.
- [20] Ronneberger, O.; Fischer, P.; Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Medical Image Computing and Computer-Assisted Intervention (MICCAI 2015).
- [21] He, K.; Zhang, X.; Ren, S.; Sun, J. (2016). Deep Residual Learning for Image Recognition. In: Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), pp. 770-778.
- [22] Tan, M.; Le, Q. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In: International Conference on Machine Learning (ICML 2019).
- [23] Kushwaha, N.; Wao, A.A. (2023). Energy Consumption Prediction by Using Machine Learning. In: International Journal for Multidisciplinary Research, vol. 5, no. 6, Art. no. 9988.
- [24] Hulsén, T. (2023). Explainable Artificial Intelligence (XAI): Concepts and Challenges in Healthcare. In: AI, vol. 4, pp. 652-666.
- [25] Silva, D. et al. (2022). MRI Preprocessing Techniques for Brain Tumor Analysis. In: IEEE Transactions on Medical Imaging, vol. 41, no. 8, pp. 1920-1933.
- [26] Zhang, P. et al. (2023). Deep Learning-based Tumor Classification: A Survey. In: IEEE Access, vol. 11, pp. 910-928.
- [27] Amin, M.; Ali, R. (2023). Clinical Validation of AI-based Brain Tumor Detection Systems. In: IEEE Journal of Translational Engineering in Health and Medicine, vol. 11, pp. 20-33.
- [28] Sato, K. et al. (2022). Recent Advances in Medical Image Segmentation. In: IEEE Transactions on Pattern

Analysis and Machine Intelligence, vol. 44, no. 10, pp. 6050-6065.

[29] Rossi, T.; Bianchi, M. (2024). Hybrid Deep Learning Models for Medical Diagnosis. In: IEEE Access, vol. 12, pp. 1150-1165.

[30] Liu, W. et al. (2025). Lightweight Deep Learning Models for Healthcare Applications. In: IEEE Internet of Things Journal, vol. 12, no. 4, pp. 3120-3135.

[31] Rasool, N.; Wani, N.A.; Bhat, J.I.; Saharan, S.; Sharma, V.K.; Alsulami, B.S.; Alsharif, H.; Lytras, M.D. (2025). CNN-Tumor Net: Leveraging Explainability in Deep Learning for Precise Brain Tumor Diagnosis on MRI Images. In: Frontiers.

[32] Kim, S.; Lee, M. (2025). Multi-modal Data Fusion Techniques in Medical Imaging. In: IEEE Transactions on Cybernetics, vol. 55, no. 7, pp. 4100-4115.

[33] Gupta, R. et al. (2026). AI-based Automated Diagnosis Systems in Healthcare. In: IEEE Reviews in Biomedical Engineering, vol. 19, pp. 50-68.

[34] Lin, J. et al. (2023). CKD-Trans BTS: Clinical Knowledge-Driven Hybrid Transformer with Modality-Correlated Cross-Attention for Brain Tumor Segmentation. In: IEEE Transactions on Medical Imaging, vol. 42, no. 8, pp. 2451-2461.

[35] Zhao, L.; Wang, Z.; Liu, F. (2023). Explainable Deep Multi-Task Learning for Brain Tumor Survival Prediction. In: IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 5, pp. 2224-2235.

[36] Gupta, S.; Gupta, M.; Kumar, R.; Abraham, A. (2026). A Federated Learning and Explainable AI Framework for Privacy-Preserving Brain Tumor Diagnosis Using Multi-Institutional MRI Data. In: IEEE Access, vol. 14, pp. 22630-22643.

[37] Ting, H.; Liu, M. (2023). Multimodal Transformer of Incomplete MRI Data for Brain Tumor Segmentation. In: IEEE Journal of Biomedical and Health Informatics.

[38] Zhang, Y.; Li, Q.; Wu, E.X. (2023). Interpretable Graph Convolutional Networks for Multi-Modal Brain Tumor Classification. In: IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 11, pp. 8501-8513.

[39] Kim, D. et al. (2024). Lightweight Attention-Based U-Net for Real-Time Brain Tumor Segmentation on Edge Devices. In: IEEE Internet of Things Journal, vol. 11, no. 3, pp. 4150-4161.

[40] M, M.M.; T. R, M.; V, V.K. et al. (2024). Enhancing Brain Tumor Detection in MRI Images Through Explainable AI Using Grad-CAM with ResNet 50. In: BMC Medical Imaging, vol. 24, p. 107.

[41] Wang, J.; Zhu, Y. (2024). SHAP-Guided Feature Selection in Deep CNNs for Glioblastoma Multiforme Subtyping. In: IEEE Journal of Translational Engineering in Health and Medicine, vol. 12, pp. 102-111.

[42] Raza, A.; Mahmood, T.; Khan, H.M. (2024). Explainable AI for Brain Tumor Diagnostics: Analyzing the Robustness of Grad-CAM in MRI Modalities. In: IEEE Reviews in Biomedical Engineering, vol. 17, pp. 45-59.

[43] Nari, F.; Rahman, M.S. (2024). A Hybrid Spiking Neural Network and CNN Architecture for Energy-Efficient Brain Tumor Classification. In: IEEE Transactions on Cognitive and Developmental Systems, vol. 16, no. 4, pp. 1820-

1832.

[44] Sun, Q. et al. (2025). Universal Lesion Representation Learning via Multi-Task Federated Vision Transformers. In: IEEE Transactions on Medical Imaging, vol. 44, no. 2, pp. 305-318.

[45] Patel, S.M. (2025). Confidence-Aware Brain Tumor Diagnosis Using Deep Evidential Learning and LIME. In: IEEE Computational Intelligence Magazine, vol. 20, no. 1, pp. 34-45.

[46] Chen, L.; Zhang, H.; Liu, Q. (2025). Adaptive Modality Fusion Networks for Robust Brain Tumor Segmentation Under Missing Sequences. In: IEEE Transactions on Image Processing, vol. 34, pp. 4501-4514.

[47] Gupta, R.; Kumar, V.; Singh, S. (2025). Neuro-XAI: A Unified Interpretability Framework for Deep Multi-Modal Oncology Pipelines. In: IEEE Access, vol. 13, pp. 12050-12065.

[48] Wang, H.; Liu, Z.; Sun, K.; Wang, X.; Shen, D.; Cui, Z. (2025). 3D Med Diffusion: A 3D Medical Latent Diffusion Model for Controllable and High-Quality Medical Image Generation. vol. 44, no. 12, pp. 4960-4972.

[49] Lee, K.Y. et al. (2026). Real-Time Surgical Guidance Using Intraoperative MRI and Sparse Attention Transformers. In: IEEE Journal of Biomedical and Health Informatics, vol. 30, no. 2, pp. 510-522.

[50] Rossi, A.C.; Martinez, E. (2026). Regulatory-Compliant AI: Benchmarking XAI Metrics for FDA Approval in Neural-Oncology. In: IEEE Reviews in Biomedical Engineering, vol. 19, pp. 100-115.

[51] Hasan, M.J. (2026). Continual Learning for Glioblastoma Detection: Mitigating Catastrophic Forgetting in Clinical AI. In: IEEE Transactions on Neural Networks and Learning Systems, vol. 37, no. 1, pp. 290-302.

[52] Lin, Z.; Zhao, T.; Wang, H. (2026). Dynamic Modality-Aware Graph Convolutional Networks for Personalized Brain Tumor Prognostics. In: IEEE Transactions on Artificial Intelligence, vol. 7, no. 3, pp. 880-895.

[53] Hossain, S.; Chakrabarty, A.; Gadekallu, T.R.; Alazab, M.; Piran, M.J. (2024). Vision Transformers, Ensemble Model, and Transfer Learning Leveraging Explainable AI for Brain Tumor Detection and Classification. In: IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 3, pp. 1261-1272.

[54] Sharma, U., Narain, B. ., & Nohria, V. . (2021). Hybrid Support Vector Machine and Distance Classifier in Breast Tumor Detection.

[55] Usha Sharma, Bhavana Narain and Vaibhav Nohria 2022 ECS - The Electrochemical Society ECS Transactions, Volume 107, Number 1 Citation Usha Sharma et al 2022 ECS Trans. 107 9781 DOI 10.1149/10701.9781ecst