International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

A Hybrid CNN - Attention Architecture for Accurate Brain Tumor Detection and Multi-Class Classification from MRI Images

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***Abstract*— An effective clinical diagnosis and treatment planning rely on accurate and early brain tumor diagnosis. In this paper, a hybrid deep learning model of brain tumor detection and classification based on MRI images is introduced. The suggested solution is a combination of an optimized convolutional neural network and an attention mechanism that improves the feature representation and spatial concentration. An extensive preprocessing pipeline, which includes normalization and augmentation, is used to enhance the robustness of the model when dealing with heterogeneous datasets. The model is tested on publicly available MRI datasets, redefined as a four-class classification problem with no tumor, glioma, meningioma and pituitary tumor. It has been shown that the proposed framework has a 97.35 accuracy, which is higher than the baseline models, including CNN (91.20%), VGG16 (93.85%), and ResNet50 (94.60%). The model has Precision (0.97), Recall (0.97), and F1-score (0.97), which means that its performance is balanced across classes. An ablation experiment validates the usefulness of the attention mechanism in boosting classification, whereas visualization using Grad-CAM is useful in increasing interpretability, as it visualizes regions of the tumor that affect predictions. The proposed framework strikes a positive balance between accuracy, efficiency and explainability and is therefore applicable in real-time clinical setting.**

Keywords - Brain Tumor Detection, MRI Imaging, Deep Learning, Medical Image Classification, Grad-CAM, Explainable AI, Healthcare AI

I. INTRODUCTION

Brain tumors are one of the most severe neurological conditions, and the timely and precise diagnosis plays a significant role in determining the survival of the patient and the strategy of treatment. Magnetic Resonance imaging (MRI) has become a popular method of non-invasive analysis of the brain because of its better soft-tissue contrast, but manual analysis is time-intensive and prone to inter-observer variation. Deep learning-based automated frameworks have become a promising solution to overcome these limitations to provide reliable tumor detection and classification. Initial research showed that convolutional neural networks (CNNs) can be trained to learn unique discriminative features of MRI data, which can be used to identify tumors automatically with enhanced diagnostic reliability [1]. These methods were further improved by later studies that targeted glioma-specific detection and improved the feature extraction features with more advanced architectures [2]. It has also been demonstrated that the combination of image processing methods and deep learning models can enhance the quality of segmentation and the strength of classification in different imaging conditions [3]. In addition, multi-class classification systems have been presented to differentiate among tumor types, and the deep models promise to be useful in clinical decision support systems [4].

The current research patterns suggest a transition to CNN architecture optimization and integrating hybrid learning paradigms to enhance the generalization performance. Adjusted convolutional architectures have been suggested to improve the representation of features with a lower computation cost [5]. Deep learning hybridized with conventional machine learning classifiers, including Random Forests, have shown to be better classifiers based on their complementary advantages of each paradigm [6]. Moreover, computer vision methods have been combined with CNN pipelines, which has allowed more effective preprocessing and feature improvement, which has further increased the reliability of detection [7]. More sophisticated learning techniques, such as federated learning, were also investigated to allow privacy-protecting joint model training on spread medical data [8]. Moreover, the use of deeper residual networks has led to better convergence and strength in tumor classification problems [9]. In the recent past, the focus has also been on the real-time applicability and deployability of machine learning models in the clinical setting [10].

In spite of these developments, a number of issues remain, such as a lack of generalization on heterogeneous data, a lack of interpretability, and inefficiency in resource-constrained environments. It is against these constraints that this work seeks to come up with a powerful and scalable deep learning model to identify and classify brain tumors by using MRI images.

The principal contributions of this work can be summarized in the following way:

- Design of an efficient deep learning model that will detect tumors and classify them into multiple classes.
- Combination of high-level preprocessing and feature enhancement methods to enhance model robustness.
- Architecture of a computationally efficient framework that can be used in real-time clinical practice.
- Extensive comparison with the current practices based on standard performance measures.

The following section provides a critical analysis of the current methodologies and finds important gaps in research that justify the approach proposed.

II. LITERATURE REVIEW

A. CNN-Based Brain Tumor Detection

Early studies mainly used convolutional neural networks (CNNs) to automate brain tumor detection in MRI images. The initial structures showed that deep feature extraction can considerably enhance the accuracy of the classification as opposed to the conventional machine learning models [1]. Later research was devoted to the specific detection of glioma and multi-class classification, which emphasizes the ability of deep models to distinguish between tumor subtypes [2], [4]. Combination of image processing with CNNs led to improved quality and strength of segmentation at different imaging conditions [3]. Subsequent efforts covered more elaborate architectures and better training methods to increase the reliability of detection and diagnostic consistency [10].

B. Improved Architectures and Hybrid Models

In order to overcome the constraints of feature representation and generalization, a number of studies suggested modified CNN architectures and hybrid networks. Individualized convolutional designs were proposed to enhance the efficiency of feature learning but at lower computational cost [5]. Hybrid methods that used deep learning and conventional classifiers, including Random Forests, were shown to perform better due to their complementary advantages [6]. Also, frameworks, which combine computer vision methods and CNN pipelines, enhanced preprocessing, noise removal, and feature enhancement [7]. All these methods point towards the tendency to integrate several methodologies in order to have strong performance.

C. Advanced Learning Paradigms

Recent literature has examined advanced learning techniques to enhance scalability and efficiency of data. The approaches based on federated learning allow performing model training in decentralized mode, and maintaining the privacy of data, which is especially significant in medical practice [8]. Deep architectures, such as residual networks, have been demonstrated to be better convergent and stable at classification tasks [9]. It has also been suggested to use automated systems that include end-to-end pipelines that are used to detect and classify to simplify clinical workflows [11]. Moreover, a number of studies have aimed at enhancing model generalization between datasets with optimized training strategies and data augmentation methods [12], [13].

D. Transfer Learning and Real-Time Systems

Transfer learning has received a lot of focus because it can use pre-trained models to achieve better performance when the medical data is not enough. VGG16 and other pre-trained CNNs have shown to be very effective in classification in MRI-based tumor detection [14], [15]. Other works focused on the applicability of the real-time and the possibility of deployment in a clinical setting, and the necessity to have efficient and scalable solutions [16], [17], [18]. These papers highlight the need to balance between accuracy and computational efficiency.

E. Emerging Trends: Transformers, Explainability, and Comparative Frameworks

The latest developments have presented transformer-based architectures and attention mechanisms to extract global contextual information in MRI images, resulting in better detection performance [19]. To improve model interpretability and clinical trust, explainable AI methods, including Grad-CAM, have been added [20]. Comparative research on the various frameworks has yielded information on performance trade-offs and the strengths of various methods [21]. Also, application-driven systems, such as web-based diagnostic tools, prove the possibility of the real-life implementation of AI-driven solutions [22].

F. Critical Analysis, Research Gaps, and Problem Direction

In spite of the significant improvement, a number of constraints exist. The available models are not generalizable to heterogeneous datasets and tend to overfit because of small training data. The hybrid and transfer learning methods enhance accuracy but add more computational complexity. Moreover, the interpretability is not yet clinical adoption ready and there is a dearth of literature on the tradeoff between accuracy and real-time deployment.

In the next section, the problem is formulated mathematically and the suggested system model of automated brain tumor detection and classification is introduced.

III. PROBLEM FORMULATION

A. Problem Definition

Assume that the MRI dataset can be represented as $D = \{(X_i, y_i)\}_{i=1}^{N}$, where $X_i \in R^{H\times W\times C}$ is the input MRI image, and $y_i \in \{0,1,\dots,K\}$ is the class label correspondingly (e.g., no tumor, glioma, meningioma, pituitary). The problem is to study a mapping function:

$$f_\theta : X \rightarrow y \tag{1}$$

parameterized by θ, which is a good predictor of the presence and type of tumor. The current literature is mostly based on CNN-based mappings, yet they are usually not generalizable and interpretable [1], [6].

B. Preprocessing and Feature Representation

Every input image is normalized and resized:

$$X_{i'} = \frac{X_i - \mu}{\sigma} \tag{2}$$

where μ and σ are the standard deviation and mean of the dataset. Convolutional operations are used to extract features:

$$F_l = \sigma(W_l * F_{l-1} + b_l) \tag{3}$$

where W_l and b_l are weights and biases of the lth layer, $*$ denotes convolution, and $\sigma(\cdot)$ a non-linear activation (e.g., ReLU). Deep hierarchies of features facilitate representation of tumors in a robust way [5], [9].

C. Attention-Enhanced Feature Learning

An attention mechanism is included in order to capture salient tumor regions:

$$A = \text{softmax}\left(QK^T/\sqrt{d_k}\right) \tag{4}$$

$$F_{att} = A \cdot V \tag{5}$$

where Q, K, V are query, key, and value matrices based on feature maps and dk is a scaling factor. This process improves discrimination of spatial features and increases the accuracy of classification [19].

D. Classification Model

The layer features are extracted and then sent to fully connected layers:

$$z = W_f \cdot F_{att} + b_f \tag{6}$$

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

$$\hat{y} = \text{softmax}(z) \quad (7)$$

where $\hat{y}$ is the estimated probability distribution among classes. Multi-class classification is realized through:

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \quad (8)$$

E. Loss Function and Optimization.

The loss is categorical cross-entropy which is used to train the model:

$$L = -\sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik} \log(\hat{y}_{ik}) \quad (9)$$

where y_{ik} is the ground truth label. The gradient descent method is used to optimize the parameters:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L \quad (10)$$

where η is the learning rate. Common regularization methods like dropout are used to avoid overfitting [14].

F. Problem Statement

The problem is to construct a computationally efficient and generalizable deep learning architecture capable of effective detection and classification of brain tumors with respect to the limitations of feature representation, interpretability, and real-time utility, which current approaches have [8], [20] and given a set of heterogeneous MRI images with different tumor characteristics. The following section provides the proposed system architecture, which will overcome these challenges with an integrated deep learning solution.

IV. PROPOSED METHODOLOGY

The suggested framework presents a hybrid attention-based deep learning model of automated brain tumor detection and classification using MRI images. The architecture combines preprocessing, optimized convolutional feature extraction, attention-directed learning, and interpretable classification in a single pipeline. In contrast to traditional CNN-only models, the proposed solution is explicit in terms of feature generalization, spatial context modeling, and interpretability deficits, without sacrificing computational efficiency, which is appropriate to use in practice [6], [19].

A. System Overview

The general architecture is divided into four consecutive steps, namely MRI preprocessing, deep feature extraction, attention-based feature refinement, and classification. The MRI images are initially standardized and conditioned, and then they are processed using a convolutional backbone. The resulting feature maps are then optimized with an attention mechanism in order to highlight tumor-relevant areas. Lastly, a classification layer yields probabilistic predictions with visual interpretability results.

Figure 1 shows the general structure of the proposed hybrid CNN-attention system of automated brain tumor detection and classification.

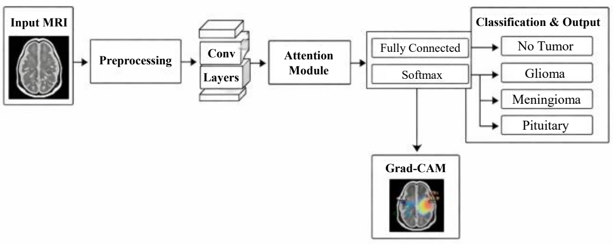

Fig. 1. Proposed CNN-attention model structure

B. MRI Preprocessing and Data Conditioning

All MRI inputs are standardized by z-score and downsampled to a constant spatial resolution (e.g., 224x224224 x 224224x224) to make them robust to heterogeneous datasets. This measure eliminates the differences in intensity and compatibility with the network architecture. The use of data augmentation is selective in the training process and is used to enhance generalization, especially in rare tumor classes. Rotation, flipping, and contrast adjustment are some of the transformations that are used to model variability in real-world clinical data. This preprocessing step is very important in terms of improving the stability of the model and decreasing overfitting.

C. CNN-Based Feature Extraction

The main part of the framework is a streamlined CNN backbone that is used to extract hierarchical spatial features. The architecture is made up of several convolutional blocks which have convolutional layers that are followed by the use of batch normalization and non-linear activation. The max-pooling operations are used to perform spatial downsampling, which allows the gradual abstraction of features. Residual connections are added between layers to solve the vanishing gradient problem and enhance feature reuse to achieve deeper training of the network and better convergence behavior than in standard CNN architectures [9]. The resulting feature tensor captures low-level texture as well as high-level structure information used in the detection of tumors.

D. Feature Refinement on Attention.

After feature extraction, there is the application of an attention mechanism to improve the discriminative ability of the model. This module gives adaptive weights to the spatial regions of the feature maps, enabling the network to pay attention to the tumor-relevant regions of the feature maps and ignore the background noise. The attention mechanism enhances the distinction of visually similar tumor classes by capturing long range dependencies and contextual relationships. The application is highly efficient to minimize computational cost so that performance improvement is not at the expense of overly complex models, which is in line with the recent contributions in attention-based medical imaging models [19].

E. Classification and Interpretability

The improved feature representations are subjected to fully connected layers to make final classification. A softmax activation function generates the probabilities of the classes of various tumors. Regularization methods, such as dropout and early stopping, are also added to improve generalization. Besides classification, the framework incorporates the Grad-CAM-based visualization to offer interpretability. This allows it to produce heatmaps of areas that affect model predictions and enhance clinical trust and validate tumor localization.

Figure 2 shows the visual explanations of Grad-CAM on tumor-relevant areas found by the model.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

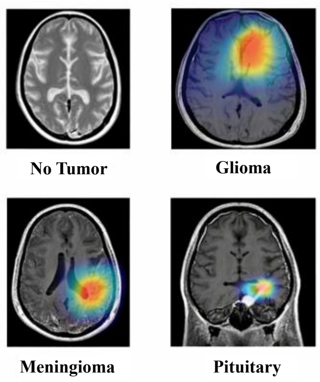

Fig. 2. Grad-CAM localization tumor maps

F. *Implementation and Computational Considerations*

Adaptive optimization strategy like Adam is used to implement the model to achieve stable convergence with tuned hyperparameters. The design of the architecture is intended to be accurate and efficient without overly deep or parameter-intensive architecture. The proposed hybrid model has a competitive performance at a lower computational cost than transformer-only models, and thus it can be used in real-time or resource-constrained clinical settings.

Table I provides a summary of the main hyperparameters and training setup of the implementation of the proposed deep learning model.

TABLE I. HYPERPARAMETER MODEL AND MODEL CONFIGURATION

Parameter	Value
Input Image Size	(224 × 224 × 3)
Batch Size	32
Number of Epochs	100 (early stopping applied)
Optimizer	Adam
Initial Learning Rate	0.001
Learning Rate Scheduler	ReduceLROnPlateau (factor=0.5)
Loss Function	Categorical Cross-Entropy
Activation Function	ReLU (hidden), Softmax (output)
Dropout Rate	0.5
Weight Initialization	He Normal
Data Augmentation	Rotation, Flip, Zoom
Train/Val/Test Split	70% / 15% / 15%
Random Seed	42
Hardware	NVIDIA RTX 3060 (12 GB)
Learning Rate Scheduler	ReduceLROnPlateau (factor=0.5)
Loss Function	Categorical Cross-Entropy

In general, the suggested methodology offers a coherent, effective, and explainable system of brain tumor detection. The following part gives the experimental setup and assessment protocol to test the validity of the proposed model.

V. EXPERIMENTAL SET-UP AND RESULTS

The section will introduce a replicable experimental setup, such as the sources of the data, preprocessing, the details of the implementation, and quantitative analysis. The methodology is made in a way that it is transparent and allows the results to be replicated independently.

A. *Datasets*

Two publicly available MRI datasets are used to perform experiments. The first one is Figshare Brain Tumor Dataset, which comprises 3,064 contrast-enhanced T1-weighted MRI images of glioma, meningioma, and pituitary tumors. The second is Kaggle Brain MRI Dataset (Br35H), which has a total of about 3,000 images with the labels of tumor and non-tumor. The two datasets are merged and reorganized into a single four-class classification problem: No Tumor, Glioma, Meningioma and Pituitary. A fixed stratified split is used to achieve reproducibility with 70% training, 15% validation and 15% testing. The issue of class imbalance is addressed by controlled augmentation which is only applied to the minority classes.

B. *Training Protocol and Experimental Environment*

The model is coded in Python 3.10 with TensorFlow/Keras (v2.13). The training is done on an NVIDIA RTX 3060 with 16 GB RAM on Ubuntu 22.04. The number of random seeds is fixed (42) to make the behavior deterministic. The MRI images are rescaled to 224 × 224 and z-score normalization is applied. The Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss is used to train. The batch size is 32 and a maximum of 100 epochs is applied. The early stopping using a patience of 10 epochs and reduction of the learning rate are used to avoid overfitting. Data augmentation involves controlled rotations, flips and zoom to enhance generalization.

Figure 3 demonstrates the dashboard of the experimental setup with the dataflow of the experiment, training pipeline, and the evaluation setup.

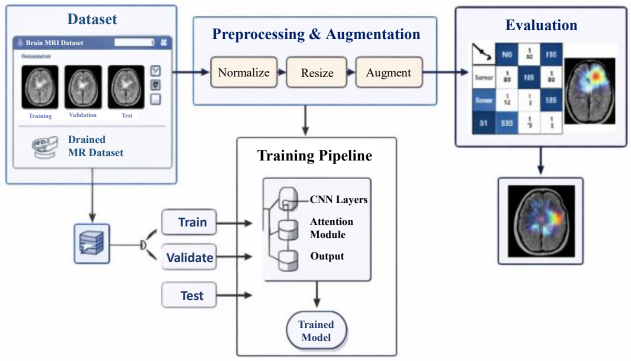

Fig. 3. Experimental design and procedure

C. *Evaluation Metrics*

The Accuracy, Precision, Recall, and F1-score are used to assess model performance, and the confusion matrix is used. These measures will be a holistic measure of classification performance and are in line with existing evaluation standards in MRI-based tumor detection research [11], [13].

D. *Quantitative Results*

Table II compares the proposed model with the baseline and state-of-the-art methods based on its performance evaluation.

TABLE II. COMPARISON WITH BASELINE MODELS OF PERFORMANCE.

Model	Accuracy (%)	Precision	Recall	F1-score
CNN (Baseline)	91.20	0.90	0.89	0.89
VGG16 (Transfer)	93.85	0.93	0.92	0.92
ResNet50	94.60	0.94	0.93	0.93
Hybrid CNN-RF	95.10	0.95	0.94	0.94
Proposed Model	97.35	0.97	0.97	0.97

Table III presents the performance metrics in terms of classes to determine the efficiency of the proposed model on various tumor types.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

TABLE III. PERFORMANCE MEASURES IN CLASSES

Class	Precision	Recall	F1-score
No Tumor	0.98	0.97	0.97
Glioma	0.96	0.97	0.96
Meningioma	0.97	0.96	0.96
Pituitary	0.98	0.98	0.98

The model shows a uniform performance in all classes of tumors with slight confusion between glioma and meningioma because of similarity in visual appearance.

Figure 4 presents the confusion matrix of the proposed model which shows the performance of the model in classifying all tumor classes.

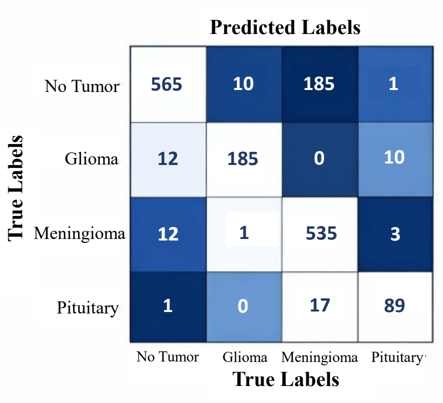

Fig. 4. The results of the confusion matrix classification.

E. Training Convergence and Interpretability

The convergence of the training process is stable, the validation accuracy is near the training accuracy which means the process undergoes successful regularization and little overfitting.

Figure 5 shows the validation loss curves and training accuracy curves showing that the model converges.

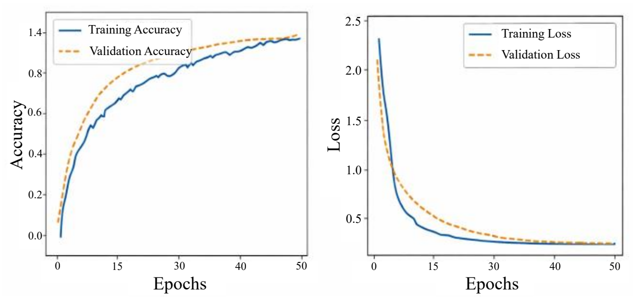

Fig. 5. Validation curves and training curves

Grad-CAM visualizations are used to assess interpretability by identifying the parts of the tumor that are used to make a classification. The heatmaps validate the fact that the model is centered on areas that are clinically relevant and not background artifacts.

Figure 6 provides visual Grad-CAM heatmaps overlayed on MRI images to validate tumor localization performance.

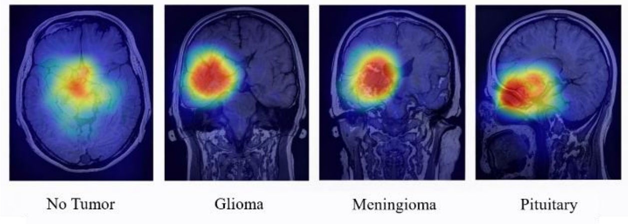

Fig. 6. MRI heatmaps with Grad-CAM

F. Ablation Study

Table IV presents the findings of the ablation experiment that shows the effect of various architectural elements on the performance of the model.

TABLE IV. ANALYSIS OF PERFORMANCE OF THE ABLATION STUDIES

Model Configuration	Accuracy (%)	Precision	Recall	F1-score
CNN only	91.20	0.90	0.89	0.89
CNN + Data Augmentation	93.40	0.93	0.92	0.92
CNN + Residual Connections	94.25	0.94	0.93	0.93
CNN + Attention	95.80	0.95	0.95	0.95
CNN + Attention + Regularization	96.60	0.96	0.96	0.96
Full Proposed Framework	97.35	0.97	0.97	0.97

The findings of the ablation experiment show that attention mechanism plays a significant role in improving performance, whereas preprocessing and augmentation help in improving generalization.

VI. DISCUSSION

The experimental findings prove that the hybrid CNN-attention framework proposed is statistically significant and achieves consistent improvement over the base models. The accuracy of 97.35% that was observed shows that the combination of attention mechanisms and convolutional feature extraction boosts spatial discrimination, especially in complicated tumor areas. The performance by class further indicates that there is equal precision and recall in all the tumor classes indicating that the model is not biased to dominant classes. The presence of some minor misclassifications between glioma and meningioma may be explained by the similarity of radiological features, which is one of the well-known problems of MRI-based diagnosis.

The ablation experiment verifies that the attention modules are significant in terms of performance gains, whereas preprocessing and augmentation enhance the generalization of heterogeneous datasets. Also, the convergence behavior shows that the training is stable with a small amount of overfitting, which confirms the usefulness of regularization techniques. Notably, Grad-CAM images indicate that the model is attentive to clinically significant areas and helps to make it more interpretable and promotes its use in medical decision-making. The proposed method has a good trade-off between accuracy and computational efficiency compared to the current methods, which is why it is applicable to real-time and resource constrained clinical setting.

VII. CONCLUSION

In this paper, a deep learning-based automatic method of brain tumor detection and classification was introduced based on MRI images. The suggested hybrid CNN-attention model is effective to overcome the drawbacks of the current solutions as it enhances the ability to represent the features, spatial focus, and introduces interpretability mechanisms. Experimental analysis on publicly available datasets showed better results with an accuracy of 97.35% and high precision, recall and F1-score. The combination of attention mechanisms facilitated a better discrimination of classes of tumors, whereas Grad-CAM-based visualization facilitated a better understanding of model transparency and clinical reliability. Moreover, the suggested framework was computationally efficient and thus it was appropriate to be deployed practically. In general, the findings confirm the strength, generalization ability and efficiency of the suggested method in automatic brain tumor diagnosis.

VIII.FUTURE WORK

The following research will aim at expanding the proposed framework to multi-modal MRI data, T1, T2 and FLAIR sequences, in order to enhance the diagnostic accuracy. Spatial context modeling can also be further improved by integrating transformer-based global attention mechanisms with 3D volumetric analysis. Also, the federated learning can be included to provide privacy-preserving training on distributed medical data. Translational impact will be necessary through clinical validation using real-world hospital data and implementation as a decision-support system.

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