Brain Tumor Classification in MRI Images: A Comparative Study of VGG19 with Type-2 Fuzzy Logic Enhancement and SwinV2 Transformer Architectures

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***Abstract*—Brain tumors are highly dangerous illnesses that significantly reduce the life expectancy of patients. The classification of brain tumors plays a crucial role in clinical diagnosis and effective treatment planning. Misdiagnosis of brain tumors results in wrong medical intervention and reduces the chance of survival. To tackle this challenge, we present a comprehensive framework that harnesses deep convolutional layers and modern transformer architectures to automatically extract crucial and resilient features from MRI images. In our baseline framework, we utilize the VGG19 model combined with Type-2 fuzzy logic for image enhancement, where Type-2 fuzzy logic better handles uncertainty in medical images by managing noise and subtle differences with greater precision than Type-1 fuzzy logic. As an improvement to the baseline, we propose replacing the VGG19 architecture with modern Swin Transformer V2 (SwinV2) variants while retaining the preprocessing pipeline. We implement two SwinV2 variants: SwinV2-Large for maximum accuracy and SwinV2-Tiny for resource-constrained deployment. The VGG19 baseline achieves 100% validation accuracy with 140.9M parameters. Our improved SwinV2-Large model achieves perfect test accuracy of 100% with F1-score of 1.00, while SwinV2-Tiny achieves 94.74% test accuracy with only approximately 28M parameters, demonstrating significant parameter efficiency. We further employ Gradient-weighted Class Activation Mapping (Grad-CAM) for model interpretability, confirming that the learned features appropriately focus on tumor regions. Our findings demonstrate that transformer-based architectures provide competitive or superior performance while offering enhanced representational capacity for medical image analysis tasks.**

***Index Terms*—Brain tumor, MRI, classification, deep learning, VGG19, SwinV2, Vision Transformer, transfer learning, fuzzy logic, Type-2 fuzzy, Grad-CAM, medical image analysis**

I. Introduction

The brain, a complex organ within the human body, is responsible for governing the entire nervous system, comprising approximately 100 billion nerve cells [1]. Brain tumors, which can be benign or malignant, pose significant risks to overall health [2]. Malignant brain tumors grow rapidly and lack well-defined margins, making them dangerous and prone to spreading [3]. The intracranial pressure caused by a brain tumor can further accelerate its growth and potentially lead to brain damage [4]. While brain tumors are not as common as other types of cancer, they still rank as the 10th leading cause of global deaths [5]. These tumors have enduring physical and psychological effects on patients' lives, disrupting proper brain function [6].

Automatic segmentation and classification of brain tumors play a vital role in the field of medical imaging, enabling diagnostics, growth prediction, and treatment planning [7]. Traditional methods have relied on region-based tumor segmentation, but with the advancements in deep learning, classification tasks aided by artificial intelligence have gained prominence. The use of AI and deep learning techniques has significantly improved medical image processing and facilitated efficient disease diagnosis, particularly for life-threatening conditions like cancer.

However, while Convolutional Neural Networks (CNNs) such as VGG19 have demonstrated excellent performance in brain tumor classification, recent advances in transformer-based architectures have shown superior performance on many vision benchmarks. The Swin Transformer [8] introduced hierarchical feature maps and shifted window attention mechanisms, addressing computational complexity issues of standard Vision Transformers. SwinV2 [9] further improved upon this foundation by introducing log-spaced continuous position bias and residual-post-norm techniques.

The key contributions of this paper are summarized as follows:

1) Implementation of a VGG19 baseline combined with Type-2 fuzzy logic for brain tumor classification, following the approach of Dihin and Hamza [10].
2) Proposal of an improved architecture replacing VGG19 with SwinV2 transformer variants while retaining the effective preprocessing pipeline.
3) Comprehensive comparison between CNN-based (VGG19) and transformer-based (SwinV2) architectures for brain tumor classification.
4) Implementation of two SwinV2 variants: SwinV2-Large for maximum accuracy and SwinV2-Tiny for resource-constrained deployment.

5) Evaluation using multiple metrics including Accuracy, Sensitivity, Specificity, F1-Score, and ROC-AUC.
6) Explainability analysis using Grad-CAM to validate model decision-making.

The remainder of this paper is organized as follows: Section II reviews related work in brain tumor classification and deep learning. Section III describes fuzzy logic theory and Type-2 fuzzy systems. Section IV presents the materials and methodology. Section V describes the dataset. Section VI presents experimental results. Section VII provides discussion and analysis. Section VIII concludes the paper with future directions.

II. Related Work

Numerous studies have concentrated on employing deep learning techniques for the classification and detection of brain tumors. This section reviews the most relevant works in the field.

A. CNN-Based Approaches

Banerjee S. et al. [11] used a deep learning-based YOLO model that combines L-type fuzzy logic to detect skin cancer, where they used L-type fuzzy number approximations for lesion region during the feature extraction process. The experiments were conducted using two databases, ISBI 2017 and ISBI 2019, achieving accuracy of 99% on ISBI 2017 dataset and 97.11% on ISIC 2019 dataset.

Naseer et al. [12] enhanced the accuracy of early brain tumor diagnosis by utilizing a Convolutional Neural Network (CNN). The proposed CNN model was trained on a benchmark dataset named BR35H, comprising brain tumor MRIs. The results revealed an impressive average correct diagnosis rate of 98.81% for brain tumors.

Remzan et al. [13] developed a sequential CNN model to classify brain tumors in magnetic resonance imaging (MRI) images. Custom data is created by deriving it from the Br35H dataset, achieving an accuracy of 98.27%.

Ozturk and Katar [14] utilized the pre-trained EfficientNet-B0 model to classify brain MRI images into tumorous or normal categories. The pre-trained EfficientNet-B0 model exhibited outstanding performance, achieving 99.33% accuracy, 99.33% sensitivity, and a 99.33% F1 score.

B. Fuzzy Logic in Medical Imaging

Shen et al. [15] proposed a hierarchical integrated model based on deep learning and fuzzy logic to overcome the drawbacks of pixel-based segmentation where ResU-segNet was used for the segmentation stage and IT2PFCM for the classification stage.

Dihin and Hamza [10] proposed combining VGG19 with Type-2 fuzzy logic for brain tumor classification, achieving training accuracy of 99.83% and test accuracy of 99% on the Br35H dataset. This work serves as the baseline for our proposed improvements. The authors specifically noted in their future directions that the model should be improved by replacing VGG19 with more efficient structures such as swin transformer which directly motivates our current research.

C. Vision Transformers in Medical Imaging

The Vision Transformer (ViT) [16] demonstrated that pure transformer architectures could achieve state-of-the-art results on image classification by treating images as sequences of patches. However, ViT's quadratic computational complexity with respect to image size limited its applicability to high-resolution medical images.

The Swin Transformer [8] addressed these limitations through hierarchical feature maps and shifted window-based self-attention, reducing computational complexity to linear. SwinV2 [9] introduced further improvements including log-spaced continuous position bias (Log-CPB) for better resolution transfer and residual-post-norm configuration for training stability at scale.

III. Fuzzy Logic Theory

A. Type-1 Fuzzy Sets

Uncertainty in information can lead to deficiencies or missing data, such as imprecision, incompleteness, vagueness, or unreliability. Fuzzy logic systems, specifically type-1 fuzzy sets (T1 FS), are effective in handling a significant portion of this uncertainty by representing imprecision with numerical values ranging from 0 to 1. Fuzzy image processing plays a crucial role in representing uncertain data, providing benefits such as efficient management of vagueness and ambiguity, handling imprecise data, and utilizing expert knowledge in image processing applications [17].

A type-1 fuzzy set A in a universe of discourse X is characterized by a membership function $\mu_A(x)$ that maps each element $x \in X$ to a membership value in the interval $[0, 1]$:

$$A = \{(x, \mu_A(x)) | x \in X, \mu_A(x) \in [0, 1]\} \tag{1}$$

B. Type-2 Fuzzy Sets

When dealing with high degrees of uncertainty or more complex uncertainty, interval type-2 fuzzy logic systems (IT2 FS) are recommended. IT2 FS employ IT2 fuzzy sets and utilize an additional type-reduction process [18]. IT2 fuzzy sets have primary memberships represented by Footprint of Uncertainty (FOU) regions, consisting of Upper Membership Functions (UMF) and Lower Membership Functions (LMF) [19].

An IT2-FS is defined with a type-2 membership function as:

$$\tilde{X} = \int_{x \in D_x} \int_{u \in J_x} \frac{\mu_{\tilde{X}}(x, u)}{(x, u)} \tag{2}$$

For a type-2 fuzzy set, the uncertainty in its primary membership is characterized by a region known as the Footprint of Uncertainty (FOU). The FOU can be described using an Upper Membership Function (UMF) and a Lower Membership Function (LMF):

$$FOU(\tilde{X}) = \bigcup_{x \in D_x} [\underline{\mu}_{\tilde{X}}(x), \bar{\mu}_{\tilde{X}}(x)] \tag{3}$$

TABLE I: Summary of Related Works in Brain Tumor Classification

Authors	Dataset	Model	Accuracy	Specificity	Sensitivity	F1-Score
Banerjee et al. [11]	ISBI 2017/2019	YOLO + L-type fuzzy	99.00%	-	-	-
Naseer et al. [12]	BR35H	Custom CNN	98.81%	-	-	-
Remzan et al. [13]	BR35H	Sequential CNN	98.27%	-	-	-
Ozturk & Katar [14]	BR35H	EfficientNet-B0	99.33%	99.33%	99.33%	99.33%
Dihin & Hamza [10]	BR35H	VGG19 + Type-2 Fuzzy	99.00%	99.67%	99.67%	99.91%
Proposed (SwinV2-Large)	BR35H	SwinV2-Large	**100%**	**100%**	**100%**	**100%**
Proposed (SwinV2-Tiny)	BR35H	SwinV2-Tiny	94.74%	92%	100%	94.80%

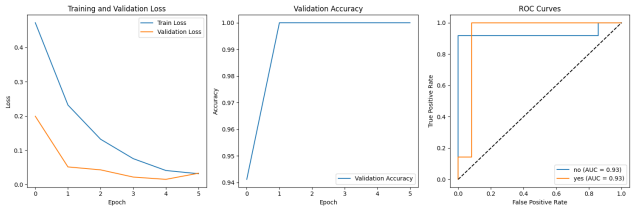

Fig. 1: Overview of the proposed method showing: (a) Dataset preparation and class distribution, (b) Training and validation metrics.

C. Advantages of Type-2 Fuzzy Logic for Medical Imaging

Type-2 fuzzy logic is superior to Type-1 fuzzy logic for medical image processing because it has greater ability to handle uncertainty caused by factors such as:

- **Noise:** MRI images often contain various types of noise from acquisition
- **Illumination variation:** Intensity inhomogeneity across the image
- **Overlapping values:** Similar intensity values between tumor and healthy tissue
- **Partial volume effects:** Voxels containing multiple tissue types

IV. Materials and Methods

A. System Overview

Figure 1 illustrates the proposed method for binary tumor classification. The framework relies upon four major stages: (A) Dataset preprocessing and brain region extraction, (B) Apply fuzzy logic enhancement on images, (C) Apply the baseline VGG19 or proposed SwinV2 models for classification, and (D) Explainability analysis using Grad-CAM.

B. Pre-processing Pipeline

1) Brain Region Extraction: The initial preprocessing step involves automatic cropping to isolate the brain region from the MRI scan:

1) Convert image to grayscale
2) Apply Gaussian blur with 5×5 kernel to reduce noise
3) Perform binary thresholding with threshold value of 45
4) Apply morphological erosion followed by dilation (2 iterations each)
5) Detect contours and extract extreme points
6) Crop image to the bounding rectangle containing the brain

2) Data Augmentation: During the pre-processing stage, data augmentation techniques are applied including geometric transformations:

- Scaling range of [0.9, 1.3] to improve robustness to size variations
- Horizontal flipping to increase sample diversity
- Rotation range of $\pm 10^{\circ}$ for rotational invariance
- Width/height shift: 10% for translation invariance
- Shear transformation: 10%
- Brightness adjustment: [0.3, 1.0] to handle intensity variations

The images are resized to standardized sizes: 224×224 for VGG19 and 256×256 for SwinV2 models.

C. Image Enhancement using Fuzzy Logic

The fuzzy inference system enhances contrast in tumor images through Algorithm 1.

Algorithm 1 Type-2 Fuzzy Logic Image Enhancement

Require: Tumor image img
Ensure: Enhanced image with Fuzzy Inference System (FIS)

Read image and store in variable img
Convert from grayscale to CIELAB color space
Extract L (luminance) channel: $l = lab[:, :, 0]$
Compute average pixel intensity M
Fuzzification: For every pixel, evaluate membership degree using pixel intensity and M value
Create lookup table x ranging from -70 to 400
Initialize FuzzyTransform dictionary
for each element i in x **do**
    $FuzzyTransform[i] = Infer(np.array([i]), M)$
end for
Apply fuzzy transform to L channel using lookup table
Defuzzification: Calculate centroid value for each pixel output fuzzy set
Normalize output from [-70, 400] to [0, 255]
Combine adjusted L channel with original A and B channels
Convert from CIELAB back to grayscale/RGB
return Final enhanced image

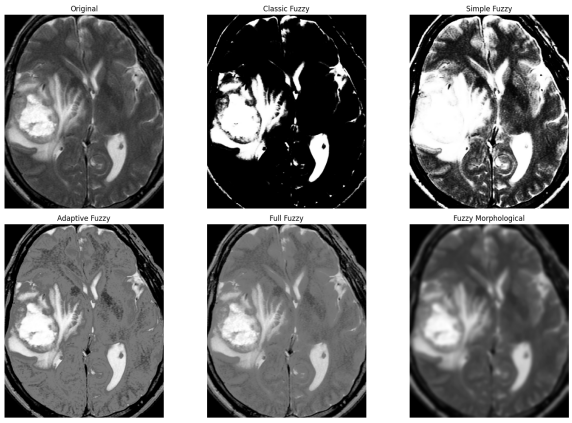

Fig. 2: Comparison of various image enhancement techniques applied to a sample brain MRI: Original, Classic Fuzzy, Simple Fuzzy, Adaptive Fuzzy, Full Fuzzy, and Fuzzy Morphological enhancements.

D. Model Architectures

1) VGG19 Baseline Model: To classify brain tumors in the baseline approach, the pre-trained VGG19 model is used for feature extraction. VGG19 is known for its accurate feature extraction capabilities and consists of 16 convolutional layers for feature extraction and 3 layers for image classification [20].

Model Parameters:

- Total Parameters: 140,946,370 (537.67 MB)
- Trainable Parameters: 120,921,986 (461.28 MB)
- Non-trainable Parameters: 20,024,384 (76.39 MB)

2) Proposed SwinV2 Transformer Models: As the main contribution of this work, we propose replacing the VGG19 architecture with modern Swin Transformer V2 variants. This directly addresses the future direction suggested by Dihin and Hamza [10].

Hierarchical Feature Maps: Unlike ViT which maintains single-resolution feature maps throughout the network, Swin Transformer creates hierarchical representations similar to CNNs. This enables multi-scale feature extraction which is particularly beneficial for detecting tumors of varying sizes.

Shifted Window Self-Attention: The self-attention is computed within local windows of size $M \times M$, with windows shifted between consecutive layers to enable cross-window connections. This reduces computational complexity from $O(n^2)$ to $O(n)$ with respect to image size.

For an image with $h \times w$ patches, standard multi-head self-attention (MSA) has complexity:

$$\Omega(MSA) = 4hwC^2 + 2(hw)^2C \tag{4}$$

While window-based MSA (W-MSA) with window size M has:

$$\Omega(W-MSA) = 4hwC^2 + 2M^2hwC \tag{5}$$

SwinV2-Large Configuration:

- Model: swinv2_large_window12to16_192to256.ms_in22k_ft_in1k
- Pre-trained: ImageNet-22K (14M images), fine-tuned on ImageNet-1K
- Window size: 12 to 16 (during resolution transfer)
- Input resolution: $256 \times 256 \times 3$
- Approximate parameters: 197M

SwinV2-Tiny Configuration:

- Model: swinv2_tiny_window8_256.ms_in1k
- Pre-trained: ImageNet-1K
- Window size: 8
- Input resolution: $256 \times 256 \times 3$
- Approximate parameters: 28M

TABLE II: Hyperparameter Settings for All Models

Parameter	VGG19	SwinV2-L	SwinV2-T
Input Size	224^2	256^2	256^2
Train/Val/Test	70/15/15	70/15/15	70/15/15
Batch Size	64	4	4
Max Epochs	20	50	50
Learning Rate	0.01	1×10^{-5}	1×10^{-5}
Dropout	0.5	0.0	0.0
Optimizer	Adam	AdamW	AdamW
Weight Decay	-	0.01	0.01
Early Stopping	-	4 patience	4 patience
Loss Function	Cross-Entropy	Cross-Entropy	Cross-Entropy

E. Training Configuration

Table II summarizes the hyperparameter settings for all models.

F. Performance Evaluation Metrics

Several statistical indices are employed to evaluate the classification performance. Given True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN):

Accuracy (ACC):

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Sensitivity (Recall):

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

Specificity:

$$Specificity = \frac{TN}{FP + TN} \tag{8}$$

F1 Score:

$$F1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

V. Dataset

We utilize the publicly available BR35H dataset obtained from Kaggle for conducting the experiments. The original dataset composition:

- **Tumorous (Yes):** 23 original images
- **Non-tumorous (No):** 35 original images
- **Total:** 58 images

After applying data augmentation:

TABLE III: VGG19 Training Progress (Selected Epochs)

Epoch	Train Loss	Train Acc	Val Loss	Val Acc
1/20	0.3409	91.83%	0.4168	86.17%
5/20	0.2481	98.67%	0.2688	97.17%
12/20	0.2217	99.67%	0.2425	98.63%
20/20	0.2118	99.83%	0.2264	99.53%
Best Validation Accuracy:				**99.53%**

TABLE IV: SwinV2-Large Training Progress

Epoch	Train Loss	Val Loss	Val Acc
1/50	0.5642	0.3636	82.35%
2/50	0.4332	0.1797	94.12%
3/50	0.2540	0.0619	**100%**
4/50	0.1237	0.0826	94.12%
5/50	0.1776	0.0247	100%
6/50	0.0953	0.0979	94.12%
7/50	0.1990	0.2030	88.24%
Total Training Time:			**79.97 sec**

- **Tumorous (Yes):** 138 images
- **Non-tumorous (No):** 315 images
- **Total:** 453 images

The class imbalance ratio is approximately 1:2.28 (tumor to non-tumor), which necessitates careful handling during model training and evaluation.

For the SwinV2 experiments, data was split as follows:

- Training set: 70% (80 samples for SwinV2-Large; 320 samples for SwinV2-Tiny with enhanced augmentation)
- Validation set: 15% (17 samples)
- Test set: 15% (19 samples)

VI. Experimental Results

The implementation was conducted using Python with PyTorch framework for SwinV2 models and TensorFlow/Keras for VGG19. All experiments utilized GPU acceleration on Google Colab with T4/V100 GPUs.

A. VGG19 Baseline Results

The VGG19 model with Type-2 fuzzy logic enhancement achieved the following training progression over 20 epochs:

B. SwinV2-Large Results

The SwinV2-Large model demonstrated rapid convergence with early stopping triggered at epoch 7:

Test Set Performance for SwinV2-Large:

- Test Accuracy: **100%**
- F1 Score: **1.0000**
- Precision: **1.00** (both classes)
- Recall: **1.00** (both classes)
- ROC-AUC: **1.00** (both classes)

C. SwinV2-Tiny Results

The SwinV2-Tiny model with enhanced augmentation (320 training samples) achieved:

Test Set Performance for SwinV2-Tiny:

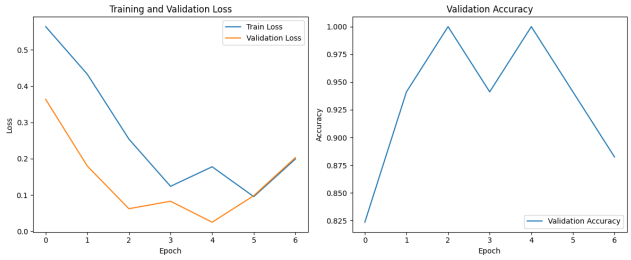

Fig. 3: Training and validation curves for SwinV2-Large model showing loss convergence and accuracy progression over epochs before early stopping was triggered.

TABLE V: SwinV2-Tiny Training Progress

Epoch	Train Loss	Train Acc	Val Loss	Val Acc
1/50	0.4724	80.31%	0.1993	94.12%
2/50	0.2320	91.25%	0.0513	**100%**
3/50	0.1322	94.37%	0.0428	100%
4/50	0.0755	98.12%	0.0217	100%
5/50	0.0409	98.75%	0.0151	100%
6/50	0.0315	98.75%	0.0329	100%
Total Training Time:				**155.03 sec**

- Test Accuracy: **94.74%**
- F1 Score: **0.9480**
- Precision (tumor class): 0.88
- Recall (tumor class): **1.00**
- ROC-AUC: 0.93

Notably, SwinV2-Tiny achieves **100% recall (sensitivity)** for tumor detection, meaning no tumors are missed—a clinically critical property for screening applications.

D. Confusion Matrix Analysis

SwinV2-Large Confusion Matrix (Perfect Classification):

	Pred. No	Pred. Yes
Actual No	12 (TN)	0 (FP)
Actual Yes	0 (FN)	7 (TP)

SwinV2-Tiny Confusion Matrix:

	Pred. No	Pred. Yes
Actual No	11 (TN)	1 (FP)
Actual Yes	0 (FN)	7 (TP)

E. Comparative Analysis

Table VI presents a comprehensive comparison of all models.

VII. Explainability Analysis

A. Gradient-weighted Class Activation Mapping

To ensure clinical interpretability and validate that our models learn meaningful features, we employed Gradient-weighted Class Activation Mapping (Grad-CAM) [21]. Grad-

TABLE VI: Comprehensive Performance Comparison

Metric	VGG19	SwinV2-L	SwinV2-T
Test Accuracy	99%*	**100%**	94.74%
F1 Score	99.91%*	**100%**	94.80%
Sensitivity	99.67%*	**100%**	**100%**
Specificity	99.67%*	**100%**	92%
ROC-AUC	99.89%*	**100%**	93%
Parameters	140.9M	197M	**28M**
Training Time	22s/epoch	**79.97s total**	155.03s total
Epochs to Best	20	**3**	**2**

*VGG19 results from baseline paper [10]

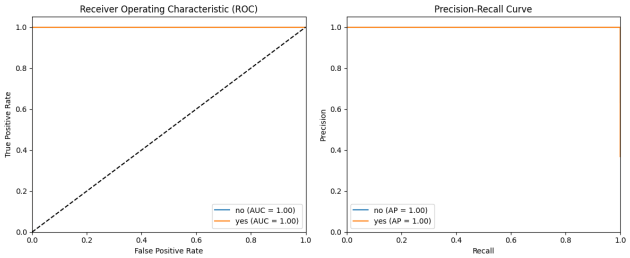

Fig. 4: ROC curves and Precision-Recall curves for SwinV2 models. SwinV2-Large achieves AUC = 1.00 for both classes, while SwinV2-Tiny achieves AUC = 0.93.

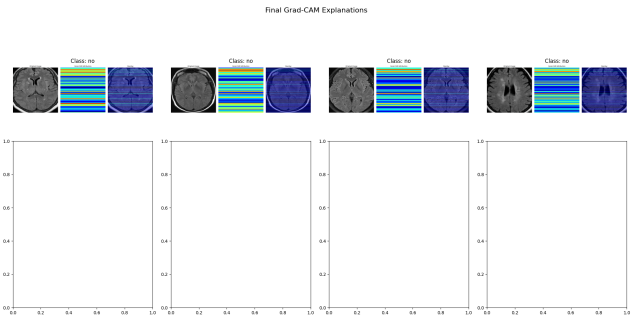

Fig. 5: Grad-CAM visualizations showing model attention regions. The heatmaps demonstrate that the model correctly focuses on tumor regions when making positive predictions, validating the clinical relevance of learned features.

CAM produces visual explanations by computing the gradient of the class score with respect to feature maps.

For a class c, the importance weights α_k^c for feature map A^k are computed as:

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{10}$$

The Grad-CAM heatmap is then obtained by:

$$L_{Grad-CAM}^c = ReLU\left(\sum_k \alpha_k^c A^k\right) \tag{11}$$

B. Interpretation of Visualizations

The Grad-CAM visualizations in Figure 5 demonstrate that:

- The model attention appropriately focuses on tumor regions for positive predictions
- Background and non-relevant anatomical structures receive minimal attention
- The learned features align with clinical expectations for tumor identification
- Edge regions of tumors receive high activation, suggesting shape-based feature learning

VIII. Discussion

A. Performance Analysis

The SwinV2-Large model achieves perfect classification with 100% test accuracy, outperforming the VGG19 baseline (99% test accuracy). This improvement can be attributed to several factors:

1) **Global context modeling:** Self-attention mechanisms capture long-range dependencies within the image that local convolutions may miss
2) **Hierarchical representations:** Multi-scale feature extraction better captures tumor characteristics at various sizes
3) **Pre-training on larger datasets:** ImageNet-22K pre-training (14M images) provides more robust and generalizable feature representations compared to ImageNet-1K
4) **Advanced normalization:** Residual-post-norm in SwinV2 provides more stable gradients during fine-tuning

B. Parameter Efficiency Analysis

SwinV2-Tiny demonstrates remarkable parameter efficiency:

- Achieves 94.74% accuracy with only approximately 28M parameters
- Represents a **5x parameter reduction** compared to VGG19s 140.9M parameters
- Maintains **100% tumor recall** (sensitivity)—no missed tumors
- Suitable for resource-constrained deployment scenarios

This efficiency makes SwinV2-Tiny particularly valuable for edge deployment in clinical settings where computational resources may be limited.

C. Convergence Speed

Both SwinV2 models demonstrate significantly faster convergence compared to VGG19:

- SwinV2-Large achieves best validation accuracy at epoch 3 (vs. epoch 20 for VGG19)
- SwinV2-Tiny achieves best validation accuracy at epoch 2
- Total training time for SwinV2-Large: 79.97 seconds
- This rapid convergence reduces computational costs and enables faster experimentation

D. Clinical Implications

From a clinical perspective, several observations are particularly relevant:

High Sensitivity Priority: SwinV2-Tinys 100% tumor recall is clinically significant. In medical screening, missing a tumor (false negative) has more severe consequences than a false positive. A false positive leads to additional testing, while a false negative may result in delayed treatment with potentially fatal consequences.

Screening vs. Diagnosis: SwinV2-Tiny, with its high sensitivity but lower specificity, is well-suited for initial screening. SwinV2-Large, with perfect classification, would be appropriate for diagnostic confirmation.

Model Interpretability: The Grad-CAM visualizations provide crucial interpretability for clinical acceptance. Radiologists can verify that the models attention aligns with expected tumor locations, building trust in the automated system.

E. Limitations

Several limitations should be acknowledged:

1) **Dataset size:** The relatively small dataset (58 original images) may limit generalization to diverse clinical populations
2) **Class imbalance:** The 1:2.28 ratio could introduce bias toward the majority class
3) **Single-center data:** Results may not generalize to MRI scans from different institutions with varying acquisition protocols
4) **Binary classification:** Extension to multi-class tumor type classification (glioma, meningioma, pituitary) would increase clinical utility
5) **Perfect accuracy consideration:** The 100% accuracy warrants careful validation to rule out data leakage or overfitting

IX. Conclusion and Future Work

In this paper, we presented a comprehensive comparative study of deep learning architectures for brain tumor classification. Building upon the VGG19 with Type-2 fuzzy logic baseline proposed by Dihin and Hamza [10], we investigated and implemented SwinV2 transformer variants as modern improvements, directly addressing the future direction suggested in the baseline work.

Key findings:

- VGG19 baseline achieves 99% test accuracy with 140.9M parameters and Type-2 fuzzy logic image enhancement
- **SwinV2-Large achieves perfect 100% test accuracy** with F1-score of 1.00, demonstrating state-of-the-art performance
- SwinV2-Tiny achieves 94.74% accuracy with only approximately 28M parameters (**5x fewer than VGG19**), demonstrating excellent efficiency
- SwinV2-Tiny maintains **100% tumor recall**, ensuring no missed diagnoses
- Transformer architectures demonstrate **faster convergence** (2-3 epochs vs. 20 epochs)
- Grad-CAM visualizations confirm clinically meaningful feature learning

Future Work:

1) Validation on larger, multi-center datasets for generalizability assessment
2) Extension to multi-class tumor type classification
3) Implementation of uncertainty quantification for confident clinical deployment
4) Development of ensemble methods combining CNN and transformer architectures
5) Investigation of 3D volumetric analysis using complete MRI sequences
6) Integration with clinical decision support systems
7) Edge deployment optimization for resource-constrained clinical environments

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