BrainScanAI: Revolutionizing Brain Tumor Detection and Segmentation Using Transfer Learning and Deep Learning Approaches

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Abstract. This work aims at the important task of explainable and transparent diagnosis of brain tumors. Though deep learning models are highly accurate, the majority are "black boxes," with minimal interpretability for clinicians. To bridge this, the proposed BrainScanAI system combines state-of-the-art CNN models—ResNet50, RegNet-Y, DenseNet201, and MobileViT—as explainable prediction models with Grad-CAM. Of these, the ResNet50 demonstrated the best performance with 99.31% accuracy, 99.67% AUC, 97.65% precision, 94.471-score, and 97.65% recall, beating DenseNet201 (98.87%) and EfficientNet (90.09%). The visualizations with Grad-CAM point to the tumor-dominant areas, revealing the model transparency, and encouraging clinician trust. The system meets the dual mandate of diagnostic accuracy and interpretability, providing the reliable, AI-supported decision.

Keywords: Explainable AI, Brain tumor detection, Deep learning, Grad-CAM, Medical image analysis

1 Introduction

Brain tumors are fatal diseases with a rising worldwide incidence, requiring rapid, precise, and low-cost diagnosis. Their symptoms of headaches, seizures, and motor dysfunction overlap with other disorders, resulting in delayed diagnosis. Though MRI yields better soft-tissue contrast and high-resolution tumor delineation, its interpretation is subjective, time-consuming, and reliant on skilled radiologists. The introduction of artificial intelligence, particularly deep learning, has transformed medical imaging by overcoming these challenges. Convolutional neural networks (CNNs) can automatically learn complex MRI features and recognize subtle tumor patterns with over 95% classification and segmentation accuracy. Transfer learning enhances performance by using pre-trained networks like ResNet50, EfficientNet, and DenseNet201 to improve generalization on small medical data sets [3]. The suggested research combines ResNet50 with

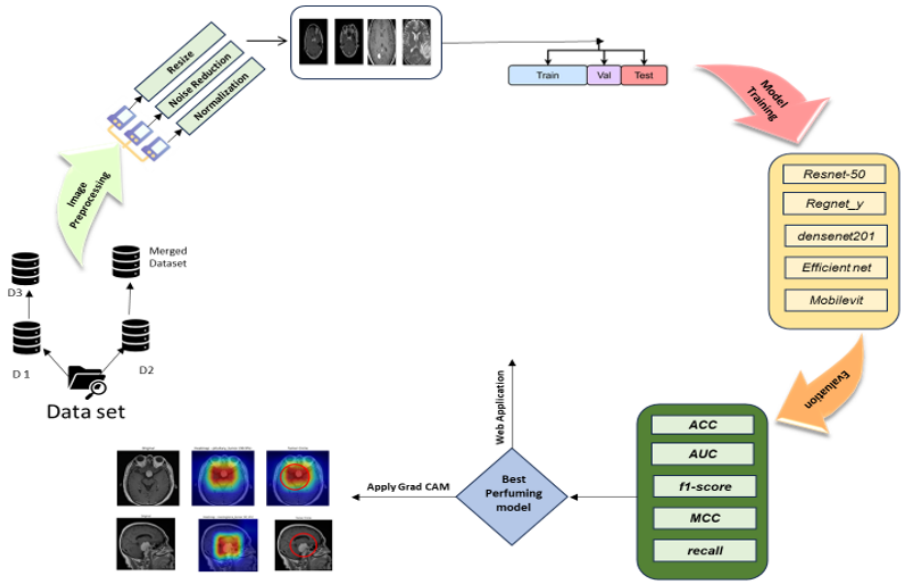

Fig. 1. Overall Workflow of the Study

Grad-CAM to classify tumors and generate interpretable heatmaps of relevant decision areas. MRI preprocessing includes resizing, noise removal, and augmentation for four classes—glioma, meningioma, pituitary, and no tumor. Measured by accuracy, recall, precision, F1-score, and AUC, BrainScanAI provides strong, explainable performance. Apart from innovation, it provides scalable, clinician-friendly AI, minimizing risks of misdiagnosis and advancing precision medicine in neurology, especially in low-resource environments [12]. All the workflows are shown in figure 1.

2 Related Works

2.1 Deep Learning Approaches

The study compares transfer learning-based CNN architectures—Inception and Intussusception—with a novel BRAIN-TUMOR-net model for brain tumor classification in MRI images. The performance of the model is 96% accuracy on pre-trained networks and 95.44% accuracy, 95% recall, and a 95.36% F1-score in multiclass classification (Normal, Glioma, Meningioma, Pituitary). On a database of normal and tumorous brain images, the CNN-based system demonstrates itself as a fast, accurate, and efficient tumor detection system. These results illustrate the potential of CNNs and the proposed BRAIN-TUMOR-net framework, offering a reliable tool for medical image analysis and clinical decision-making.

2.2 Hybrid and Ensemble Deep Learning Approaches

Current studies demonstrate the capability of deep learning in distinguishing between brain tumors based on MRI images. GoogLeNet employing transfer learning achieved 98% accuracy for the three tumor classes even with very small training data, emphasizing the efficacy of transfer learning. In a four-class classification with a class "no tumor," InceptionV3 achieved 98.1% training and 94.5% test accuracy with weighted F1 score of 0.945, even though there was some slight overfitting for glioma and meningioma. Pitting these models, ResNet50, EfficientNetV2-S, ResNet152V2, VGG16, and Xception, against one another, Xception produced the highest 99.5% training and 98.2% test accuracy with F1 scores as high as 1.00, demonstrating robust, consistent tumor classification over MRI datasets[5].

3 Methodology

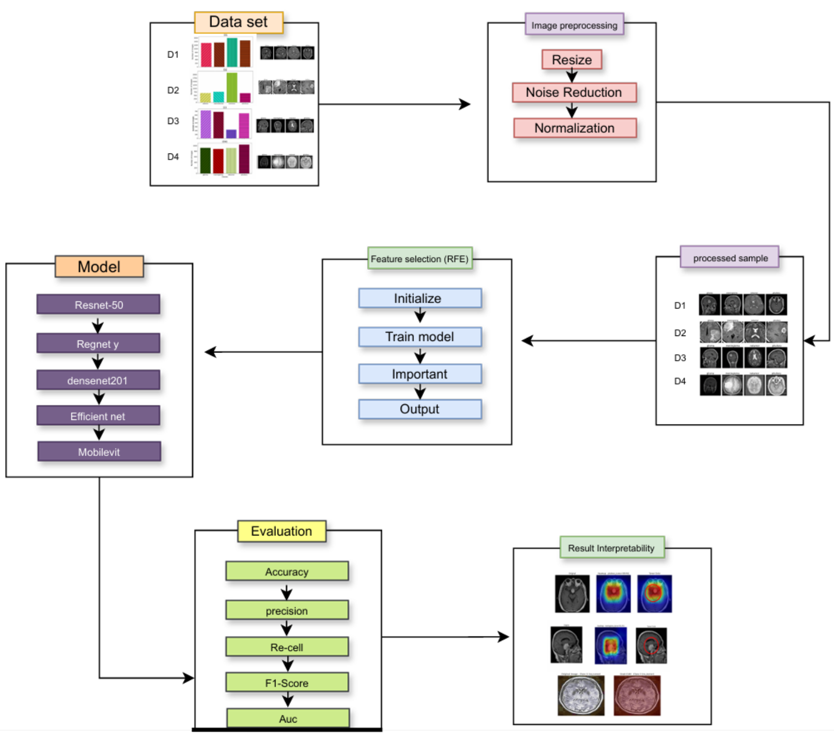

Fig. 2. Overview of the proposed methodology.

Figure 2 presents an automated MRI-based brain tumor detection pipeline. MRI datasets (D1–D4) with four tumor classes undergo preprocessing via bilinear resizing (224×224) and anisotropic diffusion filtering. Transfer learning is applied using ResNet50, DenseNet201, and EfficientNet models in PyTorch and 15 epochs on an NVIDIA RTX 3050 GPU. Grad-CAM heatmaps enhance interpretability by visualizing tumor-focused regions. ResNet50 achieved the best accuracy (99.31%), outperforming DenseNet201 (98.87%). Overall, CNN-based models proved highly accurate, interpretable, and clinically applicable[10].

3.1 Data Description

The data used in this study consists of MRI images with tumor and non-tumor class labels. The images are preprocessed by normalizing pixel values and resizing them to the same size of 224×224 pixels.

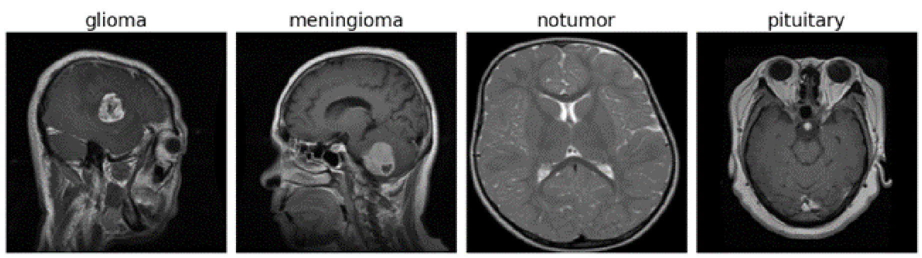

Fig. 3. MRI Brain Tumor Declaration Dataset (D1)

Glioma images demonstrate malignant tumors that are produced by glial cells in the brain parenchyma. They appear as irregularly shaped, infiltrative masses of variable intensity on MRI scans, typically involving surrounding brain tissue[8].

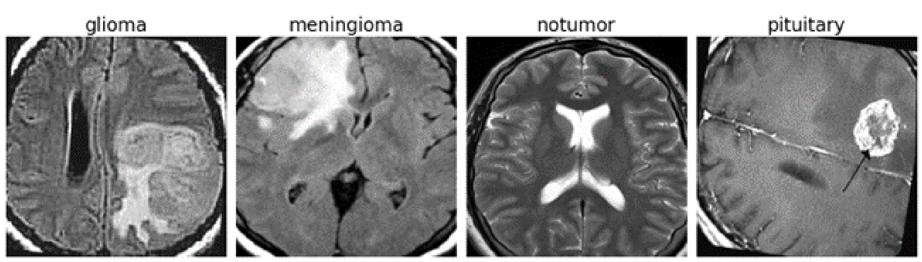

Fig. 4. MRI Brain Tumor Declaration Dataset (D2)

Meningioma images depict benign tumors that develop in the meninges, which are protective coverings that surround the brain and spinal cord. Meningiomas grow slowly and compress adjacent brain tissue without invading it, making them radiologically different from gliomas [20].

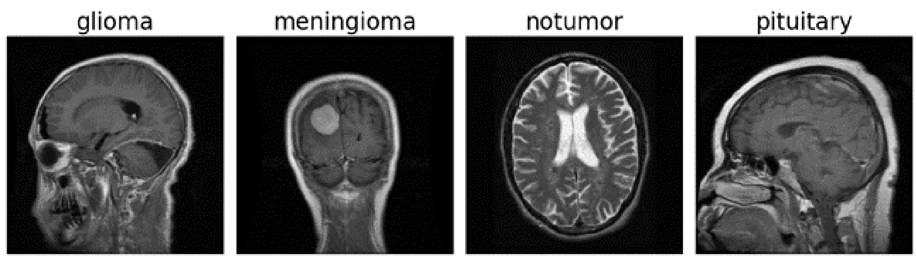

Fig. 5. MRI Brain Tumor Declaration Dataset (D3)

No tumor images serve as healthy brain references, displaying normal brain structures without any abnormal masses or contrast enhancement. These scans are essential for model learning and comparison, as they help distinguish pathological cases from healthy anatomy[2].

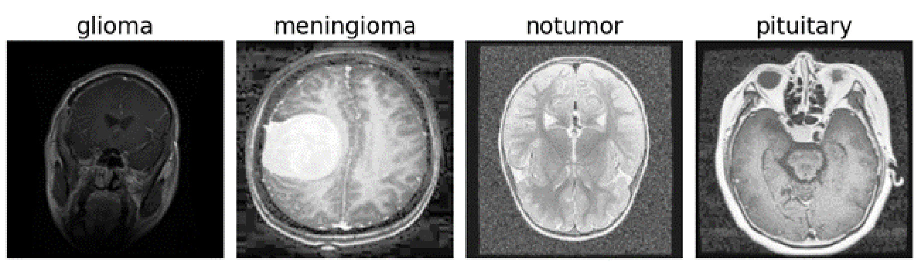

Fig. 6. MRI Brain Tumor Declaration Dataset (D4)

Pituitary tumor MRI scans show lesions in the pituitary gland, usually benign adenomas that may compress nearby structures like the optic chiasm. They appear as well-defined Sella turcica lesions with clear margins[7].

The figure 3–6 show the distribution of MRI brain tumor images in four datasets (D1–D4) and in their merged version (Merged Dataset). All four datasets include four classes of tumors: glioma, meningioma, no tumor, and pituitary. The lengths of the bars are the number of images per class. D1 1600-1800 images, D2 4000-5000 images, D3 2400-3000images and D4 3600-4000 images resulting in a reactively balanced dataset.

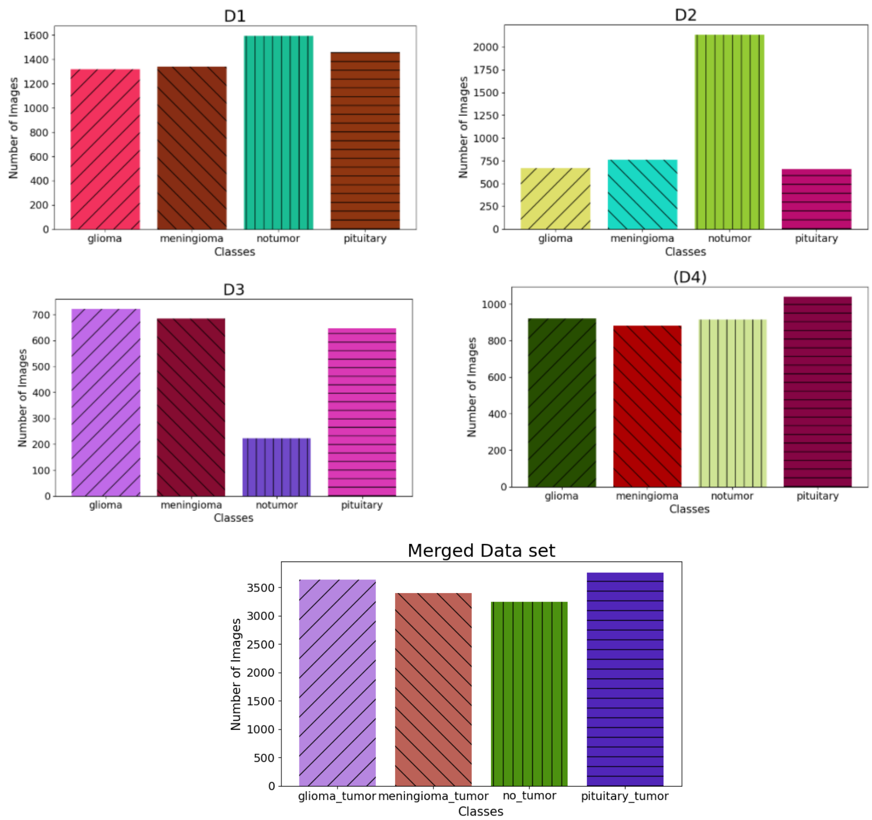

Fig. 7. Class distribution of experimental datasets

Overall, the merged dataset represents the combination of D1, D2, D3, and D4. It contains a significantly higher number of total images: 14000. This merged version effectively reduces the class imbalance observed in some of the individual datasets. Figure 7 shows the class distribution of all datasets.

3.2 Data Preprocessing

Image Resizing : For having consistent input sizes for deep learning models, all MRI images were resized to a consistent size of 224×224 pixels. The resizing process used bilinear interpolation, a method that approximates a weighted average of the intensity values of the four neighboring pixels of the original image. Such interpolation is performed in a manner that the resized image has important features but avoids artifacts.

3.3 Model Architecture

ResNet-50 : The figure 8 illustrates a mixed deep learning model of FCN-32 and ResNet-50 for tumor segmentation of brain tumors from MRI brain scans

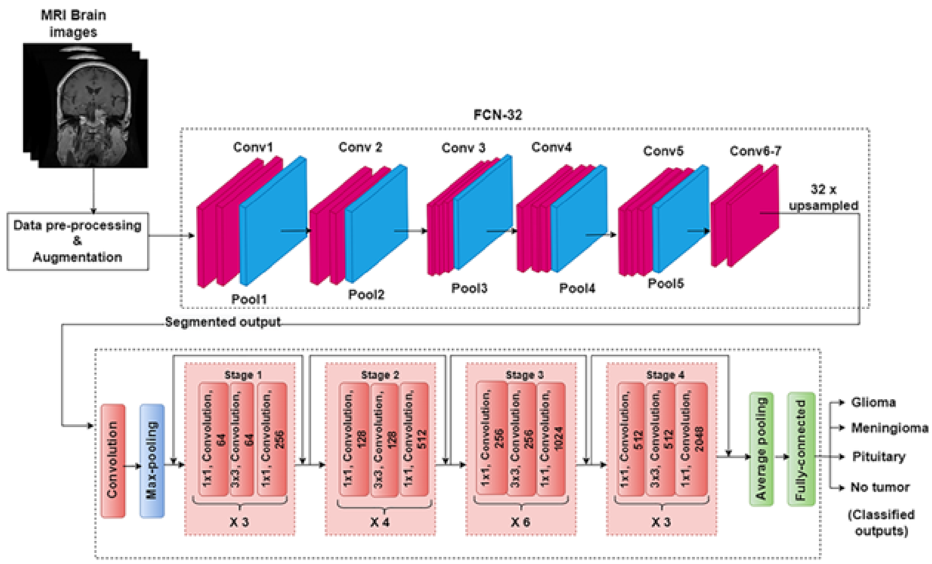

Fig. 8. ResNet-50 architecture used for brain tumor

The model performs data augmentation and preprocessing followed by convolution and max-pooling layers. It outputs segmented to identify tumor areas, and finally, the MRI scans are classified into four classes[15].

EfficientNet : EfficientNet balances accuracy and computational efficiency through compound scaling, harmonizing depth, width, and resolution. Its residual connections mitigate vanishing gradients, ensuring smoother gradient flow and effective learning of complex MRI patterns, enabling fine-grained tumor feature extraction while remaining lightweight and optimized for limited hardware resources [14].

4 Result Analysis

Training Parameters : The model needed a high-performance computing setup to execute efficiently.Training was done on a workstation with an NVIDIA RTX 3050 GPU (12 GB RAM), Intel Core i7 processor, and 64 GB of RAM and Python 3.12.9, PyTorch, and CUDA 12.01 .

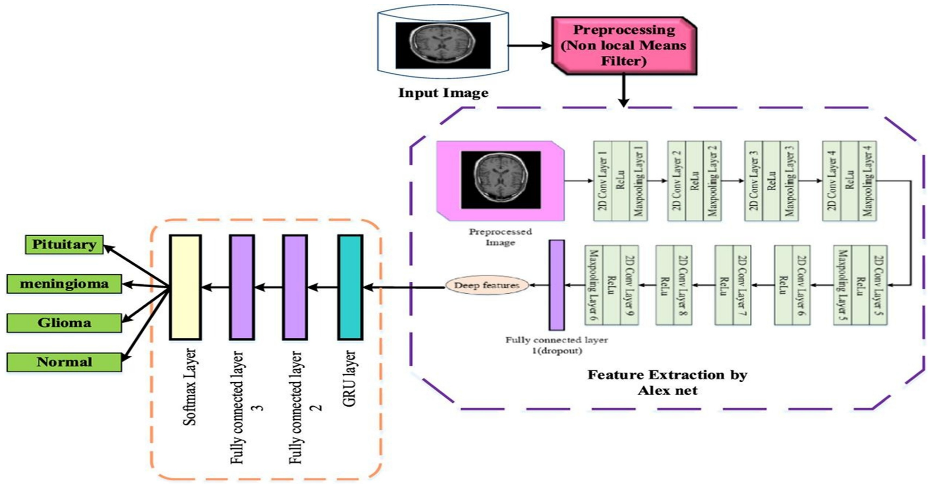

Fig. 9. EfficientNet architecture used for brain tumor

4.1 Performance Results

Table 1. Model performance on the test set

Model	*ACC*	*AUC*	*f1-score*	*precision*	*MCC*	*recall*
Resnet-50	99.31	99.67	94.47	97.65	94.71	97.65
Regnet_y	84.84	99.86	93.88	95.52	86.77	94.61
densenet201	98.87	99.97	99.69	93.33	91.91	90.06
Efficient net	90.09	99.15	89.18	88.02	90.02	84.41
Mobilevit	94.00	94.00	92.00	92.00	94.00	1.00

From Table 1 we can see that among all models, ResNet-50 demonstrated the highest and most balanced performance, achieving 99.31% accuracy with strong precision. DenseNet201 closely followed, while MobileViT showed perfect recall but lower accuracy. EfficientNet remained stable, whereas RegNet-y lagged.

Accuracy and loss curve: Figures 10, 11 and 12 compare MobileViT and ResNet-50 over 15 epochs. MobileViT achieves stable validation accuracy above 90% with minimal overfitting, while ResNet-50 surpasses 99% accuracy with negligible loss. Its overlapping curves indicate excellent convergence and reliability, proving superior segmentation precision through deep transfer learning.

Confusion matrix and Roc curve: Figures 13 and 14 show confusion matrices and ROC curves for brain tumor segmentation. High diagonal dominance

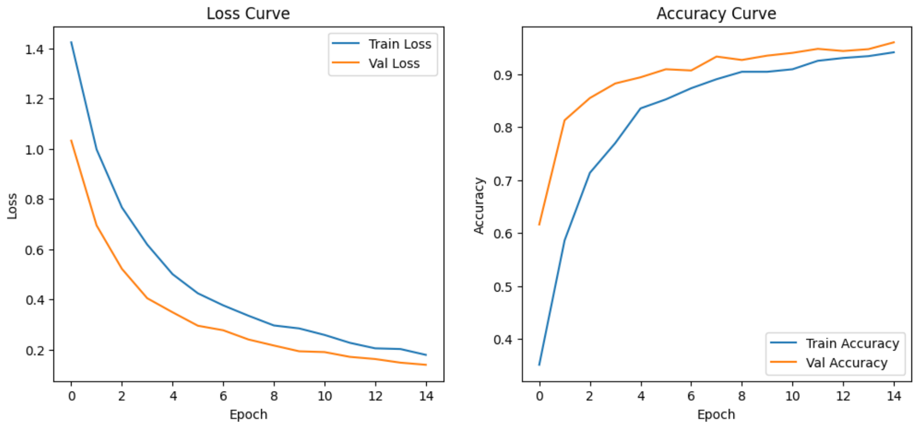

Fig. 10. MObileVit model Training and validation accuracy and loss analysis

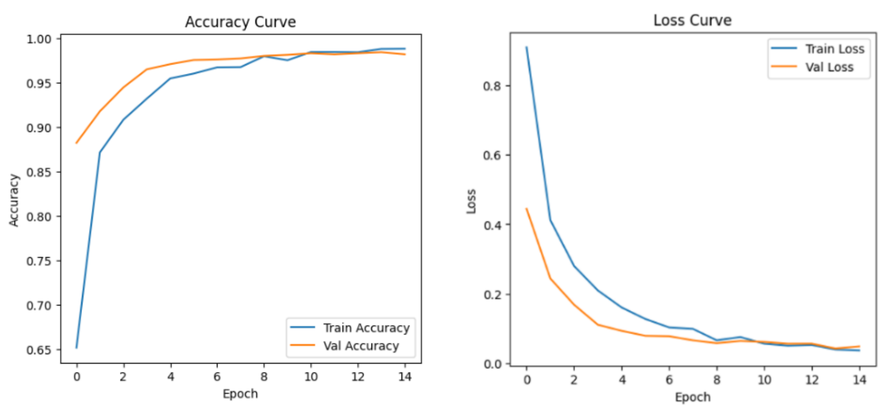

Fig. 11. ResNet-50 model Training and validation accuracy loss analysis

and AUC values above 0.98 demonstrate strong accuracy, stability, and reliable generalization, confirming the models' suitability for precise clinical tumor detection.

Table 2 compares previous brain tumor detection studies with the proposed BrainScan AI model. Earlier works, such as H. Khan et al. (2020) and T. Hossain et al. (2019), used small datasets with two classes, achieving 75%–97% accuracy, limited by dataset size. Mid-scale studies employing CNN and MobileNet reached 94%–97%, while ViT-based models underperformed (65%). In contrast, BrainScan AI uses a large dataset of 14,400 MRI images across four classes—Glioma, Meningioma, Pituitary, and No Tumor—achieving superior performance, with ResNet-50 at 99.31% and DenseNet201 at 98.87%. This demonstrates its robust-

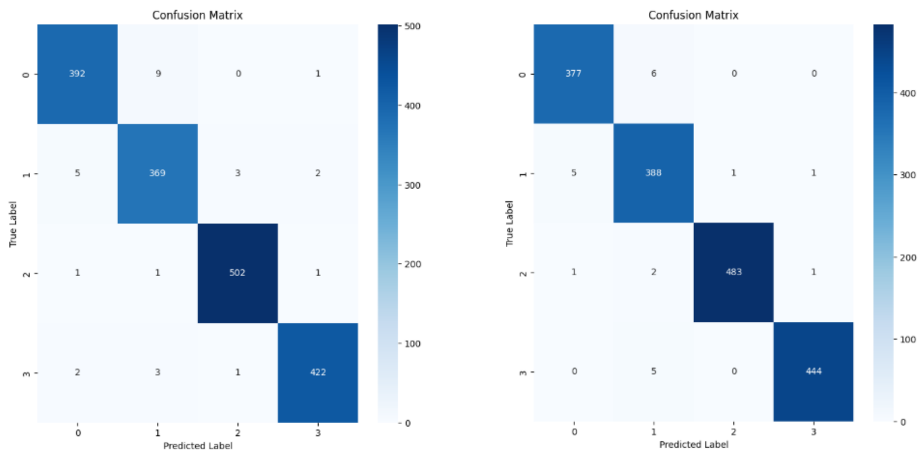

Fig. 12. Confusion matrix analyses of the proposed model representing TP, TN, FP, and FN

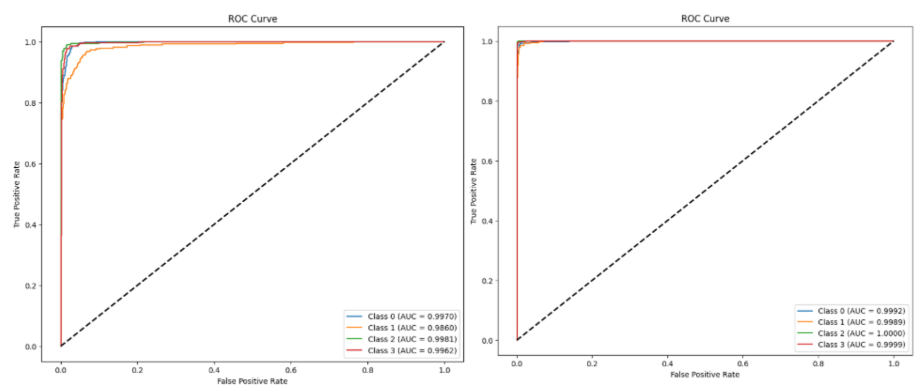

Fig. 13. Roc plots

ness, scalability, and reliability, making it highly suitable for real-world clinical applications.

4.2 Interpret ability with Grad-CAM

Grad-CAM (Gradient-weighted Class Activation Mapping) provides explanations visually by highlighting areas on the MRI that are affecting model predictions. Grad-CAM heatmaps in this work showed high concentration on tumor areas—red and yellow spots

Table 2. Comparative analysis of proposed work with previous works

Contribution	Model	Dataset	Classe	Accuracy (%)
	VGG			96.43(%)
H.Khan et al.(2020)[1]	ResNet-50	253	2	89(%)
	Inception-v3			75(%)
S.Das.et al.(2019) [16]	CNN	3064	3	94.39(%)
	MobileNetV2			94.17(%)
	MobNetV2-lr	3000	2	94.83(%)
S.pokhrel et al.(2020)[17]	MobNetV2-sm			94.83(%)
	VGG16			97(%)
	VGG19			97(%)
	CNN			97.17(%)
	SVM	217	2	92.42(%)
T.Hossain et al.(2019)[21]	CNN			97.17(%)
	CNN	2065	2	89(%)
P.Gokila Brindha at(2021) [19]	vit			65.21(%)
	DCNN			96(%)
M.Abu et al.(2020)[9]	VGG16	2065	2	86(%)
	ResNet-50			99.31(%)
	RegNet-y			84.84(%)
Proposed BrainScan AI	DenseNet201	14400	4	98.87(%)
	EfficientNet			99.09(%)
	MobileVit			94(%)

indicating high concentration—confirming accurate localization for glioma, meningioma, and pituitary tumors. This enhances interpretability, suggesting the model examines accurate anatomical regions during diagnosis. Visual confirmation provides confidence to AI-assisted medical systems by making them more transparent and clinically reliable [4]. Where heatmaps deviate from tumor areas, they may signal model misinterpretation, guiding further optimization and offering trustworthy diagnostic performance in clinical imaging[11].

5 Discussion

The manuscript is a critical comparison between classic image processing and current state-of-the-art deep learning techniques for the detection and segmentation of brain tumors from MRI images, their advantages and disadvantages. CNN architectures such as EfficientNet, ResNet50, DenseNet201, and MobileNet are more accurate, more sensitive, and more specific than the classic approaches (region growing, watershed, and quadtree). EfficientNet-B0 provides robust de-

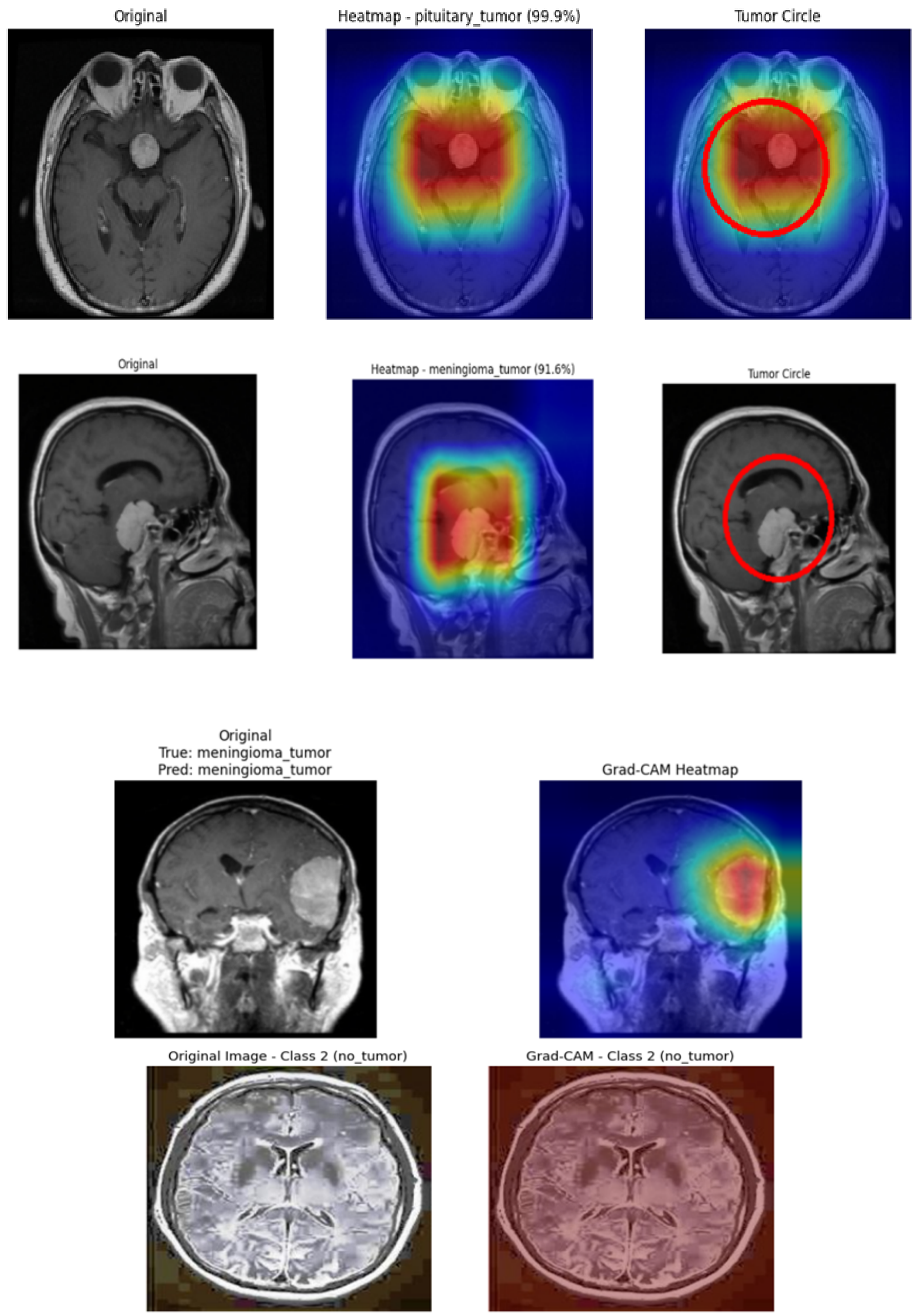

Fig. 14. Grad-CAM visualization showing tumor regions

tection with reduced computation, while deeper models such as ResNet18 boost sensitivity with fewer false positives. Classic approaches are proficient at visual interpretability with fewer annotated images but are not efficient with noisy or cluttered images [18][13]. Preprocessing techniques—normalization, augmentation, and morphological filtering—are indispensable for stable CNN training and to combat overfitting. The disadvantages are a weak set size and limited cross-validation, impacting generalization to other MRI modalities. The future lines of investigation are the integration of classical techniques with deep learning techniques that exploit the interpretability and efficiency of classical techniques and the flexibility of CNN to achieve accurate, robust, and clinically trustworthy computer-assisted detection and segmentation of brain tumors [6].

6 Conclusion

This study compares classical image processing techniques (region growing, watershed, and quadtree) with CNNs (EfficientNet-B0, ResNet18, DenseNet121, and MobileNetV2) for the detection and segmentation of brain tumors from MRI images. Results demonstrate that CNNs achieve higher accuracy, Dice score, and IoU than classical techniques due to the potential for learning intricate spatial and intensity patterns, adequately describing tumor behavior. EfficientNet-B0 and ResNet18 achieve good precision-recall balance, indicating that small CNNs with stable performance are also feasible. Classical techniques are less precise but highly interpretable with minimal data dependency and can be utilized for preprocessing or establishing baseline models. Visualization, e.g., with watershed, improves clinical interpretability and results in AI-assisted diagnosis with higher confidence.

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