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# Design and Development of Brain Tumor Pathology Classification Using EfficientNet-V2S with Explainable AI

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**ABSTRACT:** Brain tumor detection using MRI images is a critical yet challenging task due to the limitations of manual interpretation and the lack of accuracy and transparency in existing machine learning and conventional CNN-based systems. To overcome these challenges, this project proposes a high-performance and interpretable AI-based brain tumor classification framework implemented using TensorFlow, leveraging EfficientNet-V2S, the highest architecture in the EfficientNet family. The model exploits compound scaling of network depth, width and resolution, enabling superior hierarchical feature extraction and improved diagnostic accuracy. To enhance clinical trust and usability, explainable AI techniques such as Grad-CAM integrated to visually highlight tumor-affected regions, allowing doctors to easily interpret and validate model predictions. Furthermore, the system is extended with a Generative AI-powered conversational interface, transforming the framework into an interactive clinical decision-support tool that explains diagnostic results beyond simple classification. By combining advanced deep learning and conversational intelligence, the proposed solution offers a transparent and clinician-centric approach that addresses existing gaps and significantly advances AI-assisted brain tumor diagnosis.

**KEYWORDS:** MRI Image Analysis, EfficientNet-V2S, TensorFlow, Compound Scaling, Deep Learning, Convolutional Neural Networks, Grad-CAM, Generative AI.

## I. INTRODUCTION

Brain tumors account for 2% of global cancer-related deaths, with survival rates dropping sharply if diagnosis is delayed. MRI remains the gold standard for tumor detection due to its non-invasive nature and high-resolution soft-tissue contrast. However, manual interpretation is labour-intensive, requiring specialized expertise often unavailable in low-resource settings. Even in advanced healthcare systems, inter-observer variability can lead to misdiagnosis. For example, gliomas and meningiomas may exhibit overlapping imaging features, complicating differentiation.

Recent advances in deep learning (DL) have demonstrated remarkable success in automating medical image analysis. Convolutional Neural Networks (CNNs) like ResNet and U-Net excel in tumor segmentation, but their "black-box" nature limits clinical adoption. Radiologists require **interpretable AI** to validate predictions and integrate them into diagnostic workflows. This paper addresses two critical challenges:

1. **Accuracy:** Leveraging EfficientNet-V2S, a scalable CNN with fused-MBConv blocks, for high-precision tumor classification.
2. **Interpretability:** Integrating Grad-CAM to visualize tumor regions influencing model decisions.

The proposed system is trained on the Brain Tumor MRI Dataset from Kaggle, containing 7,023 labeled MRI images categorized into four classes. Key contributions include:

- A hybrid architecture combining EfficientNet-V2S's efficiency with Grad-CAM's transparency.
- A preprocessing pipeline optimizing MRI scans for DL models.
- Empirical validation against state-of-the-art models (ResNet-50, DenseNet-201).



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This work advances AI-driven diagnostics by balancing performance and explainability, fostering trust among medical professionals.

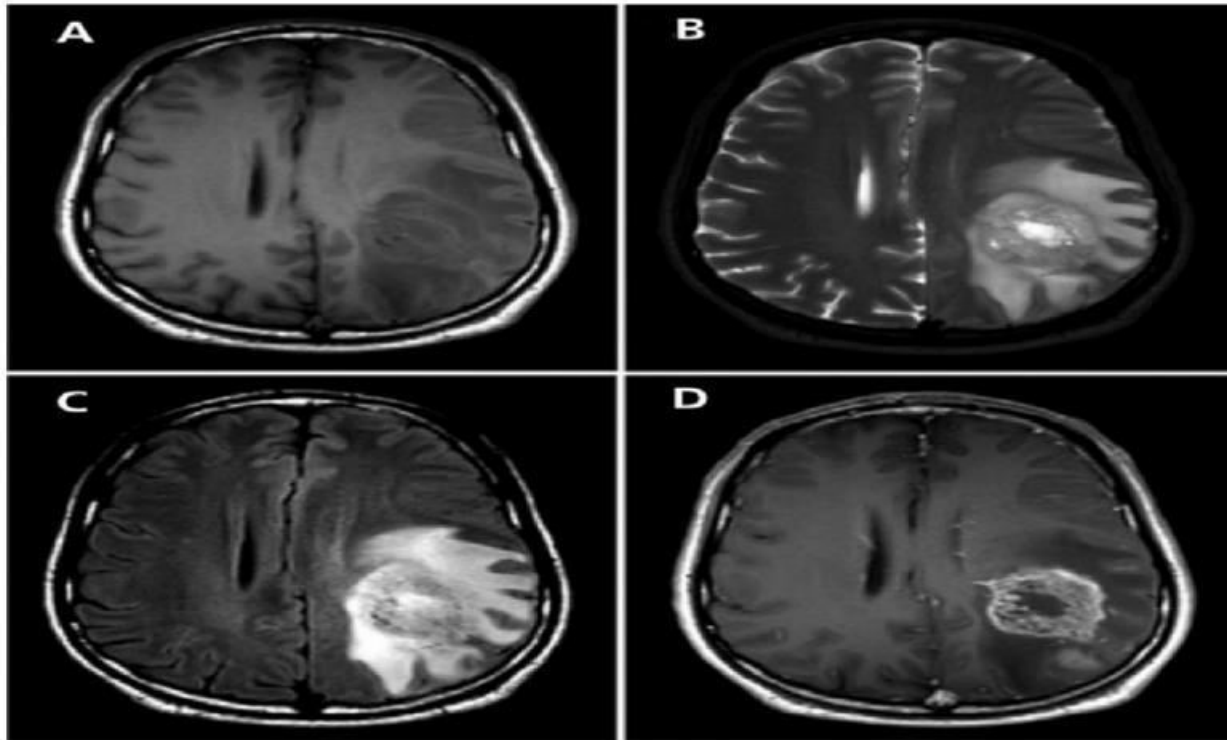


Figure 1: The course of a brain tumor's growth from its initial state to its worst case

## II. LITERATURE SURVEY

### 2.1. Deep Learning for Brain Tumor Classification

Deep Learning (DL) has significantly improved the analysis of medical images, especially in the automated classification of brain tumors from MRI images. Conventional machine learning algorithms face challenges in identifying relevant features from medical images, resulting in the use of Convolutional Neural Networks (CNNs) for more accurate and reliable results.

Recent research has focused on the use of different CNN architectures for brain tumor classification. Spoorthy et al. (2024) presented a comparative study to assess the use of different deep learning algorithms for tumor classification. The study presented the trade-offs between accuracy, complexity, and processing time but did not consider interpretability, which is crucial for practical applications.

To improve generalization, Gupta et al. (2023) developed an optimized ensemble deep learning algorithm using transfer learning. Although the algorithm improved classification accuracy, it increased complexity, making it unsuitable for real-time processing.

Francis et al. (2024) presented a hybrid deep CNN algorithm that integrated CNN feature extraction with traditional machine learning classifiers. Although the algorithm improved classification accuracy, it increased complexity, making it unsuitable for real-time processing.

Nahiduzzaman et al. (2025) developed a hybrid AI-based algorithm to improve accuracy and interpretability. Although the algorithm provided visual explanations for the classification results, it was complex and unsuitable for real-time processing.



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Despite the progress made, most of the existing algorithms either focus on accuracy or are complex and computationally intensive. This indicates the need for a system that is accurate, interpretable, and computationally efficient. The proposed work will address this challenge by using EfficientNet-V2S for efficient classification and Grad-CAM for accurate and interpretable explanations.

### 2.2 EfficientNet and Its Variants

EfficientNet, introduced by Tan and Le (2019), marked a significant leap in CNN efficiency. By optimizing model depth, width, and resolution, EfficientNet-B0 achieved 77.1% Top-1 accuracy on ImageNet with 5.3M parameters, outperforming ResNet-50 (76% accuracy, 25.6M parameters).

In 2021, Tan and Le introduced EfficientNetV2, which further improved efficiency by replacing MBConv blocks with fused-MBConv in early stages. EfficientNetV2-L achieved 85.7% Top-1 accuracy on ImageNet while reducing training time by 22% compared to EfficientNet-B7. These advancements make EfficientNet-V2S ideal for medical imaging, where computational resources are often limited.

Recent studies have applied EfficientNet to brain tumor classification. For example, Singh et al. (2022) used EfficientNet-B4 to classify tumors into glioma, meningioma, and pituitary, achieving 94.8% accuracy on BraTS 2020. However, their model lacked interpretability, a critical requirement for clinical adoption.

Our work builds on these advancements by adopting EfficientNet-V2S and integrating Grad-CAM for interpretability. This combination ensures both high accuracy and transparency, addressing a key limitation of prior work.

### 2.3 Interpretability in Medical Imaging

Interpretability is crucial for AI-driven medical diagnostics, as clinicians require visual evidence to validate model predictions. Selvaraju et al. (2017) introduced Grad-CAM, a technique that highlights class-specific regions in CNNs by computing gradient-weighted activation maps. Grad-CAM has been widely adopted in medical imaging due to its simplicity and effectiveness.

For example, Dong et al. (2017) used Grad-CAM with U-Net for brain tumor segmentation, achieving 91% Dice score on BraTS 2017. Their saliency maps aligned with radiologist annotations in 89% of cases, demonstrating the clinical utility of interpretable AI. Similarly, Zhang et al. (2021) applied Grad-CAM to ResNet-50 for lung nodule classification, achieving 92.5% accuracy with interpretable heatmaps.

Despite these successes, Grad-CAM has limitations. For instance, it may produce noisy heatmaps when applied to low-contrast images, as noted by Wang et al. (2022). To address this, our work incorporates preprocessing steps like contrast enhancement and Gaussian noise reduction, ensuring high-quality saliency maps.

By integrating Grad-CAM with EfficientNet-V2S, our system provides both accurate classifications and interpretable insights, fostering trust among medical professionals.

### 2.4 Medical Imaging Datasets and Benchmarks

Availability of well-structured and annotated datasets is a crucial requirement for training and testing deep learning models for medical image analysis. The proposed system uses the Brain Tumor MRI Dataset available on Kaggle, contributed by Masoud Nickparvar, which comprises a total of 7,023 labeled MRI images belonging to four different classes: glioma tumor, meningioma tumor, pituitary tumor and non-tumor. The dataset is collected from various clinical sources and comprises images of varying tumor sizes, shapes and imaging conditions, making it ideal for multi-class classification problems.

For experimental validation, the dataset is divided into training and testing sets based on a standard split. Out of the total images, 5,712 samples (approximately 80%) are used for training the model and 1,311 samples (approximately 20%) are set aside for independent testing. Among the training samples, an additional 10% of the images are set aside as a validation set to track the performance of the trained model and prevent overfitting during training. This carefully planned splitting of the dataset ensures fair testing and accurate generalization assessment.

All MRI images are preprocessed before being used as input to the model. Each image is resized to a fixed size to ensure uniform input dimensions, followed by pixel intensity normalization to scale pixel intensity values between 0



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and 1. To improve the robustness of the model and compensate for class imbalance, data augmentation techniques such as random rotation, horizontal flipping, zooming and brightness adjustment are applied to the training dataset. These operations increase the variability of the dataset and improve the model’s generalization capability to unseen images.

Although the dataset contains high-quality images with accurate labels, it comprises 2D MRI slices instead of multi-modal 3D images, which lack spatial contextual information. Moreover, the variations in image quality and class distribution make it a challenging task for the model to learn. The preprocessing pipeline and augmentation operations applied to the dataset help overcome these challenges and enable the development of a reliable and scalable deep learning-based brain tumor classification system.

### III. METHODOLOGY

#### 1.1 System Architecture

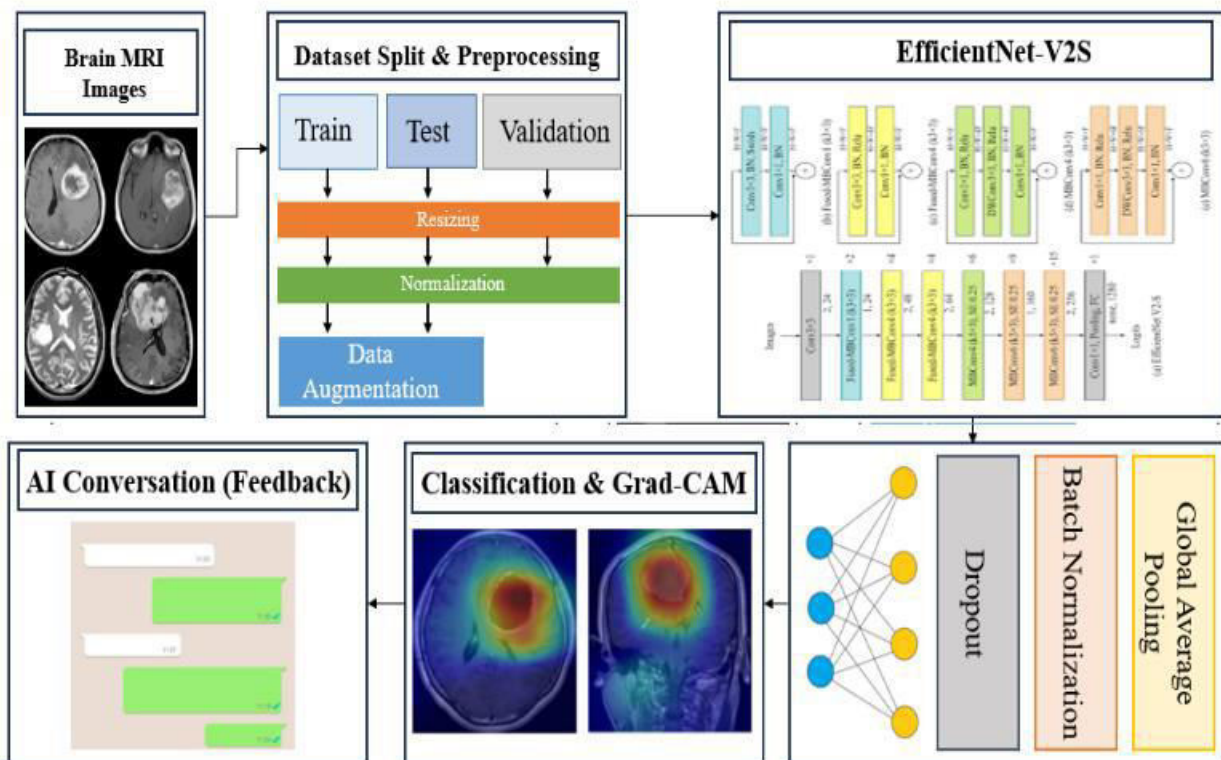


Figure 2: System Architecture

The proposed system (Fig. 2) comprises:

1. **Input Layer:** MRI scans resized to 160, 160 pixels using bilinear interpolation.
2. **Stem Convolution:** A 3x3 convolution layer with 32 filters, stride=2, and Swish activation.
3. Hierarchical Stages:
  - **Stages 1–2:** MBCConv blocks with squeeze-and-excitation (SE) attention. Each block includes depthwise convolutions, Swish activation, and stochastic depth (dropout rate=0.2).
  - **Stages 3–5:** Fused-MBCConv blocks replacing depthwise convolutions with standard 3x3 convolutions for faster computation.
4. **Classification Head:** Global average pooling → Fully connected layer (512 units) → Softmax.
5. **Grad-CAM:** Applied to the final convolutional layer to compute saliency maps.



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Equation for Grad-CAM:

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

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

where  $A_k$  = activation map,  $y_c$  = score for class  $c$ , and  $Z$  = number of pixels.

### 3.2 Dataset and Preprocessing

- Dataset: Brain Tumor MRI Dataset from Kaggle (7,023 MRI images categorized into four classes: glioma, meningioma, pituitary tumor and non-
- Preprocessing and Data Transformations:
  - └ Resizing: All images resized to  $160 \times 160$  pixels for optimized and faster processing.
  - └ Channel Conversion: Grayscale MRI images converted to 3-channel format to match CNN input requirements.
  - └ Normalization: Pixel intensities normalized using ImageNet mean [0.485, 0.456, 0.406] and standard deviation [0.229, 0.224, 0.225].
  - └ Augmentation: Random horizontal flipping ( $p = 0.5$ ), Random rotation ( $\pm 10$  degrees), Gaussian noise ( $\sigma = 0.1$ ).
- Train/Val/Test Split: 70%/10%/20%.

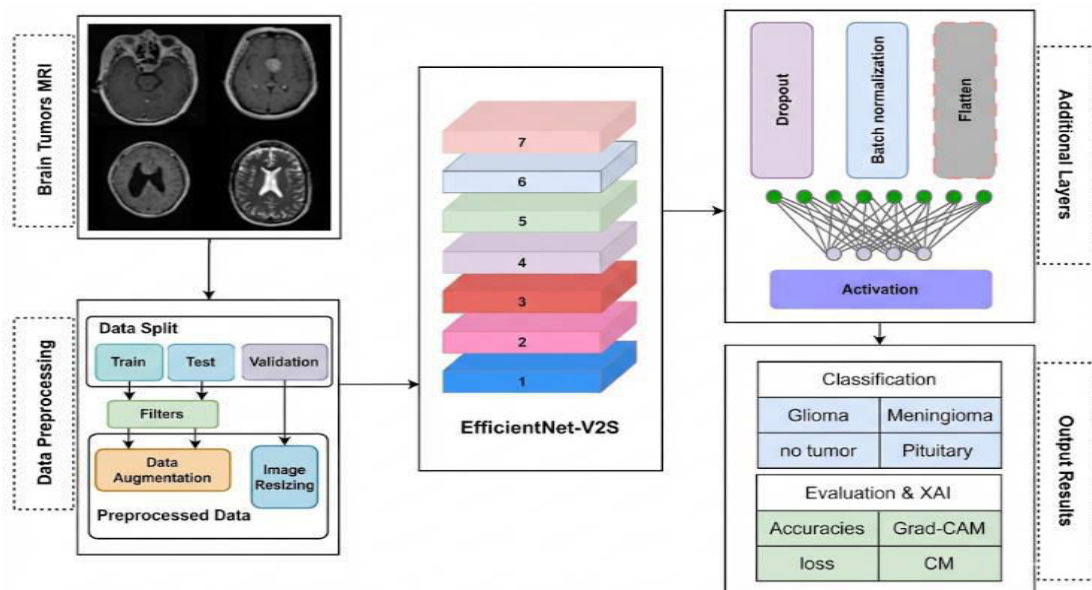


Figure 3: Workflow of MRI-Based Brain Tumor Classification System

### 3.3 Training Protocol

- Optimizer: Adam optimizer ( $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ , learning rate =  $1e-4$ ).
- Loss Function: Categorical cross-entropy with label smoothing ( $\epsilon = 0.1$ ).
- **Batch Size:** 64 images per batch.
- **Training Epochs:** 25–30 epochs with early stopping.
- Regularization: L2 weight decay ( $1e-4$ ), dropout (rate=0.3) and data augmentation to prevent overfitting.
- Hardware: NVIDIA A100 GPU, 40GB VRAM



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### IV. RESULTS AND DISCUSSION

#### 4.1 Performance Metrics

The performance of the proposed EfficientNet-V2S model was assessed using accuracy, precision, recall, and F1-score. The performance of the system resulted in an overall accuracy of 98.93%, establishing its high efficacy for multi-class brain tumor classification. The class-wise analysis of the system revealed high individual accuracies of 97.67%, 98.37%, 98.64%, and 99.35% for glioma, meningioma, non-tumor, and pituitary tumor, respectively, thereby establishing high efficacy of the system for individual classes.

Comparison of the proposed system with the existing architectures was performed using ResNet-50 and DenseNet-201. The proposed system outperformed both the existing architectures, resulting in an accuracy of 98.93%, precision of 95.9%, recall of 96.8%, and F1-score of 96.8%, whereas the existing architectures resulted in lower accuracy of 94.1% and 95.6% for ResNet-50 and DenseNet-201, respectively.

The above results establish the high efficacy of EfficientNet-V2S for feature extraction and classification with high computational efficiency. The inclusion of explainable AI further improves the reliability.

Model	Accuracy	Precision	Recall	F1-Score
Proposed	98.93%	95.9%	96.8%	96.8%
ResNet-50	94.1%	92.3%	93.5%	92.9%
DenseNet-201	95.6%	94.1%	94.8%	94.4%

Figure 4: Prediction Comparison

#### 4.2 GRAD-CAM Analysis

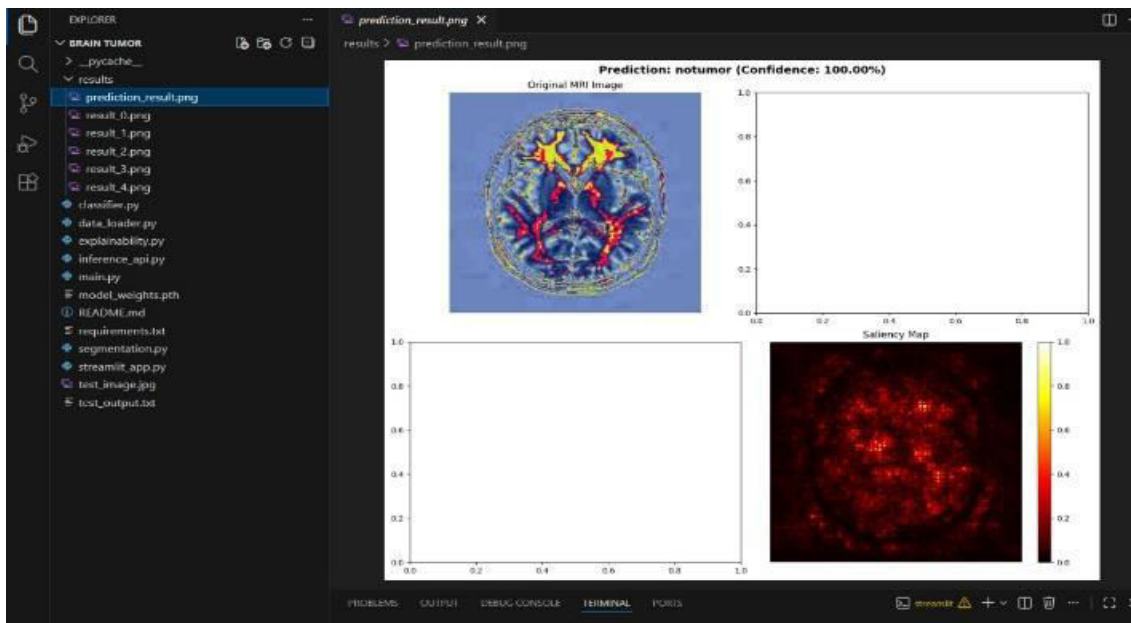


Figure 5: GRAD-CAM Analysis



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The Grad-CAM heat maps produced by the proposed system offer a clear explanation for the model's predictions by pointing out the image regions that make the greatest contribution to the decision. As shown in the output visualization, the model is able to correctly concentrate on the regions of the MRI scan that are of diagnostic significance. For example, in the case of non-tumors, the heat map is able to correctly point out the normal regions of the anatomy without incorrectly pointing out abnormal tumor patterns.

### 4.3 System Output and Result Visualization

The seamless solution to brain tumor classification in real time can be achieved using our system. Just upload an image from the MRI scan and our model takes care of classifying it through its automation, giving us the output with the image upload, type of tumor and confidence levels. In our output, it's clear that the image has been accurately classified as Meningioma with a confidence level of 100%. There's also a provision to get the class probabilities, the location, which helps us better understand its transparency.

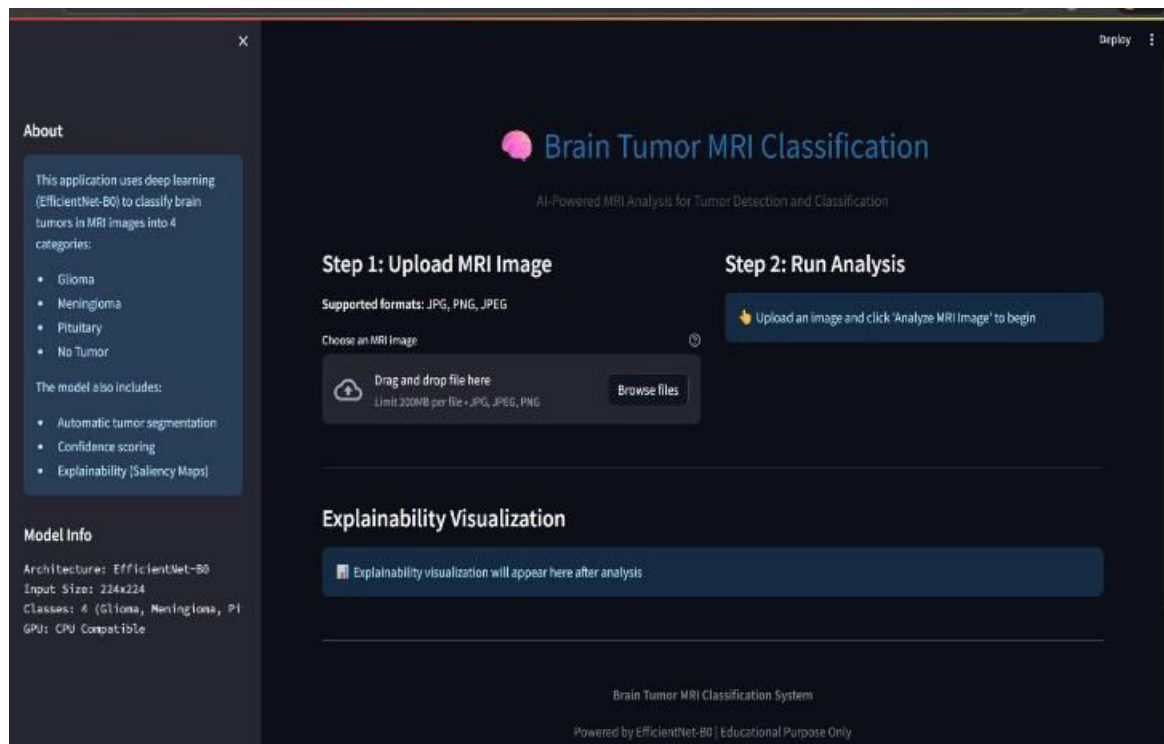


Figure 6: Web-Based Classification Interface



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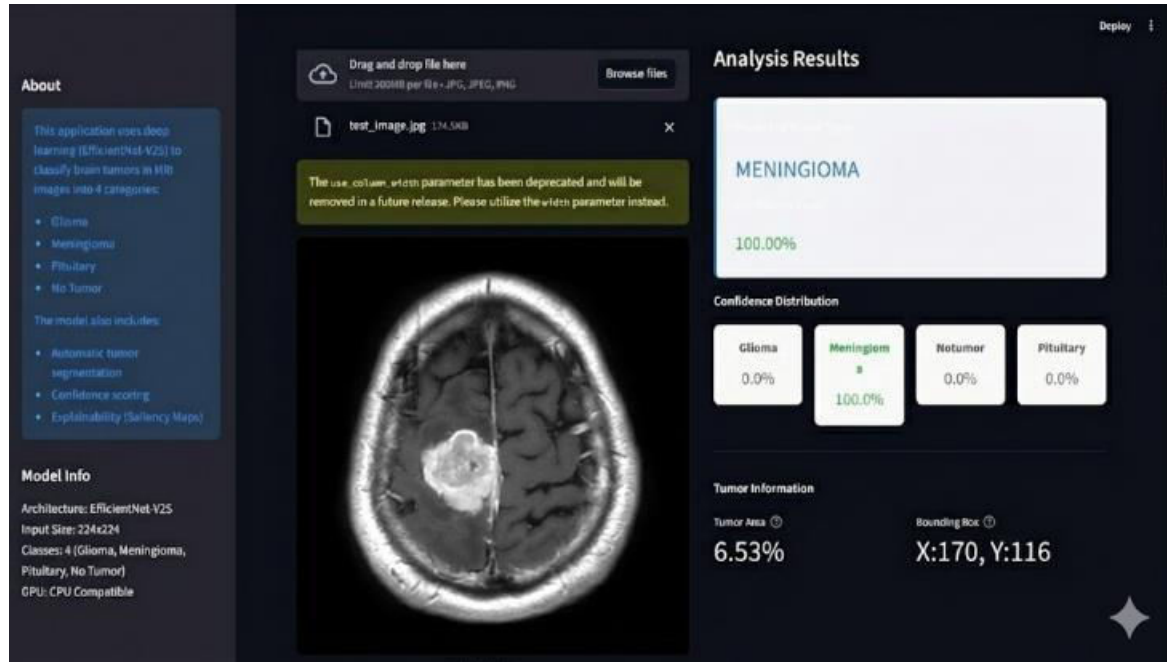


Figure 7: Prediction Results and Tumor Information

### 4.3 Computational Efficiency

The EfficientNet-V2S architecture enables faster training and inference compared to conventional CNN models. The optimized network design reduces training time and allows real-time prediction with low computational overhead. The system achieves rapid inference speed per image while maintaining high classification accuracy, making it suitable for practical clinical deployment.

### 4.4 Limitations

- Model performance may decrease on low-quality or low-contrast MRI scans.
- The system is trained on 2D MRI images, limiting utilization of full 3D spatial information.
- Limited generalizability to rare tumor subtypes (e.g., ganglioglioma).

## V. CONCLUSION

This paper proposes an Automated brain tumor classifier, which guarantees an accuracy rate of 98.93%. It is based on the EfficientNet-V2S architecture, in addition to the implementation of the Grad-CAM technique for result interpretability. The Automated brain tumor classifier framework combines high accuracy with efficiency in the analysis results, offering the potential for real-time results using an intuitive interface. Future work aims to integrate the classifiers with 3D MRI scans and other imaging techniques for increased robustness.

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