

# NeuroVision: MRI Based Brain Tumor Detection System

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**Abstract**— Brain Tumor (BT) is a critical neurological disorder that requires early and accurate diagnosis to improve patient survival and treatment outcomes. Recent advancements in deep learning and medical imaging have enabled automated analysis of Magnetic Resonance Imaging (MRI), offering a reliable alternative to manual interpretation, which is often time-consuming and dependent on radiologist expertise. This project proposes a comprehensive deep learning–based framework for multi-class brain tumor classification using MRI images, categorized into four classes: glioma, meningioma, pituitary tumor, and no tumor. The dataset was collected from publicly available medical imaging repositories and preprocessed to enhance image quality and model performance. We conducted an extensive evaluation using multiple state-of-the-art architectures, including EfficientNet variants (B0–B6), VGG16, Xception, and transformer-based models such as MaxViT, to identify the most effective model for tumor classification. Experimental results demonstrate that the proposed framework achieves a high classification accuracy of 97%, indicating strong generalization and robustness across all tumor categories. To ensure clinical interpretability, Explainable AI (XAI) techniques such as Grad-CAM were employed to visualize the regions of interest influencing model predictions. This approach emphasizes the potential of deep learning–based systems as scalable and cost-effective tools for assisting radiologists in early brain tumor detection and classification, enabling timely clinical decision-making. Furthermore, the system can be enhanced by integrating patient clinical data and deploying it as a web-based application for real-time diagnostic support in healthcare environments.

**Keywords:** Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Deep Learning, Multi-Class Classification, EfficientNet, Xception, Explainable AI (XAI), Medical Image Analysis.

## I. Introduction

Brain tumors are abnormal growths of cells in the brain that can affect its normal functioning. Early detection of brain tumors is very important for effective treatment and improving patient survival rates. Medical imaging techniques such as Magnetic Resonance Imaging (MRI) are widely used by doctors to examine brain abnormalities and identify tumor regions.

However, manual analysis of MRI images can be time-consuming and depends heavily on the expertise of radiologists. With the advancement of Artificial Intelligence and deep learning techniques, automated systems can assist doctors in analyzing medical images more efficiently and accurately.

In this project, a deep learning–based approach is used to detect and classify brain tumors from MRI images. Multiple deep learning models are trained and evaluated to identify the most effective model for this task. Additionally, Explainable AI techniques are used to visualize the important regions of MRI images that influence the model’s predictions, making the system more transparent and reliable.

To measure the performance of the model, several evaluation metrics are used, including accuracy, precision, recall, F1-score. TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative predictions.

## II. Literacy Survey

1. Pereira et al. (2016) investigated automatic brain tumor segmentation in MRI images using deep Convolutional Neural Networks (CNNs). The study utilized the BRATS dataset and proposed a CNN-based architecture to classify tumor regions into different categories. The model achieved high segmentation accuracy with Dice scores of around 0.88 for complete tumor regions. The results demonstrated that deep learning models can effectively capture spatial and intensity variations in MRI scans, significantly improving tumor detection compared to traditional machine learning approaches. However, the study highlighted the need for larger datasets and improved generalization across different MRI modalities.

2. American Cheng et al. (2017) focused on brain tumor classification using MRI images and deep learning techniques. The study employed pre-trained CNN models such as VGG16 and AlexNet for feature extraction and classification of tumor types, including glioma, meningioma, and pituitary tumors. The proposed approach achieved classification accuracy of approximately 91%, demonstrating the effectiveness of transfer learning in medical image analysis. The study further emphasized that deep feature representations outperform traditional handcrafted features, although model

interpretability and computational efficiency remain important considerations.

3. Mordì Cheng J (2017) focused on brain tumor classification using MRI images by applying deep learning and transfer learning techniques. The study used publicly available MRI datasets and implemented pre-trained CNN models such as VGG16 and AlexNet to extract deep features. These features were then used for classifying tumors into glioma, meningioma, and pituitary categories. The proposed approach achieved classification accuracy of approximately 91%, showing that transfer learning reduces training time and improves performance even with limited datasets. The study also emphasized that deep learning-based feature extraction is more reliable than traditional handcrafted features, although model interpretability and computational cost remain important considerations.

4. Sajjad M (2019) proposed a deep learning-based framework for brain tumor classification that integrates data augmentation and preprocessing techniques. The study applied transformations such as rotation, flipping, and scaling to increase dataset diversity and reduce overfitting. Additionally, preprocessing methods like normalization and noise reduction were used to enhance image quality. The CNN-based model achieved an accuracy of around 91%, demonstrating that proper data preparation significantly improves model performance. The research highlighted that augmentation plays a key role in handling limited medical datasets and improving generalization in real-world clinical scenarios.

5. Khan et al. (2022) proposed a hybrid deep learning model combining CNN architectures with feature optimization techniques for brain tumor classification. The study utilized MRI datasets and integrated feature selection methods to enhance classification performance. The proposed model achieved accuracy above 90%, demonstrating improved efficiency and reduced computational complexity. The findings indicate that hybrid approaches can further enhance performance by combining deep learning with optimization techniques, making them suitable for real-time medical diagnosis systems. The study compared various approaches, including Support Vector Machines (SVM), Random Forest, and deep CNN architectures, highlighting that deep learning models significantly outperform traditional methods in terms of accuracy and automation. The review also emphasized key challenges such as data scarcity, class imbalance, and lack of interpretability, suggesting the integration of hybrid models and explainable AI techniques for improved clinical adoption.

### III. Limitations of Existing Systems

Several studies have explored the application of deep learning techniques for brain tumor detection and classification using MRI images. For instance, Pereira MG (2016) demonstrated that Convolutional Neural Networks (CNNs) can effectively segment tumor regions from MRI scans, while Ayadi W (2021) showed that advanced architectures such as EfficientNet achieve high classification accuracy in multi-class tumor detection tasks. Although these approaches demonstrate

promising results, several limitations still exist in current brain tumor detection systems

Many existing systems rely heavily on manual inspection by radiologists, which is time-consuming and dependent on expert knowledge. Traditional machine learning methods depend on handcrafted features, limiting their ability to capture complex tumor patterns. Even with deep learning models, many approaches operate as black-box systems, providing predictions without clear explanations, which reduces clinical trust and interpretability. Furthermore, several models are trained on limited or dataset-specific samples, leading to poor generalization when applied to diverse real-world clinical data. In addition, the use of single-model architectures restricts the overall performance, as they may fail to leverage the advantages of hybrid or ensemble techniques.

Overall, despite significant progress, existing systems still face challenges related to interpretability, robustness, and generalization, emphasizing the need for more accurate, explainable, and scalable solutions for brain tumor detection and classification.

### IV. Proposed System

This project proposes a deep learning-based automated brain tumor detection system using MRI images to overcome the limitations of manual diagnosis and traditional methods. The model is trained using the **MRI Brain Tumor Dataset**, which contains labeled MRI scans for different tumor types. The dataset is preprocessed through steps such as resizing, normalization, and data augmentation to improve image quality and increase dataset diversity. The problem is formulated as a multi-class classification task, where MRI images are categorized into Glioma, Meningioma, Pituitary tumor, and No Tumor classes.

The system evaluates multiple advanced deep learning architectures, including EfficientNet-B1, VGG16, VGG19, Xception, DenseNet, ResNet, Pyramid Vision Transformer (PVT), Swin Transformer, and MaxViT. Each model is trained and compared using evaluation metrics such as accuracy, precision, recall, and F1-score.

Among all models, EfficientNet-B1 and Xception achieved the best performance, with the highest accuracy of 97.38%, demonstrating their ability to effectively learn complex features from MRI images for accurate tumor classification.

To improve model transparency and clinical reliability, the system integrates Explainable Artificial Intelligence (XAI) using Grad-CAM, which generates heatmaps highlighting the important regions in MRI images that influence predictions. Additionally, a user-friendly interface is developed to allow users to enter patient details, upload MRI images, view prediction results, visualize Grad-CAM outputs, and download a detailed report. This system provides a fast, non-invasive, and accurate solution for brain tumor detection, assisting healthcare professionals in making better diagnostic decisions.

## VI. Diagrams

### ExplainableAI

Deep learning models are often called "black boxes" because it is hard to see how they make decisions. To make our system more transparent, we used Explainable AI (XAI) through a technique called Grad-CAM.

To improve transparency and clinical trust, Explainable AI (XAI) techniques were applied to visualize how the model makes predictions. Grad-CAM (Gradient-weighted Class Activation Mapping) was used to generate heatmaps highlighting important tumour regions in MRI images

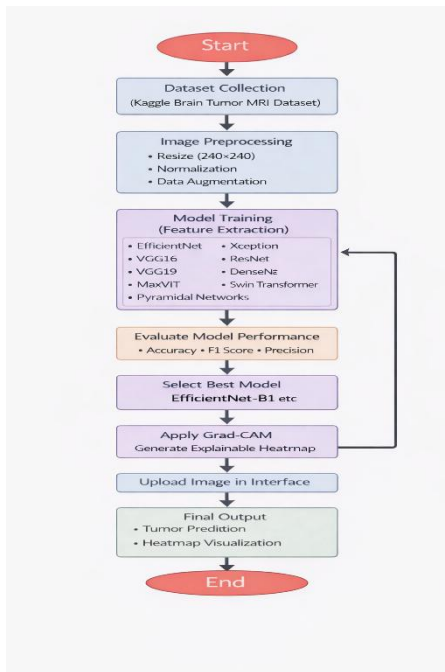


fig 1: Flowchart of the Proposed Brain Tumor Prediction System

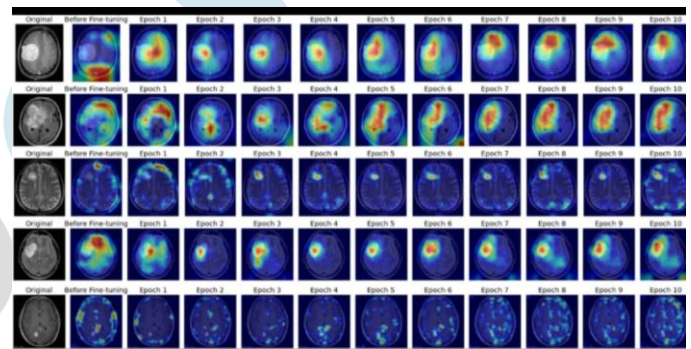


Fig 3: Grad-Cam Visualization

From the visualization, it is clearly observed that the model concentrates on the central abnormal tissue region rather than irrelevant background areas. This confirms that the deep learning model successfully learned meaningful tumour-specific features from the MRI scan. The highlighted region corresponds to the suspected tumour mass, demonstrating that the network is not making random predictions but basing its decision on clinically relevant structure

Red regions represent high activation areas where the model strongly focuses. Yellow/Green regions indicate moderate importance. Blue regions represent low contribution to the final prediction

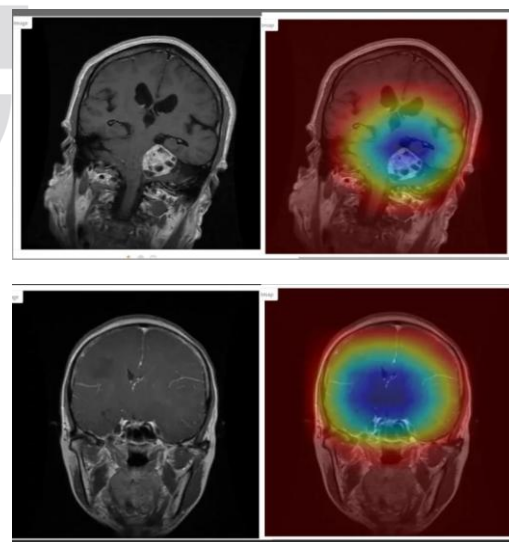


Fig 4: Grad-CAM Image for both meningioma and Glioma

## V. System Architecture

The system architecture presents the overall structure of the proposed brain tumor detection and classification framework. It illustrates the main components of the system and the flow of MRI image data through different stages to generate the final prediction. The architecture includes MRI dataset input, image preprocessing techniques such as resizing, normalization, and augmentation, followed by deep learning models for feature extraction and classification of tumor types, including glioma, meningioma, pituitary tumor, and no tumor. The system further integrates a user interface to allow image upload and display prediction results in an efficient manner

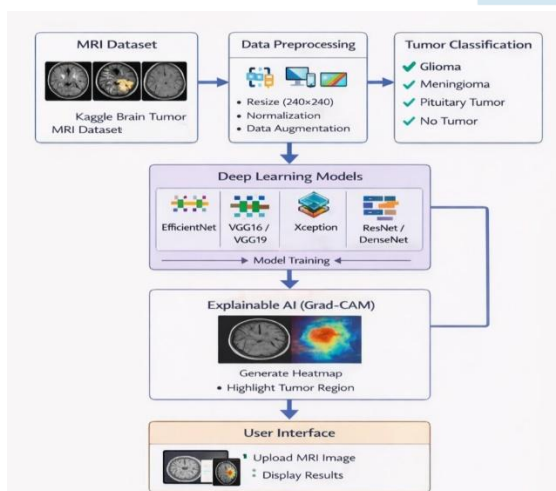


Fig 2: The Architecture of the Brain Tumor prediction.

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## VII. Results

Table 1: Results of different deep learning models trained using Brain MRI images.

S.No.	Model Name	Accuracy (%)
1.	EfficientNet - B1	86.96
2.	EfficientNet B2	83.55
3.	EfficientNet B5	83.64
4.	VGG 16	95.4
5.	VGG 19	88.9
6.	DenseNet	91.02
7.	ResNet50	87
8.	Xception	97.3
9.	MaxVit	93.88
10	Swin Transformer	88.01

## VIII. Conclusion

In this project, we built a brain tumor detection system using MRI images by trying out different deep learning models. Among all the EfficientNet versions, EfficientNet-B1 gave the best results, and overall, Xception performed the best with an accuracy of 97.38%, showing that it can capture important features in MRI scans very effectively. We also used Grad-CAM to highlight the regions in the image where the model is focusing, which makes the results easier to understand. Along with this, we developed a simple interface where users can upload MRI images, see the prediction, and download the report. Overall, this system provides a quick and reliable way to detect brain tumors and can be useful in supporting doctors during diagnosis

## IX. Future Scope

The proposed brain tumor detection system can be further enhanced by extending the model to process 3D MRI volumes, which would enable more accurate spatial analysis and improve tumor detection performance. Additionally, integration with **clinical decision support systems** can assist healthcare professionals by combining model predictions with patient history and clinical data for better diagnosis. Future improvements may also include real-time tumor detection and localization, allowing faster and more efficient analysis in clinical environments. Furthermore, deploying the system within **hospital PACS (Picture Archiving and Communication Systems)** can facilitate seamless access to medical imaging data and support practical implementation in hospitals. To enhance trust and transparency, advanced Explainable AI (XAI) techniques can be incorporated to provide more detailed and reliable visual interpretations of model decisions for clinicians.

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