# **Comparative Analysis of Models on Brain Tumor MRI Dataset**

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# **abstracrt**

Accurate classification of brain tumors using MRI scans is highly critical for successful treatment and diagnosis. In this research, the use of five different convolutional neural network (CNN) architectures—EfficientNetB2, VGG16, VGG19, ResNet18, and DenseNet121—is investigated to classify brain tumors using the Brain Tumor MRI Dataset. The dataset includes MRI images categorized into four classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor. To improve model performance and generalizability, robust preprocessing techniques were applied, including image resizing, normalization, and data augmentation. The objective was to compare and evaluate the models using classification accuracy and computational complexity. Experimental data revealed ResNet18 achieved the best accuracy of 98.25%, followed by DenseNet121 (97.71%), EfficientNetB2 (98%), VGG19 (91%), and VGG16 (69%). The findings suggest the potential of deep learning techniques in assisting diagnosis of brain tumors as well as possible clinical application in the future.

# **introduction**

Medical imaging has revolutionized the practice of medicine by providing accurate information about various physiological conditions. Of these, magnetic resonance imaging (MRI) has come to be used as a useful diagnostic tool for diagnosing brain tumors [1]. However, MRI scans must be interpreted correctly with effort and in reliance on the expertise of radiologists. Brain tumors are malignancies or benign tumors of great medical significance that need to be diagnosed rapidly and treated. Conventional diagnosis methods consist of labor-intensive manual scan assessment of MRI, not only labor-intensive but also subjective. Under pressure to provide accurate and prompt detection of brain tumors, investigators have turned to models of deep learning. These architectures, such as VGG16, VGG19, and Custom CNN, leverage the power of convolutional neural networks (CNNs) to learn and identify patterns indicative of brain tumors in MRI images.

In this study, we examine the performance of these deep learning architectures over the Brain Tumor MRI Dataset. Through training and testing every model on this database, we aim to put their ability to accurately detect brain tumors from MRI scans to the test. We aim to develop a reliable and effective method capable of assisting healthcare providers in making timely and accurate diagnoses, thus improving patient outcomes, and saving lives. Contributions of the Study: Evaluation of Several Deep Learning Architectures

**III. Data description and preprocessing steps**

The **Brain Tumor MRI Dataset** typically includes a collection of MRI scans of the brain, categorized into various classes based on the presence and type of brain tumors. The most common classes include:

Glioma, Meningioma, Pituitary Tumor, No Tumor

Image Resolution: Varies, but common resolutions are 256x256 or 512x512 pixels. Color Channels: Usually grayscale (single channel), but sometimes RGB if enhanced with color for better visualization. Number of Images: Typically ranges from a few hundred to several thousand, depending on the dataset's scope. Annotations: Ground truth labels indicating the presence and type of tumor.

Preprocessing steps:

**Data Loading, Resizing: Data Augmentation:**

**IV. Methodology/approach**

The primary objective of this study is to create a precise and optimal deep learning model for brain tumor classification using MRI images. Brain tumor diagnosis at the right time along with correct identification is crucial for the treatment as well as improved management of patients. Therefore, we have used a cascade of latest convolutional neural network (CNN) models, namely EfficientNetB2, VGG16, VGG19, ResNet18, and DenseNet121. These models also demonstrate performance on image classification and possess diverse architectural strengths like depth, parameter efficiency, and computational speed.  
The data set utilized in this instance is the Brain Tumor MRI Dataset that contains MRI images with four classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The datasets were divided into train, validation, and test for suitable model evaluation to avoid overfitting.  
  
All the MRI scans were preprocessed to meet the input requirements of the CNN models. This meant resampling the scans into a consistent size (224x224 pixels) and pixel intensity normalization to the range  
  
[0  
, 1  
]  
[0,1]. To enhance model generalizability to unseen data, we used data augmentation methods such as rotation of images.  
All models were optimized with the Adam optimizer, and training after accurate hyperparameter tuning like batch size and epochs from performance on the validation set. The advantages of the selected architectures are given below:  
  
VGG16 and VGG19: Renowned for having deep layers and feature extraction.  
  
ResNet18: Consists of residual connections preventing vanishing gradients, therefore leading to better training of deeper networks.  
  
DenseNet121: Enabling reuse of features as well as back propagation of gradients by associating all the layers with each other feed-forward.  
  
EfficientNetB2: Enabling network depth, width, as well as input resolution scaling with no parameters and excellent performance in fewer parameters.  
  
ResNet18 recorded the best during training and testing based on accuracy (98%), followed by DenseNet121 (97%), EfficientNetB2 (96%), VGG19 (91%), and VGG16 (80%).  
  
For the purpose of availing convenient access and usage of the model for real-scenario, Graphical User Interface (GUI) was executed using the support of Gradio. The interface offers a user interface for uploading an MRI image and availing an instant classification result, providing a convenient-to-use interface that can be leveraged to support radiologists and clinicians in real-scenario diagnostic applications.

**V. Results**

The empirical evaluation of brain tumor classification models revealed significant variation in performance across selected Convolutional Neural Network (CNN) architectures.

EfficientNetB2 achieved the highest classification accuracy of 98%, demonstrating an optimal balance of network depth, width, and resolution scaling. Its ability to maintain high accuracy with fewer parameters underscores its efficiency in extracting meaningful features from brain MRI scans while remaining computationally lightweight.

ResNet18 also attained an impressive 98.25% accuracy, owing to its residual learning framework, which effectively mitigates the vanishing gradient problem and facilitates deeper network training. This architecture proved particularly effective in medical image classification, enhancing both training stability and model accuracy.

DenseNet121 closely followed with a 97.71% accuracy, leveraging its densely connected layers to improve feature reuse and gradient flow. This design enhances representational capacity and contributes to its strong performance in tumor classification tasks.

VGG19 delivered a solid 91% accuracy, with its structured, deep architecture of repeated convolutional and pooling layers enabling the model to capture fine-grained features from MRI images. Its simplicity and consistency in design supported its robustness in this medical imaging task.

In contrast, VGG16 performed relatively poorly, achieving only 69% accuracy. Despite being a foundational model for image classification, its increased complexity may have led to overfitting, especially given the class imbalance and relatively limited dataset size. This outcome emphasizes that deeper networks are not universally superior and must be appropriately matched to the dataset and task at hand.

Overall, these results highlight that advanced architectures like EfficientNetB2, ResNet18, DenseNet121, and VGG19 offer reliable, high-performance solutions for brain tumor classification, particularly when designed with architectural efficiency and feature reuse in mind. Simpler models like VGG16 may struggle under similar conditions, reinforcing the need for architecture-task alignment in medical image analysis.

**VI. Conclusion**

In this study, we implemented and evaluated multiple Convolutional Neural Network (CNN) architectures for the classification of brain tumors using MRI images. The tested models included EfficientNetB2, VGG16, VGG19, ResNet18, and DenseNet121, trained and validated on the Brain Tumor MRI Dataset containing 7,023 labeled images across four categories: glioma, meningioma, no tumor, and pituitary tumor.

The dataset was preprocessed through resizing, normalization, and augmentation techniques to enhance model generalization and robustness. Empirical results demonstrated that ResNet18 achieved the highest classification accuracy at 98.25%, followed closely by

EfficientNetB2 with 98%, and DenseNet121 with 97.71%. VGG19 achieved a respectable 91%, while VGG16 lagged behind with 69% accuracy.

These results confirm that modern architectures like ResNet18, DenseNet121, and EfficientNetB2 are well-suited for medical image classification tasks, offering an effective balance between accuracy and computational efficiency. Their performance highlights the importance of architectural innovations such as residual and dense connections in improving feature extraction and gradient flow. In contrast, traditional models like VGG16 may struggle with more complex medical datasets due to limited representational power and potential overfitting.

Overall, the study underscores the potential of advanced CNN architectures in supporting automated and accurate diagnosis of brain tumors, paving the way for their integration into real-world clinical decision support systems.

**References**

1. Nickparvar, M. (2021). Brain Tumor MRI Dataset