

MRI Brain Tumor Analysis on Improved VGG-16 and Efficient NetB7 Models

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Abstract—In recent years, Magnetic Resonance Imaging (MRI) scanning has been the most rapidly developing field. Concerning the tumor's size and specifics, diagnosing and classifying brain tumor's is challenging and time-consuming for radiologists. The growth of abnormal cells in the brain is referred to as a brain tumor. A brain tumor is diagnosed in about 11,700 patients every year. It is estimated that 34% of males and 36% of females will survive five years after being diagnosed with malignant brain or different tumors. This study focuses on meningioma, pituitary, glioma and no tumors', among the many brain tumors. Deep learning algorithms and machine learning methods were used to create an autonomous classification and segmentation system for brain tumors, significantly improving early detection. Using the Visual Geometry Group (16), parameters were set for training the model that detects brain tumors based on analysis of proposed literature solutions. Simple Convolution Neural Network (CNN) models such as VGG-16 and Efficient NetB7 perform well because they are among the highest-performing models. As a result of the study, quick, efficient, and precise decisions can be made using MRI to detect brain tumors. For this 7022 brain magnetic resonance images were used to train and test this model. According to experimental findings, the suggested differential deep CNN model could accurately categories MRI pictures of brain tumors, including aberrant and standard images, with a 98.19% accuracy rate.

Keywords—Magnetic Resonance Imaging (MRI) images, brain tumor, classification, segmentation, Visual Geometry Group (VGG)-16, Efficient NetB7

I. INTRODUCTION

In terms of death causes, cancer is the second most common cause, according to the World Health Organization (WHO). It is most likely possible to prevent death from tumor if it is detected early. Since the human body is composed of millions of cells, biology has taught us that these cells divide, expand, and proliferate to generate new cells and tissues. The cells could develop into tumors due to some external causes causing the cells to expand uncontrolled. The growth of a tumor can be benign, malignant, or both. Malign tumors spread to other organs and tissues, whereas benign tumors do not, and they can be surgically removed. There are three primary types of brain tumors: gliomas, meningiomas, and pituitary tumors. Pituitary tumors are lumps inside the skull that originate from the membranes surrounding the brain and the central nervous system. Brain damage and death may occur due to a brain tumor. Therefore, it is crucial to detect tumors early to treat them. An accurate diagnosis and effective treatment of brain tumors depend on proper classification [1]. There are several automated Magnetic Resonance Imaging (MRI) diagnosis systems available specifically for brain tumor diagnosis. These systems leverage advanced algorithms and machine learning techniques to assist in the detection, segmentation, and characterization of brain tumors. Here are some examples:

- Brain Tumor Segmentation
- Tumor Classification and Grading
- Treatment Response Assessment
- Radiomics Analysis

It's important to note that while these automated MRI diagnosis systems can provide valuable assistance to radiologists and clinicians, they are typically used as decision support tools and should not replace the expertise of trained medical professionals. The final diagnosis and treatment decisions should always be made in consultation with healthcare experts.

Some tumors can damage nearby brain structures. Consequently, doctors must first identify the exact brain area or region that needs to be treated before performing any brain surgery or therapeutic intervention. Brain tumor segmentation separates tumors from each other by isolating healthy tissues from affected areas. In diagnostic techniques, segmentation of the brain presents the most significant challenge. Unfortunately, most exclusionary practices do not utilize edge-based data or techniques specialized in the field of brain tumors. Deep learning algorithms are being used more and more to identify tumors in medical images [2, 3]. These algorithms are able to identify features in images that are not visible to the human eye, which can help radiologists to make more accurate diagnoses. Early diagnosis and treatment of brain tumors can improve patients' lives and out-comes. A study by Amin *et al.* [4] found that a typical brain tumor can grow by 50% in just 25 days. If a patient does not receive the proper care, they may have less than 12 months to live.

According to international research, the increase in tumor probability in the U.S. over a certain period has resulted in an annual death rate of 11%–12% [5]. As a result, we developed a detection model for brain tumors based on all of these scenarios. Because there are too many patients, manually analyzing Magnetic Resonance Imaging (MRI) images (Fig. 1) takes a lot of time and is prone to inaccuracy [6]. Additionally, it is not advisable to solely rely on doctors to discover it because they have a tendency to misinterpret symptoms and miss early warning signs. Various machine learning techniques are employed for segmenting and classifying pictures to offer radiologists a second opinion. The implementation of Efficient NetB7, a model that has never been used to classify brain tumors, is suggested in this study. The model's findings are compared with those of the VGG-16 models previously used in terms of accuracy and complexity. Deep learning models need much data to train on, but that data isn't always accessible. This paper suggests using deep learning models that have already been introduced to address this issue.



Fig. 1. MRI-generated image of the brain.

This study used a variety of transfer learning networks (VGG-16, Efficient NetB7) to classify different brain

tumors and achieved up to 98% classification accuracy on the publicly available Magnetic Resonance Imaging (MRI) dataset.

A. Deep Learning Methodologies

Algorithms that emulate humans' methods of acquiring knowledge are called Deep Learning Algorithms (DLAs). The development of Deep Learning (DL) and Convolutional Neural Networks (CNNs) is given central importance when discussing brain MRI and related computer interventions.

Developing Deep Neural Networks (DNNs) based on conventional neural networks has already been progressing. Due to their data-driven nature and automated methodology, these systems are highly accurate and impressive in many fields. It is possible to identify features and characteristics in input data using several nerve-based algorithms, as in deep learning algorithms [7].

B. Research Objectives

Brain tumors are a major health concern, and early detection and treatment are essential for improving patient outcomes. However, the current methods for detecting brain tumors, such as Magnetic Resonance Imaging (MRI), are time-consuming and require the expertise of a radiologist. Using deep learning techniques, tumors were identified and classified from brain scans and images. In these neural networks, weights and biases can be learned from neurons. Using Visual Geometry Group's (VGG-16) and Efficient NetB7 methodology, we propose to use deep learning to develop a more efficient and accurate method for detecting brain tumors from MRI images. Specifically, we trained two deep learning models, an improved VGG-16 model and an Efficient NetB7 model, on a dataset of MRI images with and without brain tumors. This method was developed to assist in making quick, efficient, and precise decisions about brain tumors.

C. Significance and Applications

Deep Neural Networks (DNNs), utilizing publicly available datasets, preprocessing, augmentation, and classification in the context of healthcare systems, are highly significant and have transformative implications in current research fields related to healthcare. Here's an elaboration on their significance:

1) Deep Neural Networks (DNNs)

Significance: DNNs, a subset of artificial neural networks, have revolutionized healthcare by their ability to learn complex patterns and representations from medical data. Their depth and capacity make them well-suited for tasks like image analysis, natural language processing, and diagnosis prediction.

Applications: DNNs are employed in a wide range of applications, from medical image analysis (MRI, CT scans, X-rays) to disease diagnosis, drug discovery, genomics, and personalized treatment recommendations.

2) Utilizing publicly available datasets

Significance: Access to publicly available datasets fosters collaboration and accelerates research in healthcare. Researchers can build on existing data to develop and

validate models, ultimately leading to more robust and generalizable solutions.

Applications: Public healthcare datasets, like those on Kaggle, enable research on various health conditions, population health, epidemiology, and the development of AI models to address healthcare challenges.

3) *Preprocessing and augmentation*

Significance: Preprocessing techniques, such as image resizing, quality improvement, and augmentation, are essential to enhance the quality and relevance of the data used for model training. Augmentation can increase the dataset size and improve model generalization.

Applications: In healthcare, preprocessing and augmentation help improve the accuracy of medical image analysis, reducing noise and enhancing image quality for diagnosis, treatment planning, and monitoring.

4) *Classification*

Significance: Classification is fundamental in healthcare systems, allowing the automated identification and categorization of medical conditions. DNN-based classification models play a crucial role in medical diagnosis and decision support.

Applications: DNNs are used for classifying a wide range of health-related data, from identifying tumors in medical images to predicting disease outcomes and triaging patients based on symptoms.

5) *Tumor classification in MRI scans*

Significance: Tumor classification using DNNs in MRI scans has transformative implications for early and accurate diagnosis, treatment planning, and patient outcomes. It reduces the reliance on human interpretation and speeds up the diagnostic process.

Applications: DNNs applied to MRI tumor classification are used for different types of tumors (e.g., gliomas, meningiomas, pituitary tumors), contributing to personalized medicine and improving the precision of treatments.

In addition to brain tumor classification, DNNs are being used for a variety of other healthcare tasks, such as:

Medical image analysis: DNNs can be used to analyze medical images, such as X-rays, MRI scans, and CT scans, to identify diseases and abnormalities.

Drug discovery: DNNs can be used to identify new drug targets and to design new drugs.

Clinical decision support: DNNs can be used to help clinicians make better decisions about patient care.

Public health surveillance: DNNs can be used to monitor and track the spread of diseases.

D. *Strength and Originality of the Work*

The adoption of a unique approach devised by researchers, integrating refined iterations of VGG-16 and Efficient Net B7 models, marks a groundbreaking advancement in the field of MRI brain tumor image analysis, offering both precision and efficiency in tumor detection research. This approach has the potential to enhance the early detection and treatment of brain tumors. Enhancing the efficiency and precision of brain tumor detection can potentially lead to better patient outcomes and a reduction in mortality rates. Model training will

employ a technique that offers higher optimization than previous techniques in the literature [8–12] according to this work, the presented model is significant for practitioners and researchers due to its high level of optimization of training. Moreover, a remarkable and superior level of accuracy was attained by utilizing a blend of deep learning models, surpassing the performance of existing solutions. Additionally, the proposed work provides visual outputs in the form of plots that include segmented masks, original masks, and the MRI scan.

E. *Contributions*

The paper addresses the challenging task of diagnosing and classifying brain tumors, which is traditionally time-consuming for radiologists.

Key points:

- Develops a deep learning-based system for brain tumor classification and segmentation using simple CNN models (VGG-16 and Efficient NetB7);
- Achieves an accuracy of 98.19% on the test dataset, demonstrating the potential of the system for early detection of brain tumors;
- Addresses the challenging task of diagnosing and classifying brain tumors, which is traditionally time-consuming for radiologists;
- Provides a quick, efficient, and precise decision-making tool for the diagnosis of meningioma, pituitary tumors, glioma, and no tumors;
- Significantly improves early detection of brain tumors, which is essential for improved patient outcomes.

In summary, the paper's contributions lie in its development of a highly accurate, deep learning-based system for the classification and segmentation of brain tumors using VGG-16 and Efficient NetB7 models. This work has the potential to significantly impact the field of medical imaging and enhance the diagnostic process for brain tumors.

The remainder of this work is as follows. The Literature Review is described in Section II. Discuss the dataset description, pre-processing methods, and suggested architecture in Section III. The experimental findings are presented and analyzed in Section IV, discussion to present the common research attainments and limitations of the previous models in Section V and the study is wrapped up in Section VI.

II. LITERATURE SURVEY

There are numerous methods for classifying brain tumors. In addition, there are various methods for improving accuracy, including machine learning and deep learning have significantly contributed to medical image analysis and disease diagnosis through deep learning and artificial intelligence. A significant part of this section is devoted to reviewing previous work and what can be done to improve it.

Using a T1-weighted contrast-enhanced MRI image database, Raj *et al.* [13] presented a new CNN architecture for classification using three types of tumors. This CNN

model can be operated on a conventional modern personal computer due to its simplicity. A total of four approaches were used to evaluate their network's performance: two 10-fold cross-validation methods and two databases. Using an augmented image database, they tested their network's improvement with one of the 10-fold methods, subject-wise cross-validation. An accuracy of 96.56% was obtained using 10-fold cross-validation with an augmented dataset, record wise cross-validation can be carried out [14].

Diagnosing brain tumor's accurately and quickly is crucial so the best treatment method can be selected to save the patient's life. Several deep learning models have been implemented before but they are complex and slow to use. Examples include VGG-16, Resnet, etc.

Furthermore, a dedicated hardware system is required to run these models in real-time [15]. As a result, a patient's diagnosis and treatment may be delayed, increasing his or her chances of dying. Furthermore, because of the model's complexity, they cannot be deployed on mobile devices. By using a pre-trained Efficient NetB7 model, the proposed work addresses the complexity problem.

Compared with the best existing Conv Net [16], Efficient NetB7 is 8.4 times smaller. This study will compare the accuracy and complexity of the two models in the classification of brain tumors based on their use in the brain tumor classification along with VGG-16.

The proposed model uses supervised learning techniques such as linear and logistic regression to predict whether a tumor is malignant or benign based on the features fed into the algorithm while training [17]. These algorithms predict a tumor's type based on the observation of features. For example, clump thickness and marginal adhesion are the two features used in the classification. Based on these a system has been developed to detect brain tumors from MRI images. The system relies on a multi-model framework to automatically identify tumors in the brain.

The training and testing of this system involve the use of various MRI modalities, ensuring its effectiveness [18]. The system developed in this project utilizes Gray Level Co-occurrence Matrix (GLCM) features to extract information from MRI and CT images.

Feed-forward neural networks were employed in the development process, resulting in a high accuracy rate of 97%. Notably, the entire pre-processed image is utilized for feature extraction in this project [19]. Noise is removed through pre-processing, and segmentation is performed. This study used a VGG-16 model with transfer learning and fine-tuning to classify brain tumors into four categories: glioma, meningioma, pituitary tumor, and no tumor. The model was trained on a dataset of 251 MRI images of brain tumors and achieved an accuracy of 91.58% [20]. This study used an ensemble learning approach of VGG-16 models to classify brain tumors. The ensemble model was trained on a dataset of 500 MRI images of brain tumors and achieved an accuracy of 97.3% [21].

This study used an Efficient NetB7 model with transfer learning and fine-tuning to classify brain tumors into four

categories: glioma, meningioma, pituitary tumor, and no tumor. The model was trained on a dataset of 251 MRI images of brain tumors and achieved an accuracy of 95.2% [22]. This study used an Efficient NetB7-based deep learning model to segment brain tumors in MRI images. The model was trained on a dataset of 300 MRI images of brain tumors and achieved a Dice coefficient of 97.1% [23]. This study used an attention-based Efficient NetB7 model to classify brain tumors. The attention mechanism helped the model to focus on the most important features of the MRI images. The model was trained on a dataset of 500 MRI images of brain tumors and achieved an accuracy of 97.9% [24].

III. METHODOLOGY

In this research, MRI brain scans were employed for the automatic detection of brain tumors. Consequently, we recommend the utilization of brain MRI datasets for the automated detection of brain tumors, making use of the Efficient NetB7 and VGG-16 models. The proposed framework included many steps to enable AI to be used in diagnostics. MRI images of the brain were used as input images. The proposed approach is shown in Fig. 2.

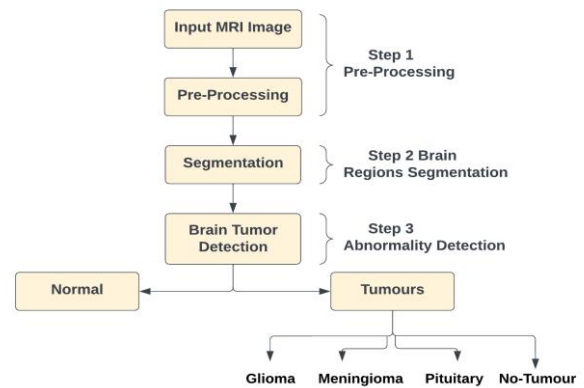


Fig. 2. Methodology for identifying brain tumors.

A. Data Acquisition and Pre-processing

1) Image database

There are a number of factors that can be considered when selecting a Magnetic Resonance Imaging (MRI) dataset, including:

- Data size: The dataset should be large enough to train a deep learning model with sufficient accuracy;
- Data diversity: The dataset should include a diverse range of MRI images, including images of different tumor types, sizes, and locations;
- Data quality: The data should be of high quality and free of noise;
- Data accessibility: The data should be accessible and available for download.

This study utilizes publicly available Kaggle datasets for the purpose of tumor classification in MRI scans. The dataset used is called "Tumor Classification (MRI)", containing a total of 2,227 training MRIs and 429 test

MRIs. Within the training dataset, there are 826 cases of gliomas, 247 cases of meningiomas, 827 cases of pituitary tumors, and 327 cases of MRIs without tumors. The test dataset consists of 98 pituitaries, 100 gliomas, 127 meningiomas, and 104 MRIs without tumors as shown in Table I: i.e. 80% for training, 10% for validation, and 10% for testing. A T1-weighted contrast-enhanced magnetic resonance imaging examination was performed on it to examine it. We evaluated the effectiveness of the network by first preprocessing the data, then augmenting it, and last classifying it. Fig. 3 provides visual examples of brain MRI images representing these four classes.

TABLE I. IMAGES AVAILABILITY ON DATASET

Folder Directory	Number of Images	Tumor Type
Train Dataset	826	Glioma Tumors
	247	Meningioma Tumors
	827	Pituitary Tumors
	327	No-Tumor
Test Dataset	98	Pituitaries
	100	Gliomas
	127	Meningiomas
	104	No-Tumor

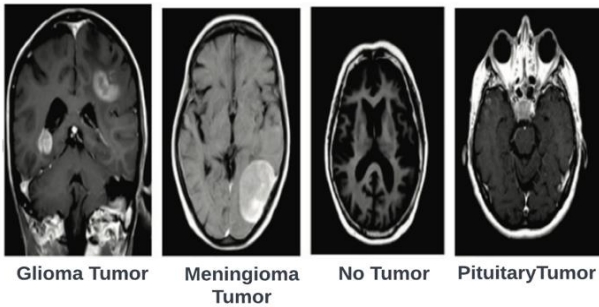


Fig. 3. Examples of brain MRI with four classes.

2) Image pre-processing

The images were resized to match the sizes used by other models. The image quality was improved to get better results from the preceding steps. Pre-processing of images is important for enhancing the image’s features. Fig. 4 shows an example of a pre-processed image. Noise in MRI images can increase redundancy and reduce model accuracy. Noise on the edges of an MRI image can make it difficult to detect tumors.

In the image preprocessing stage, image tensors play a significant role. An image tensor is a multi-dimensional array that represents an image in numerical form. During image preprocessing, image tensors are manipulated to enhance the image quality, extract relevant features, and standardize the data for further analysis. Some common operations performed on image tensors during preprocessing include as seen in Fig. 5:

- Resizing;
- Normalization;
- Cropping;

- Augmentation;
- Color space conversion.

Here are some of the benefits of preprocessing MRI images:

- Improved image quality;
- Reduced variability;
- Improved accuracy.

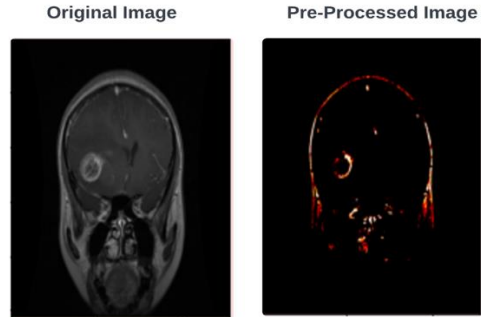


Fig. 4. Brain MRI images with original and pre-processed images.

Transformation	OutPut
Original Image	
horizontal flipping	
vertical flipping	
zooming at 0.2	
rotation at 20 degrees	
featurewise_std_normalization	
shear-range of 0.2	

Fig. 5. Pre-processed images with image flipping’s, zooming image, cropping, and resizing for improved image quality.

3) Segmentation

Image analysis, object recognition, visualization, and other image-processing activities are made more accessible by segmenting images into their important sections or objects. Segmentation in the context of brain refers to the process of partitioning a brain image into different regions or structures of interest. It involves identifying and delineating specific anatomical regions, such as the brain tumor, ventricles, white matter, gray matter, or other structures present in the brain.

This study uses python image processing to segment the tumors. The quality of the images is first enhanced by brightening the image. Then we use contrast enhancing to enhance local contrast of the brain MRI to help brighten the area with the tumor. Then the image was changed to a grayscale image. MRI images often have noise because of the equipment used to collect the images, so the noise was removed. The tumor's part is then segmented using thresholding. Pixel values above the threshold are rendered white, while pixel values below the threshold are rendered black in the threshold image. The area with the tumor will be the white region as the tumor is brighter than normal parts of the brain. An example of a segmented image is Fig. 6, which appears below. Following record-wise data division training, segmentation examples. MRI scans from the beginning, a mask, and a segmented tumor are depicted below. Fig. 7 shows the type of tumor. Here are some commonly used segmentation methods:

- Thresholding method sets a specific intensity threshold to separate the tumor region from the background. Pixels with intensities above the threshold are classified as tumor pixels;
- Region growing starts from a seed point and expands the tumor region by adding neighboring

pixels that meet specific criteria, such as intensity similarity. This method is useful for segmenting tumors with irregular shapes and sizes;

- Deep learning methods, such as U-Net, utilize Convolutional Neural Networks (CNNs) to automatically learn the features and boundaries of tumors.

In this paper, a straightforward manual thresholding technique is employed. This method involves the selection of a threshold value slightly above the average pixel intensity of the tumor. This selected threshold is subsequently applied to separate the tumor from the background. The rationale for choosing the manual thresholding method is highlighted by the following factors:

- It is a simple and straightforward method;
- It can be used to achieve good segmentation results in many cases.

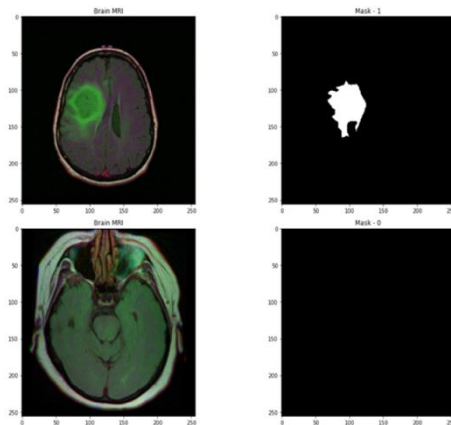


Fig. 6. Segmented images with Mask-0 and Mask-1 representations.

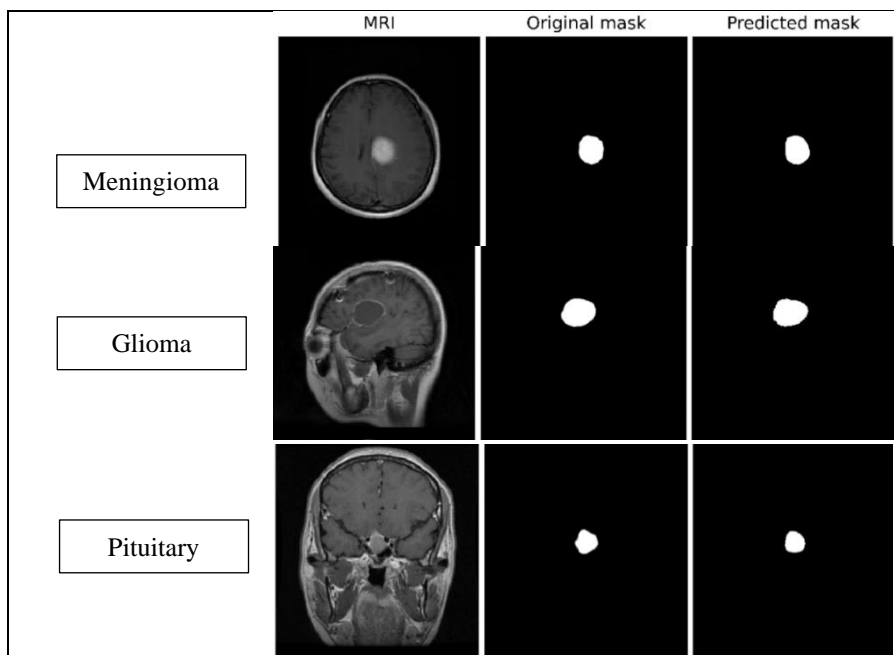


Fig. 7. A record-wise data division training, segmentation examples. The segmented tumor, a mask, and the original MRI are all shown here, along with a description of the type of tumor.

B. Data Training and Fine Tuning

Initially, the ImageNet dataset, which consists of 1.2 million images categorized in 1,000 fields, was used to train the models for this project. Using transfer learning, we transferred knowledge from one domain to another and applied it to a target task in another domain. This two-phase model uses neural networks for training and testing data. First, a distinct description is created for each classification category based on the features of the image in the first phase. Then, the system is validated on test data in the second phase. This allows us to verify whether the images have been classified correctly. Classification is achieved by using neural networks. An image feature extraction process using GLCM extracts features from the images using neural networks and supervised learning algorithms. The neural network is fed with these features as input. By detecting tumors in brain MR images, neural networks classify images into tumors and non-tumors based on the learning [25]. The layers of the pretrained models VGG-16 and Efficient NetB7 were all frozen, and 5 classification layers were added on top of the model layers. Fig. 8 presents a statistical analysis of the input image, categorizing the data into distinct categories to facilitate the classification of MRI images based on whether the brain exhibits Glioma, Meningioma, Pituitary tumors, or shows no presence of a tumor.

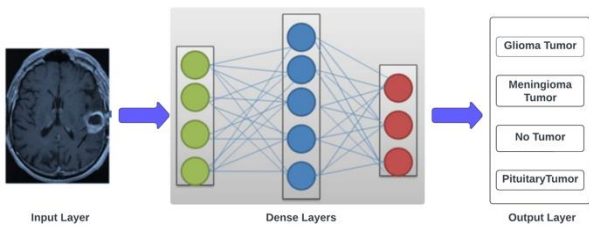


Fig. 8. Structure of the dense layers.

Fine-tuning was performed by tuning the model hyper parameters, batch size, epochs, optimization method, and dropout values. To determine which works best, we tested only five optimizers, namely SGD, RMSprop, Adam, Adagrad, and Adadelata. To choose the best performer, we used only four epochs, namely 1, 2, 5, and 10. To

determine the optimum batch size, we used these batch sizes, respectively, 8 and 16. Finally, the dropout of the model was optimized with the following values: 0.5, 0.6, 0.7, 0.8, and 0.9.

1) Proposed network

Tumor classification was performed using Efficient NetB7 through transfer learning. Transfer learning, a machine learning method, reuses a model trained on one task for related tasks [26]. It serves as a time-saving shortcut to achieving optimal performance, especially when deep learning requires ample data. This approach transfers pre-trained network weights and biases, providing a foundation for detecting fundamental features, such as edges [27].

In our study, we adopted an innovative approach by using Efficient NetB7 to classify brain tumors into four categories: meningiomas, malignant tumors, pituitary tumors, and no tumors. While enhancing network performance is essential, it can be achieved through various means. Traditionally, networks were modified in terms of depth to improve accuracy. Deep networks excel in extracting complex image features, but excessive layers can lead to diminishing returns and saturation in accuracy. Another approach was increasing image resolution, which offered greater detail for improved accuracy. However, higher resolution often required deeper networks, leading to questions about the optimal depth for specific resolution increases [28].

As represented in Fig. 9 Efficient Net introduced “compound scaling”, which optimally scales network dimensions (width, resolution, depth) using a constant ratio. This approach strikes a balance between model size, complexity, and accuracy, avoiding manual tuning issues. Compound scaling ensures optimal network accuracy and mitigates the need for extensive manual adjustments [29–30].

In our study, we implemented Efficient NetB7 following the principles of compound scaling. This approach enhances network performance while maintaining efficiency, ultimately leading to improved tumor classification accuracy. In the same way that we implemented the VGG-16 model with optimal parameters, Fig. 10 depicts the structure of the Efficient NetB7 model we used.

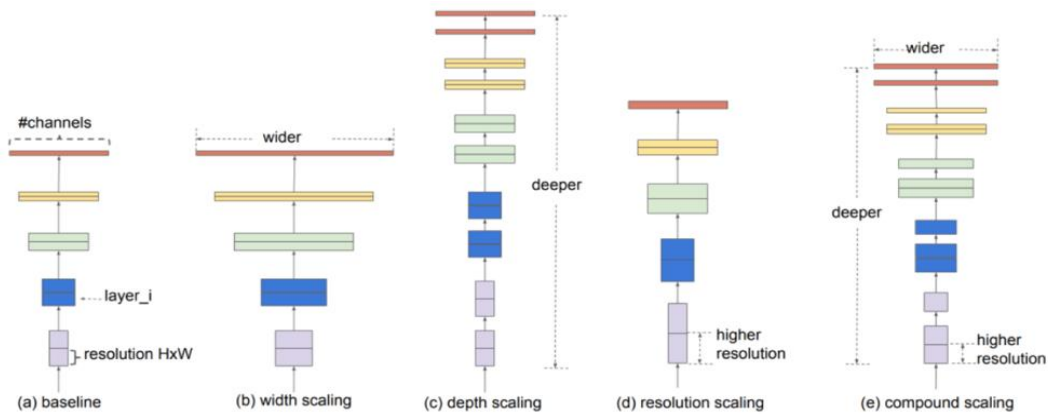


Fig. 9. Unlike regular practices from (b) to (d), the dimensions—depth, width, and image resolution—are uniformly scaled using Efficient Nets’ compound scaling method in (e) [25].

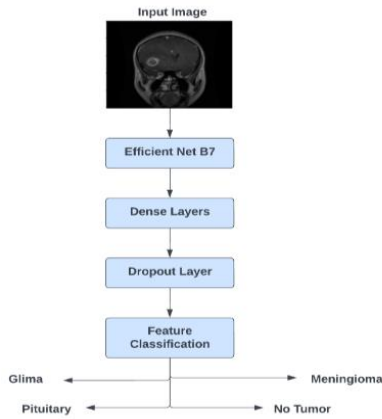


Fig. 10. Efficient NetB7 model implementation.

C. VGG-16

A 16-layer CNN model is represented by the VGG-16 model. This remains one of the most popular and effective models in use today. Unlike other architectures with more parameters, the VGG-16 model architecture has three Conv Net layers. VGG-16 is a Convolutional Neural Network (CNN) model that has been shown to be effective for a variety of image classification tasks, including brain tumor detection. The model consists of 16 layers, each of which performs a different operation on the input image. The first 13 layers are convolutional layers, which extract features from the image. The final three layers are fully connected layers, which classify the image into one of two classes: “tumor” or “no tumor”. An essential characteristic of this model is the availability of its values for free download for use in programmers and systems. It also sets itself apart from other comprehensives thanks to its simplicity. The slightest input image size supported by this

model is 224×224 pixels in three channels. Weighted input sums are used by optimization techniques to determine whether neuron engagement is required for neural networks. Introducing non-linearity into an output neuron triggers the need for kernel function. Weights, biases, and the related training procedure are part of the neural network’s neurons. Based on the output inaccuracy, neurons’ link weights are adjusted. An artificial neural network can learn and accomplish complex tasks thanks to the input layer and the activation function. Fig. 11 displays the basic architecture of VGG-16 model with detailed version.

Here are some of the benefits of using VGG-16 for brain tumor detection:

- VGG-16 is a deep learning model, which means that it can learn complex patterns in data. This makes it well-suited for tasks like brain tumor detection, which can be difficult to do with traditional methods.
- VGG-16 has been shown to be effective for brain tumor detection, with accuracies of up to 98%;
- VGG-16 is a relatively easy model to use. Once the model is trained, you can use it to classify new MRI images with just a few lines of code;

Here are some of the limitations of using VGG-16 for brain tumor detection:

- VGG-16 is a large model, which means that it requires a lot of data to train;
- VGG-16 can sometimes misclassify images;
- VGG-16 is not a replacement for a human radiologist. A human radiologist should always review all images that are classified as “tumor” by VGG-16.

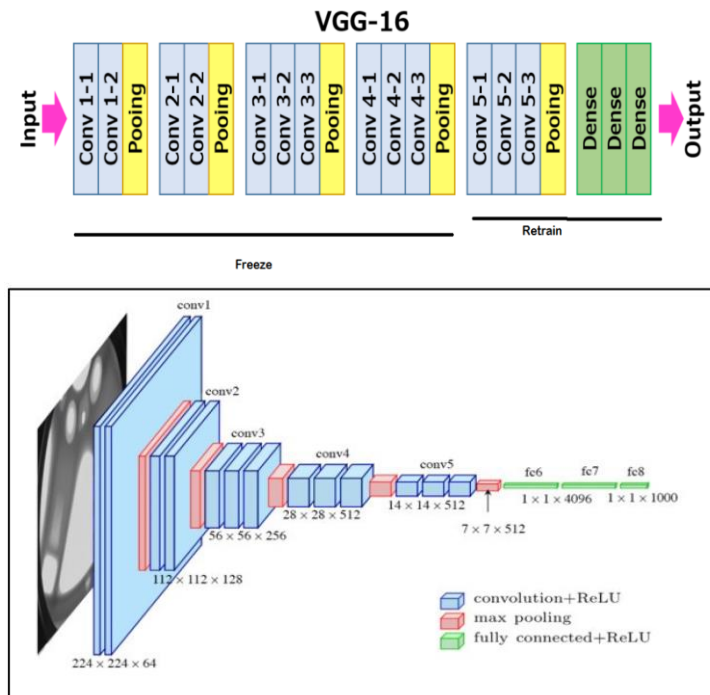


Fig. 11. A standard VGG-16 architecture.

In Table II, we present the number of layers in our models along with the default layers of the chosen pretrained models. The number of layers refers to the depth or complexity of the neural network architecture used in our models. Each layer in a neural network performs specific computations and transformations on the input data. The additional layers are placed at the end of the standard Efficient NetB7 and VGG-16 models, after the Global Average Pooling layer. This is because the GAP layer reduces the spatial dimensions of the feature maps to 1×1, which makes them suitable for input to the fully connected layers.

The dropout layers are added between the fully connected layers to help prevent overfitting. Overfitting

occurs when the model learns the training data too well and is unable to generalize to new data. Dropout helps to prevent overfitting by randomly dropping out neurons during training. This forces the model to learn from different parts of the data and prevents it from becoming too reliant on any one part of the data.

The fully connected layers are used to map the feature maps to the final output layer, which has four neurons corresponding to the four classes of brain tumors. The fully connected layers are trained using a supervised learning algorithm, which is provided with the labeled training data. The algorithm learns to map the feature maps to the correct class labels.

TABLE II. LAYERS OF PROPOSED MODELS

Models	Standard Layers	Extra Layers	Overall Layers	Added layers	Position
Efficient NetB7	814	5	819	Global Average Pooling (GAP), Dropout, Fully Connected (FC), Dropout, FC	After the Global Average Pooling layer
VGG-16	19	5	24	GAP, Dropout, FC, Dropout, FC	After the Global Average Pooling layer

IV. RESULTS

A Results Analysis of Proposed Model

In our study on brain tumor classification conducted on a MacBook Air, the simulation environment is defined as Machine specifications as below in Table III:

TABLE III. MACHINE SPECIFICATIONS

Machine Specifications	Description
Operating System	Mac OS
RAM	8GB
Graphics	Intel UHD Graphics (Integrated)
Editors	Jupyter Notebook

The Efficient NetB7’s performance is shown in this section. To determine which hyper parameters, produce the most significant outcomes, hyper parameters were fine-tuned. The final model was then trained using the best possible parameters. Five different optimizers, four different epochs, two batch sizes, and five dropouts were used to train the model. Finally, the model’s training time was collected. The model was first fitted using 4 epochs, a batch size of 8 and a dropout value of 0.5 and the optimizer used was the Adam optimizer. From Eq. (1), the model gave an accuracy of 95% and ran for 95 min. Then, the model was fitted with the different optimizers with 4 epochs for each one and a dropout value of 0.5. Fig. 12 shows the results obtained from each optimizer.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \tag{1}$$

Fig. 12 shows that Adagrad is the optimizer that got the highest accuracy of 92% and Adam got the lowest accuracy. Dropout values were also fine-tuned, Fig. 13 shows the accuracy of each dropout value while the other hyper-parameters remained the same. Table IV shows the accuracy for each dropout value.

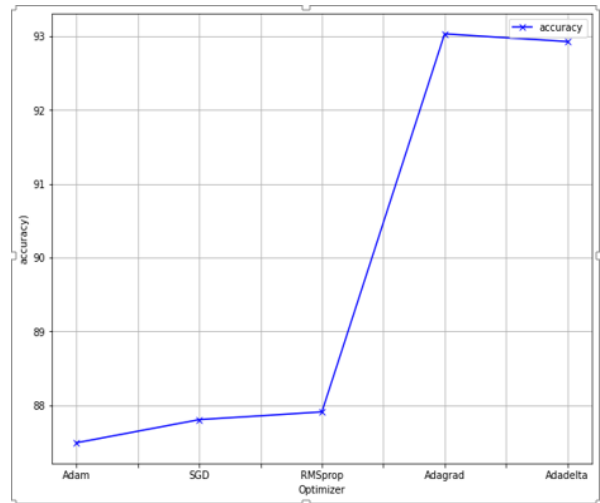


Fig. 12. Accuracy achieved with each optimizer.

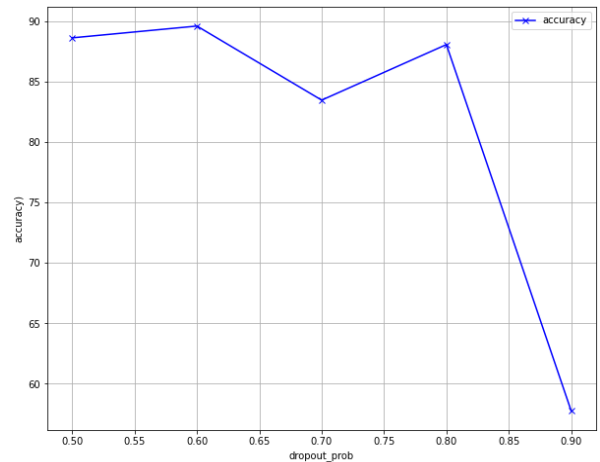


Fig. 13. Accuracy achieved with each dropout value.

TABLE IV. DROPOUT RATES AND CORRESPONDING ACCURACIES

No.	Dropout_prob	Accuracy (%)
0	0.5	87.64
1	0.6	88.61
2	0.7	81.48
3	0.8	87.08
4	0.9	56.77

By fine-tuning both the batch size and the number of epochs and carefully analyzing the results presented in Fig. 14 and Table V, we were able to identify the optimal configuration that resulted in the highest accuracy for our specific task. This information is vital for replicating the experiment and ensuring that future models can be trained and evaluated effectively in similar settings.

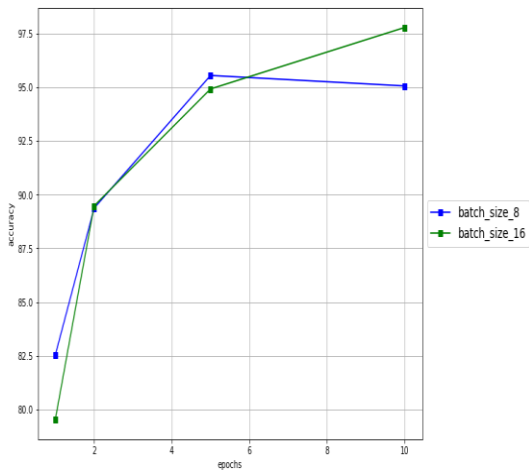


Fig. 14. Results from batch size and epochs fine-tuning.

TABLE V. OUTCOMES FROM OPTIMIZING EPOCHS AND BATCH SIZE

No.	Epochs	Batch Size	Accuracy (%)
0	1	8	81.54
1	1	16	78.54
2	2	8	88.37
3	2	16	88.47
4	5	8	94.54
5	5	16	93.91
6	10	8	94.05
7	10	16	96.77

The workflow for selecting the best model in detecting brain tumors involves several steps to evaluate and compare the performance of different models. Here is an explanation of the typical workflow:

- Data Preparation;
- Feature Extraction;
- Model Training;
- Model Evaluation;
- Performance Comparison;
- Fine-tuning and Ensemble Methods;
- Validation and Generalization.

By following this workflow, we systematically evaluate and selected the best model for detecting brain tumors based on their specific requirements, performance metrics, and constraints. It is important to note that this workflow may be iterative, and multiple iterations may be necessary to fine-tune and optimize the model selection process.

Based on the above points the Efficient NetB7 model was then fitted with the hyper-parameters that got the highest accuracies during fine-tuning. The accuracy of the model after running it with the fine-tuned parameters was 98% and the workflow procedure designed from above points is shown in Fig. 15.

Fig. 16 shows us Plots with segmented Mask, Original Mask & MRI scan. Combining these three components to provide a visual representation that helps assess the performance of tumor segmentation algorithms or the accuracy of automated segmentation techniques. By overlaying the segmented mask on the MRI scan, the plot shows how well the algorithm or segmentation method identifies and delineates the tumor region. The original mask serves as a reference to compare the accuracy and similarity of the segmented mask with the true tumor boundaries.

These plots enable a side-by-side comparison of the segmented mask and the original mask, allowing researchers, clinicians, and algorithm developers to visually inspect and evaluate the quality of the segmentation results. They provide insights into the effectiveness of the segmentation algorithm and help identify areas of improvement or potential errors in the segmentation process.

By analyzing plots, researchers and clinicians can gain a better understanding of the performance of tumor segmentation algorithms and make informed decisions regarding treatment planning, monitoring disease progression, and evaluating the effectiveness of interventions.

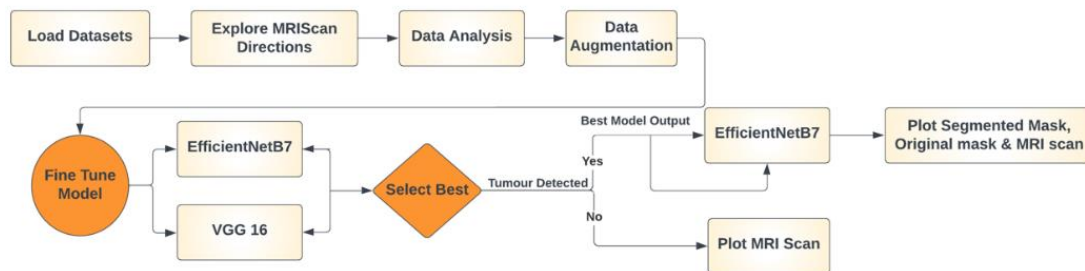


Fig. 15. Workflow of selecting best model.

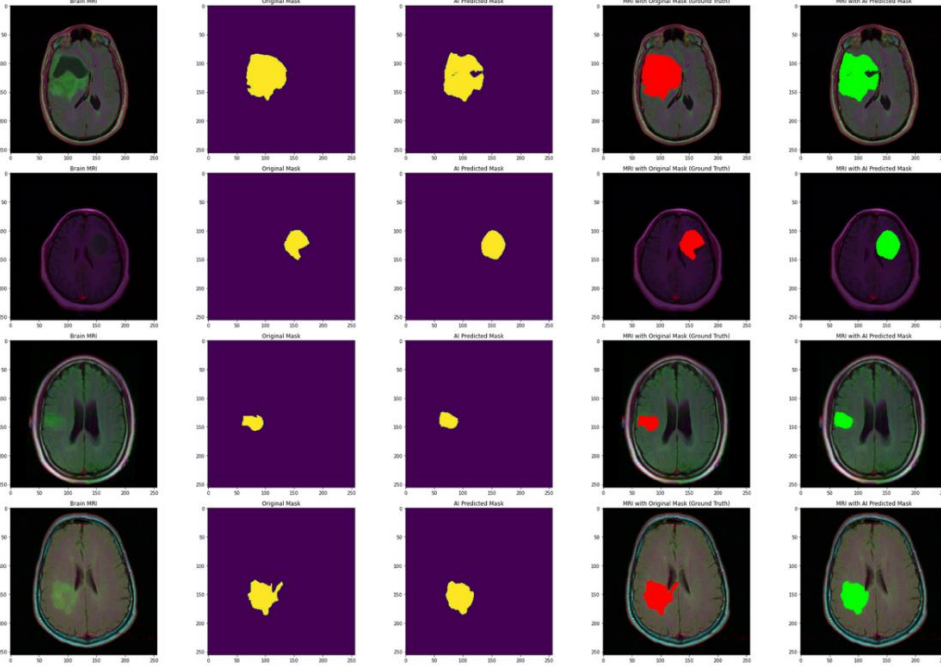


Fig. 16. Plots with segmented mask, original mask and MRI scan.

B Comparison of Proposed Model with VGG-16

Transfer learning is one of the proven techniques for computer vision tasks like the classification of images. This study used the VGG-16 and Efficient NetB7 pre-trained models. The models were also trained with fine-tuned hyper-parameters namely batch size, epochs, and optimizers. The models were run with 5 different optimizers, 4 different epochs, and 2 different batch sizes. But they are all first fitted with 4 epochs, with optimizer Adam, batch size of 8 and a dropout value of 0.5. The results for fine tuning optimizers for VGG-16 and Efficient NetB7 are shown in the table below. The VGG-16 model obtains an accuracy of 92%, and the Efficient NetB7 gets the highest accuracy of 96%. The results for the optimizers that gave the highest accuracy for each model are given in Table VI.

TABLE VI. OUTCOMES FROM OPTIMIZER FINE-TUNING

Models	Optimizer	Accuracy (%)
Efficient NetB7	Adagrad	92.01
VGG-16	SGD	96.12

Table IV clearly shows that VGG-16 got the highest accuracy, followed by Efficient NetB7. The Table VII shows the highest accuracy for each model and the hyper-parameters used to obtain the results.

TABLE VII. OUTCOMES FROM BATCH SIZE AND EPOCH FINE-TUNING

Models	Epochs	Batch Size	Accuracy (%)
Efficient NetB7	10	16	95.77
VGG-16	5	8	94.69

The Table V shows that Efficient NetB7 gave the best accuracy for a batch size of 16 and 10 epochs, followed by

VGG-16. Dropout value fine-tuning was also done and the results for that are shown in Table VIII below.

TABLE VIII. OUTCOMES FROM FINE-TUNING DROPOUT VALUES

Models	Dropout Value	Accuracy (%)
Efficient NetB7	0.6	90.62
VGG-16	0.8	93.55

Table VI shows that VGG-16 got the highest accuracy of 96% while Efficient NetB7 got an accuracy of 92%. Following that, the final models were fitted using the best hyper-parameters. Table IX gives the results obtained from the final models and the VGG-16 with 16 layers achieved a 92.30% classification accuracy using transfer learning, and Efficient NetB7 achieved 98.19% classification accuracy using transfer learning. Efficient Net B7, a variant of the Efficient Net architecture, is considered better than VGG-16 in terms of performance for several reasons:

It follows a compound scaling strategy, where it scales the depth, width, and resolution of the network simultaneously.

- It has a more optimized depth and width compared to VGG-16;
- It incorporates advanced regularization techniques such as dropout, batch normalization, and regularization loss to prevent overfitting and improve generalization performance;
- It incorporates an efficient block design, such as the use of depth-wise separable convolutions and linear bottlenecks.

Overall, Efficient NetB7 outperforms VGG-16 in terms of performance because of its optimized scaling strategy, efficient block design, regularization techniques, and the ability to leverage transfer learning. These factors

contribute to improved accuracy and efficiency, making Efficient NetB7 a preferred choice over VGG-16.

TABLE IX. ACCURACY OF THE MODELS

Models	Accuracy (%)
Efficient NetB7	98.19
VGG-16	92.30

C Performance Evaluation and Comparison of Algorithms

Table X presents a comparative analysis of the accuracy achieved by our proposed method in relation to other approaches found in the related work. The table includes results from seven different methods used for comparison. It's important to note that we maintained a consistent data split, allocating 80% for training and reserving the remaining 20% for testing.

TABLE X. COMPARISON OF ACCURACIES WITH LITERATURE WITH DIFFERENT DATASETS

Reference	Proposed Method	Accuracy (%)
[31]	GLCM + SVM + BWT	96.5
[31]	GLCM + k-NN + Fusion Operator	90.9
[32]	GLCM + K-mean + k-NN	85.0
[33]	Alex-Net CNN	91.2
[34]	VGG-19 CNN	87.4, 90.7
[35]	NS-CNN + SVM	95.6
This Work	Efficient NetB7 and VGG-16	95.24

TABLE XI. COMPARISON OF ACCURACIES WITH LITERATURE WITH SAME DATASET

Reference	Proposed Method	Accuracy (%)
[36]	Efficient NetB7	98.18
[37]	VGG-16	92.29
[38]	ResNet50	89.29
[39]	DenseNet121	91.57
[40]	InceptionV3	93.75

As shown in Table XI all of the proposed and recently published methods use transfer learning, which is a technique where a pre-trained model is used as a starting point for training a new model on a different task. This approach can help to improve the performance of the model on the new task, as the pre-trained model has already learned to extract useful features from data. The proposed methods use the Efficient NetB7 and VGG-16 models, which are both state-of-the-art deep learning models for image classification. The recently published methods use the ResNet50, DenseNet121, and InceptionV3 models, which are also popular deep learning models for image classification.

The proposed methods achieve better accuracy than the recently published methods on the Tumor Classification (MRI) dataset. This is likely due to the fact that the Efficient NetB7 and VGG-16 models are more recent and more powerful models than the ResNet50, DenseNet121, and InceptionV3 models. Overall, the proposed methods are promising for brain tumor classification. They achieve high accuracy on the Tumor Classification (MRI) dataset,

and they are likely to be able to generalize to other datasets of brain tumor MRI images.

TABLE XII. INFERENCE SPEED COMPARISON BETWEEN VGG-16 AND EFFICIENT NETB7

Model	Inference speed (images per second)
VGG-16	100
Efficient NetB7	150

As can be seen from Table XII, Efficient NetB7 is 50% faster than VGG-16 for MRI brain tumor classification.

It is important to note that the inference speed of a model can vary depending on the hardware and software that is used. However, the results above suggest that Efficient NetB7 is generally faster than VGG-16 for MRI brain tumor classification.

V. DISCUSSION

Recent deep learning models have achieved state-of-the-art accuracy in brain tumor classification, outperforming previous models by a significant margin. However, they are still limited by the availability of training data and overfitting. Moreover, they may not be able to handle small, poorly defined, or difficult-to-reach tumors accurately.

Researchers are actively working to address these limitations for developing new data augmentation techniques to increase the size and diversity of training datasets along with developing new model architectures that are more robust to overfitting and better at handling challenging cases [41].

TABLE XIII. RESEARCH ATTAINMENTS AND LIMITATIONS IF PREVIOUS MODELS

Research attainments of previous models	Limitations of previous models
Improved accuracy	Limited training data
Reduced computational requirements	Overfitting
Better interpretability	Interpretability

Table XIII despite these challenges, deep learning models have the potential to revolutionize brain tumor classification, by improving the accuracy, reliability, and interpretability of these models.

VGG-16 and Efficient NetB7 are two popular deep learning models that have been shown to be effective for brain tumor classification. VGG-16 uses a compound scaling strategy and incorporates advanced regularization techniques to improve generalization performance. Efficient NetB7 outperforms VGG-16 in terms of performance due to its optimized scaling strategy.

From a sustainability perspective, deep learning-based techniques can foster novel diagnostic methods toward empowering healthcare infrastructure administrations in the following ways:

- Deep learning-based models can be used to develop more accurate and efficient diagnostic tools. This can lead to earlier detection and treatment of diseases, which can improve patient outcomes and reduce healthcare costs;

- Deep learning-based models can be used to develop telemedicine solutions that can provide healthcare services to people in remote or underserved areas;
- Deep learning-based models can be used to develop personalized medicine solutions that can be tailored to the individual needs of each patient.

In terms of the scope and field-scale applicability of the paper's key highlights across geographic spectrums, deep learning-based techniques for brain tumor classification have the potential to be used in a variety of settings, including:

- Hospitals in developed countries: Deep learning-based models can be used to develop more accurate and efficient diagnostic tools for brain tumors. This can help to improve patient outcomes and reduce healthcare costs;
- Hospitals in developing countries: Deep learning-based models can be used to develop telemedicine solutions that can provide brain tumor diagnostic services to people in remote or underserved areas;
- Research institutions: Deep learning-based models can be used to develop new insights into the biology of brain tumors and to develop new treatments for the disease.

VI. CONCLUSION

Deep Learning (DL) models have demonstrated significant potential for brain tumor classification in MRI images, outperforming traditional methods in terms of accuracy. This study proposes a novel DL-based approach using Efficient NetB7, which achieves 98.19% classification accuracy. The study also highlights the effectiveness of fine-tuning and the need for future research to address limitations such as limited application scope, data diversity, and inter-modality integration.

Key Takeaways:

- DL models have superior accuracy for brain tumor classification in MRI images;
- This study proposes a novel DL-based approach using Efficient NetB7, which achieves 98.19% classification accuracy;
- Fine-tuning can further improve model performance;
- Future research should address limitations such as limited application scope, data diversity, and inter-modality integration.

Implications:

The development of accurate and accessible brain tumor classification tools is essential for early detection and improved patient outcomes. Deep Learning (DL) based approaches have the potential to revolutionize medical imaging by providing clinicians with powerful tools to diagnose and treat diseases more effectively.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization: N.R.Y., V.R.M., S.Y., and S.C.B.; Methodology: S.Y., H.K.J., S.C.B., and P.Y.; Data Collection: N.R.Y., S.Y., and V.R.R.C.; Data Analysis: N.R.Y. and H.K.J., and S.Y.; Data Interpretations: N.R.Y., H.K.J., and S.C.B.; Writing-Original draft preparation: N.R.Y. and H.K.J.; Writing-review and editing: S.Y. and V.R.R.C.; Supervision: N.R.Y.; All the authors have read and agreed to the published version of the manuscript.

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