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RESEARCH ARTICLE

A Novel Approach of Progressive Transfer Learning for MRI Brain Tumor Classification Using VGG16 and MobileNet Architectures

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Abstract

Around the world, brain tumors are a major cause of human mortality. Accurate brain tumor detection is essential for effective treatment and improved patient outcomes. This study introduces the progressive transfer learning method, using VGG16 and MobileNet for the brain tumor identification and classification task. The outcome demonstrated the importance of the proposed models. The final accuracy of VGG16 and MobileNet on the test data was 98% and 87%, respectively, highlighting the superiority of VGG16 over the MobileNet framework. In addition, future work suggests advanced fine-tuning strategies, regularization techniques, and other methods to improve model performance for helping medical professionals in brain tumor diagnosis.

Keywords: brain tumor classification, transfer learning, VGG16, MobileNet, model fine-tuning.

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1 Introduction

The human brain is a vital and complex organ, performing numerous essential tasks. Sometimes, due to health issues, multiple unwanted cells grow in the brain. This medical condition is very harmful, and it is termed a brain tumor [1]. Millions of people in the world die at an early age due to tumors. Brain tumors are commonly categorized as benign and malignant [2]. Benign tumors are non-cancerous, and malignant tumors are cancerous. The other important category of brain tumors is primary tumors, which originate from the brain structure, and secondary tumors, which originate from other body parts and spread to the brain structure. In the brain tumor treatment procedure, the main aim of medical professionals is to detect it in the early stage. Early-stage diagnosis can decrease the mortality rate and increase the chances of survival for the patient. In modern days, several computerized methods are employed to diagnose brain tumors. Among all the computerized methods, MRI is the most promising tumor detection method due to its various applications.

In today's era, manually analyzing millions of MRI pictures is a difficult task, and it leads to wrong diagnoses. With the evolution of artificial intelligence, researchers want to use an automatic tumor detection system with no human intervention using various

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advanced techniques. However, ML frameworks have more time complexity, with less accuracy, and are expensive. Compared to it, deep learning algorithms, especially deep CNN, can easily recognize complex image patterns automatically and have self-learning features, which make it suitable for an automatic brain tumor diagnosis system [3]. Although deep learning algorithms, CNN, fulfill all the requirements for an automatic tumor detection system, they require a high volume of image data for training purposes. To overcome this type of limited and expensive input data problem, transfer learning has appeared as a Progressive technique, which can speed up and improve the process. The transfer learning technique performs the image classification task more effectively and reliably [4]. In modern times, various transfer learning frameworks have been employed from deep learning algorithms, which emphasize the "knowledge transfer" process. Using the transfer learning technique, a deep learning model does not require training from scratch, but also transmits the high-level attributes from pre-trained models to newly developed deep learning-based frameworks. It can reduce computational time and resources, and traditional MRI analysis provides outstanding results in the field of medical image processing. Conversely, various transfer learning research has been carried out for brain tumor classification, but most of them have some limitations, such as old, noisy data sets, low performance, improper analysis results on various performance metrics [5]. In the present research, we examined and compared the effectiveness of multiple pre-trained models for MRI brain tumor classification under a limited training data set. By examining two pre-trained models, VGG16 and MobileNet [6], within the progressive transfer learning architecture, the research aims to identify the various adjustments between accuracy, efficiency, and generalizability, and develop and evaluate the progressive transfer learning framework for the MRI tumor detection system.

The following are the main contributions of this research work:

- Introduce the progressive transfer learning framework, using two popular pre-trained models [7].
- Describe a complete data pre-processing step, including resizing, normalization, and data augmentation [8].
- Applied regularization and fine-tuning methods to enhance the accuracy of proposed models [9].
- Experimented to evaluate the working performance of the frameworks using multiple standard performance parameters [10].
- At last, we provide a comparative analysis of our experiment.

The remaining paper is arranged in such a manner that section 2 critically analyses the previous studies, section 3 describes the materials and methods, section 4 discusses the results and experiment, and the last section discusses the final conclusion and future research scope.

2 Related Work

Many researchers have proposed several advanced methods to predict various tumors using AI and related advanced methods. This related work section provides an overview of the development of this domain.

2.1 Conventional method for Brain tumor identification

Before applying deep learning, tumor classification mainly depended on traditional machine learning methods using conventional algorithms with feature extraction.

The study [11] proposed a method for tumors classification using hyperspectral Imaging (HSI) in combination with supervised Machine Learning (ML) algorithms. It presents a comparative analysis of support vector (SVM) and Random Forest (RF) algorithms. The final result shows that SVM achieves 97% and RF achieves 100% mean accuracy on training data. The main limitations were a limited data set.

Another important study [12] was performed on a malignant brain tumor data set. Various machine learning algorithms were used for predicting classification accuracy. Based on the different machine learning algorithms, the accuracy on test data was 88.44%, 92.6%, and 95.87% respectively.

2.2 Brain tumor classification using Deep Learning

In modern days, DL technology is popular for tumor classification tasks. The study [13] applies various deep learning frameworks to train their data set. The F1 scores on test data were 98.75%, 97.50%, and 97.25% respectively. These accuracies provide a positive impact on tumor classification. Paper [14] proposed a DL based model to classify various types of brain tumors. The data set contains 3046 and 516

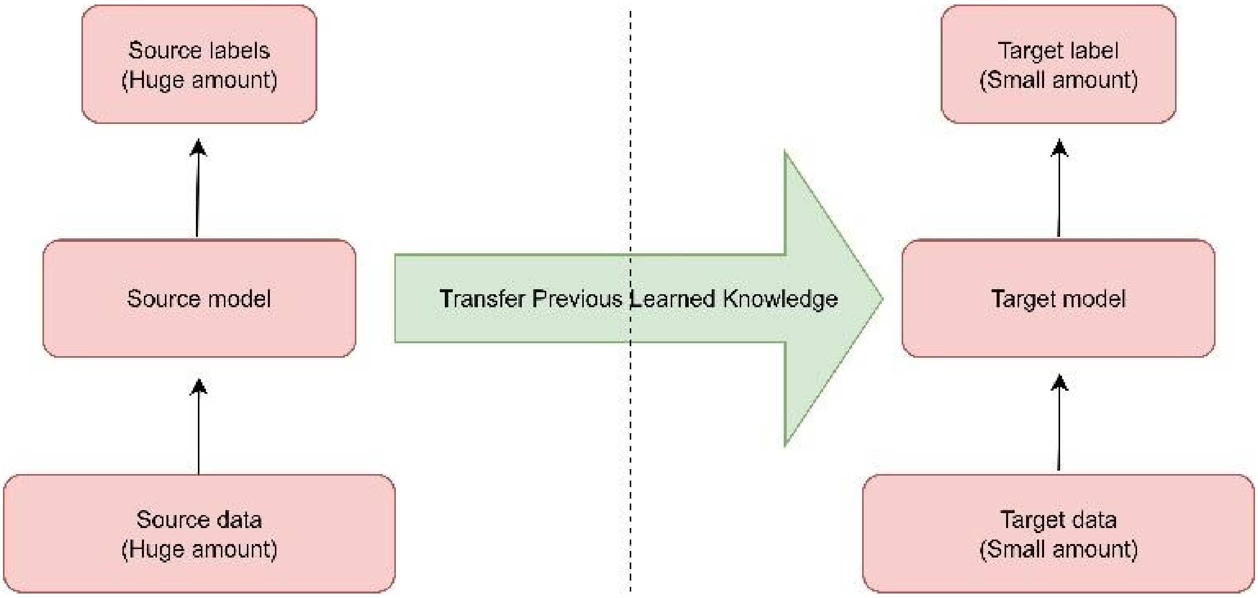

Figure 1. Transfer learning method.

images for experimental purposes. The suggested architecture achieves 96.14% and 98.6% accuracy. Paper [15] suggested a novel CNN architecture. The suggested CNN classifier provides high performance in classifying brain tumors into various classes. The suggested model provided more than 98% accuracy results. The research work [16] suggested an intelligent framework for various tumor-related activities. It provided 92.13% accuracy, which indicates the superiority of the proposed model. The study [17] proposed a hybrid DL architecture called DeepTumorNet, for the classification of brain tumors. The suggested architecture provides high-performance metrics, achieving 99.67% accuracy.

2.3 Transfer learning in brain tumor classification

Transfer learning has various advantages related to brain tumor classification. It is very useful when the data size is limited. In paper [18], the authors proposed a method to detect brain tumors. It employs a thresholding method. In their experimental work, they used a transfer learning method using AlexNet and GoogleNet architectures. The effectiveness of this research work was examined by various standard parameters. The research [19] was conducted on AlexNet, GoogleNet, and VGG19 architectures. In the end, VGG19 achieved the highest training accuracy of 98.69%. The study [20] proposed an AI-based brain tumor classification model. The input images classify brain tumors into malignant and benign. The data set consists of 969 images. The proposed model achieved a super accuracy of 99.04%. The results signify the importance of the proposed algorithm in brain tumor classification. Existing tumor classification techniques have limited input data. Progressive transfer learning overcomes this issue and is gaining popularity day by day.

3 Methods and Materials

The following section describes the various methods and materials used in this research study. It explains the multi-class tumor classification with transfer learning using multiple pre-trained frameworks. The experimental work defines various essential steps of image data processing. In addition, the experimental output is examined by applying multiple parameters. This section is categorised into multiple sub-sections according to the methodology.

3.1 Data Collection and Pre-processing

In the initial phase, we collect a dataset from various sources to ensure diversity in input data. After the data collection, we performed a pre-processing operation [21] to make the data set as clean as possible. It is the most effective way to improve the appearance of the provided data. Furthermore, it enhances the quality of the images. Since all the input images are different in size, we resize them equally to 128 x 128 dimensions. It will reduce the computational complexity of the proposed framework.

3.2 Data Augmentation

It is an efficient technique in deep learning that increases the amount of input data by adding more images using minimal alteration in the previous

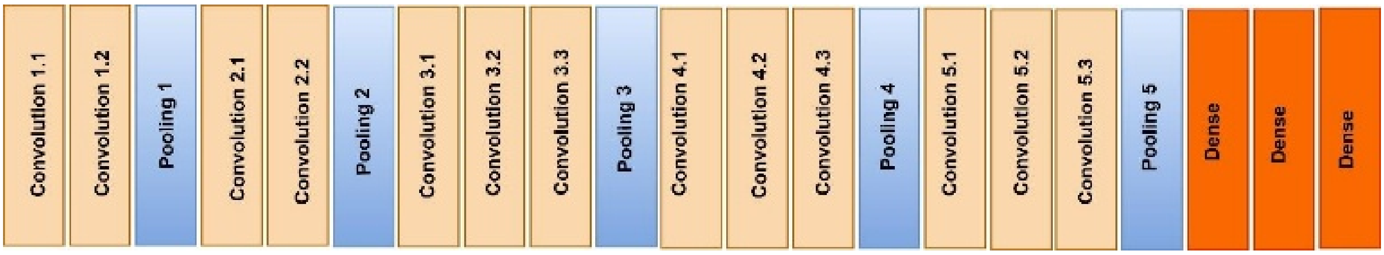

Figure 2. The VGG-16 pre-trained model architecture.

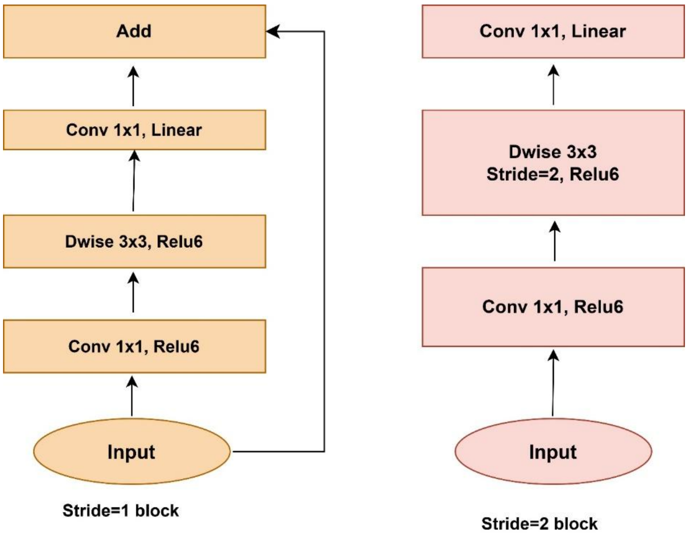

Figure 3. The MobileNet pre-trained model architecture.

images. In the proposed study, various augmentation methods [22] like rotation, shifting, rescaling, and zooming have been applied.

3.3 MRI Dataset Description

The experimental datasets were collected from the online source Kaggle, where all datasets are publicly available. All pictures were stored in JPG format. The images represented Glioma, Meningioma, Pituitary tumor classes, and one no-tumor class [23]. All the input pictures were divided into categories like training data, test data, and validation data. The Following table represents the overview of the MRI data set (Table 1).

3.4 Transfer Learning

It is an advanced popular technique that reuses previously acquired knowledge (Figure 1). It uses previously learned features and uses them on new, related tasks using already trained models. This approach improves training activity and enhances the working framework's performance. Due to the popularity of the transfer learning [7] approach, we include two famous pre-trained frameworks, including VGG16 and MobileNet, in our research methodology. These frameworks have outstanding feature extraction skills with accurate image classification capabilities. These frameworks were already trained on the popular huge ImageNet dataset [24]. In addition, various factors of the frameworks are fine-tuned to enhance the accuracy of the proposed frameworks. The above two pre-trained models are explained in Figure 1:

3.4.1 VGG16 Framework

It is a CNN [25] based pre-trained architecture, which is often used as a base model for transfer learning due to its simplicity and effectiveness. It has deep architecture consisting of 16 convolutional and FC layers. It constructs a sequential architecture, with alternating convolutional and max-pooling layers, followed by FC layers. A standard VGG-16 framework has 5 convolutional blocks with filter size 3×3, stride 1, and the same padding. In addition, a max pooling layer followed by 3 FC layers is also present in the framework. The FC layers contain thousands of neurons. Furthermore, two activation functions, "ReLU" and softmax [26], are used in the picture classification task. The architecture is designed to

Table 1. MRI dataset description.

Sr. No.	Attribute	Description
1.	Total Number of Images	13674
2.	Resolution	128X128
3.	Format	JPG
4.	Types of Tumors	Glioma, Meningioma, Pituitary
5.	Positive Cases	10735
6.	Negative Cases	2939

capture the hierarchical features of images through progressively deeper layers, as presented in Figure 2.

3.4.2 MobileNet Pre-trained Model

MobileNets were introduced by Google in 2017 to fulfill the increasing demands of smartphones and other handheld devices [27]. They focused only on performance without any compromise. They reduced the parameters and their computational cost. They are available in different versions, like V1, V2, and V3. Version V1 (Figure 3) achieved 89.9% of accuracy on the benchmark ImageNet dataset.

It is developed on standard depth-wise separable convolutions that factorize a simple convolution into a point-wise convolution. The depth-wise convolution uses only one filter for every channel. Furthermore, a 1x1 convolution is used to combine the outputs of the depth-wise convolution. The factorization drastically reduces computation and model dimension.

3.5 Fine-Tuning Strategies

The next important step in transfer learning is parameter fine-tuning [28]. The fine-tuning of parameters experts the model according to the new application and data set requirements. It ensures that the model uses the existing knowledge learned from the previous data set and extracts and refines the knowledge learned from the new data set.

In our proposed experiment, the last three layers of frameworks are fine-tuned. Our proposed "Sequential base model" integrates the flattened, dropout, dense layer, and a "ReLU" activation function. A special "softmax" function is also used here. The various weights are initialized with some random values. All the images were resized to 128x128 to reduce intricacy in the proposed model. To overcome the overfitting problems, we increased the training data using data augmentation techniques. We employed the Adam optimizer, setting dropout rates at 0.5 to reduce overfitting. The models were trained on 30 epochs with early stopping.

3.6 Model Evaluation Metrics

Evaluating a model's performance is very important to determine its efficiency and reliability. Therefore, our proposed research work uses the following evaluation matrices to evaluate the suggested framework [29].

- **Accuracy:** It determines the correct prediction percentage against the total test data. The following equation presents the formula.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

- **Precision:** It determines the correct class compared to the positive predictions generated. Precision is presented by the equation below.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- **Recall:** Determining all positive values of the targeted class is called recall. The following formula represents recall.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- **F1-score:** It does not determine using the simple average; instead, it uses the harmonic average of precision and recall to distinguish itself.

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

In the above equations, TN, TP, FN, and FP are the commonly used abbreviations that represent various classification values.

- **AUC-ROC:** The ROC curve plots the recall value against the 1-specificity for different threshold values. The AUC score 1 indicates the 100% accuracy of the framework, and score 0 represents the 0% accuracy of the proposed framework [30].

3.7 Experimental Environment

The experiments were performed on Google Colab with a Python 3 environment. The default GPU session of Colab was used. The RAM and hard disk were utilized in standard computing. The experimental coding is based on the TensorFlow framework and Keras library [31].

4 Results and Discussion

This section visualizes the various outputs and discusses the experiments. It evaluates the detailed performance of the applied frameworks on the dataset and its outcomes.

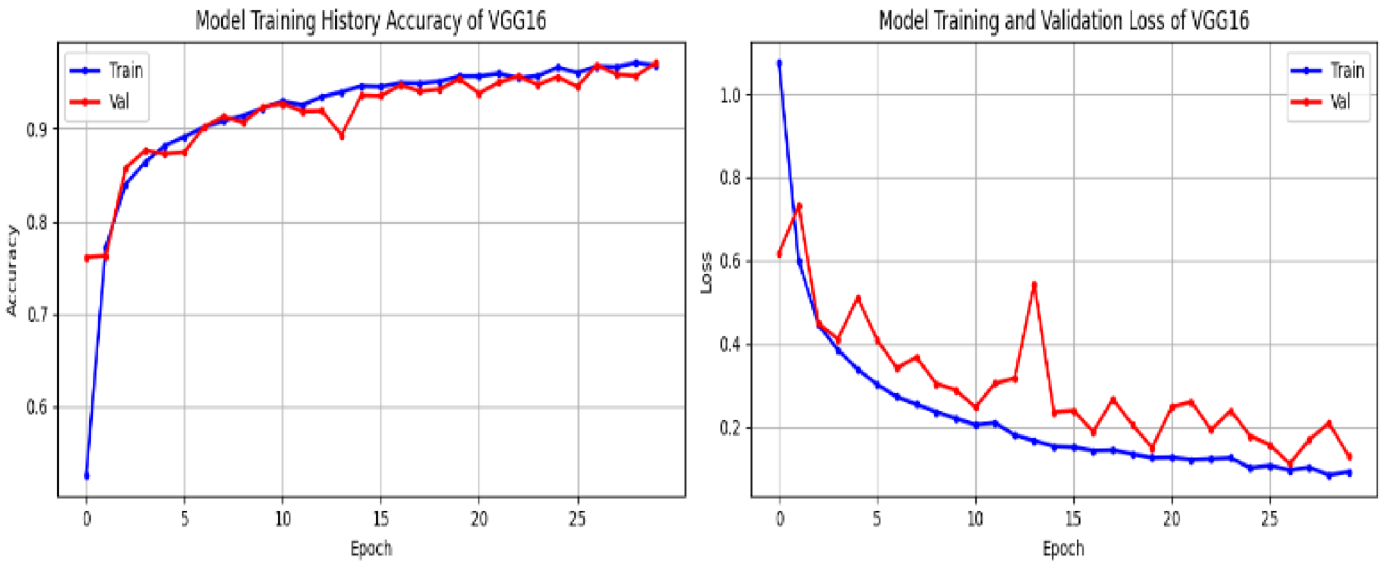

Figure 4. Accuracy Graph based on VGG16 model.

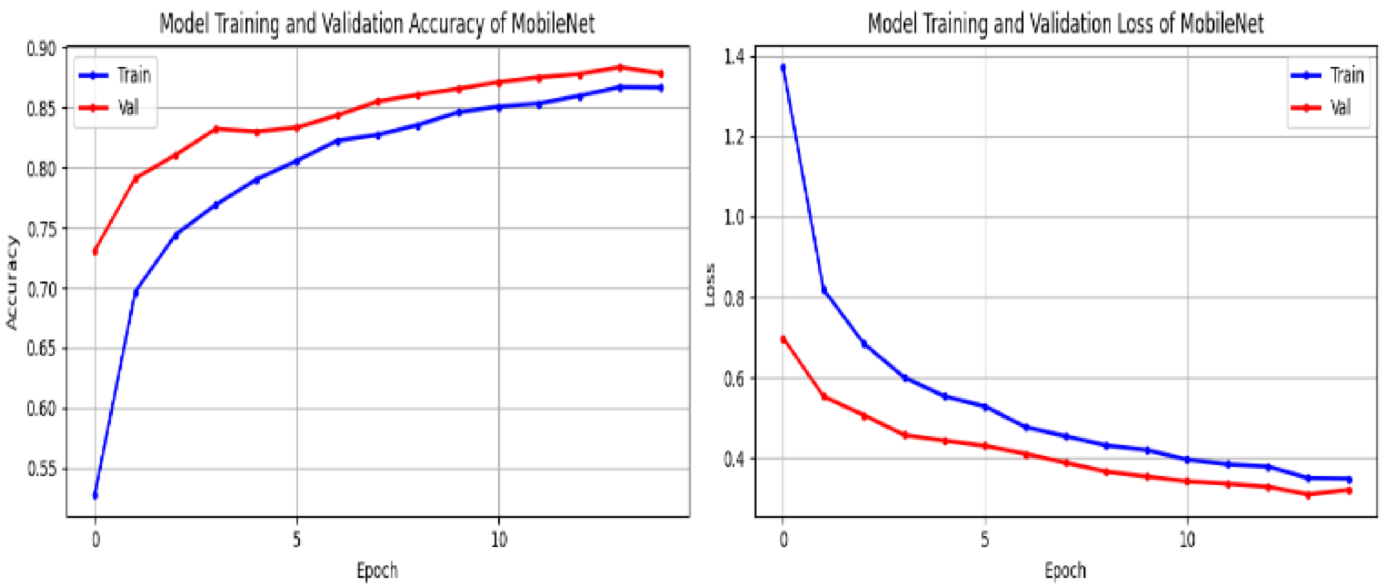

Figure 5. Accuracy Graph based on MobileNet model.

4.1 Training and Validation Performance

As we can see, the classification algorithm provided excellent results using MR images. According to the output, the accuracy on test data using VGG16 was 98%, and using MobileNet was 87%. The robust and consistent output of the VGG16 and MobileNet frameworks suggests their significance in accurate brain tumor diagnosis. The accuracy and loss performance are visualized using Figures 4 and 5.

4.2 Confusion Matrix

The diagram below (Figures 6 and 7) represents the popular confusion matrix for the VGG16 and MobileNet frameworks. This confusion matrix shows the actual counts of positive and negative parameters for each tumor class [32]. It provides a detailed performance overview, highlighting misclassifications and helping to visualize each tumor class.

4.3 Classification Report

The classification report and charts (Figures 8, 9, 10 and 11) present key performance metrics for each tumor class, along with the overall accuracy, as well as the macro and weighted averages across all tumor classes.

4.4 AUC-ROC Curve

Figures 12 and 13 present the popular ROC curve and report the AUC for each tumor class. It examines the

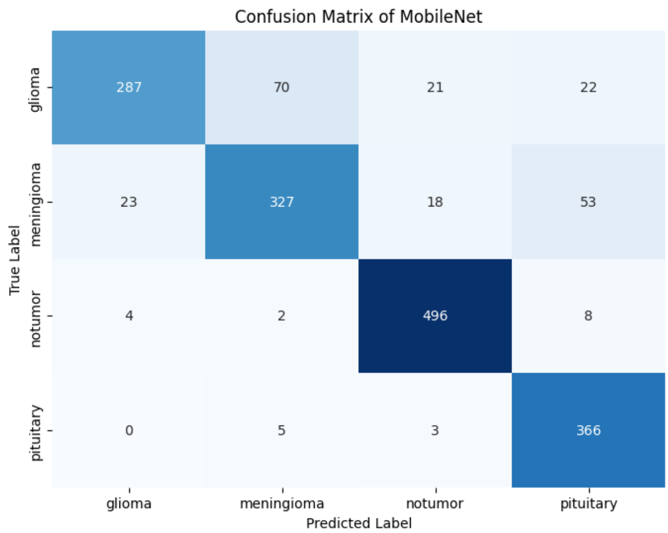

Figure 6. Confusion Matrix using VGG16.

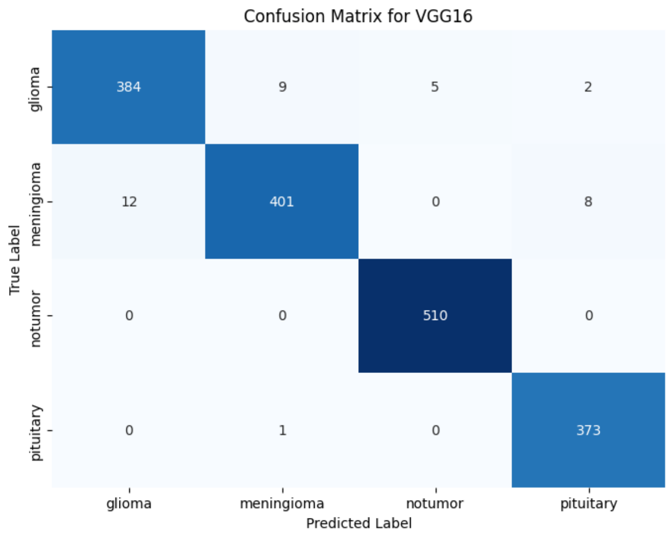

Figure 7. Confusion Matrix using MobileNet.

	precision	recall	f1-score	support
0	0.97	0.96	0.96	400
1	0.98	0.95	0.96	421
2	0.99	1.00	1.00	510
3	0.97	1.00	0.99	374
accuracy			0.98	1705
macro avg	0.98	0.98	0.98	1705
weighted avg	0.98	0.98	0.98	1705

Figure 8. Classification report using VGG16.

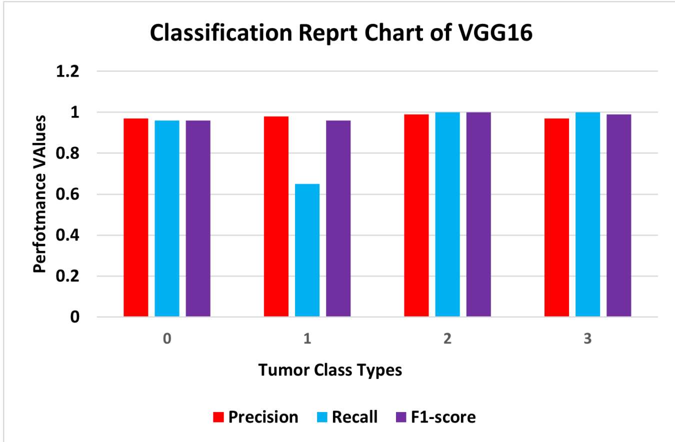

Figure 9. Classification report chart of VGG16 tumor classes.

	precision	recall	f1-score	support
0	0.91	0.72	0.80	400
1	0.81	0.78	0.79	421
2	0.92	0.97	0.95	510
3	0.82	0.98	0.89	374
accuracy			0.87	1705
macro avg	0.87	0.86	0.86	1705
weighted avg	0.87	0.87	0.86	1705

Figure 10. Classification report using MobileNet.

model's reliability to differentiate all tumor classes. The curve highlights several advantages, such as assessing discriminative power, robustness to class imbalance, and visualizing the relation between TPR and FPR of various tumor classes. Based on the above result, it is clear that VGG16 has outperformed the MobileNet pre-trained model. The test accuracy of VGG16 is higher than that of MobileNet. Other performance parameters also suggest that VGG16 is superior to the MobileNet framework, and it is a reliable model for image processing task. A Comparative result analysis of VGG16 and MobileNet is represented in Table 2.

Table 2. Comparative analysis of VGG16 and MobileNet architecture.

	VGG16 Pretrained Model			MobileNet Pretrained Model		
Tumor Class	Precision	Recall Parameter	F1-Score Parameter	Precision Parameter	Recall Parameter	F1-Score Parameter
0	**0.97**	**0.96**	**0.96**	0.91	0.72	0.80
1	**0.98**	**0.95**	**0.96**	0.81	0.78	0.79
2	**0.99**	**1.00**	**1.00**	0.92	0.97	0.95
3	**0.97**	**1.00**	**0.99**	0.82	0.98	0.89

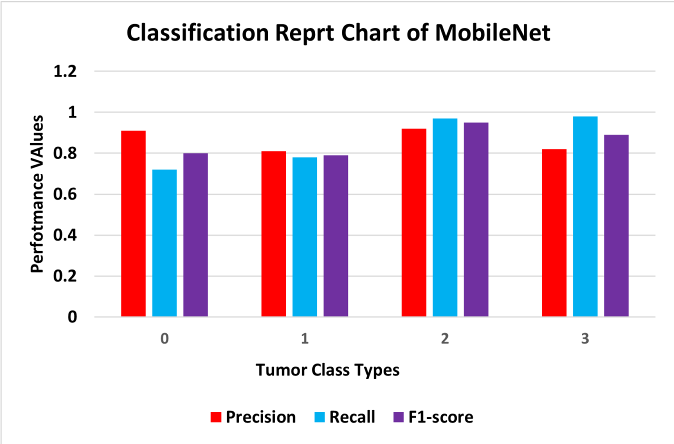

Figure 11. Classification report chart of MobileNet tumor classes.

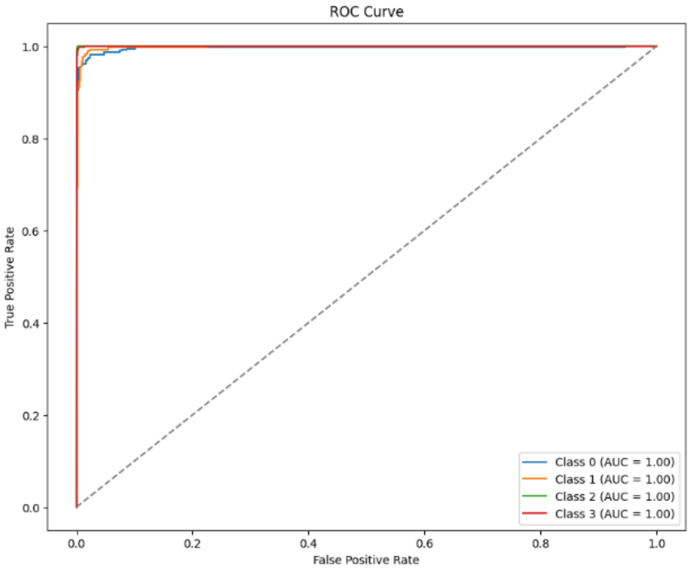

Figure 12. AUC-ROC Curve among Various Tumor Classes using VGG16.

5 Conclusion

The performed research used the famous VGG16 and MobileNet architectures, which have been pretrained on the ImageNet dataset. They apply the PTL technique to classify MR images into different classes.

The models were fine-tuned, and the acquired images were categorized into three groups to assess generalization performance. Experimental accuracy indicates the pretrained model's ability to work significantly better than arbitrary chance and the potential for further performance enhancements. The model's high accuracy has significant implications for clinical practice, providing valuable support to medical professionals.

Additionally, the popular ROC-AUC curve defines the proposed model's discriminative ability to explain

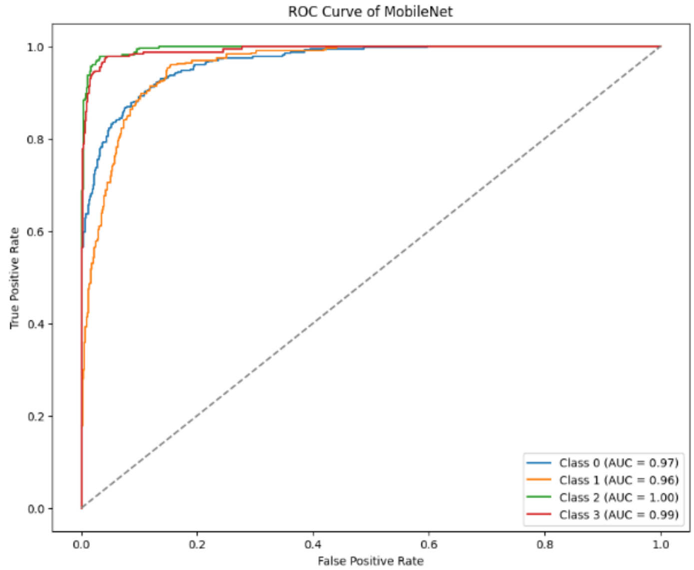

Figure 13. AUC-ROC Curve among Various Tumor Classes using MobileNet model.

the efficiency of each tumor class against the rest. The training process is visualized using graphs. The training accuracy increases and training loss decreases over epochs. In brief, as we have observed, the fine-tuned VGG16 and MobileNet model provides a foundational baseline for a brain tumor MRI classification method on the suggested dataset. The experimental outcome indicates the importance of transfer learning in this area, while also emphasizing the need for further enhancement.

In upcoming experimental work, our focus will be on reducing the overfitting problem, exploring alternative fine-tuning approaches, and potentially investigating more advanced data augmentation methods to improve generalization and achieve higher brain tumor MRI classification accuracy across all experimental tumor classes.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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