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Transfer learning architectures with fine-tuning for brain tumor classification using magnetic resonance imaging

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ABSTRACT

Deep learning methods in artificial intelligence are used for brain tumor diagnosis as they handle a huge amount of data. Compared to computerized tomography (CT), Ultrasound, and X-ray imaging, Magnetic Resonance Imaging (MRI) is effectively used for machine vision-based brain tumor diagnosis. However, due to the complex nature of the brain, brain tumor diagnosis is always challenging. This research aims to study the effectiveness of deep transfer learning architectures in brain tumor diagnosis. This paper applies four transfer learning architectures- InceptionV3, VGG19, DenseNet121, and MobileNet. We used a dataset with data from three benchmark databases of figshare, SARTAJ, and Br35H to validate the models. These databases have four classes: pituitary, no tumor, meningioma, and glioma. Image augmentation is applied to make the classes balanced. Experimental results demonstrate that the MobileNet outperforms competing methods by exhibiting an accuracy of 99.60%.

1. Introduction

The brain is an essential part of the human body and is involved in all aspects of perception, cognition, emotion, and behavior. There are many billions of neurons in the brain, and they communicate electrical and chemical signals with one another. It is divided into various regions, each of which performs a specific purpose, such as the cerebral cortex, which is in charge of consciousness, and the cerebellum, which is in charge of balance and coordination.

A tumor, also referred to as a neoplasm, is an abnormal growth of cells that appears as a mass or lump in the body. There are two types of tumors named benign and malignant. Mostly slow-growing and confined to one area of the body, benign tumors do not spread. But, if they expand into or close to critical organs or tissues or get too big, they may become problematic. Each of the body's organs, such as the brain, breast, lung, liver, colon, and skin, can develop tumors [1]. A brain tumor is a mass or abnormal growth of brain cells. Brain tumors can grow from the brain tissue itself or from cancer that first spreads from another part of the body to the brain (metastasis). Brain tumor diagnosis frequently involves imaging tests like computerized tomography (CT) or Magnetic Resonance Imaging (MRI) scans, as well as a biopsy to identify the tumor type [2]. There are many different types of brain tumors including Gliomas, Meningiomas, Pituitary, Schwannomas, and Glioblastomas [3].

- Gliomas - These are glial cell-derived malignancies, which are the brain's supporting cells. They can grow anywhere in the brain, either low-grade or high-grade.
- Meningiomas - Meninges are the protective layers that protect the brain and spinal cord, and these tumors grow there. Meningiomas are typically benign.
- Pituitary adenomas - These are tumors that arise in the pituitary gland, a little organ that makes hormones and is situated at the base of the brain.
- Schwannomas - Schwann cells, which create the myelin coating that protects nerve fibers, is the source of these malignancies.
- Glioblastomas - These gliomas are the most dangerous and aggressive kind.

Deep learning and artificial intelligence (AI) have made significant advancements in the field of medical imaging analysis and have played a crucial role in the classification of different types of cancer, including lung and breast cancer. A pre-trained model that has been trained on a sizeable dataset for a certain task is used as a starting place for

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a new, related task using the machine learning technique known as transfer learning (TL). TL enables us to benefit from the knowledge and attributes that have been obtained by the pre-trained model rather than having to train a new model from scratch. There are numerous transfer learning models named VGG (Visual Geometry Group), ResNet (Residual Network), Inception, MobileNet, DenseNet, and so on.

In [4], brain images with a tumor are initially classified into three categories: normal, Low-Grade Glioma (LGG), and High-Grade Glioma (HGG). Tumor identification is carried out using the VGG19 transfer learning model. In the second phase, they use the superpixel segmentation method to split the tumor from surrounding muscles in LGG and HGG images. In [5], it is important to alter the model hyper-parameters and learning parameters in order to use deep pre-trained convolutional neural networks (CNNs) based on transfer learning in medical imaging. They suggested a new approach to classify MRI images of the brain using transfer learning. In [6], the CNN method is used to categorize brain MRI scan images into cancerous and non-cancerous. Using the transfer learning method, they evaluated the efficacy of their scratched CNN model against the pre-trained VGG16, ResNet50, and InceptionV3 models. The investigation reveals a 96% accuracy for the suggested VGG16 model.

In order to categorize the brain MRI images effectively, we evaluated four transfer learning models including VGG19, InceptionV3, DenseNet121, and MobileNet. The main contribution of this paper is as follows.

- Classify the brain tumor into four classes using transfer learning and fine-tuning based on magnetic resonance images.
- Preprocess and use three benchmark datasets for high accuracy and apply fine-tuning on the transfer learning models.
- Modify VGG19, InceptionV3, MobileNet, and DenseNet121 models by adding a single fully connected layer.
- Establish standard comparisons between the proposed transfer learning approaches and existing works.
- Achieve the best accuracy with MobileNet obtaining 99.60% accuracy in the epoch scenery and InceptionV3 obtaining 98% accuracy in performance.

The majority of the work is organized as follows. In Section 2, we briefly summarized the literature. The proposed approach is given in Section 3, which also covers experiment setup, model training, and assessment. Section 4 provides the result analysis and discussion. In Section 5, the paper is completed.

2. Literature review

Some works have been done by researchers on the classification of brain MRI images. S. Kumar et al. [7] extracted the features and submitted them to the Deep CNN. The proposed model has performed remarkably well with a maximum accuracy of 96.3%. In [8], the authors suggested artificial neural networks (ANN) and additional classifiers used to categorize the tumor grades. The suggested algorithm has 99% of accuracy. In [9], the authors applied machine learning models named extreme gradient boosting for detecting brain tumors and their model achieved 97% of accuracy. In [10], the researcher applied the Support Vector Machine (SVM) classifier to obtain several cross-validations on the feature set. According to the comparison analysis, the proposed method has a 97.1% accuracy. In [11], the CNN and conventional architecture are combined in the author's application of the correlation learning mechanism (CLM) for deep neural network designs. Their findings indicate that the CLM model achieves an accuracy of roughly 96%. In [12], the researchers used the U-Net model for segmenting the brain tumors using MRI images and they got only 89% of accuracy. The researchers proposed a model based on a statistical approach and machine learning technique with an accuracy of 98.9% along with the surviving brain cancer, they created an interactive web-based tool [13]. In [14], the authors proposed machine learning and deep learning for classifying hydrocephalus in brain tomography images with an accuracy of 98.5%. In [15], the authors presented a deep learning architecture for classifying the brain tumor images with an accuracy of 98.69%. In [16], the AlexNet model was used by the researcher to identify brain tumors. With the highest accuracy of 99.04%, the planned arrangement achieves a notable performance. In [17], the researcher categorizes the tumor portion for the process of classifying brain tumors using a deep autoencoder (DAE)based Jaya optimization algorithm(JOA). The suggested method had a 98.5% classification accuracy rate. In [18], the study offers a CNN architecture for the classification of brain tumors and got an accuracy of 96.56%. In [19], the authors presented a deep residual network for classifying brain tumor images with an accuracy of 99%. In [20], a novel deep learning-based strategy is suggested in the investigator study for the identification of tiny brain tumors and the classification of tumor types. The initial stage is to create a 3D CNN architecture to extract brain tumors, and the extracted tumors are then sent to a pre-trained CNN model for feature extraction. The investigation reveals a 92.67% accuracy for the suggested CNN model. In [21], the researcher describes a hybrid deep method named transformer model and the self-attention unit for classifying brain tumors with an accuracy of 99.30%. In [22], the authors proposed the BrainMRNet model for the classification of the brain MRI images and they got 96.05% of accuracy. In [23], the researchers proposed two hybrid deep-learning models named ExpDHO-based ShCNN (Exponential deer hunting optimization-based Shepard CNN) and ExpDHO-based Deep CNN for detecting and classifying brain tumors effectively. The models achieved an accuracy of 92.9% and 91.7% respectively. In [24], the refined VGG16 architecture achieved the maximum accuracy up to 98.69% in terms of classification and detection in the investigator-proposed studies. In [25], the authors proposed a convolutional neural network for segmenting brain tumor MRI images with an accuracy of 98.81%. In [26], the authors presented a model named attention-convolutional-LSTM (long short-term memory) for classifying brain tumors with an accuracy of 98.90%.

In [27], the researcher applied three transfer learning approaches. VGG16, InceptionV3, and ResNet50 are used in this paper. VGG16 model achieves 91.58%, the highest accuracy among these three models. In [28], the researcher works with deep characteristics that have been extracted from the tumor regions and also used pre-trained AlexNet, ResNet18, GoogleNet, and ShuffleNet networks and the accuracy is 98.02%. In [29], the authors established a model to detect brain tumors using MRI images with an accuracy of 99.3%. In [30], five well-known convolutional neural networks—AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50 were used by the researcher. For training and testing, the five-fold cross-validation methodology was used. The method named Fluid attenuated inversion recovery (FLAIR) MRI achieves 98.88% of accuracy. In [31], the researchers proposed a CNN model for classifying different types of brain tumors through MR images. The accuracy of the model is 98.32%. In [32], the researcher proposed the Brain Tumor Classification-Fast Convolution Neural Network (BTC-fCNN) model to achieve 98.63% average accuracy using five iterations with the help of transfer learning, and they got 98.86% using retrained five-fold cross-validation. In [33], the researcher pre-trained five EfficientNets variants: EfficientNetB0 – EfficientNetB4. The proposed method EfficientNet achieves 98.86% accuracy and showed better performance with the help of EfficientNetB2. In [34], the researcher employs pre-trained deep convolutional neural network (DCNN) architecture, VGGNet. It was trained with large data before applying it to the dataset. With the help of this approach, the suggested method provides 98.93% accuracy. In [35], the authors compared the AlexNet, ResNet, VGG16, and UNet for classifying the brain tumor images. After this comparison, their proposed model achieves 99.30% accuracy for benign and malignant. In [36], the researcher builds an improved version of the Hunger Games Search algorithm

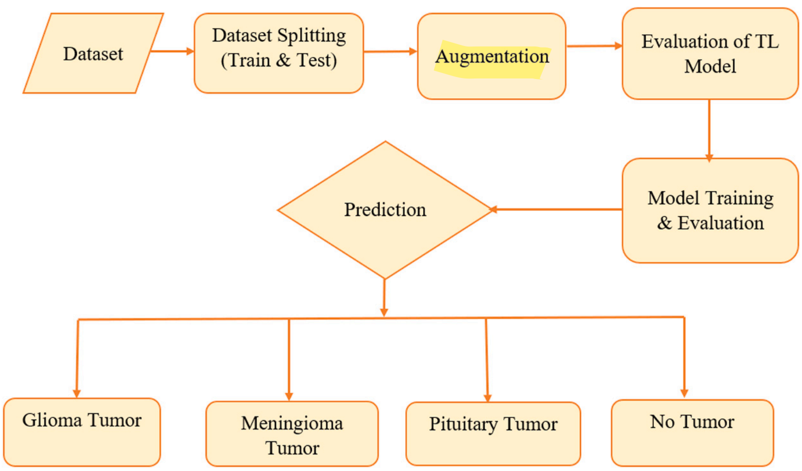

Fig. 1. Methodological block diagram.

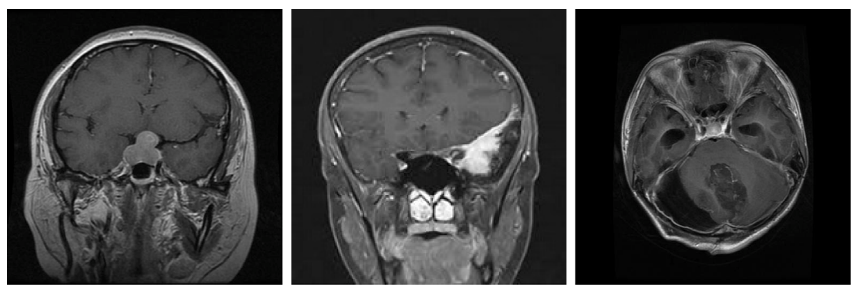

Fig. 2. Sample Data from various classes of data.

(I-HGS) and suggests an optimal residual learning architecture for categorizing various brain tumors. For the three datasets, I-HGS-ResNet50 obtained accuracy is 99.89%, 99.72%, and 99.88%.

In this paper, we applied four TL models for classifying the MRI brain images. Among the models, MobileNet achieves the highest accuracy of 99.60%.

3. Proposed methodology

Fig. 1 shows the block diagram of the prospective methodology. Four renowned transfer learning techniques are used in this work in order to identify four classes to analyze and estimate our suggested frame utilizing transfer learning models named VGG19, InceptionV3, MobileNet, and DenseNet121. With the use of these four transfer learning techniques, we test our dataset. We divided our dataset into training and testing parts based on the data. We separated the data this way because the training data will be used to learn the model, the validation data, which is sample data, will be used to assess the model, and the test data will be used to assess the proposed model in its entirety. Our proposed model is confident in various phases.

3.1. Dataset description and splitting

For our model, we used the brain tumor dataset from Kaggle [37], which contains brain MRI pictures of 7023 patients, both healthy individuals and those with brain tumors. The pituitary, no tumor, meningioma, and glioma types of brain tumors are all included in this dataset. Each class in the collection has more than 1600 photos, all of which are in excellent resolution. The dataset sample is displayed in Fig. 2.

Table 1 describes the number of test train splitting images. There are a total of 7023 images. Among them, training images are 5712 and testing images are 1311, 2000 images are with no tumors and 5023 are tumors.

Table 1
Training and testing dataset for each class.

Set	Brain Tumor	No Tumor	Total
Training	4117	1595	5712
Testing	906	405	1311
Total	5023	2000	7023

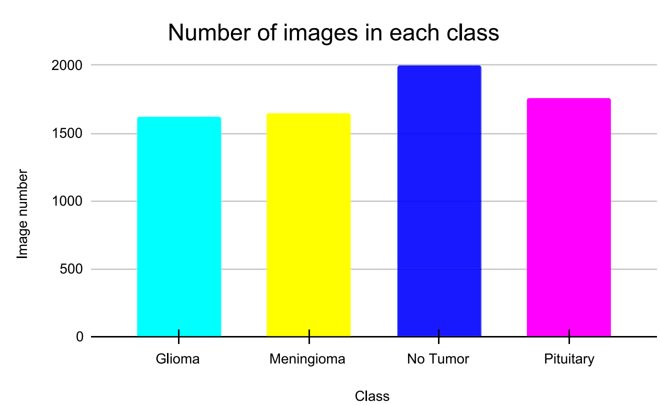

Fig. 3. Images from each class are depicted in a bar graph.

Fig. 3 depicts the quantity of each brain tumor image class. It demonstrates that there are more than 1800 photos in the No Tumor class, 1757, 1645, and 1621 images in the classes of pituitary, glioma, and meningioma, respectively.

3.2. Data augmentation

Image Augmentation is a method of applying various modification methods to real photos, resulting in altered duplicates of the same image. This allows deep learning models to be trained on more picture variants than are present in the real dataset. Keras' ImageDataGenerator class is used to perform picture augmentation. It can automatically create enhanced pictures during model training, making the overall mode more resilient as well as accurate [38].

3.3. Applied transfer learning models

A model that has been trained for one job can be used to solve a different but related task using the machine learning technique known as transfer learning. In transfer learning, the weights of a pre-trained model are adjusted for the new task and utilized as the foundation for a new model. Transfer learning is based on the notion that a model that has already been trained can reuse features that it has already learned from a big dataset for the new assignment. Transfer learning enables us to leverage the knowledge from the pre-trained model to save time and resources instead of starting from zero and training a new model from scratch. Transfer learning has been successfully used in a variety of applications, such as image recognition, natural language processing, and speech recognition. By reusing pre-trained models, transfer learning has enabled state-of-the-art performance on many tasks with limited training data. Transfer learning has been applied in diverse deep-learning applications, including image classification, object finding, and tumor detection. In this paper, we used four TL models. In all models, we used a fixed size of (224 × 224) RGB image as input for our model. It defines that the matrix shape was (224,224,3).

- **DenseNet121** is made up of a dense network with 121 layers, including convolutional, pooling, and dense block layers. Each layer is joined to all preceding layers by DenseNet by concatenating their feature maps. The number of parameters is reduced, feature reuse is increased, and gradient flow is improved thanks to the dense connectivity design. The architecture of DenseNet121 is based on the idea of densely connected layers, where each layer is connected to every other layer in a feedforward fashion. The input of each layer is a concatenation of the feature maps from all previous layers, which allows for more efficient parameter reuse and reduces the risk of overfitting. It has also been adapted for transfer learning and fine-tuning on other datasets with fewer classes or different image characteristics [39].
  We sometimes obtain the same layer, which is why we employ x2, x3, and x4. Moreover, this model is divided into four blocks. DenseNet121 design is shown in Fig. 4.
- **VGG** stands for Visual Geometry Group and contains multiple layers. There are 19 layers total in the VGG19, containing a mix of convolutional, pooling, and fully linked layers. The key feature of the VGG19 architecture is its use of small (3 × 3) convolutional filters throughout the network, which allows for a more detailed analysis of the input image. The model also uses max pooling layers to reduce the spatial size of the feature maps and increase the model's translation invariance. With transfer learning, we can work to attain high accuracy on new datasets with narrow training data [40].
  We employed kernels that were 3 × 3 in size with these multiple convolutional (conv) layers. Max pooling was done over the 2 × 2 pixel windows with a stride of 2, while the convolution stride and pixel padding size are also 1. Also, we added one fully connected (FC) layer and a softmax function as the model's final layers. Fig. 5 shows the construction of the VGG19.

Table 2
Hyperparameters of all exploit Transfer Learning models.

Metrics	Metrics value
Batch size	128
Optimizer	Adam
Epochs	50
Learning rate	0.001
Criterion	Cross Entropy Loss

- **InceptionV3** is a popular pre-trained model. This model is built using a number of convolutional layers with various kernel sizes, pooling techniques, and dimensionality reductions. The architecture uses a combination of different convolutional filters, including 1 × 1, 3 × 3, and 5 × 5 convolutions, as well as max pooling and average pooling layers. It also incorporates a number of other techniques, such as batch normalization and dropout, to improve the model's performance. It also includes a few other architectural features such as batch normalization, factorized convolution, and auxiliary classifiers. Overall, InceptionV3 has achieved state-of-the-art performance on several benchmark datasets for image recognition [40].
  We have divided the TL InceptionV3 model into numerous components to make it easier to grasp. We sometimes obtain the same layer, which is why we employ x2, x3, and x4. Fig. 6 displays the InceptionV3 architectural layout.
- **MobileNet** is a family of neural network architectures designed for efficient computation on mobile devices with limited computing power and memory resources. The MobileNet architecture uses a combination of depth-wise divisible complications to reduce the number of parameters and calculations demanded to perform image recognition and classification tasks. It uses depth-wise separable convolutions, which break down a standard convolution into two separate operations: a depth-wise convolution and a pointwise convolution. This reduces the number of parameters required and makes the network much more efficient. Additionally, MobileNet uses a technique called "bottlenecking" to further reduce computational complexity by compressing the input feature map before processing it with the convolutional layers. Mobile Net architecture has many variations, including MobileNet, MobileNetV2, and MobileNetV3 [41].
  This model has so many different types of layers like convolution layers, and Flatten Dense blocks. We separate the diagram into blocks to understand the TL MobileNet model easily. Sometimes, we get the same layer, so we use x2 and x6. Also, we separate the model into three blocks. The architecture of the proposed MobileNet is presented in Fig. 7.

3.4. Experimental preparation and assessment

This experiment uses a dataset with a huge number of photos. Our model was trained in Google Collab. A reliable configuration machine is what we need to train and test our model. The dataset's train names are reposted using Kaggle. For all of the advanced models, we use the same dataset. We have divided our dataset into a training dataset and a test dataset. We used the test dataset to evaluate the TL model and the training dataset to train the TL model. The models combine the strengths of Sklearn, TensorFlow, and Keras. The block size for all advanced models is 128. The hyperparameters for our developmental format are defined in Table 2.

We apply the cross-entropy loss to each epoch's train and test sets. Each model has undergone 50 epochs of training. Adam is an optimizer that we use; its learning rate is 0.001.

Fig. 8, shows the model trained over a series of epochs. For InceptionV3, VGG19, DenseNet121, and MobileNet models train loss and

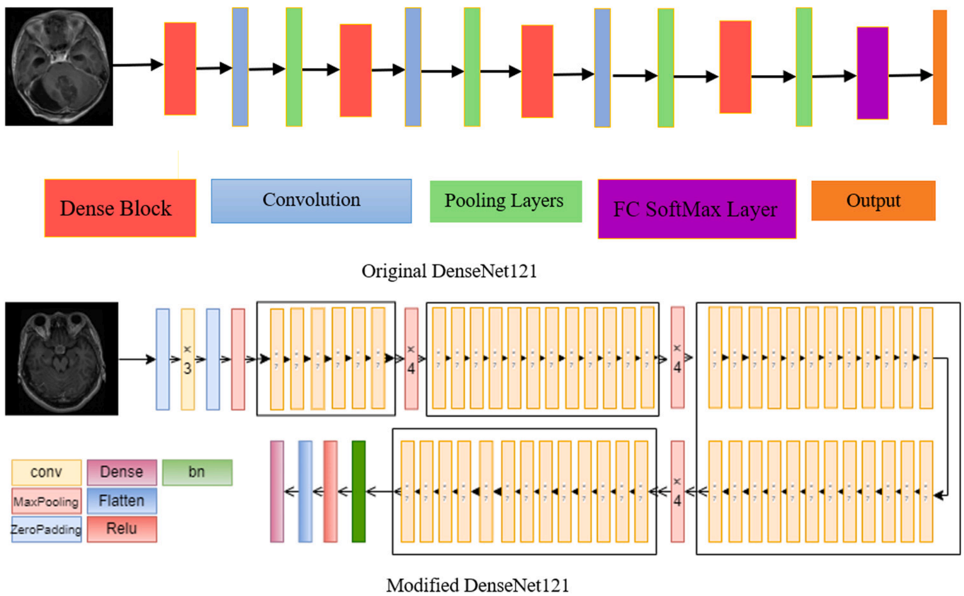

Fig. 4. DenseNet121 & TL DenseNet121 architecture.

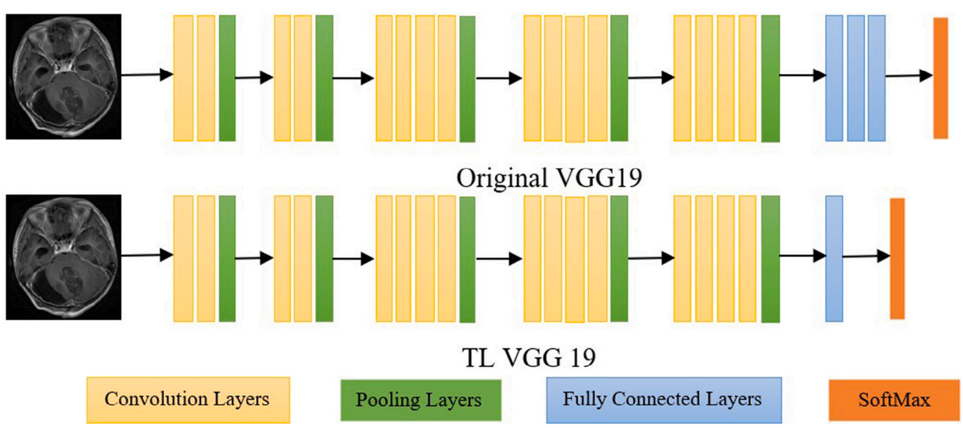

Fig. 5. VGG19 & TL VGG19 architecture.

validation loss are so close to each other, sometimes they overlay each other. But the DenseNet121 model is very different from them. We see while train loss is decreasing on the other hand the validation loss is increasing in every epoch. From Figure, we can see that train loss is increasing and loss of validation is decreased after the first epoch. The training loss is 0.6370 and the validation loss is 0.5961 after 2nd epoch. Train and validation loss is not so fluctuating for Mobile Net. The highest validation loss is at epoch 23 and the lowest validation loss is at epoch 8. The validation loss fluctuates but training loss does not fluctuate throughout the epochs. The final training loss is 0.0467 and the validation loss is 0.1265 for the VGG19 model. The final training loss is 0.0605 and the validation loss is 0.1862 for the InceptionV3 model.

DenseNet121 has generated the highest validation loss. The minimum loss of the DenseNet model is 0.0260 at epoch 39. And the minimum validation loss is 0.0664 at epoch 18. Both train and validation loss fluctuated rapidly. We can say, the InceptionV3 model shows better performance than VGG19, DenseNet121, and MobileNet.

Fig. 9 demonstrates the accuracy of the proposed models. The pair of validation accuracy and training accuracy has been explained here.

InceptionV3 achieves the highest accuracy. The training accuracy of the InceptionV3 model is 98.76% and the validation accuracy is 96.64%. The training accuracy of the VGG19 model is almost similar to InceptionV3. Training accuracy is 98.97% and validation accuracy is 96.72% for the VGG19 model. Both training and validation accuracy is not so fluctuating in this model. DenseNet121 gives an accuracy of 99.12% and 98.32% correspondingly for the pair of validation accuracy and training accuracy. DenseNet121 has the most fluctuation in the pair of training accuracy and validation accuracy compare to the other models. MobileNet model has gained 99.60% training accuracy and 99.39% validation accuracy. Training accuracy is not very fluctuating for this model while validation accuracy has quite fluctuated in some epochs.

Table 3
Overall performance of each model of 50 epochs.

Model	Training Accuracy	Training loss	Testing accuracy	Testing loss
InceptionV3	98.76%	0.0605	96.80%	0.1862
VGG19	98.97%	0.0467	95.50%	0.1265
DenseNet121	99.12%	0.0260	97.41%	0.0965
MobileNet	99.60%	0.0368	98.40%	0.1296

Table 3 shows the overall performance of each model of 50 epochs. The highest training accuracy from 50 epochs of each model has shown in this table. The experiment result shows the accuracy of 98.76%, 98.97%, 99.12% and 99.60% for models InceptionV3, VGG19, DenseNet121 and MobileNet respectively. We have learned that the MobileNet model got the highest testing accuracy.

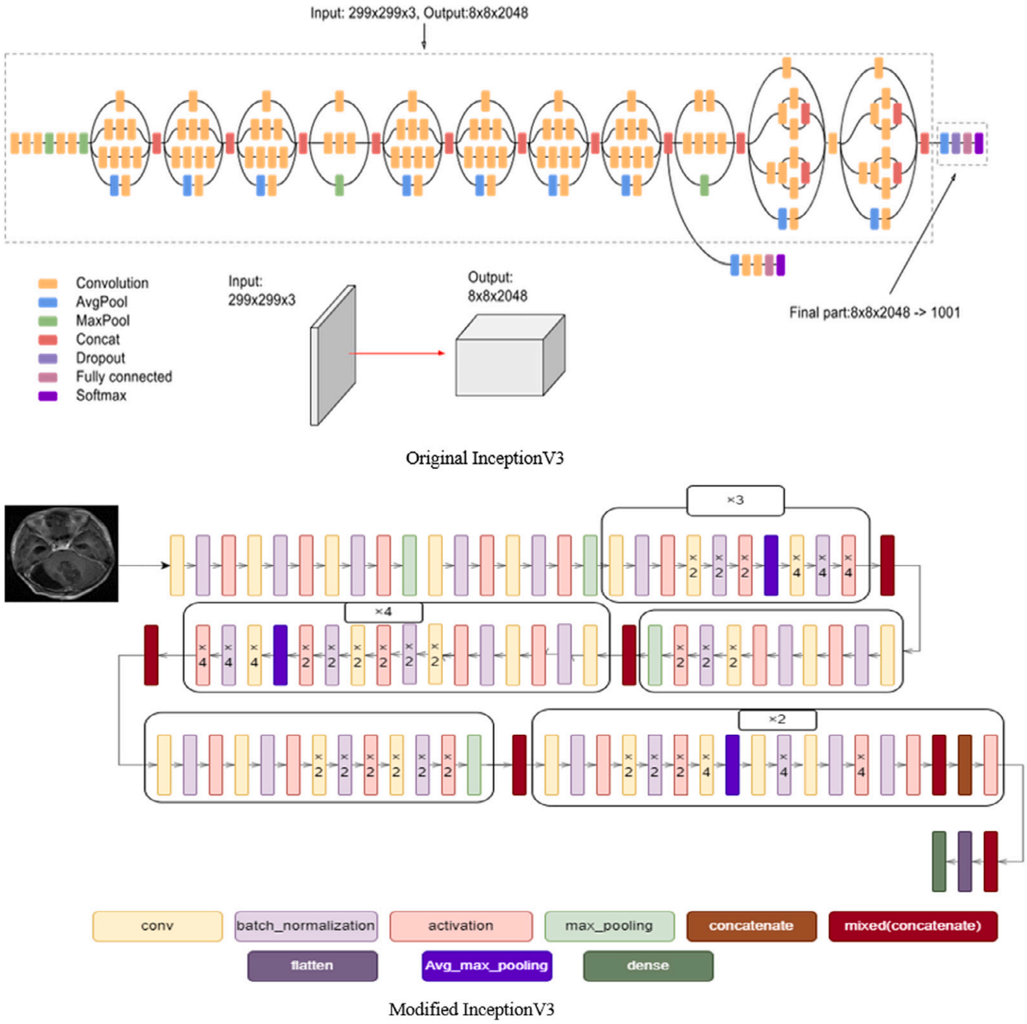

Fig. 6. InceptionV3 & TL InceptionV3 architecture.

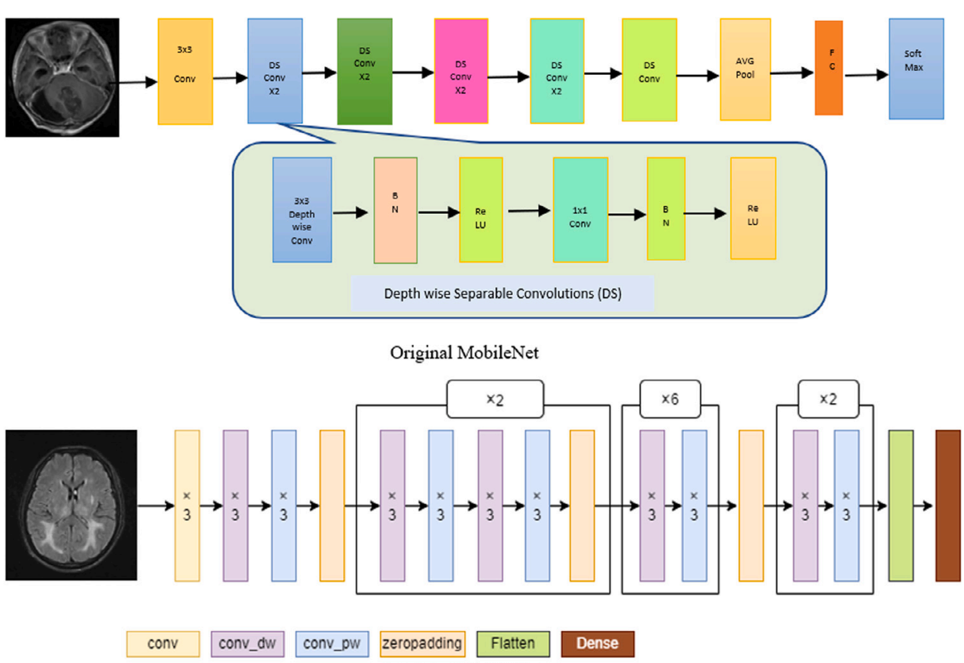

Fig. 7. MobileNet & TL MobileNet architecture.

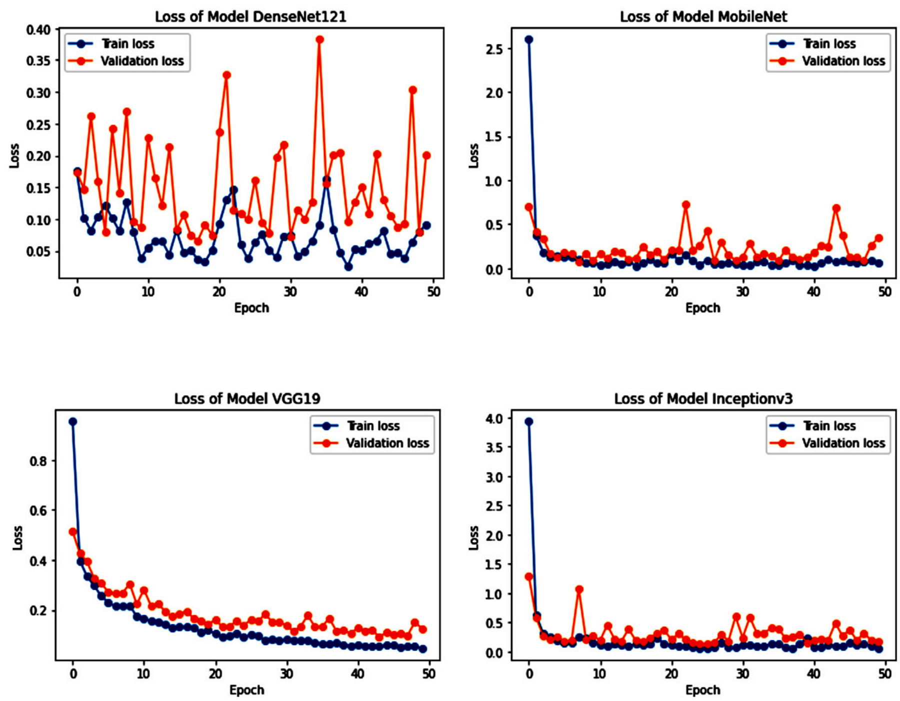

Fig. 8. The loss of all TL models.

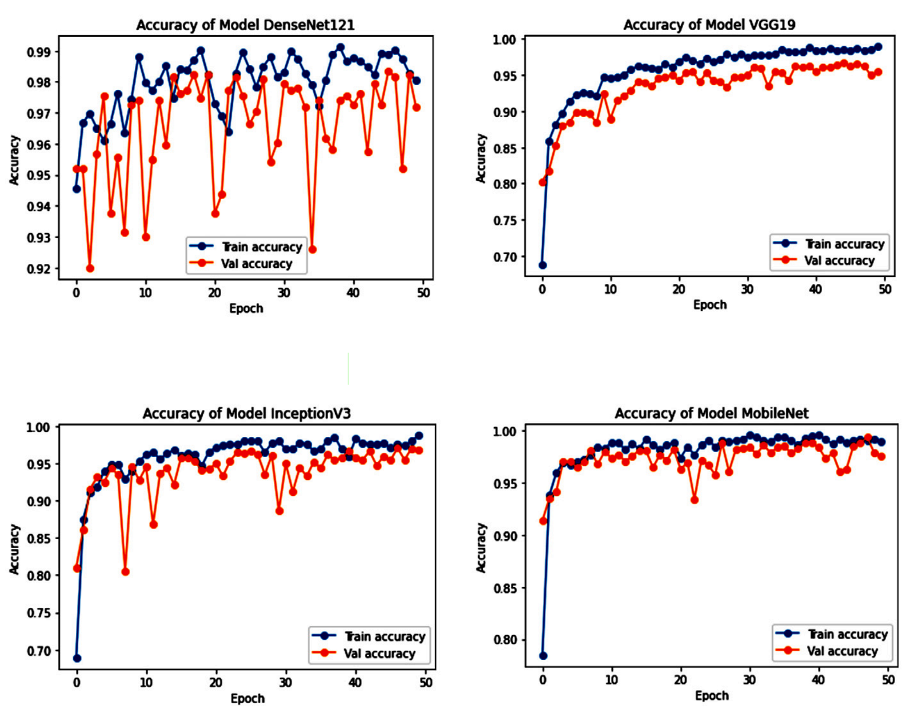

Fig. 9. Train and validation accuracy of all TL Models.

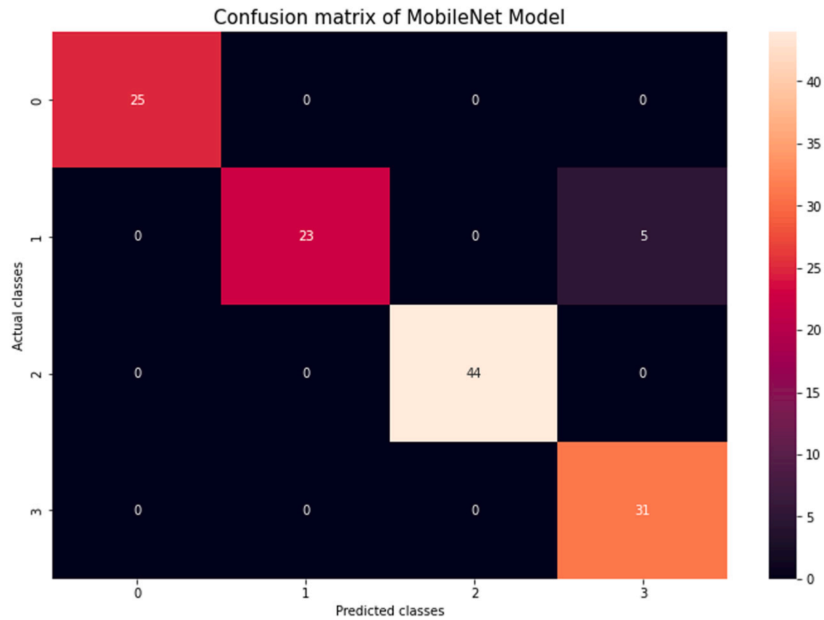

Fig. 10. Confusion matrix of MobileNet.

Table 4
Confusion Matrix.

	Actual Positive	Actual Negative
Predict Positive	True Positive (TP)	False Negative (FN)
Predict Negative	False Positive (FP)	True Negative (TN)

4. Result investigation and discussion

Our models use the confusion matrix to calculate the precision, F1 Score, recall, and accuracy. These are all the fundamental criteria used to categorize the models. Typically, we know that the Confusion Matrix output will be a matrix. It specifies how well all of the models perform overall. Table 4 provides a summary of the confusion matrix.

Here TP represents True Positive, FP represents False Positive and FN represents False Negative. Also, the F1 score, the P representing Precision and R representing recall.

We assessed the performance metrics in our model. We show the confusion matrix of the MobileNet model here in Fig. 10. In the confusion matrix, the tumor classes are shown as classes of numbers 0 to 3 where 0 means "Pituitary", 1 means "No tumor", 2 is "Meningioma", and 3 is "Glioma". For the confusion matrix of MobileNet, the "Pituitary" class was recognized 25 times correctly, "No tumor" was correctly recognized 23 times but 5 times was not recognized correctly. Meningioma" which 44 times are correctly recognized. Also, "Glioma" which 31 times images are recognized correctly.

Table 5 describes the performance metrics of every model. Various numbers of scores are set into the test dataset for separated experimental models. Among the models, InceptionV3 outperforms the accuracy. We took 50 epochs for InceptionV3, VGG19, DenseNet121, and MobileNet of the training set.

Table 6 exhibits the accuracy of all models as per the maximum and minimum epochs number. The MobileNet model achieves the highest train accuracy of 99.60% over the 50th epoch and it also achieves the highest validation accuracy of 99.39% over the 45th epoch among all other models. Here, we denote the Maximum Accuracy as Max Acc, Minimum Accuracy as Min Acc, Maximum Epochs as MA_E, and Minimum Epochs as MinA _E. Table 7 represents the length of the training set for each epoch that we run on the Google Collaboratory its Graphics Processing Unit (GPU) runtime.

Table 5
Performance Metrics of all TL models on dataset.

Model	Class	P	R	F1	A
InceptionV3	Pituitary	1.00	0.92	0.96	0.98
	No tumor	0.96	1.00	0.98	
	Meningioma	1.00	1.00	1.00	
	Glioma	0.97	1.00	0.99	
VGG19	Pituitary	1.00	0.88	0.94	0.96
	No tumor	0.93	0.93	0.93	
	Meningioma	1.00	1.00	1.00	
	Glioma	0.91	1.00	0.95	
DenseNet121	Pituitary	1.00	0.86	0.93	0.96
	No tumor	0.85	1.00	0.92	
	Meningioma	1.00	1.00	1.00	
	Glioma	1.00	1.00	1.00	
MobileNet	Pituitary	1.00	1.00	1.00	0.96
	No tumor	1.00	0.82	0.90	
	Meningioma	1.00	1.00	1.00	
	Glioma	0.86	1.00	0.93	

Table 6
Summary of models Accuracy as per epochs number.

Model	Train/Test	Max Acc(%)	MA_E	Min Acc (%)	MinA_E
TL VGG19	Train	98.97	50	68.77	1
	Test	96.72	45	80.24	1
TL InceptionV3	Train	98.76	50	68.91	1
	Test	97.10	47	80.47	8
TL DesneNet121	Train	99.12	39	94.54	1
	Test	98.32	46	91.99	3
TL MobileNet	Train	99.60	31	78.47	1
	Test	99.39	48	91.38	1
All	Train Max Acc	99.60	TL MobileNet at Epoch 31		
	Test Max Acc	99.39	TL MobileNet at Epoch 48		
	Both Max Acc	99.60	TL MobileNet at Epoch 31		

Table 7
Training length each-epoch of TL models.

Model	Duration (h:mm:ss)
InceptionV3	3:25:08
VGG19	3:48:15
DenseNet121	2:50:08
MobileNet	2:44:44

Table 8
Comparison of the proposed model using similar existing studies.

Source	Method	Dataset	Accuracy
[7]	Deep CNN	BRATS, SimBRATS	96.3%
[8]	Artificial neural networks	RIDER and BRATS 2018	99%
[10]	Support Vector Machine	Harvard, RIDER & Local	97.1%
[11]	Correlation learning mechanism	Kaggle	96%
[16]	Alex Net	TCIA	99.04%
[17]	DAE + JOA + SoftMax regression	BRATS 2015	98.5%
[18]	CNN	Own	96.56%
[20]	CNN	BraTS 2018	92.67%
[22]	AlexNet, GoogleNet, VGG16	Own	96.05%
[24]	VGG16	Figshare	98.69%
[27]	VGG16, InceptionV3, and ResNet50	–	91.58%
[28]	[ResNet18 + ShallowNet] + SVM	–	98.02%
[30]	AlexNet, VGG16, ResNet18, GoogleNet, ResNet50	TCIA (REMBRANDT)	FLAIR-MRI (98.88%)
[31]	ResNet50, VGG19, DensetNet121 and InceptionV3	–	98.32%
[32]	BTC-fCNN	FIGSHARE	98.86%
[33]	EfficientNet	FIGSHARE	98.86%
[34]	VGG-16 CNN	FIGSHARE	98.93%
[35]	ResNet, AlexNet, UNet, and VGG16	–	99.30%
Proposed	InceptionV3	Figshare, SARTAJ and Br35H	99.60%

4.1. Discussion and comparison

Medical images include a wide range of heterogeneity; hence image detection is important in their elucidation. We used MRI and CT scan pictures to identify brain tumors. For the detection and categorization of brain tumors, MRI is frequently used. In this work, we employ TL models for brain tumor identification since they can accurately forecast the tumor cells. In Table 8, We have drawn up a comparison table of the existing work with the proposed work. The proposed model named MobileNet gives the highest accuracy of 98%.

5. Conclusion

In this paper, we used MRI to represent the transfer learning methods for classifying brain tumors. We used four transfer learning methods in the experimental evaluation, including InceptionV3, VGG19, DenseNet121, and MobileNet on the three brain tumor image datasets. We have utilized the terms accuracy, precision, f1-score, and recall as performance metrics. InceptionV3 beats all other models in using the terms of performance parameters by achieving an accuracy of 98% as well as MobileNet outperforms 99.60% in the case of experimenting on epochs experiments. The narrowness of this paper is that the authors used a secondary dataset. In the future, they can also apply the proposed model to CT images. The proposed model will be helpful for medical applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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