

A novel algorithmic approach of progressive transfer learning for MRI braintumor classification using VGG16 architecture

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Abstract

Many diseases exist worldwide. Among them, a brain tumour is the most dangerous and critical disease for human survival. Early detection of this abnormality is essential for effective patient treatment. The objective of the present research is to define a progressive transfer learning technique with the help of the VGG16 model to accurately identify and classify human brain tumour MR images. The results provide evidence of the significance of the applied framework. The experimental efficiency of the framework was 98.15%, demonstrating the importance of the VGG16 model over other frameworks. Moreover, future work suggests important concepts related to improving the fine-tuning process, regularisation methods, and other related work to enhance the overall performance of the suggested framework.

Subject Classification: Primary 68T07, Secondary 68U10.

Keywords: Brain tumour MRI classification, Transfer learning, VGG-16, Fine-tuning.

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1. Introduction

In the human brain, sometimes, multiple unwanted cells grow due to health issues. These unwanted cells are very unfavorable for human beings and are recognised as brain tumors [1]. In modern days, medical professionals use MRI as the most effective tool for brain tumor detection.

Today, due to the varied conditions of brain tumors, manual analysis of multiple MR Images, are complex and inefficient task. Due to this complexity, an automatic brain tumor MRI detection and classification method is required. To develop this automatic system convolutional neural network (CNN), which is a part of deep learning, is most appropriate [2]. The most critical problem of deep learning is the limited training dataset. To overcome this problem, a popular technique called transfer learning appeared as a progressive and effective technique to increase the performance of the applied framework [3]. In the present research work, by examining the popular pre-trained model, VGG16, with the help of progressive transfer learning, the aim is to recognise trade-offs among various performance metrics and assess an MRI-based automatic brain tumor identification and classification system.

2. Methods and Materials

A. Data acquisition and data Pre-processing

To maintain diversity in the training data set, we collected them from different online and offline medical sources. The next step after data acquisition was data preprocessing, which transforms the input dataset into a clean format [4]. Since all the brain tumor MRI pictures were dissimilar in dimension, we converted all these pictures into a uniform 128 x 128 dimension.

B. Data Augmentation

To increase the input image data quantity, we applied a data augmentation method using various techniques such as zooming, rotation, shifting, etc. [5].

C. Input MRI Dataset

The collected tumor images represent various tumor classes [6] and other attributes, which are sequentially arranged in Table 1.

Table 1
Description of tumor images

Serial Number	Name of features	Feature Description
1.	Quantity of tumor MRI images	13676
2.	Image density	128X128X3
3.	Image file type	JPEG
4.	Classification of tumor types	Glioma tumor, Meningioma tumor, Pituitary tumor and no tumor
5.	Tumor images	10739
6.	No tumor images	2937

D. Transfer Learning [7]

It is a knowledge transfer technique that enhances the performance of the training model (Figure 1). We included a popular pre-trained framework, VGG16, in our research work, which is trained on the large ImageNet data set [8].

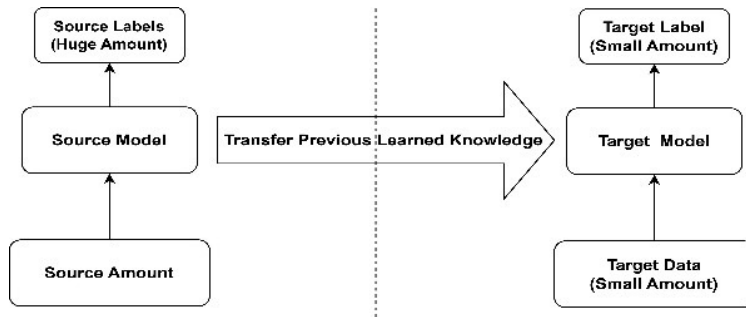


Figure 1
Transfer learning method

E. VGG16 architecture

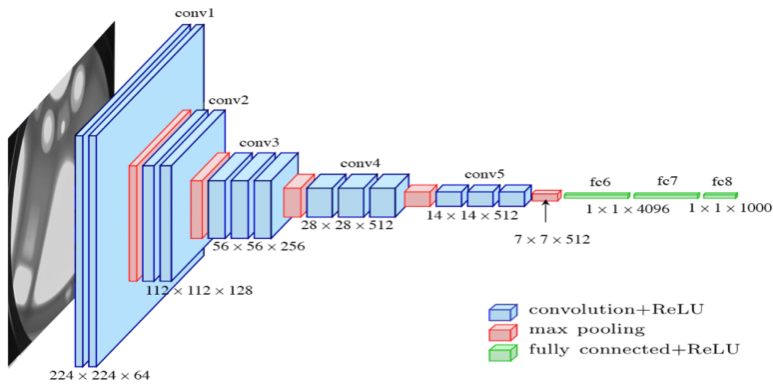


Figure 2
VGG-16 architecture

This popular pre-trained deep learning framework contains 16 convolutional layers and corresponding fully connected layers [9]. It consists of alternate layers, which demonstrate it as a sequential framework [10]. The architecture basically extracts deep features of input image data through multiple layers, as shown in Figure 2.

F. Fine-Tuning Strategies

It is a popular technique which applied to various parameters of the framework to specialise the framework according to the requirements of new working applications. In our present research work, the last three layers of

architecture were fine-tuned [11], according to requirement of the framework. Dimensionality reduction of all input images overcome computational complexity of working framework. Figure 3 represents the functional algorithm of VGG16.

Algorithm1: Proposed brain tumor diagnosis VGG16 framework

Inputs: I is an input MR Image for tumor detection and classification.

Outputs: Diagnosis of the input image I .

```

1  Dataset Pre-processing:
2   $I' \leftarrow preprocess(I)$ 
3  Tumor Detection System  $\rightarrow$  tumor, no tumor
4   $p_1 \leftarrow VGG16\ Model(I)$ 
5   $d_i \leftarrow \min_{j=1}^N d_{ij}, i=1, 2, \dots, K; d_{ij} : \text{is the distance between } P_1 \text{ and the coverage of neuron } j \text{ in the class } i.$ 
6   $Class_1 = \arg \min_{i=1}^K d_i, i = 1, 2, \dots, K \text{ the class that } I' \text{ belongs to.}$ 
7  If  $Class_1 = \text{tumor}$  than
8    Tumor Classification  $\rightarrow$  glioma, meningioma, pituitary
9     $P_2 \leftarrow VGG16\ Model_2(I')$ 
10    $d_i \leftarrow \min_{j=1}^N d_{ij}, i=1, 2, \dots, L; d_{ij} : \text{is the distance between } P_2 \text{ and the coverage of neuron } j \text{ in the class } i.$ 
11    $Class_2 = \arg \min_{i=1}^L d_i, i = 1, 2, \dots, L \text{ the class that } I' \text{ belongs to.}$ 
12 Else
13    $I' : \text{Healthy brain image.}$ 
14 End
```

Figure 3
The VGG-16 framework Algorithm

G. Model Evaluation Metrics

The present study applied various performance metrics to examine the working efficiency of the current architecture [12]. The values of these metrics are evaluated and obtained through the confusion matrix.

- Model Accuracy: This performance parameter indicates the actual predicted percentage against the all-test data.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (1)$$

- Model Precision: It indicates the ratio between actual classes and generated positive classes.

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

- Model Recall: It indicates the total positive classes from the model's targeted classes.

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

- Model F1-score: It applied the harmonic mean of the previously calculated positive predictive value (PPV) and sensitivity to differentiate itself from other parameters.

$$F1 - Score = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

- AUC-ROC: The ROC is an important tool that plots the curve using previously calculated recall parameters and 1-specificity for various determined models' threshold quantity [13].

H. Proposed Experimental Setup

The proposed work was implemented on google cloud based, google colab ecosystem with the popular Python programming language. The famous deep learning framework TensorFlow, with the keras library also used for experimental work [14].

3. Results & Discussion

A. Training and Validation Performance

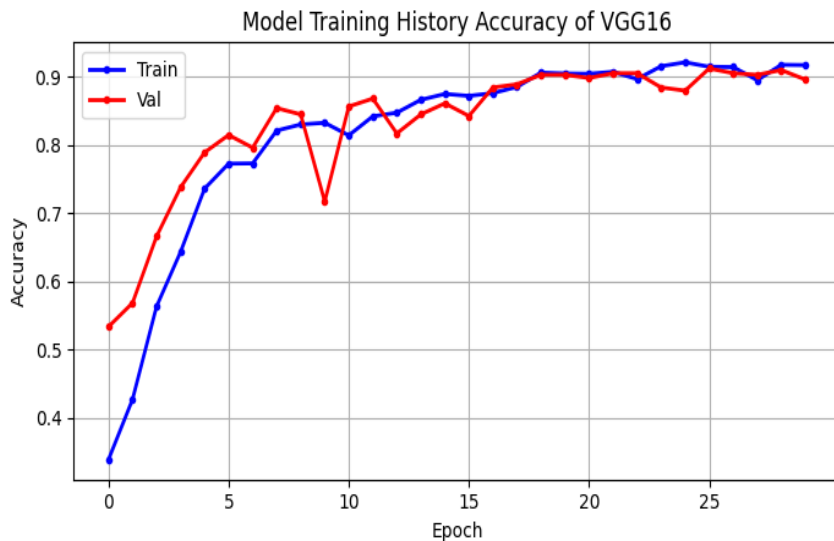


Figure 4
Correctness rate and loss rate chart

After performing experimental work, the VGG 16 framework achieved 98.15% of accuracy on test data. The reproducible performance and stable representations of the framework suggest their importance in the brain cancer MRI detection. The predicted correctness rate and error rate are visualised in Figure 4.

B. Confusion matrix output

The visualisation of it presents the true labels of hit and miss counting for every tumor MRI group (Figure 5). It also suggests the overall performance of the experimental framework.

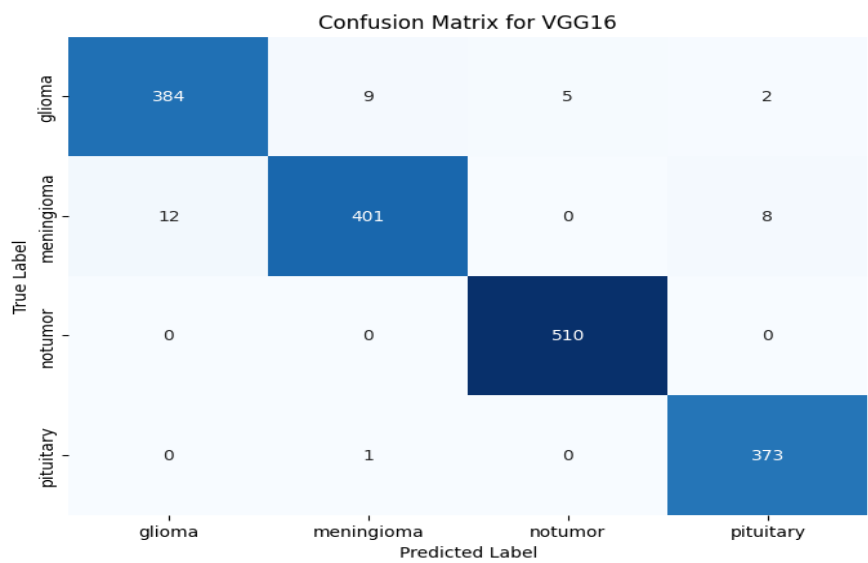


Figure 5
Confusion Matrix output

C. Model Classification summary

	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 6
VGG16 classification report

The acquired classification report of the experimental framework and the related graph represent the performance of each brain tumor class (Figures 6 and 7). The analysis of each tumor class with various performance parameter represented in Table 2.

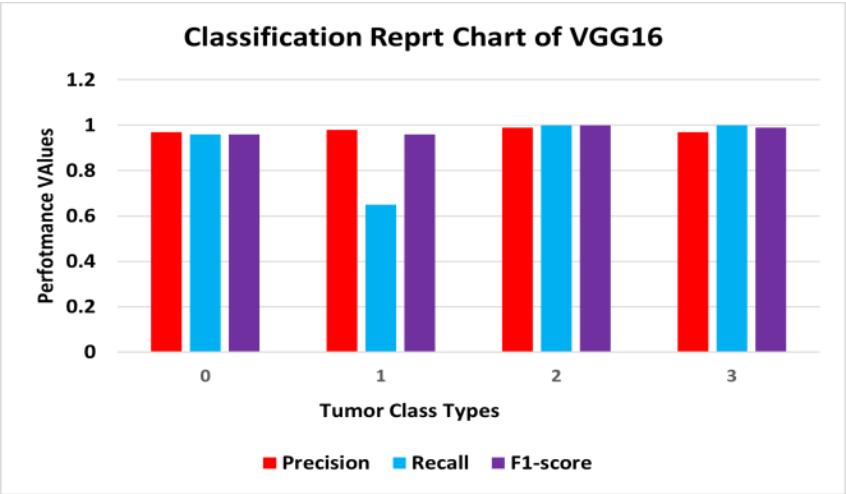


Figure 7
VGG16 Classification report chart

D. AUC-ROC Curve

This efficient curve examines the framework’s efficiency to classify all brain tumor MRI classes (Figure 8). The presented curve demonstrated several key features, including robustness to class imbalance, and illustrated the association between TPR and FPR for multiple brain tumor MRI classes.

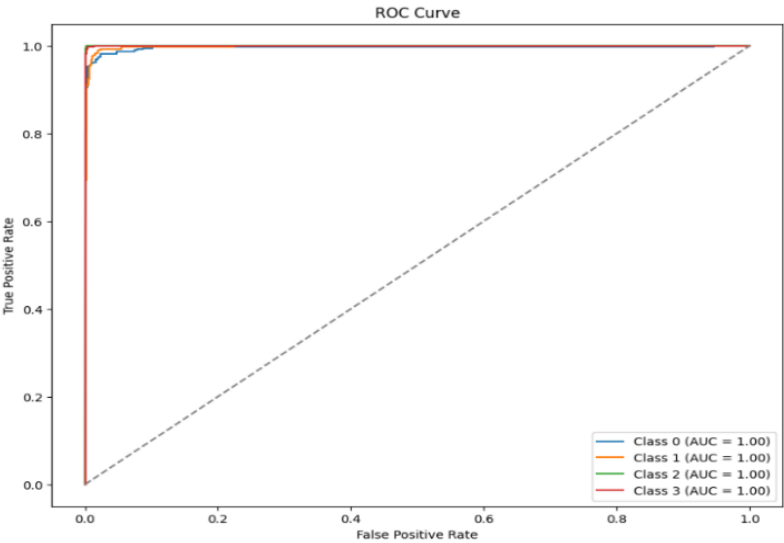


Figure 8
Acquired AUC-ROC Curve OF VGG16

Table 2
Analysis of VGG16 FRAMEWORK

Performance of the VGG16 framework			
Brain tumor MRI Classes	Brain tumor MRI precision Outcome	Brain tumor MRI recall Outcome	Brain tumor F1-Score Outcome
0	0.97	0.96	0.96
1	0.98	0.95	0.96
2	0.99	1.00	1.00
3	0.97	1.00	0.99

4. Conclusion and future work

The implemented research work applied a popular pre-trained deep neural network, VGG16 architecture. It used a progressive transfer learning method to identify and classify brain tumor MRI into distinct tumor classes. The resultant accuracy of the experimental framework demonstrates its efficiency. Moreover, the ROC-AUC curve of the experimental framework indicates its strategic strength to demonstrate the effectiveness of every brain cancer group. The experimental results have been visualized using graphs.

In addition, we have seen that a fine-tuned pre-trained architecture generates a reference model for MRI categorisation. The model's results provide the potential of applied TL in this domain. In future experiments, our goal will be to minimise the overfitting issue, explore various enhanced fine-tuning concepts and use some data enhancement methods to achieve maximum classification efficiency.

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