Design of Transfer Learning based Deep CNN Paradigm for Brain Tumor Classification

NEHA BHARDWAJ, MEENAKSHI SOOD, SS GILL
ECE Department, NITTTR, Chandigarh,
Panjab University,
INDIA

Abstract: - Brain tumor is a fatal illness causing worldwide fatalities. The existing neuroimaging modalities to detect brain tumors are invasive and are observer-biased. Automatic CAD frameworks using sophisticated AI techniques lessen human intervention and can effectively handle large amounts of data. Automatic CAD frameworks using Machine learning techniques require the use of time-consuming and error-prone manual feature extraction procedures. Deep learning techniques involve automatic feature extraction; hence, appreciable classification results are attained quickly. However, training DL models from scratch takes a significant investment of time, money, and large datasets, which are difficult to attain in the medical domain. Therefore, the trade-off is utilizing the well exhaustively learned models like VGG16, VGG19, AlexNet, etc. to design a novel framework for the classification of brain tumors. The paper aims to develop a CNN-based deep learning framework by fine-tuning the pre-trained VGG16 architecture via transfer learning for brain tumor detection. The designed framework employing the transfer-learning technique gives better results with less data in less time. The brain tumor binary classification using brain MR images using transfer learning achieved an appreciable accuracy of 97%. The training and validation accuracy obtained was 100% and 97%, respectively, with 30 epochs. The loss for classification was as low as 0.0059% and the run time of 32ms/step time, much less than the existing models.

Key-Words: - Convolutional Neural Networks, Deep Learning, Computer Aided Diagnosis, Classification, Hyperparameter tuning, Magnetic Resonance Imaging.

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1 Introduction

Diseases have stumbled and been vanquished over the past decades due to human knowledge and biomedical advancement, but cancer, due to its unstable nature, remains a burden to mankind. Brain tumor malignancy is a severe as well as rapidly progressing disorder. The brain is an important and complicated organ in the human body, comprising nerve cells and tissues that control the majority of the body's operations.

As per the research report published in the International Association of Cancer Registries (IARC), in June 2023, approximately 28000 cases of brain tumor are reported in India each year, with approximately 24000 fatalities. According to research published in Business Insider by doctors, this lethal condition affects 20% of the young Indian population, [1]. One of the most critical aspects of saving a person's life is the quick diagnosis and prognosis of this hazardous disease.

There exist many neuroimaging modalities like MRI, CT Scan, and PET Scan to detect brain tumors, but decoding the type and grade requires biopsy measures, which are prone to human subjectivity. Nowadays, advancements in Computer-Assisted Diagnosis (CAD), and AI methods enable radiologists to identify brain tumors more accurately. Artificial Intelligence (AI) tools are now widely used in biomedical exploration and the development of robust diagnostic systems for a variety of diseases due to their success in prediction particularly in clinical analysis to characterize brain tumors. Outmoded machine learning methods for disease characterization require manual feature extraction, which brings human-biased outcomes. Deep learning approaches, on the other hand, can be developed in such a way that no handmade feature extraction is required while producing correct classification results.

Machine learning techniques use feature abstraction methods, such as thresholding-based, clustering-based, contour-based, and texture-based, to segregate the tumor from normal anatomical surroundings . However, Deep Learning techniques tackles this issue by using automatic feature extraction techniques through the use of Convolutional Neural Networks (CNN), Long Short Term Memory Networks (LSTM), and Recurrent

Neural Networks (RNN) deep learning models. Training DL models from scratch involves time and resources and requires huge datasets, which are not always easily available. In machine learning, it is possible to lose significant knowledge from the actual data by employing manual feature extraction. Therefore, the trade-off is a transfer learning approach, which enables using a pre-trained classification model and fine-tuning it on a new relatable classification problem. In transfer learning, a model already trained with other enormous databases linked to a different field is used for classification. Transfer learning saves resources and time as the model is not trained from scratch. This knowledge enables the model to attain appreciable accuracy on a smaller database.

This paper proposed a deep CNN-based framework by fine-tuning the pre-existing model, VGG16, to classify brain tumor MR images into healthy and tumor images by fine-tuning the last layers to 2 on a publically available benchmark dataset. The resizing of the image dataset is done to match the image dimension requirement of VGG16, and pre-processing of the acquired database is done to achieve appreciable classification accuracy with low errors and in less time.

The paper is organized as follows: Section 2 provides the related literature survey carried out by researchers in a similar field. Section 3 presents the methodology of the process, starting from data acquisition to fine-tuning and, finally, binary classification of the brain tumor. Section 4 represents the results and discussions, and Section 5 concludes the paper.

2 Background

A brain tumor identification and classification network using Recurrent Convolutional Neural Network was developed and a classification accuracy of 95.17% was obtained on the Kaggle dataset, [2]. A survey was conducted on the available brain tumor detection and its grading techniques and the importance of timely diagnosis of a tumor for saving a person's life as tumor changes shape and size quickly was concluded, [3]. A transfer learning technique was developed for multi-classification of brain tumors into three types using CNN, and classification was done using classifiers like Support Vector Machine, and K-Nearest Neighbour on the Figshare database, [4], [5], [6].

A multiclassification framework using transfer learning on VGG16 was developed and achieved a classification accuracy of 97.80% on a publicly available database of 3064 brain MRI images, [7]. A deep learning-based pre-trained classification models for binary classification of brain tumors was developed, by fine-tuning pretrained AlexNet, and an accuracy of 99% was achieved on The Cancer Imaging Archive (TCIA) Public Access repository containing 696 MR images, [8]. Two different techniques were developed: the first, for assessing cancer grade directly from imaging data, obtained an accuracy of 89.5%, while the second, for predicting grade from tumor ROI, obtained an accuracy of 92.98%, [9]. A pre-trained model Google Net was finetuned for multiclassification of brain MR images using the public data repository Figshare consisting of 3064 brain MR images and an accuracy of 98% was achieved, [10]. A Neural Net-based model for multi-classification of three types of brain tumors using Keras was developed and an accuracy of 95% on the Figshare brain MR image dataset consisting of 3064 brain MR images was obtained, [11].

A deep-learning CNN framework for brain tumor detection using Keras tensorboard was developed and classification accuracy of 99.40% on the publically available BraTs 2020 dataset of 3064 brain MR images was obtained, [12]. The multi-classification accuracy of 95% on the Figshare dataset of 3,064 brain MRI databases using the pre-trained model ResNet 50 was achieved. and a comparative analysis with other cutting-edge models, such as DenseNet and Mobilenet, was performed by the authors, [13]. Two CNN frameworks for brain tumor binary and multi-classification using the Kaggle database were developed, with 94% and 89% accuracy, respectively, [14]. Image pre-processing was done on a Kaggle dataset of brain tumor MRI images using a grey-level co-occurrence matrix for feature extraction and classification accuracy of 95.17% was achieved. The study comprised of a benchmark database of 3264 brain MRI images, [15]. The Multimodal MRI scans were utilized to demonstrate genomic subtyping of Glioma in the brain with an accuracy of 82.35%. The MRI image dataset BR35H: Brain Tumour Detection 2020 (BR35H) was used for the same purpose, [16]. The literature revealed that brain tumor classification and the multi-classification of the brain tumor has been achieved by researchers with appreciable classification accuracy by either developing their frameworks or by utilizing the already existing state-of-the-art classification models like VGG16, VGG19, AlexNet, ResNet, etc. that gives better accuracy results in less time with limited dataset.

3 Methodology

The design of the framework starts from data acquisition to pre-processing and fine-tuning of pre-trained VGG16 for brain tumor classification.

3.1 Data Acquisition and Data Pre-Processing

The database is taken from the official data port Kaggle, BR35H-Brain Tumor Detection 2020, a Google benchmark data repository for data scientists and machine learning practitioners, [17]. The dataset is balanced and consists of 3000 labelled brain MRI scans, 1500 tumors and 1500 non-tumor.

The acquired dataset is subjected to various preprocessing techniques like resizing the dataset to 224*224 as this size image set is fed to pre-trained VGG16. To ensure uniformity, the entire dataset is scaled to the same value before being fed into the neural net. The entire dataset is randomly shuffled before being fed to the classification framework to prevent the network from targeting specific images every time.

The proposed CNN Model is implemented using Tensorflow 2.6, Google's machine learning platform, and i5 processor with 64-bit operating system and 16 GB RAM. The acquired database is split into training and validation image bases. A validation split of 0.3 or 0.2 is frequently utilized for the split. It is a simple procedure for observing the enactment of predictive deep or machine learning models. The training image database is used to fit the deep net or machine-learning model, whereas the testing dataset is used to evaluate the model. In this brain tumor categorization paradigm, a data split of 0.3 has been used, [18].

The block diagram for brain tumor identification is presented in Figure 1.

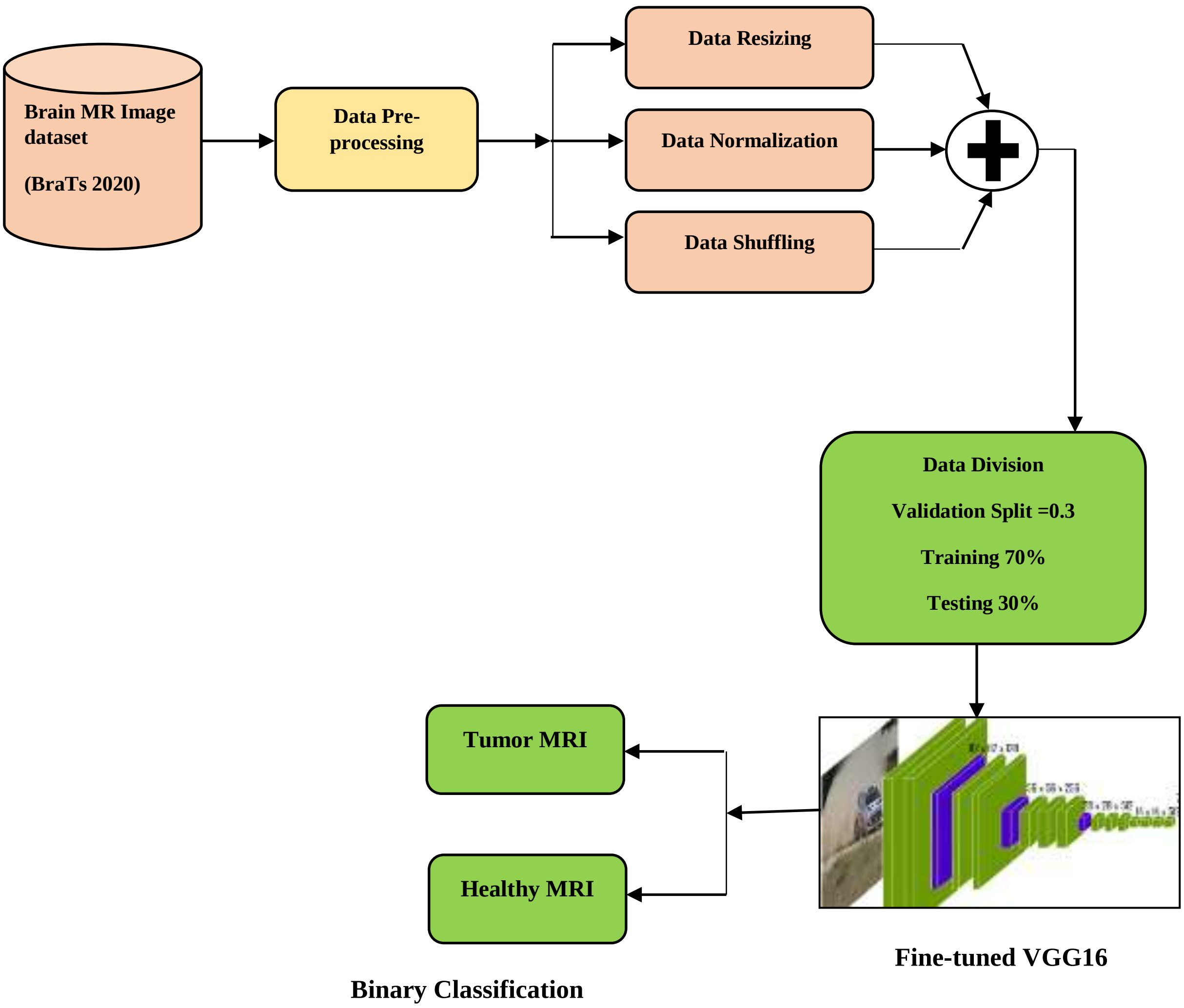


Fig. 1: Block Diagram of brain tumor detection using VGG16 by the process of transfer learning

3.2 Transfer Learning

The transfer learning method uses pre-trained classification models for learning new features to use the already learned features to solve one problem as a starting point for solving other problems with a new dataset.
VGG16 is a 16-layer deep Convolutional Neural Network developed by University of Oxford, [19]. When compared to other evolved comprehensives, it stands out for its simplicity. The acceptable input data size for VGG 16 is 224*224 pixels. It has 13 Convolutional layers, 5 max pooling layers, and 3 dense layers. The filter size varies from 64 at the start to 512 at end. The output layer has 1000 neurons accounting for 1000 classes of the ImageNet dataset, VGG16 was trained upon, [20], [21].

3.3 Proposed Fine-tuned Classification Paradigm

In this research work, the pre-trained model VGG16 has been fine-tuned by changing the last layers according to the problem undertaken, and neurons in the output layer have been changed to two to detect the brain tumor (binary classification). The activation function used is Softmax.
Transfer learning helps in fast training of the model, as the model is not trained from scratch, hence appreciable results are attained in less time, [22], [23]. The computational cost and time are also saved and model gives good results on fewer datasets. The transfer learning, sometimes may add biases from the previous models it was trained and also may sometimes add the problem of overfitting. Dropout layers are added to prevent the problem of overlearning and underlearning. The fine-tuning strategy in transfer learning allows tweaking hyperparameters like learning rate and regularisation to optimize the model as per the requirement, [24], [25].

4 Results and Discussions

4.1 Evaluation Metrics

To inspect the performance of finetuned VGG16 architecture, various evaluation parameters like Accuracy, Precision, Recall, and F1 Score are observed.
These are indications of how accurate the prediction of the designed model is. The score indicates better model performance.

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

$$Specificity = \frac{TN}{TN+FP} \tag{2}$$

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

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$F1 = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{5}$$

where: TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative respectively, [26], [27].
TP: when the model correctly interprets a normal brain image as a healthy image.
TN: when the model correctly interprets brain tumor image as tumor image.
FP: when the model incorrectly interprets the normal brain image.
FN: when the model incorrectly interprets the tumor brain image.

4.2 Classification Results

The empirical exhaustive study was done by varying the number of epochs from 10 to 50. The overall accuracy for binary classification is 92% for 10 and 97% for 30 epochs. After increasing the epochs to 50, the classification accuracy remains constant, which shows optimum learning in 30 epochs. Further, the classification accuracy was justified by other related metrics like F1 Score, Recall, and Precision, [28].

The classification reports for 10 and 30 epochs are shown in Table 1 and Table 2, respectively.

Table 1. Classification Report: (10 epochs)

	Precision	Recall	F1 Score	Support
0 (Non tumor)	0.90	0.96	0.93	468
1 (Tumor)	0.96	0.88	0.92	432
Accuracy			0.92	900
Macro Average	0.93	0.92	0.92	900
Weighted Average	0.93	0.92	0.92	

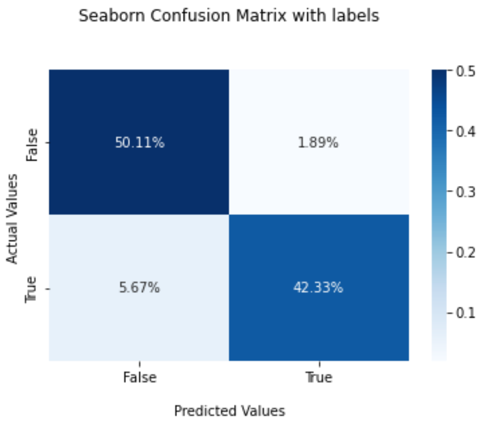
Table 2. Classification Report: (30 epochs)

	Precision	Recall	F1 Score	Support
0 (Non tumor)	0.98	0.96	0.97	460
1 (Tumor)	0.96	0.98	0.97	440
Accuracy			0.97	900
Macro Average	0.97	0.97	0.97	900
Weighted Average	0.97	0.97	0.97	

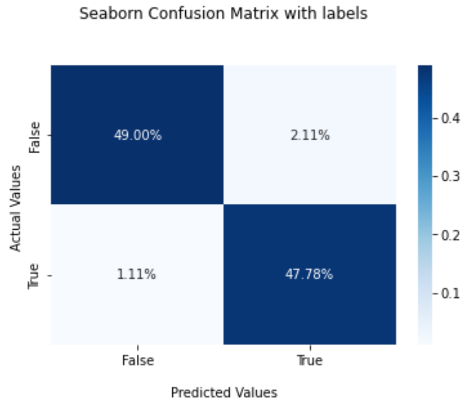
The training and validation accuracy for binary classification with 10 epochs is 99% and 92.44%, respectively. The loss and run time was also low, accounting for 0.060 % loss and 33ms/step time. The training and validation accuracy was 100% and 96.78%, respectively, with 30 epochs. The loss was also low, accounting for 0.0059% and a low run time of 32ms/step time. The accuracy graph attained a constant value even after increasing the epochs to 50, showing optimum learning achieved by the network, as shown in Figure 3(c).

The Confusion Matrix is an important performance-measuring statistic for the deep learning model, [29], [30]. It is used to summarise the predicted and actual values of the developed framework. The confusion matrix of the developed model for both 10 and 30 epochs is shown in Figure 2.

The developed model was tested on 60 MR images of tumor and non-tumor images. The developed framework predicted the tumor and healthy images correctly. The testing results of tumor and healthy images by the developed framework are shown in Figure 4, respectively.

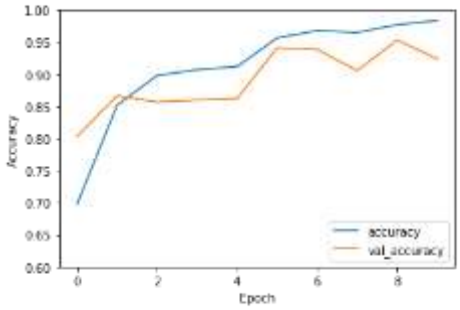


(a)

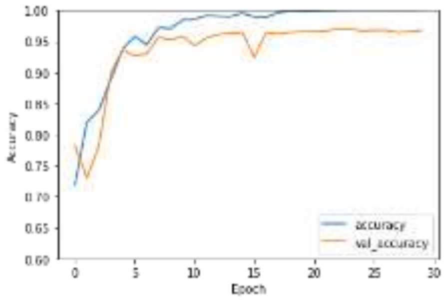


(b)

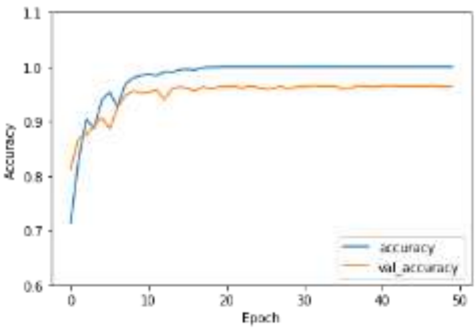
Fig. 2: Confusion Matrix of developed Model (a) 10 epochs, (b) 30 epochs



(a)



(b)



(c)

Fig. 3: ROC Curve of the developed model (a) 10 epochs (b) 30 epochs (c) 50 epochs

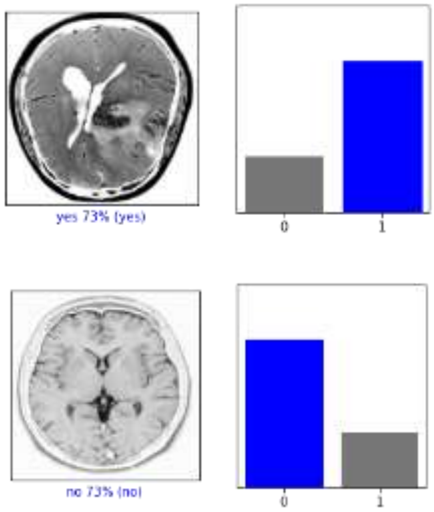


Fig. 4: Testing of developed model on (a) tumor and (b) Non tumor MR image

4.3 Comparative Analysis

The comparative analysis of the fine-tuned VGG 16 for brain tumor classification has been done by the classification frameworks developed by the authors over the time for brain tumor detection using the same dataset used in this research study as shown in Table 3. The percentage improvement in the accuracy for the developed model with the frameworks developed by the authors with the same database is shown in Figure 5.

Table 3. Comparative Analysis

Model Name	Methodology	Accuracy for Model developed by authors	Classification accuracy achieved by developed Model	Percentage improvement in the accuracy
M1	T.Tazin et al. [21]	92%	97%	5.15%
M2	Agas Eko et al. [22]	97%	97%	-
M3	F. Özyurt et al. [23]	95.62%	97%	1.42%
M4	Pereira et al. [9]	89.50%	97%	7.73%
M5	O.zkaraca et al. [14]	94%	97%	3.09%

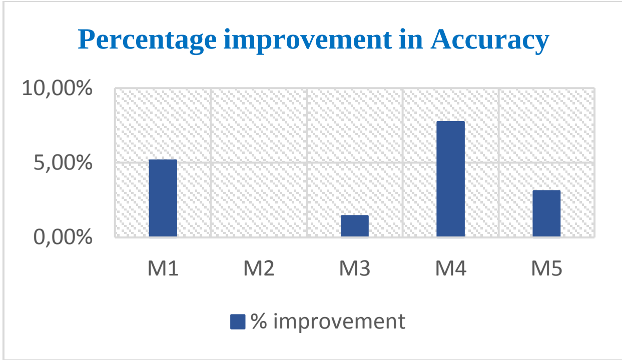


Fig. 5: Percentage Improvement Accuracy Graph

5 Conclusion and Future Work

Brain tumors are lethal, and manual discovery takes time and medical expertise. The large volume of MR data required for tumor diagnosis and type necessitates using automatic diagnostic approaches. The paper presented a fine-tuned VGG 16 architecture using the transfer learning process for automatic brain tumor uncovering in human brain MR images. The results demonstrated the effective automatic brain tumor binary classification without human intervention. The results of the F1 Score, precision, Recall, and high training and testing accuracy with a low test error of 0.0059% and low runtime of 32ms/step time. The overall accuracy obtained was 92% for 10 epochs and 97% for 30 epochs and it remains constant after increasing the number of epochs to 50.

In the future, a novel CNN-based classification model will be developed for brain tumor severity grading which will further add to the development of robust CAD systems for multi-classification. The results obtained will be compared with the existing classification models like VGG16, VGG19, AlexNet, ResNet, etc.

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The authors have no conflicts of interest to declare.