Transfer Learning Using Convolutional Neural Network Architectures for Glioma Classification from MRI Images

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Summary

Glioma is one of the common types of brain tumors starting in the brain's glial cell. These tumors are classified into low-grade or high-grade tumors. Physicians analyze the stages of brain tumors and suggest treatment to the patient. The status of the tumor has an importance in the treatment. Nowadays, computerized systems are used to analyze and classify brain tumors. The accurate grading of the tumor makes sense in the treatment of brain tumors. This paper aims to develop a classification of low-grade glioma and high-grade glioma using a deep learning algorithm. This system utilizes four transfer learning algorithms, i.e., AlexNet, GoogLeNet, ResNet18, and ResNet50, for classification purposes. Among these algorithms, ResNet18 shows the highest classification accuracy of 97.19%.

Keywords: *Brain Tumor, Deep Learning, High-Grade Glioma, Low-Grade Glioma, MRI, ResNet.*

1. Introduction

A tumor inside the brain is formed due to a collection of abnormal cells. A brain tumor can be classified into a non-cancerous (benign) and cancerous (malignant) brain tumor [1]. The glial cells encircling the neurons are the primary cause of a brain tumor. Oligodendrocytes, astrocytes, and ependymal cells are the three types of glial cells responsible for tumor growth [2].

Identifying a brain tumor is a complicated job that needed specialized skills to pinpoint the tumor's location. Capturing the brain's internal structure in high resolution with all the utmost importance features in this process. MRI machines use powerful magnets, radio waves, and computing machines to capture a detailed internal brain structure [3]. The MRI scans provide better picture details, contrast, and brightness than other methods because doctors for diagnosis [4] prefer tissue relaxation properties (T1 and T2). The manual analysis of a brain tumor is still a slow and lengthy process. The MRI machine can produce different scans (T1, T2, T1c, and flair) based on the contrast and brightness value, repetition time, and time to echo [5]. The captured MR Images are also used for automatic tumor diagnosis and classification using image processing techniques.

Convolutional Neural Networks (CNN) can process the various image and signal data using multi-dimensional arrays [6]. Two layers make up the first few CNN stages, namely the convolutional layer and the pooling layer. Units of the convolutional layer make up what is referred to as feature maps. One layer's feature map units are linked to the previous layer's feature map unit through filter banks. Filter banks can be considered as weights connecting these feature map units in consecutive layers. Locally weighted sums are passed through non-linear functions such as ReLU, with the result passed to the next layer. The pooling is then used to combine similar features. The unit in this layer calculates the maximum within a feature map. Neighboring pooling units use the shifts in rows and columns to reduce the design dimension, creating invariance to distortions and changes. Multiple convolutions and pooling layers are stacked to form the CNN, and back propagation gradients are calculated to train the filter banks. The computation complexity of these CNN requires high processing power. However, if the input is compressed to contain only the relevant information, the time to calculate the filter banks' weights can be reduced. All these various computer-aided methods are intended to assist medical doctors and radiologists in the diagnosis based on MR images and different imaging technologies, which is usually a time consuming and expensive task when done manually. It is also susceptible to human error; however, the automated human mistake becomes an irrelevant factor in the diagnosis process.

This study presents the Deep Learning (DL) approach to classify the brain MRI into HGG and LGG tumors. The brain part is segmented using the thresholding technique. The data is augmented using scaling and rotation operation to enlarge the dataset's size and introduce the generalization in the approach.

The remaining paper is organized as follow: The literature review of the existing approaches developed for the brain tumor classification is explained in Section 2. The transfer

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learning model is explained in Section 3. The model evaluation metrics are explained and illustrated in Section 4. The proposed system's methodology with a block diagram, and its explanation is elaborated in Section 5. The results of the system are discussed in Section 6. The paper is concluded with future direction is presented in Section 7.

2. Literature Survey

The state of art methodology for brain tumor detection and classification is reviewed in this section.

M. Amien et al.[7] proposed a brain tumor classification into edema, cancer, or normal classified using MRI. In this system, the noise is removed, and image enhancement techniques improve the image's quality. The texture features from the brain MRI are extracted and reduce the dimensionality using PCA. The extracted feature is classified using BPNN which utilize the Pearson correlation coefficient. The quantitative analysis shows that this system achieved an accuracy of 96.8%.

E. Dandil et al. [8] developed a CAD system for detecting tumors using T1 and T2-weighted MRI. They have evolved device segments of the brain tumor area using FCM. They have extracted the function using FIF, SF, and GLCM, choosing features using PCA. SVM classifies tumors as benign and malignant tumors. The proposed device detects accuracy, specificity and precision brain tumors, 91.49%, 90.79%, and 94.74% respectively.

C. L. Devasena et al.[9] introduced an effective Hybrid Irregular Detection Algorithm (HADA) to identify the irregularities in MRIs. The suggested methodology consisted of five stages: reducing noise, smoothing, extracting features, reducing features, and classifying. The suggested algorithm was applied, achieving 98.8% classification accuracy.
Havaei M et al. [10] used machine learning methods to perform brain tumor segmentation and increase the image's intensity features using a semi-automatic process that incorporates the image's spatial elements into consideration. It uses minimum user interaction to segment the brain tumor by training and generalization within the brain images. The method is tested by using the MIICCAI-BraTS 2013 dataset and achieved 86% accuracy for core tumor.

Latif G et al. [11] suggest an improved MR image classification algorithm using hybrid statistical and wavelet functionality. In addition to discrete wavelet transformation (DWT), 52 features were extracted using 1st and 2nd order statistical features, giving 152 features in all. Multilayer Perceptron (MLP) classifier is then introduced using the MICCAI BraTS 2015 dataset, with a precision of 96.72% for HGG and 96.04% for LGG.

Choi BK et al.[12] suggested using CNN to identify Alzheimer's disease (AD), natural regulation(NC) and moderate cognitive dysfunction (MCI) of the brain in the hippocampus region. The system achieved 92.3% accuracy for AD/NC, 78.1% for MCI/NC and 85.6% for AD/MCI. The approach suggested revealed that only a small part of the hippocampus picture would yield successful classification results.

Khan et al.[13], propose a fuzzy membership function for the classification and automatic diagnosis of liver cancer from small contract CT scan images. Images are enhanced using a fuzzy linguistic constant. They achieved a 98.3% classification accuracy using SVM.

Latif G et al.[14], suggest a system for classifying brain tumors based on MR images. The images extract wavelet features, and a random forest classifier is used to identify images as benign and malignant. In this scenario, 94.33% Classification accuracy is obtained. Then, region-growing segmentation is performed to remove the image's tumor section. Further wavelet characteristics are derived from the segmented section, and differentiation is made to determine tumor form. Classification specificity of 96.08% is obtained for tumor type classification.

3. Transfer Learning Model

Learning (TL) is an example for solving transfer learning models by using insightful knowledge to overcome related ones. It is the assignment to use pre-trained machine knowledge to learning new models generated by new data. Calibrating a pre-trained TL device is typically much faster and simpler than starting from scratch. Using pre-trained DL systems helps easily learn new work. Different scientists consider TL is a valuable tool to accelerate our AI development [15]. Traditional learning is disengaged and occurs on individual tasks or datasets, and trains standalone models. No material is stored and may be transferred from one job to the next. In TL, you can use the last model trained data (weights and features) and also tackle issues like getting fewer details for the new task.

DL systems are layered constructs that gain knowledge of different features at different stages. Ultimately, to produce the result, these layers are attached to the last layer called a fully-connected layer (FCL). This layered approach helps one use a pre-trained computer as a permanent extractor for many applications, with the last layer[16]. Suppose pre-trained networks are used without the final layer, i.e., the classification layer. In that case, a new domain image can be transformed into a multi-dimensional vector based on its hidden state, allowing us to extract features from a new domain using a pre-trained domain task. For each pre-trained network, visually differentiated features are extracted using fine-tuning (PTN). TL fine-tuning is used to improve a CNN's capabilities and utility by supplanting the network's layers. In this situation, CNN's weights are placed from the top PTN instead of replacing and retraining the classifier's entire structure. This functions by transferring PTN's weights from source to target dataset. The key task is replacing PTN's softmax layer with a softmax layer important to the proposed mission.

The dataset neurons are located in the last fully connected layer using the mentioned CNN architectures. The suggested method uses five transition structures to distinguish brain MRI into LGG and HGG. Fig.1-Fig.4 displays the transfer learning architectures used in this framework.

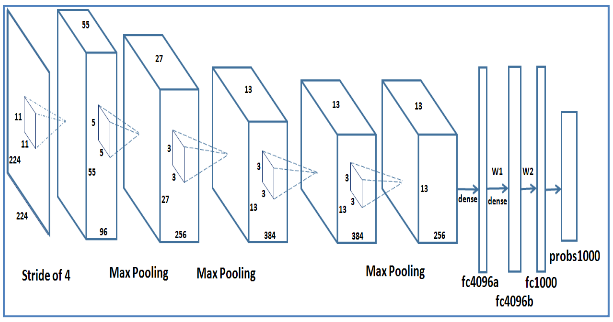


Fig. 1 AlexNet Architecture.

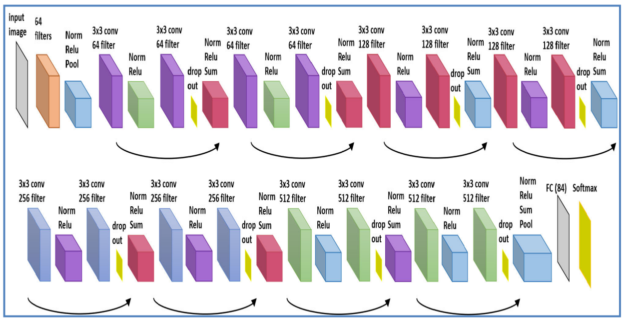


Fig. 2 ResNet18 Architecture.

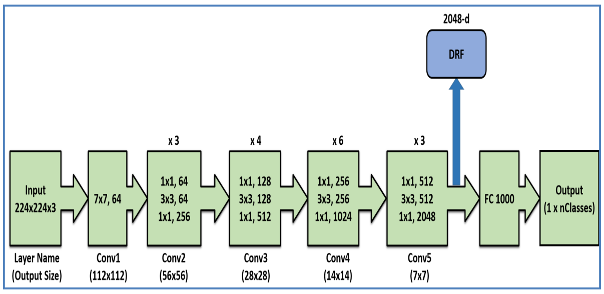


Fig. 3 ResNet50 Architecture.

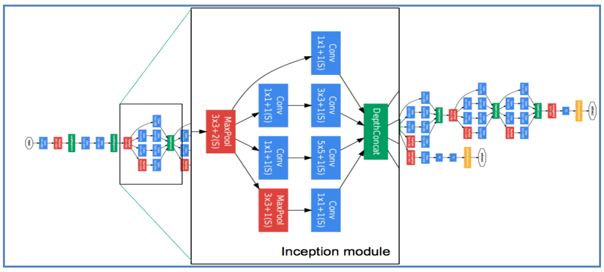


Fig. 4 GoogLeNet Architecture.

4. Model Evaluation Metrics

The proposed system's performance uses four evaluation metrics: precision, i.e., Precision, Recall, F-measure, and accuracy.

4.1 Precision

Precision is the measure of the positive rate of the predicted and actual values. It is defined by the ratio of the True positive sample to the total positive observations.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

4.2 Recall

The Recall is an evaluation metric called the True positive samples ratio to the expected positive classes.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

4.3 F-measure

F1-measure is the weighted average of precision and Recall.

$$F - measure = 2\ X\ \frac{Precision\ X\ Recall}{Precision + Recall} \tag{3}$$

4.4 Accuracy

Accuracy is the measure of correctness of the actual and predicted classes.

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

where TP is the count of the sample which predicts LGG as LGG. TN is the count of the sample which predict HGG as HGG.FP is the count of the sample, which predicts LGG as HGG.FN is the count of the sample, which predicts HGG as LGG.

5. Methodology

The proposed method is designed to identify and distinguish regular and abnormal brain MRIs reliably and then classify abnormal MRIs into HGG or LGG glioma tumors using transfer-learning CNN algorithms. Fig. 5 shows the methodology of the proposed system. First, Brain MRI is acquired by the system, preprocessing by the median filter, and then segmented by thresholding based binarization. Later the MRIs were trained and test using transfer learning algorithms like AlexNet, GoogLeNet, ResNet18, and ResNet50. The trained network is used to categorize the brain MRI into LGG and HGG.

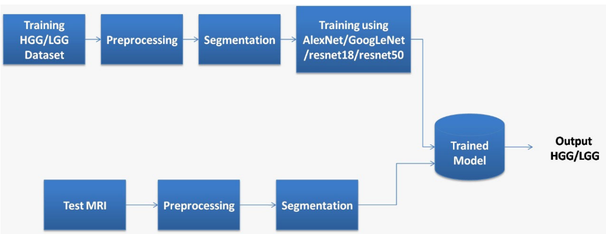


Fig. 5 Block diagram of the proposed methodology

5.1. Data Description

In this section, the MRI dataset used in the proposed algorithm is described. MICCAI BraTS 2015 MRI dataset is used in this system, which contains LGG and HGG tumor MRI [17]. The dataset comprises training samples with annotated data and testing cases without annotated data. Each sample case has T1, Flair, T1c, and T2 weighted sequence types of MR images. The MRIs are randomly divided as 80% of images are used for training and 20% for testing, as shown in Table 1.

Table 1: Database Distribution

Database	*Total MRIs*	*Training MRIs*	*Testing MRIs*
LGG	273	219	54
HGG	800	638	162

5.2. Preprocessing

The input images contain patient information and noises like salt and pepper and rician noise [17]. The preprocessing technique aims to eliminate the noises from the images and make them usable for further processing. Due to unipolar and bipolar impulse noise and salt & pepper noise, the median filter is more powerful for those noises [18]. Hence median filter is used in this method to remove salt and pepper noise. Another medical image issue is low contrast [19], which can be removed using power-law transform [20]. It is represented as

$$S = Cr^{\gamma} \tag{5}$$

Where the input image's intensity is represented by γ (gamma), the gray level of the output image is represented by S, and C is constant.

5.3. Segmentation

It is the method of extracting the region of interest from the whole image. In this system, the brain part is segmented using a thresholding algorithm, which is given by

$$f_{g(x,y)} = \begin{cases} 1 & I(x,y) > T \\ 0 & \text{else} \end{cases} \tag{6}$$

In this process, the input grayscale image denoted by $I(x,y)$. Pixel value greater than the user-defined threshold value, then pulled to value 1; otherwise pulled to 0. The resultant binary image is represented by $f_{g(x,y)}$. This binary mask is applied over the original image to get a region of interest and discard another part of an image.

5.4. Training and Classification

DL algorithm requires a large amount of data for training to get a generalized and robust model. When the database is small, we can enlarge the dataset by augmenting the data with the flip, rotate, and translate, etc. Table 2 shows the augmented parameters used in this approach.

Table 2: Database Distribution

Sr. No.	*Parameter*	*Value*
1	X-Reflection	1
2	Y-Reflection	1
3	Rotation	[0, 360]
4	X-Scale	[0.5, 1]
5	Y-Scale	[0.5, 1]
6	X-Translation	[-3, 3]
7	Y-Translation	[-3, 3]

DL is an extensively used technique to classify brain irregularities. Among the DL algorithms, CNN is one of the proven and most used methodologies. CNN studies the spatial relationship that is present within the pixels in a systematic way. The feature map is convolved with the input image to get the feature stack. The max-pooling layer then reduces the feature size, and lastly, the features are flattened for providing to the dense layer.

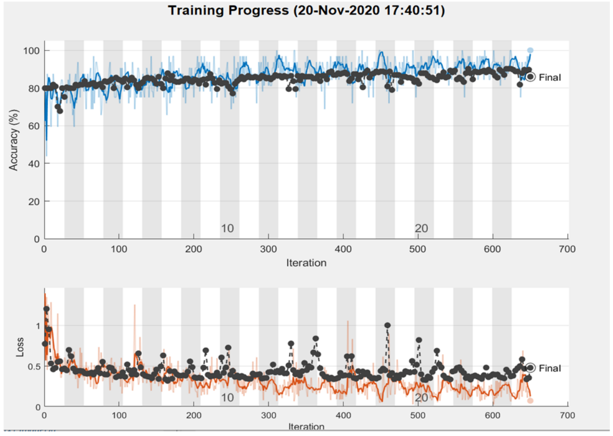
This approach utilized four CNN mentioned above TL architectures, i.e., AlexNet, GoogLeNet, ResNet18, and ResNet50 to classify brain MRI into LGG and HGG. The architectures of the TL used in this system are shown in Fig.1 - Fig.4. The training parameters used to train these network is as shown in Table 3.

Table 3: Training Parameters

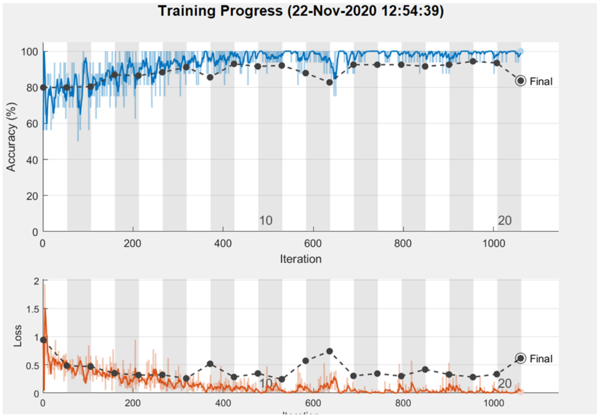
Training parameters	***Networks***			
	AlexNet	**ResNet18**	**ResNet50**	**GoogLeNet**
Learning Rate	0.0001	0.0001	0.0001	0.0001
Gradient Decay Factor	0.99	0.99	0.99	0.99
Max Epochs	25	25	25	25
Mini Batch Size	32	32	32	32
Validation Frequency	3	3	3	3
Optimizer	Adam	Adam	Adam	Adam

6. Result and discussion

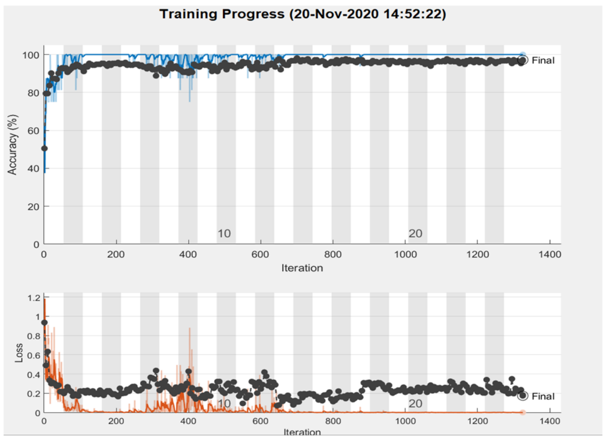
This section presents the result of the proposed system for brain MRI classification into HGG and LGG. The results are presented using qualitative and quantitative analysis. Fig.6. represents the training progress graph of the four transfer learning algorithms utilized for the training of HGG-LGG classification. The graphs show the progress of accuracy at every iteration. The training data get shuffled after every iteration, and performance was recorded at every iteration.



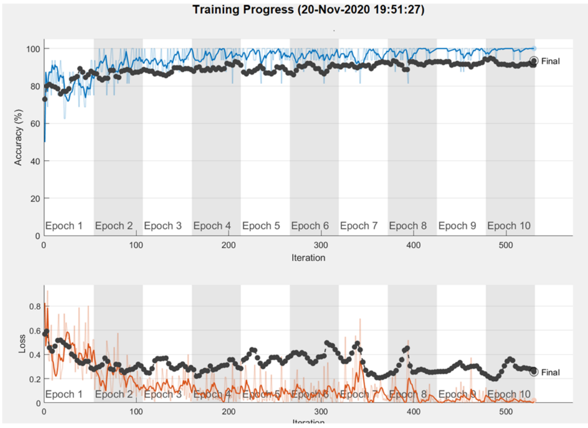
(a)



(b)



(c)



(d)

Fig. 6 Training progress of the proposed architecture (a)AlexNet (b)ResNet18 (c) ResNet50 (d) GoogLeNet

From the Fig.6. it is observed that transfer learning architectures show good classification accuracy for HGG-LGG MRI classification. Among the four architectures, ResNet18 shows the best accuracy. The performance is evaluated using the ResNet18 model as it offers high classification accuracy. Table 4 shows the quantitative analysis of the research.

Table 4: Quantitative Analysis of the proposed system

Transfer Learning Models	***Precision***	***Recall***	***F-measure***	***Accuracy***
AlexNet	0.994152	0.8543	0.9189189	0.859813
ResNet18	0.994186	0.9716	0.9827586	0.971963
ResNet50	0.94152	0.9758	0.9583333	0.933962
GoogLeNet	0.818182	0.9796	0.8916409	0.834906

Table 5 demonstrates the comparative accuracy of the proposed method with the existing system presented by [21]

Table 5: Comparative analysis of proposed and existing systems

Models	***Accuracy (%)***
Proposed (AlexNet)	85.98
Proposed (ResNet18)	97.19
Proposed (ResNet50)	93.39
Proposed (GoogLeNet)	83.49
SVM [21]	89.9
KNN [21]	86.5

The graphical analysis of the existing and proposed system's performance in terms of accuracy is presented in Fig. 7.

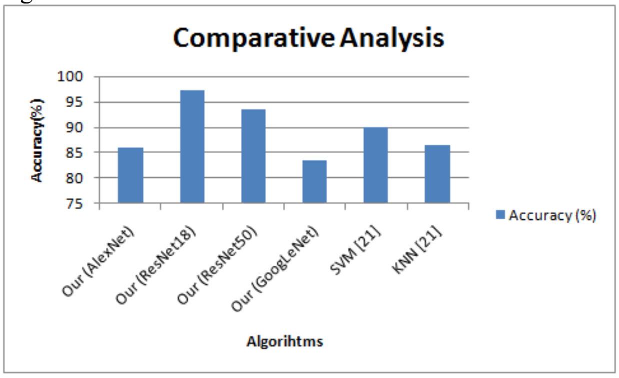


Fig. 7 Performance analysis of the proposed system with the existing system presented by [23]

From the comparative analysis of the proposed system with the existing system presented by Jyotsna Dogra et al. [21], it is observed that the ResNet18 and ResNet50 architectures of the proposed system performed superior to the SVM and KNN approaches of [21].

The training time is one of the essential factors for DL algorithms. The time taken by the different architectures used in this approach is tabulated in Table 6.

Table 6: Training Time

Models	***Time (Sec)***
AlexNet	31 min 55 sec
ResNet18	110 min 36 sec
ResNet50	116 min 12 sec
GoogLeNet	41 min 24 sec

7. Conclusion and Remarks

A DL approach is utilized in the presented approach to classifying the LGG and HGG from brain MRI. Four CNN-based transfer learning frameworks, i.e., AlexNet, GoogLeNet, ResNet18, and ResNet50, are utilized for training our LGG-HGG dataset. Among the four transfer learning algorithm, ResNet18 frameworks achieved the highest accuracy of 97.19%.

Observationally, we made some discoveries. First, various pre-trained DL networks' training results reveal that pre-trained network efficiency depends heavily on the optimizer selected. It will affect the performance of the system and computational time. Among the four utilized transfer learning architectures, ResNet50 took more training time, i.e., 116 min 12 sec using ADAM optimizer amongst the pre-trained networks. In comparison, AlexNet took the lower time to train the network, i.e., 31 min 55 sec with ADAM optimizer. Although the dataset isn't massive enough, image data growth has managed exceptionally well to deliver superior results and solve this problem.

Future experiments will be performed with the greater dataset to improve performance and minimize the time required to train the network using specialized processors.

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