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COMPARATIVE ANALYSIS OF PERFORMANCE OF DEEP CNN BASED FRAMEWORK FOR BRAIN MRI CLASSIFICATION USING TRANSFER LEARNING

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Abstract

The brain tumor is among the most hazardous and destructive diseases. The mortality rate in brain cancer is more at a later stage. Also, the brain tumor's misdiagnosis will produce danger and reduce the patient's chances of survival. The early diagnosis of a brain tumor aids in saving the life of the affected person by providing the right treatment. The computer-aided medical imaging techniques like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) aids in diagnosing the disease. Hence brain MRI classification became an active research area in recent years. Numerous methods have been presented in the earlier period for MRI categorization, right from classical methods to advance Deep Learning (DL) algorithms such as Convolutional Neural Network (CNN). The conventional Machine Learning (ML) techniques required handcrafted features while CNN performs classification by drawing features from unprocessed images directly via the convolution and pooling layer's parameter tuning. The feature extraction using the CNN algorithm is mostly influenced by the size of the training process's images. CNN models overfit after some epoch if the training dataset size is small. Therefore, transfer learning techniques have evolved. In the proposed system, conduct five studies using five transfer learning architectures such as AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet to classify the clinical dataset of brain MRI into benign and malignant. Data augmentation techniques are applied over the brain MRI to generalize the results and reduce overfitting possibilities. In this proposed system, fine-tuned AlexNet architecture achieved the highest precision, recall, and f-measure value of 0.937, 1, and 0.96774, respectively.

Keywords: AlexNet, Brain MRI, CNN, Deep learning, Transfer learning.

1. Introduction

The brain happens to be the indispensable and utmost multifarious organ within a person's body, which works in coordination with a huge cell network. In the wake of this modern century, it is observing a rapid increase in the rate of brain-related diseases. According to the World Health Organization (WHO) survey, cancer is among the foremost causes of mortality in the world [1]. The brain tumor is among those diseases that affect the appropriate operations of the brain. It is a type of neurological disorder wherein brain tissue or cell starts proliferating uncontrollably within or about the brain [2, 3]. The brain tumor is terminology following the cell corresponding to which the tissue or cell starts to grow. Tumors are categorized into primary and secondary tumors [4]. The tumor that initiates and develops inside an organ is referred to as primary tumors. In contrast, when the cell initiates in one point of the body, it starts spreading to another point in the body, referred to as a secondary tumor [4]. According to their structure, the tumors are termed as malignant and benign. Benign are non-cancerous and non-progressive tumors. Such types of cells initiate in the brain and grow gradually with lesser aggression. Also, they are not able to spread from one part to the rest of the body parts. Conversely, malignant tumors are those that are cancer-causing and advancing. They pass on speedily with indefinite contours. They may be primary and secondary tumors, as well [5-7].

The important in the case of brain cancer is to diagnose the tumor at the earlier phase. Analysing the diagnostics of patients that have brain tumors can be done with the aid of Brain MRI. MRIs give enhanced-resolution data regarding the brain's structure and abnormalities, which help in medical image processing and analysis [8]. Radiologists analyse irregularities in the brain, depending on the visual interpretation of a tumor present in MRI images. There is a slight chance of misclassifying whenever a large amount of MRI data has to be scrutinized. The other probability is that incorrect analysis can happen as a result of the decreased sensitivity of the individual's vision with an increase in the number of cases. It's a time-occupying method. Thus there is a requirement for a system to detect and classify tumors in the brain. Early identification of the brain abnormalities leads to early treatment and saves an individual's life. Nowadays, brain imaging's medical diagnosis is mostly made with MRI aid in most hospitals and clinics.

Recently, a lot of work has been done on brain tumor segmentation and classification using different image processing, ML, and DL algorithms. The utmost difficulty in this research is the database availability. Hence a robust algorithm needs to be developed that will work on the limited dataset with higher accuracy.

This study's main endeavour is to implement a robust technique to categorize the brain MRI images into cancerous (malignant) and non-cancerous (benign) class. To do this, the convolutional neural network, along with some transfer learning models AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet is used. The transfer learning model will help speed up the training and enhance the classifier performance.

This paper contains the following sections: Section 2 discusses the brief introduction and analysis of recent advancements in brain tumor classification from the brain MRI aided by ML and DL framework with its advantages and disadvantages. Section 3 offers the framework of the methodology of the presented system. Section 4, discusses the experimental results. Section 5 concludes the paper with the suggestion of future advancement.

2. Literature Survey

Classification of brain tumors plays a significant responsibility in the proposed methodology. In the latest times, DL and ML algorithms were widely used for categorization. This section elaborated the previous works in brain MRI classification using ML and DL.

Wasule and Sonar [9] demonstrated the procedure for brain MRI classification. The author uses clinical and BRATS 2012 dataset of malignant, benign, and low-grade glioma, high grade glioma image datasets. In this research, the GLCM algorithm was used for feature extraction and categorized with the ML algorithms' help, i.e., Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classification algorithm. The system is verified using the clinical and BRATS 2012 dataset. In the first case, the results were evaluated on the clinical dataset, which achieved 86% and 96% accuracy for the SVM and KNN classification algorithms. In the second case, the results were evaluated on the BRATS 2012 dataset, which achieved an accuracy of 72.50% and 85% for SVM and KNN classification algorithms, respectively.

Sonavane and Sonar [10] proposed an ML (Adaboost) based methodology for brain MRI classification. In the first phase of the system, the MRI images were pre-processed using a skull skipping anisotropic diffusion filter. In the second phase, the brain MRIs' statistical and texture features were calculated using GLCM and Discrete Wavelet Transform (DWT). In the final phase, the AdaBoost algorithm classified the extracted features.

Balakumar et al. [11] presented the use of ML Algorithm for brain tumor classification. The experiments employed the Self Organizing Map (SOM) focused on feature training and classification using SVM. GLCM and the texture and shape features are collected for each image. SOM is used to train collected feature networks and got a maximum accuracy of 89.5%.

Byale et al. [12] proposed a technique to segment and graded the brain MRI with ML Techniques. They made use of the GLCM for extracting features and used feed-forward neural networks on the MRI and CT images. This system was able to classify brain tumors with an accuracy of 99%.

Badza and Barjaktarovic [13] proposed the CNN-based classification system from brain MRI. The classification is performed on T1-weighted MRI of gliomas, meningioma, and pituitary tumors. This system got an accuracy of 96.56%.for 10-fold cross-validation with good speed and generalization capability.

Ruba et al. [14] proposed segmentation and classification approach of brain MRI. The system segments the tumor region using a convolution and pooling layer and classifies the tumor into glioma, meningioma, and pituitary using the pre-trained GoogLeNet method. The presented approach achieved a classification accuracy of 99.78%, 99.57%, and 99.56% for glioma, meningioma, and pituitary.

Zacharaki et al. [15] developed the pattern recognition approach to differentiate the brain tumor into metastasis, meningioma, glioma WHO grade 2, gliomas WHO grade 3, and glioblastoma. This system includes ROI extraction, feature extraction, feature selection, and classification. The SVM classifier is used for classification, achieving 85% classification accuracy for discrimination of metastases from gliomas and 88% for high-grade discrimination from low-grade neoplasms.

Sultan et al. [16] first proposed the CNN method for tumor classification into meningioma, glioma, and pituitary tumor. Secondly, the segmented tumor is differentiated into Grade II, Grade III, and Grade IV classes. The presented network structure achieves significant efficiency for both studies with the highest accuracy of 96.13% and 98.7%, respectively.

Deepak and Ameer [17] made use of the transfer learning technique to take out the brain MRI features. This research is focused on the classification of glioma, meningioma, and pituitary from MRI. GoogleNet architecture is utilized to draw features from brain MRI and classify KNN and SVM algorithms. This method achieved 98% accuracy.

Ismael and Abdel-Qader [18] presented the multilayer perceptron neural network for the classification of glioma, meningioma, and pituitary tumors from MRI. The features were pooled out sing 2D Gabor filter and DWT. They obtained a total accuracy of 91.9%.

Muhammad Sajjad et al. [19] described a DL method to categorize the multi-grade brain MRI. In this system, the CNN technique is used to separate the brain tumor, then the data is improved with the help of different factors to enhance the training trials and finally, the Vgg19 technique is used to train the CNN network. This technique attained a precision of 87.38% for original data and 90.67% for improved data.

Talo et al. [20] introduced the MRI CNN algorithm for multi-class brain tumor detection. They used pre-trained CNN models ResNet-18, Vgg-16, AlexNet, ResNet-34, and ResNet-50 to categorize MRI images into cerebrovascular, inflammatory, neoplastic, normal, degenerative, and inflammatory diseases. This approach got an accuracy of 95.23 ± 0.6% for the ResNet50 model.

Kumar and Kumar [21] presented brain MRI categorization by plain and residual feed-forward CNN's through transfer learning techniques. They experimented on an openly available dataset for classifying brain tumors by deep transfer learning models like AlexNet, VGG16, ResNet50, ResNet101, and GoogLeNet. Models are trained for classifying images as malignant and benign. VGG16 gave better accuracy of 98.75% within the rest of the DL models.

Talo et al. [22] presented an automated brain tumor classification with MRI Images through deep transfer learning. The experiments suggested transfer learning with the previously trained CNN ResNet34 architecture for brain image classification. The suggested model accomplished a classification precision of 100% for 613 MR images. The established techniques can also detect other brain irregularities like autism, stroke, Alzheimer's disease, and Parkinson's disease.

Swati et al. [23] presented brain MRI classification by a fine-tuned transfer learning algorithm. The experiments were performed on pre-trained VGG16, AlexNet, and VGG19. VGG16 and AlexNet attained the average precision of 89.95% and 94.65%, respectively, for 5-fold cross-validation. VGG19 attained better performance thanVGG16 and AlexNet.

Rehman and Razzak [24] presented a DL-based system for brain MRI classification using transfer learning techniques. The experiment conducted studies using three different architectures of CNN's like VGGNet, GoogLeNet, and AlexNet to classify the brain tumors like pituitary, glioma, and meningioma. The VGG16 architecture achieved accuracy up to 98.69% for detection and classification.

From the previous system's study, it is observed that earlier, the image processing techniques were used to detect the tumor from brain MRI. Later on, ML techniques were introduced to classify brain MRI into different classes like Malignant vs. Benign and Glioma vs. Meningioma. For these, different feature extraction algorithms such as GLCM, GLRLM, DWT, etc., were used. In the latest years, because of the advancements in processing capacity, DL algorithms were used. Most of the recent techniques were implemented using CNN algorithms.

3. Proposed Methodology

The comprehensive method for evaluation of the brain MRI classification has been presented in this section. The framework of the presented system is separated into the training and testing phases. In the training process, the training brain MRI dataset is employed, and the trained model is saved for the testing process. Unknown testing brain MRIs were classified with the trained model. The proposed work employs five pretrained transfer learning architectures of CNN, i.e., AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet. This system's framework is divided into pre-processing, segmentation, data augmentation, training, and testing. The architecture of the brain MRI classification system is presented in Fig. 1.

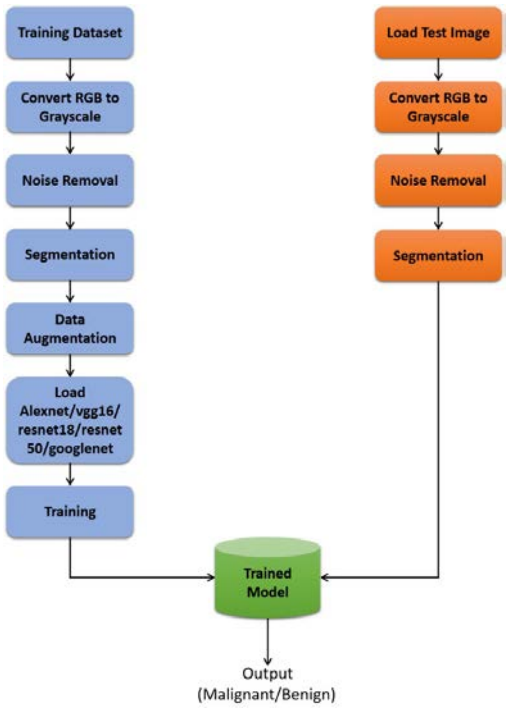


Fig. 1. Architecture of the proposed methodology.

3.1. Database

The medical dataset of brain MRI is referred for this approach. The database is collected from the hospital. The collected dataset contains T1, T2, and Flair images of benign and malignant MR images [12]. Also, the images are validated by the radiologist for each class. Table 1 presents the complete distribution of the dataset into training and testing.

Table 1. Database distribution.

Database class	Training images	Testing images
Benign	75	25
Malignant	75	25

3.2. Pre-processing

Images taken from the database are noisy, raw, and contain text data of patients and the image. At first, the images exist in the 24-bit colour format. Then the weighted average method is used to adapt the RGB colour image into grayscale. The medical images are mostly affected by impulse, salt, pepper, and Rician noise [9]. The median filter removes impulse and salt & pepper noise from MRIs [25] and an anisotropic diffusion filter to remove Rician noise [26]. In this method, these noises are removed at an earlier stage by the median filter. Clinical images also have less contrast [27]. So, these lesser contrast images need to be upgraded with the aid of power-law transformation [28]. It is arithmetically computed as Eq. (1),

$$S = Cr^{\gamma} \tag{1}$$

Here r is an intensity of an input image, γ is referred to as "gamma"; therefore, it is called gamma transformation. S is the resultant grayscale intensity of an image. C is constant.

3.3. Segmentation

The selection of an interested part, i.e., the skull, is a crucial step performed by the segmentation process. Thus in this approach, the thresholding-based segmentation technique is used to separate the brain part and discard another part. The pre-process images $I(x, y)$ segmented, with the help of the threshold process, is referred to as Eq. (2):

$$f_g(x,y) = \begin{cases} 1 & I(x,y) > Th \\ 0 & else \end{cases} \tag{2}$$

where $I(x, y)$is the intensity value of the grayscale pixel, and $f_g\,(x, y)$ is the pixel value of the segmented binary image. The pixel value less than the threshold value is replaced by 1; else pixel is replaced by 0. Now this image is again treated over morphological operation like dilation and erosion. The binary mask gets applied over the original image, due to which the brain image gets segmented out, and the entire skull part gets skipped.

3.4. Data Augmentation

The DL methods required a large amount of data with feature variability. Data augmentation is one of the foremost aspects of pre-processing, especially in the transfer learning method. If the database is significantly smaller, it starting to recall the features called overfitting. It can be avoided by making databases with notable differences, but it is a confusing medical image task. Such a practice is general while concerned with image-based data [29]. The data augmentation process involves geometrical transformation operations like scaling, translation, rotation, translation, shearing, reflection, etc. The data augmentation parameters involve in this process are given in Table 2.

Table 2. Quantitative analysis.

Sr. No.	Parameters	Value
1	X-Reflection	1
2	Y-Reflection	0
3	Rotation	[0, 0]
4	X-Scale	[1, 1]
5	Y-Scale	[1, 1]
6	X-Shear	[0, 0]
7	Y-Shear	[0 0]
8	X-Translation	[-10 10]
9	Y-Translation	[-10 10]

3.5. Training using deep learning algorithm

DL is a tremendously employed methodology for the brain MRI classification. CNN algorithm is widely used for clinical imaging for classification. CNN studies the spatial relationship that is present within the pixels in a systematic way. In this CNN based approach, the features are extracted by performing a convolution operation on the image with the feature map. The convolved feature stacks are then minimized by the MPL and reduced featured flattened and provide to the Fully Connected Layer (FCL) or dense layer.

This work employs the pre-trained CNN network called 'AlexNet.' It is a renowned architecture of Convolution Layers (CL) (five), Max Pooling Layers (MPL) (three), normalization layers (two) and FCL (two), and softmax layer (one) for training to identify 1000 objects [23]. There might be few objects beyond the original dataset. Thus the network may maintain unique layers to distinguish non-belonging objects. Figure 2 demonstrates the AlexNet architecture.

The size of the current dataset is small, and it is insufficient to generalize the model. There is a chance of overfitting; hence there is the need for a considerable increase in the database images. AlexNet can be used in three unique ways. The AlexNet classification layer is replaced with a softmax layer that comprises two classes (benign and malignant). In the next stage, weights are adjusted and backward propagate to train images. The learning rate is modified to a lower value due to which CL weights do not shift intensely, while FLC weights are set unsystematically. The weight of the network is calculated using the Stochastic Gradient Descent (SGD) algorithm.

3.5.1. AlexNet

The AlexNet architecture comprises eight layers, 3 FCL's, and 5 CL's. Following is a few of the features used that happen to be novel approaches to CNN:

i. ReLU Nonlinearity: In place of the tanh function, AlexNet employs Rectified Linear Units (ReLU). ReLU's has the edge of training time. It was seen that a CNN employing ReLU was achieving a 25% error on the CIFAR-10 dataset, which was six times better and faster than an existing CNN that used tanh.

ii. Multiple GPUs: AlexNet permits for multi-GPU training by placing one-half of the neurons in a model on one GPU and the rest on another GPU. This means that now a bigger model can be trained, and also the training time required for it will be reduced.

iii. Overlapping Pooling: CNN's conventionally pool outputs of nearby groups of neurons without overlapping. Since the neuron overlapping was introduced, it was observed that the error is reduced by the amount of 0.5%, and the models that have overlap pooling usually find it difficult to overfit.

The layered architecture on the AlexNet network is as displayed in Fig. 2.

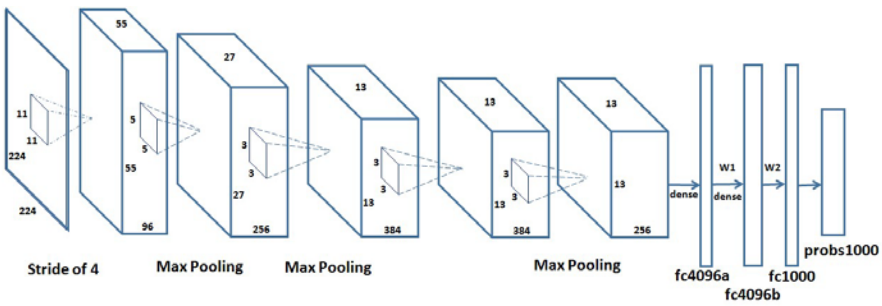


Fig. 2. Layer architecture of AlexNet.

3.5.2. Vgg16

Vgg16 has improved over AlexNet in that it replaces kernel size filter (Initially 11 and 5 later CL) with multiple 3×3 kernel-sized filters arrange one after another. The Vgg16 architecture is as shown in Fig. 3. The image of size 224×224 is taken as an input to the first CL. The image is then subjected through the stacks of CL with filter size 3×3.

It also employs 1×1 convolution filters represented by the linear transformation of an input image. The convolution pace is accessible to 1 pixel. CL input padding is given to maintain the spatial resolution after convolution. Spatial pooling is executed with the stack of MPL (five). Max-pooling is executed over a 2×2 sized window, which has a stride of 2.

A pile of CL is followed by three-layer of FCL's. The first two comprise 4096 channels each, and the third executes 1000 ILSVRC classification. The concluding layer is formed of the softmax layer. The arrangement of the FCL's is similar in every network. Every hidden layer is furnished with the ReLU activation function to get nonlinearity. Vgg16 got a test error of 7%.

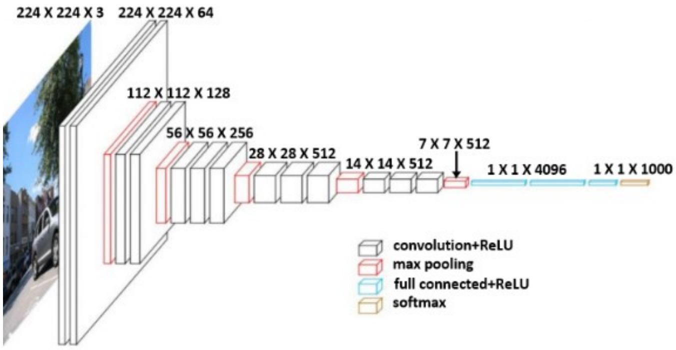


Fig. 3. Architecture of Vgg16.

3.5.3. ResNet18

The first two layers in the ResNet architecture consist of CL (of filter size 7×7) comprising 64 output channels having a stride of 2 and MPL (of filter size 3×3) having a pace of 2. In ResNet batch normalization, the layer is included after each CL. ResNet makes use of four modules that are formed out of residual blocks; each of the four modules uses numerous residual blocks having an equal number of output channels. The input channels are equal to channels in the first module in number. It employs the pooling layer having a pace of 2, thus, there is no necessity to reduce the width and height. In the subsequent module's first residual block, channel numbers get doubled compared to the earlier module, and the height and width get halved. Then it has a global average pooling layer, after which comes the FCL output. In each module, there is 4 CL (expect the 1×1 CL). There are 18 layers in total, consisting of the first CL and the last FCL. As a result, the model is known as ResNet-18. The ResNet18 architecture is as displayed in Fig. 4.

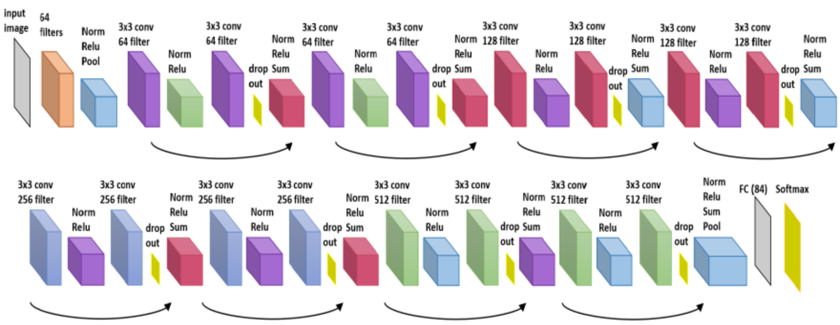


Fig. 4. Layer architecture of ResNet18.

3.5.4. ResNet50

ResNet50 architecture has 4 stages. The network takes an input image that has size multiples of 32 and colour. The architecture of ResNet50 executes the initial convolution using 7×7 and MPL using 3×3 kernel sizes. It then starts the first stage of the network, with three Residual blocks, each containing three layers. The kernels of size 64, 64, and 128 execute the convolution in three layers of the stage 1 block. As we proceed from one stage to another, the input size gets reduced to half, and the channel width gets doubled.

For each residual function (F), three layers (1×1, 3×3, 1×1) are stacked one above the other. The CL of size 1×1 is used to reducing and restoring the dimension. The CL of size 3×3 has a smaller input/output dimension. The network consists of an average pooling layer in the last stage trailed by FCL that has 1000 neurons. The layered architecture on the ResNet50 network is as displayed in Fig. 5.

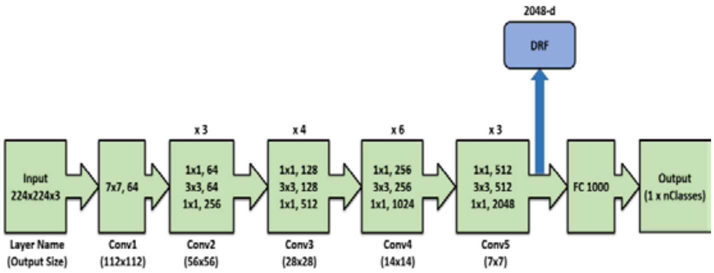


Fig. 5. Layer Architecture of ResNet50.

3.5.5. GoogLeNet

GoogLeNet has parallel pooling and CL, which helps to extract features across different kernel sizes. It is achieved to improve network depth and achieve better efficiency. The network also uses 1X1convolution to monitor the volume size passed in the initiation module for additional processing. It's nothing but a series of parallel convolution and pooling operations to pull out features using different scales. GoogleNet has 24 million parameters, resulting in lower computational complexity connected with AlexNet and VGG-16. Global pooling layer is used instead of FCL. Finally, GoogLeNet had a 6.67% error in ILSVRC-2014. Figure 6 demonstrates GoogLeNet architecture.

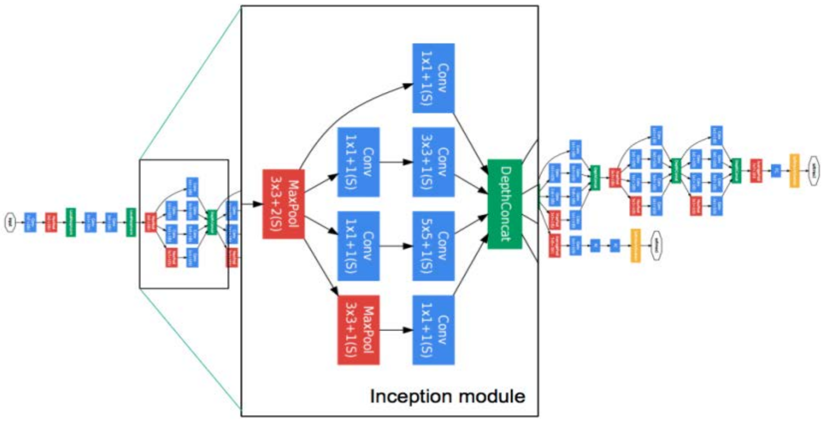


Fig. 6. Layer Architecture of GooLeNet.

4. Results

The proposed algorithms are implemented in MATLAB 2019a, 64-bit version software. The training is performed on 75% of images, while testing is performed on 25% of the dataset. The images are in RGB format. The transfer learning algorithms, AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet, are used to train the images for classifying malignant and benign tumors. The parameter selection for training the network is as tabulated in Table 3.

Table 3 shows the training progress of the networks at every epoch. The plot presents precision vs. epoch. In the existing iteration, 20% of information is employed for validation purposes, whereas 80% of information is employed for the training purpose. After every iteration, the data gets shuffled.

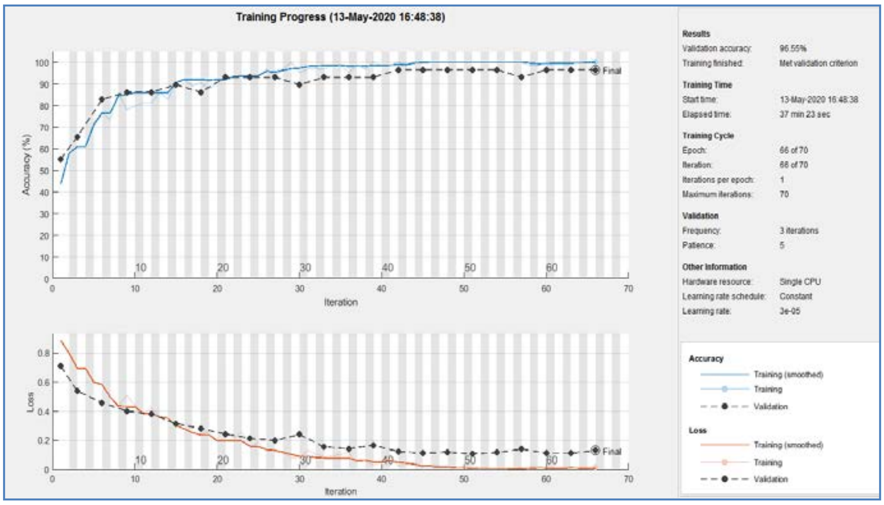
From Fig. 4 is witnessed that AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet have the competency of attaining additional exact and generalize power on unfamiliar data. However, the training needed an enormous amount of epoch to attain decent precision. CNN needs more time and epoch than the transfer learning (AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet) model.

Usually, networks that seem to learn various features and added descriptive leads to better results. The top-quality data attained in the unsupervised pre-training adds to higher perfection and classification. The training growth of the AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet transfer learning techniques is presented in Fig. 7.

For the testing stage, the unobserved brain MRI images are tested with the trained model. The result of the testing MRI is as displayed in Figs 8 and 9.

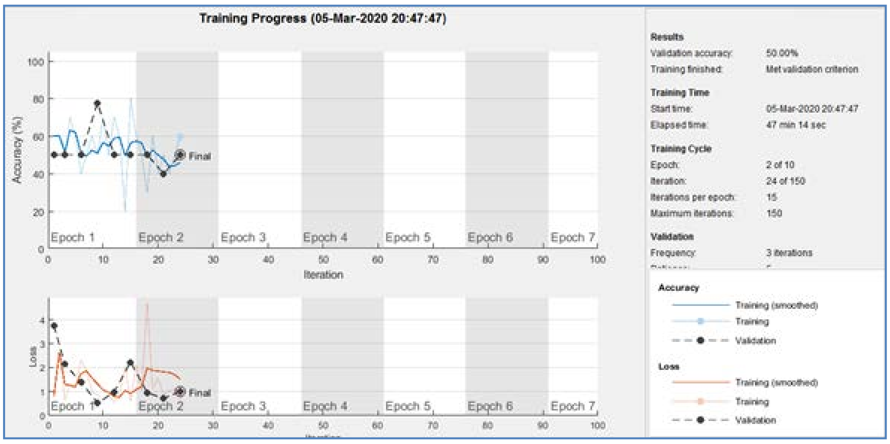
Table 3. Network training parameters.

Sr. No.	AlexNet	Vgg16	ResNet18	ResNet50	GoogLeNet
Gradient Decay Factor/ Momentum	0.90	0.90	0.90	0.90	0.90
Epsilon	1e-08	-	-	-	-
Initial Learning Rate	3e-05	0.0003	0.0001	0.0001	0.0003
L2Regularization	0.0001	0.0001	0.0001	0.0001	0.0001
Gradient Threshold Method	'l2norm'	'l2norm'	'l2norm'	'l2norm'	'l2norm'
Threshold (Gradient)	Inf	Inf	Inf	Inf	Inf
Maximum Epochs	70	100	8	10	100
Minimum Batch Size	64	10	10	2	10
Frequency (Verbose)	50	50	50	50	50



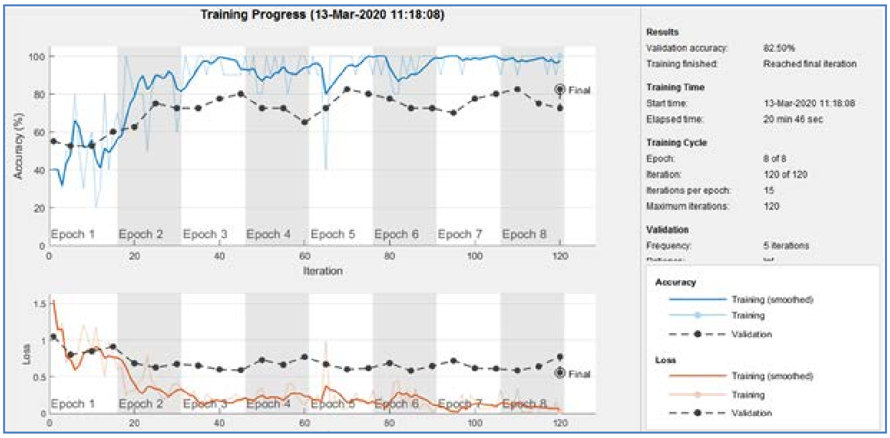
Training Progress (13-May-2020 16:48:38)
Accuracy (%)
Iteration
Final
Loss
Results
Validation accuracy: 96.55%
Training finished: Met validation criterion
Training Time
Start time: 13-May-2020 16:48:38
Elapsed time: 37 min 23 sec
Training Cycle
Epoch: 66 of 70
Iteration: 66 of 70
Iterations per epoch: 1
Maximum iterations: 70
Validation
Frequency: 3 iterations
Patience: 5
Other Information
Hardware resource: Single CPU
Learning rate schedule: Constant
Learning rate: 3e-05
Accuracy
Training (smoothed)
Training
Validation
Loss
Training (smoothed)
Training
Validation

(a)



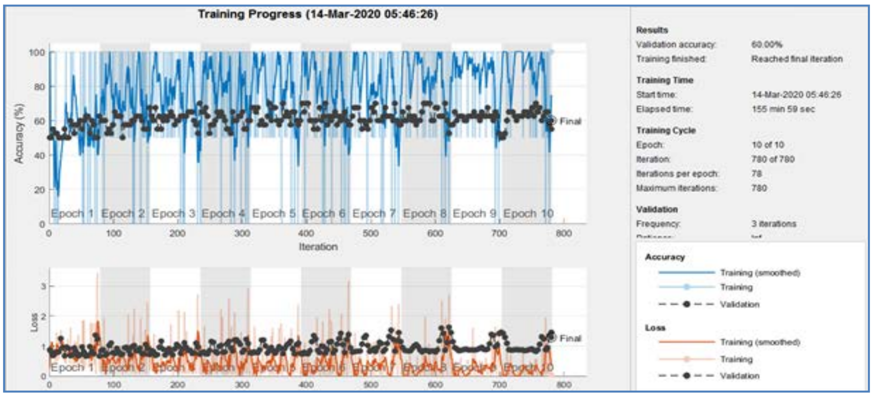
Training Progress (05-Mar-2020 20:47:47)
Accuracy (%)
Epoch 1
Epoch 2
Epoch 3
Epoch 4
Epoch 5
Epoch 6
Epoch 7
Iteration
Final
Loss
Results
Validation accuracy: 50.00%
Training finished: Met validation criterion
Training Time
Start time: 05-Mar-2020 20:47:47
Elapsed time: 47 min 14 sec
Training Cycle
Epoch: 2 of 10
Iteration: 24 of 150
Iterations per epoch: 15
Maximum iterations: 150
Validation
Frequency: 3 iterations
Accuracy
Training (smoothed)
Training
Validation
Loss
Training (smoothed)
Training
Validation

(b)

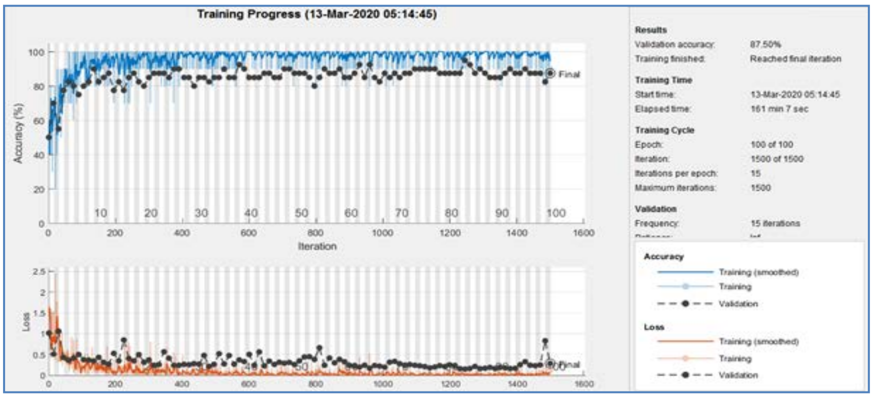


Training Progress (13-Mar-2020 11:18:08)
Accuracy (%)
Epoch 1
Epoch 2
Epoch 3
Epoch 4
Epoch 5
Epoch 6
Epoch 7
Epoch 8
Iteration
Final
Loss
Results
Validation accuracy: 82.50%
Training finished: Reached final iteration
Training Time
Start time: 13-Mar-2020 11:18:08
Elapsed time: 20 min 46 sec
Training Cycle
Epoch: 8 of 8
Iteration: 120 of 120
Iterations per epoch: 15
Maximum iterations: 120
Validation
Frequency: 5 iterations
Accuracy
Training (smoothed)
Training
Validation
Loss
Training (smoothed)
Training
Validation

(c)

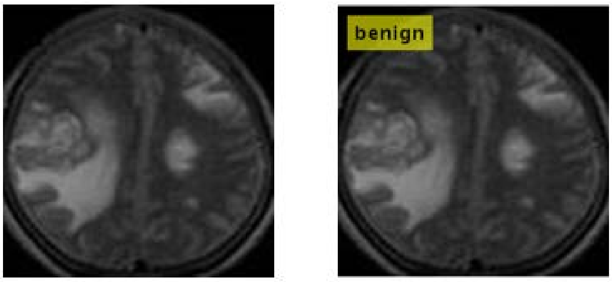


(d)



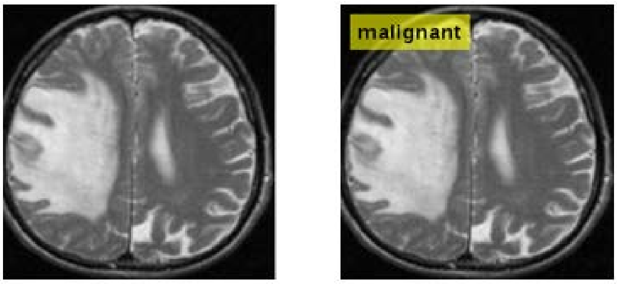
(e)

Fig. 7. Training progress of transfer learning architectures:
(a) AlexNet, (b) Vgg16, (c) ResNet18, (d) ResNet50 and (e) GoogLeNet.



(a) Input benign image . **(b) Output classified image.**

Fig. 8. Output of the AlexNet model on the benign image.



(a) Input malignant image. (b) Output classified image.

Fig. 9. Output of the AlexNet model on the malignant image.

The presented algorithm is equated with the prevailing ML method described in [9]. This technique uses a similar database as used in [9]. Table 4 shows the relative examination of DL algorithms described in this system to the ML-dependent system described by Vijay Wasule et al. [9] concerning the precision, recall, and f-measure arithmetically denoted as Eq. (3-5).

$$\Pr ecision = \frac{TP}{TP + FP} \tag{3}$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{4}$$

$$f - measure = 2 \times \frac{\Pr ecision \times recall}{\Pr ecision + recall} \tag{5}$$

where *TP* (True Positive) is the benign tumor predicted as benign, *TN* (True Negative) is the malignant tumor predicted as malignant. *FP* (False Positive) is the benign tumor predicted as malignant. *FN* (False Negative) is malignant tumor predicted as a benign.

Looking at the F-measure value in Table 4, it is understood that the suggested AlexNet provides an improved output in comparison to the prevailing techniques.

Table 4. Comparative analysis of different methods.

Methods	Precision	Recall	F-measure
SVM [9]	1	0.76	0.8636
KNN [9]	0.88	0.73	0.7999
AlexNet (Proposed)	0.937	1	0.96774
Vgg16 (Proposed)	0.55	0.5	0.5238
ResNet18 (Proposed)	0.7894	0.8333	0.8107
ResNet50 (Proposed)	0.95	0.5588	0.7036
GoogLeNet (Proposed)	0.75	1	0.8571

5. Conclusion

In this paper, 5 pretrained architecture (AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet) of the deep CNN model for classifying the brain tumors as benign and malignant are presented. Out of all the models evaluated on the clinical dataset of malignant and benign brain MRI, the fine-tuned AlexNet model proved to be best by rendering precision, recall, and F-measure value of 0.937, 1, and 0.96774, respectively. Also, the results of AlexNet claim superior to the existing classical ML and DL methods for brain MRI classification. It is proven in the context of removing pre-processing, feature extraction, and feature selection compared to classical ML methods. In the future, the work will be directed towards the exploration of powerful DL architecture for brain MRI classification with improved accuracy and less time complexity.

Nomenclatures

$f_g\ (x, y)$	The intensity value of the foreground pixel x and y.

Greek Symbols

Γ	Gamma factor.

Abbreviations

CL	Convolution Layer
CT	Computed Tomography
CNN	Convolutional Neural Network
CWT	Continuous Wavelet Transform
DL	Deep Learning
DWT	Discrete Wavelet Transform
FCL	Fully Connected Layer
FCM	Fuzzy C Mean
GLCM	Gray Level Co-Occurrence Matrix
GLRLM	Grey Level Run Length Matrix
KNN	K-Nearest Neighbor
ML	Machine Learning
MRI	Magnetic Resonance Imaging
PCA	Principal Component Analysis
ReLU	Rectified Linear Units
SVM	Support Vector Machine
WHO	World Health Organization

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