Brain tumor classification using SVM based AlexNet

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Abstract— *Advanced MRI techniques is one of the best proven technique in tumor analysis and visualization. More than a decade, several machine learning techniques have been deployed for tumor segmentation, feature extraction and classification. The outcome of Brain Tumor classification plays a critical role in diagnosis and further treatment. The efficacy of the conventional machine learning algorithms depends on the feature extraction. Spotting the suitable feature extraction technique is a tedious task in Machine Learning. At present, Deep learning networks are highly capable of extracting prominent features automatically from images for classification. In this paper, the pre-trained CNNs is used to classify three types of brain tumors from the bench mark dataset, T1 weighted contrast enhanced MRI. The pre-trained network was experimented using the segmented brain tumor image. Experimental results show that the pretrained network achieves 95% for tumor classification.*

Keywords: **T1 C+ MRI, Tumor classification, Convolution Neural Networks, AlexNet, SVM, Transfer Learning.**

1. INTRODUCTION

Brain tumors or intracranial tumors are the collection of abnormal cells in brain causing problems to the normal functionality. These tumors originate from brain tissues or brain surroundings. They can be benign of malignant. Different modalities like CT, PET, and MRI exists for tumor diagnosis. Of these, MRI [1] is an excellent tool for three dimensional visualization, analysis of soft tissues and is used for tumor location and treatment. Several techniques are proposed for brain tumor classification from conventional machine learning algorithms to the recent deep learning techniques. Human observations and interpretations have their own limitations and short comings. Computer aided diagnosis can be supplemented to overcome this issue to yield better results for the betterment of human life[2].

The objective of this paper is to analyse the existing pre-trained CNNs for brain tumor classification. The standard bench mark CE-MRI dataset is used in this paper comprises of three types of brain tumors viz, meningioma, glioma and pituitary tumor. Meningioma arises from meninges cells the lining of brain and spinal cord and are often benign. When they increase in volume they press against the other brain cells and affect their function. Timely diagnosis can even cure meningioma without surgery. Gliomas are the most common among adult brain tumors and 78 percent of them are malignant. They are caused by glia, the supporting cells of brain. They include astrocytoma, glioblastoma, ependymoma, medulloblastoma and oligodendrogliomas. Pituitory tumors originate in pituitary gland and are benign in nature. They don’t spread outside the brain but affects the endocrine system. This causes damage to human health like vision changes and headaches.

The contribution of this paper is to apply the pre-trained Convolutional Neural Networks networks AlexNet and VGG 19 for automatic feature extraction and adopt transfer learning with different classifiers and experimentally verify the best classifier to predict the brain tumor. The organization of paper is as follows: Section II highlights the recent techniques for brain tumor classification using deep CNN, Section III explains the proposed method and Section IV evaluates the performance of the method and Section V ends with conclusion and future enhancements.

2. RELATED WORKS

Deep learning techniques are gaining impulsive momentum these days as they can automatically extract the prominent image features for classification and widely used in CAD systems like lung tumor diagnosis [3], dermatology diagnostics [4] and brain tumor classification [5]. Deep transfer learning is a specialized deep learning technique attempts to transfer the knowledge from the pre-trained networks to the problem in hand with independent training and test dataset [6].

The pretrained InceptionV3 model was used for benign or malignant tumor classification from CT images. The results with ROI dataset yielded better performance when compared to RBR dataset [7]. Features are extracted from CNN and classified with other classification techniques like SVM. The results indicated better performance than the soft max classification layer in the AlexNet[8]. The performance of CNN relies on the volume of dataset. To handle the less volume dataset, data augumentation techniques like rotation, scaling, translation operations are used.

Data Augmentation to predict to predict the IDH genotype in grade II to grade IV glioma[9] showed better results without data augmentation techniques. The performance of glioma grading is compared with different pre-trained networks[10] and concluded that

GoogleNet performed well than AlexNet. To capture the low level texture patterns small window size with unit slide is used for multigrade classification of glioma tumors[11]. To capture the spatial information in images, CapsuleNET is introduced for deep learning[12].

3. PROPOSED METHOD

A. Dataset

The performance of the brain tumor is implemented on the publicly available CE-MRI dataset [13]. The dataset comprises of three different types of brain tumors, viz Meningioma, Glioma, Pituitary Tumor in three different views viz, Axial, Coronal and sagittal from 233 different patients. The images are T1 weighted contrast enhanced MRI used for analysing the tumors. The details of the dataset is given in Table I.

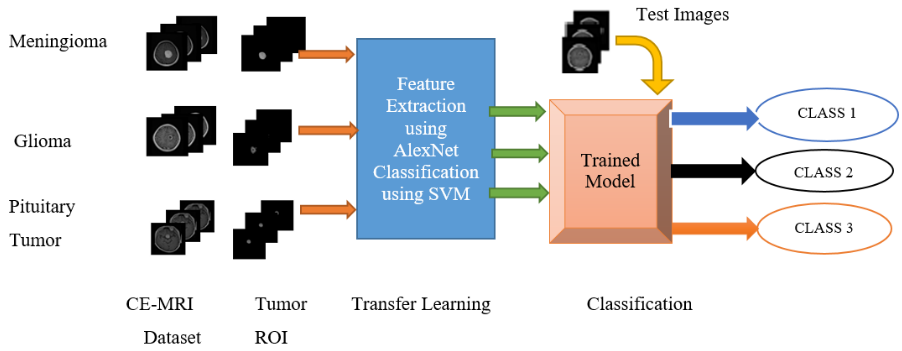


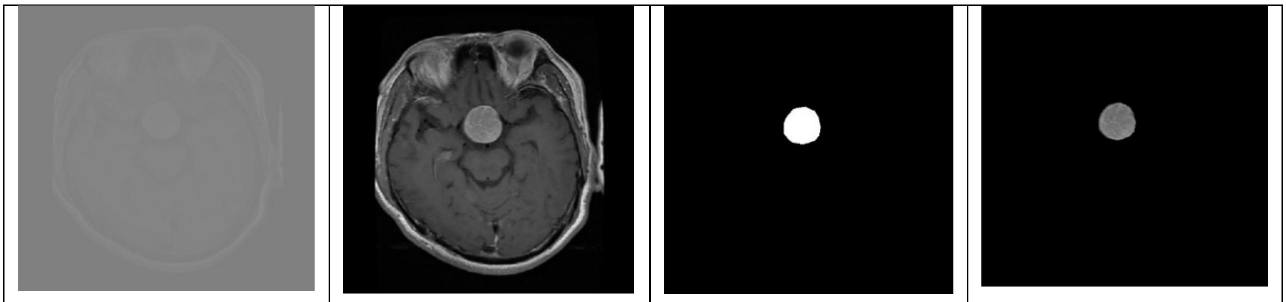
Fig 1 Proposed Methodology for Tumor Classification

B. MRI Enhancement

Image Enhancement is the first and important preliminary operation in digital image processing[15]. Only with enhanced image, prominent features can be extracted for classification. MR images. The images should be processed in such a way that the ROI is enhanced and its inherent features are not lost. MR images suffer from noise due to RF pulse, RF coil, field strength and is signal dependent. Convolution operation used in the CNN operates directly on image intensities so the intensity is normalized using min-max normalization as shown in Fig. 2. The image, I is transformed into new intensity range[0..1] with more brightness and is computed as follows,

$$y(i,j)=\frac{(I(i,j)-\min(I))}{(\max(I)-\min(I))}$$

where, the pixel in $I(i,j)$ is transformed into $y(i,j)$ based on the minimum and maximum intensity values of I. The images in the dataset are of grayscale and size 512X512. To use the pretrained AlexNet, the images are resized to 227X227 using bicubic interpolation and duplicated thrice for converting to RGB.



(a)CE-MRI (b)Min-Max Normalization (c)ROI mask (d) ROI Segmented Image

Fig. 2. Pre-processing of Dataset

C. ROI Segmetntation

In order to improve the accuracy of classification, the tumor ROI is fed to the CNN. The tumor mask is available with the fig share dataset used to segment tumor ROI for all the images in the three classes.

Table 1 Details of CE-MRI Dataset

Tumor Type	No of Patients	Number of MRI	MRI View	Number of MRI
Meningioma	82	708	Axial	209
			Coronal	268
			sagittal	231
Glioma	89	1426	Axial	494
			Coronal	437
			sagittal	495
Pituitary Tumor	62	930	Axial	291
			Coronal	319
			sagittal	320a
Total	233	3064		3064

TABLE 2 General Confusion matrix for assessing the performance of brain tumour classification

	Actual			
	Class	Meningioma	Glioma	Pituitary Tumour
Predicted	Meningioma	451	18	27
	Glioma	17	956	25

	Pituitary Tumour	24	27	600

TABLE 3 Classification Performance Evaluation (%) for the three classes using AlexNet

Results	Meningioma	Glioma	Pituitary Tumor
Accuracy (%)	95.99	95.99	95.19
Precision (%)	90.9	95.79	92.16
Recall (%)	91.6	95.5	92.02
Specificity (%)	97.63	96.3	96.58

D. Pretrained AlexNet

AlexNet addresses the problem of image classification with deep convolutional network and won the 2012 ImageNet LSVRC-2012 Competition. The network excelled in classifying 1.2 million high resolution images into 1000 different classes. The architecture comprises of five convolutional layers and three fully connected layers. The Rectified Linear Unit (ReLU) used in this CNN is faster than tanh function. AlexNet offers multi GPU support to minimize the training time. Data Augmentation and dropout techniques can be employed to reduce overfitting problem in case of small datasets [15].

4. PERFORMANCE EVALUATION

The Convolutional Neural Network with AlexNet is implemented using Matlab 2019a with 8GB onboard RAM and i2 2.7GHz CPU. The network extracts low level features in earlier layers and high level features in higher layers as shown in Fig. 3.The training progress is illustrated in Fig. 4. The features from FC layer 7 is extracted and classified using SVM. Table II illustrates the confusion matrix for the three

Fig. 3(a)Visual results of low level features in convolution layer 1 **(b)Visual results of high level features in convolution layer 5**

classes. The performance of the classification using standard metrics and is illustrated in Table III. On average the accuracy of classification for the three classes is 95.9%. Precision is computed with true positive and false positive values . The method is more than 95% effective in predicting the Glioma tumors. Recall deals with the proportionality of prediction with the actual number and evaluates the classification performance with respect to the class. The recall for the Meningioma and Pituitary tumors is less by 4% when compared to Glioma. This is because of the similarity of Meningioma and Pituitary tumors. The results shows that the method shows good performance around 95.9% in predicting Glioma.

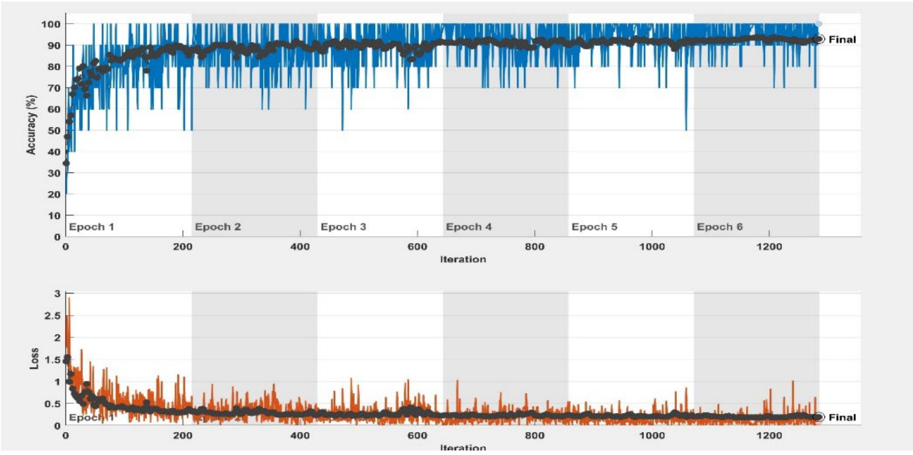


Fig. 4 Accuracy and loss history of training and validation set using AlexNet

5. CONCLUSION AND FUTURE WORK

This research work focusses to develop an automated tool to predict the type of brain tumor. The method is implemented in the standard CE-MRI dataset with three different types of tumor. The enhanced images using min max normalization are segmented to isolate the tumor ROI and fed to deep CNN. The features automatically extracted using the pretrained ALexNet is classified using SVM. The results proves the method achieves 95.9 % accuracy for classification. This work can be further extended by adding different types of tumor to the existing dataset. Future work is interested in analysing different pretrained CNN for feature extraction and to develop a new CNN architecture.

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