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OPTIMIZATION SEGMENTATION AND CLASSIFICATION FROM MRI OF BRAIN TUMOR AND ITS LOCATION CALCULATION USING MACHINE LEARNING AND DEEP LEARNING APPROACH

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ABSTRACT

The manual detection and classification finding correct location and identifying type of tumor becomes a rigorous and hectic task for the radiologists. Medical diagnosis via image processing and machine learning is considered one of the most important issues of artificial intelligence systems. Deep learning has been used successfully in supervised classification tasks in order to learn complex patterns. The main contributions of this paper are as create a more generalized method for brain tumor classification using deep learning a variety of neural networks were constructed based on the preprocessing of image data., analyze the application of tumorless brain images on brain tumor classification and empirically evaluate neural networks on the given datasets with per image accuracy and per patient accuracy. And also presents an efficient image segmentation using machine learning algorithm with some optimization techniques to detect brain tumors.

KEYWORDS – ***Deep learning, machine learning, classification, segmentation, optimization of MRI brain tumor images***

INTRODUCTION

Now days the MR Images are very useful in a Medical field like Medical image processing. The brain tumor defines the unusual growth of tissues and uncontrolled cells proliferation so due to this the natural pattern of cell growth and death is failed. The brain tumor is of two stages:- 1) Primary stage 2) Secondary stage.

When tumor spread in any part of brain then it is known as brain tumor. Now when brain tumor can identified number of symptoms including seizures, mood changing, difficulty in walking and hearing, vision, and muscular movement etc. brain tumor is classified into Gliomas, medulloblastoma, epeldymomas, CNS lymphoma and oligodendrogloma. In primary stage the tumor can be removed but in secondary stage ,the tumor disease spread, due to this after removal of tumor the seldom remains and grow back again so this is the biggest problem in the secondary stage of tumor . Why this problem occurs? It occurs due to inaccurately location of area of tumor. The next step is detection techniques. In this the any segmentation and detection are to measure detection techniques the imaging of brain tumor can be done by- 1) MRI scanning that is magnetic resonant image 2) CT scanning i.e. computer tomography 3) Ultra sound etc. There are several method to detect an brain tumor by that the tumor method we can diagnose and detect more easily .some edges are nuclear network algorithm watershed and edge detection, fuzzy c mean algorithm, asymmetry of brain is used to detect an abnormality .

The purpose of this research is to develop automated methods to aid doctors in diagnosis in order to prevent misdiagnosis and decrease patient wait time. In particular, this research achieves this automation through the classification of brain tumor types from patient brain images. Images require a doctor to examine multiple image slices to determine health issues which takes time away from more complex diagnoses. Our goal is to confidentially identify brain cancer types to reduce doctor burden, leaving the most complex diagnoses to them.

Training convolutional neural networks to detect types of tumors in brain images improves classification accuracy and provides initial steps into introducing deep learning into medicine. Not only does this method produce equal and better results when compared to Cheng et. al.'s initial work, but neural networks also utilize a more general methodology requiring only an image to understand brain tumor types. Furthermore, the accuracy per patient metric consistently remained at the levels of per image accuracy results, implying the neural network is providing consistent predictions for patient images.

Numbers of shape features are considered in this paper include Major axis length, Minor axis length, Euler Number, Solidity, Area and Circularity. For the purpose of classification some machine learning algorithms are used.

RELATED WORK

N.M. Saad et al [1]. proposed method to detect and classify a brain tumor using thresholding and a rule-based classifier. Four types of brain tumor depend on diffusion-weighted imaging were analysed such acute stroke, solid tumor, chronic stroke and necrosis. In the detection and segmentation stage, the image is divided into 8x8 macro-block regions. Adaptive thresholding technique is applied to segment the tumor's region. Statistical features are measured on the region of interest.

Amanpreet Kaur and Gangandeep Jindal [2] in 2015 has given an approach through which tumor can be detected effectively using Genetic Algorithm. It has been applied to reduce the population and then detecting the tumor present in the brain.

Yao-Tien Chen [3], a new method proposes an approach integrating 3D Bayesian level set method with volume rendering for brain tumor and tissue segmentation and rendering.

In an MRI image the highly irregular boundaries of tumor tissues is seen. For a segmentation of medical image, the deformable modes and region base methods are used. The main problems are there in MRI images like undefined location of tumor are unseen boundaries or data loss at boundaries and a silent edge not extended. By using this algorithm the silent edge is extended and found boundary of tumor location or area and once the boundary or location of tumor is seen clearly. Then removal of tumor can be take place [4].

PROPOSED METHOD

The proposed work has been implemented using some of machine learning and deep learning algorithms to compare their performance. The architecture of proposed method is illustrated in Fig. 1. MR Image's acquisition was first step in this method. Detection of tumor in the brain MR Images includes a number of methods are Sigma filtering, adaptive threshold and detection region. Shape Features method is used to extract features for MR Images.

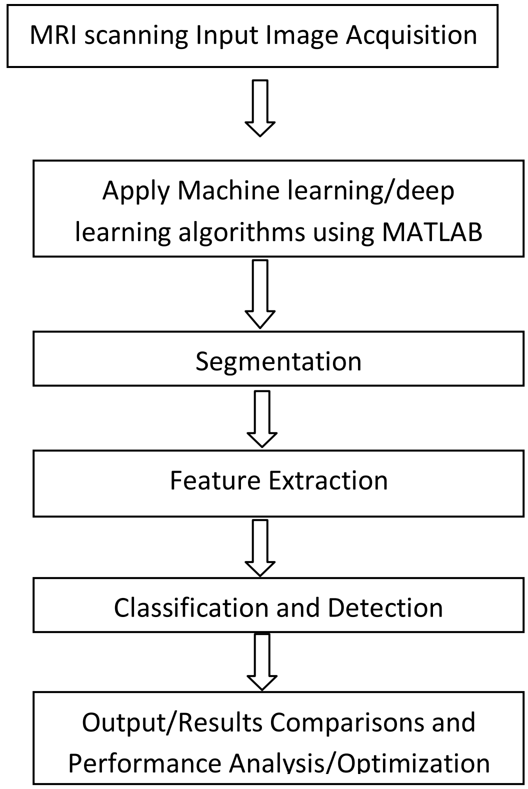
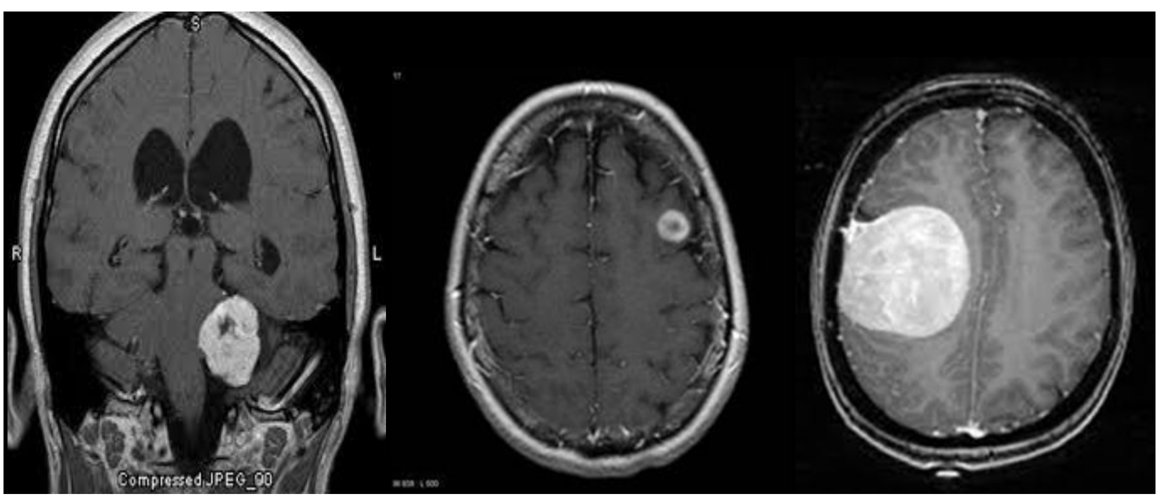


Figure 1. The Proposed System Flow



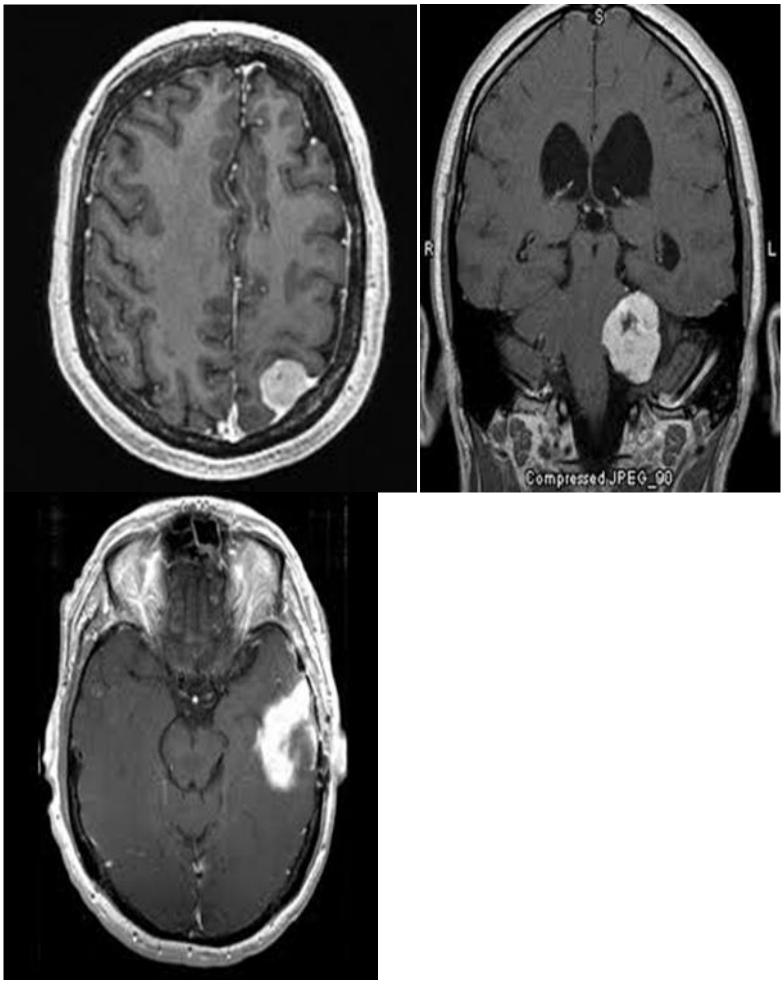


Figure 2. Brain tumor MR images Beignin type

The brain tumor dataset belongs to Malignant type and are collected from ADNI data base.

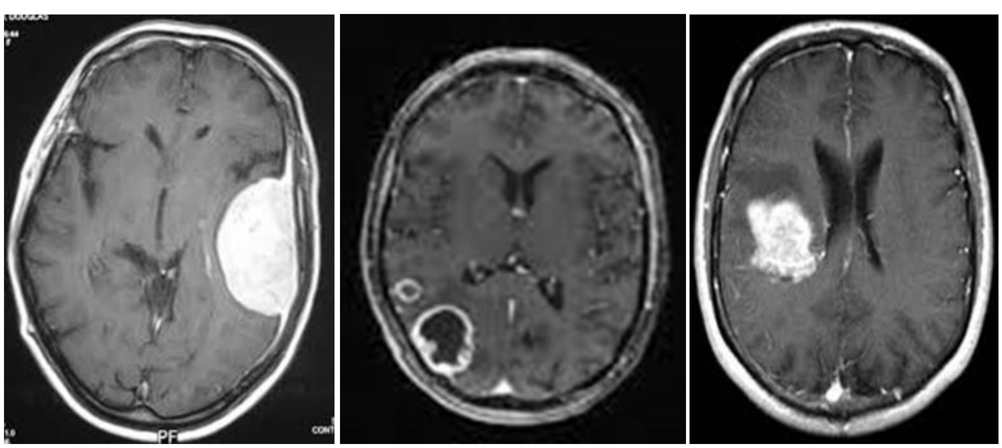


Figure 3. Brain tumor MR images Malignant type

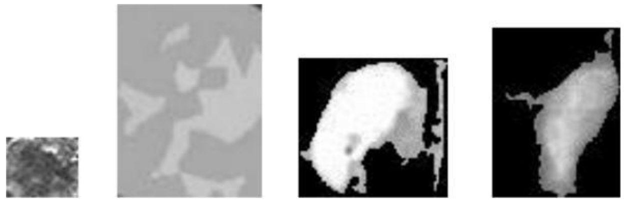


Figure 4. a) non- tumor image b) non- tumor image c) tumor image d) tumor image

IMAGE ACQUISITION

Image Acquisition The proposed method has been implemented on real data for human MR Images dataset, some of them were obtained from the hospitals and the other were obtained from the internet as there are no database is available from these types of tumors that considered in this paper.

IMAGE PREPROCESSING

Image Preprocessing It is well known that the most noise in MR Images is random and Gaussian distribution is used to characterize it statistically. In this paper we are using sigma filter for removing noise from MR Images. The sigma filter finds the average of pixels in the box that have been predetermined size which not deviate too far from the pixel which the box is centered on. Consequently, the difference in the intensity of the pixels by segmentation more than two standard deviations of the pixel in the centre box, there is a high probability that this difference is not because of the noise; Therefore Sigma filter ignores such a pixel [5].

IMAGE SEGMENTATION

Generally, The machine learning algorithms used in the process of image segmentation by putting all the pixels that are higher than the threshold level to a foreground while the other pixels to the background value. Any dynamic change according to the pixel intensity cannot be achieved when using threshold method [6]. In proposed method we used Adaptive threshold that usually take the gray or color images as input and outputs in the form of binary image representing segmentation. Adaptive thresholding techniques used to separate the object of an image from its background. The main different between threshold and Adaptive thresholding is that the Adaptive threshold value is calculated for each pixel in the image. This technique provides more robustness to changes in illumination. After used adaptive thresholding, the region detection process is performed on the binary image that results from an adaptive thresholding step. Region detection is Image segmentation technique that classifies pixels in the image to one or several separate areas or blob which is an area of touching pixels with the same logic state. The region detection consists of scanning and labeling any new regions, but also merging old regions when they prove to be connected on a lower row. Therefore, the image is scanned and every pixel is individually labeled with an identifier which signifies the region to which it belongs [7].

CLASSIFICATION

Classifications In this paper used deep learning and machine learning algorithms to classify the MR Images of brain tumor and compare their performing.

EXPERIMENTAL RESULTS

In this paper, the number of collected samples was 200 brain MR Images. The binary object features such as (Major axis length, Minor axis length, Euler Number, Area and Circularity) for each image are extracted using MATLAB program. Weka tools are used for brain MR Images classification. Brain MR Images were classified using the CART algorithm and NAÏVE BAYES with 65% percentage split. In 65% percentage split, used 65% of the samples in the training process the rest of the samples have been used in the test. It is seen from the table (1) the CART algorithm has the average TP rate and FP rate 0.786 and 0.006 respectively. The precision was of about 89%.

Table 1. Result of CART algorithm

Brain tumor type	TP Rate	FP Rate	Precision
Ependymoma	**0.923**	**0.015**	**0.923**
Meningioma	**0.818**	**0.03**	**0.818**
Lymphoma	**0.75**	**0**	**1**
Amaplastic strocytoma	**0.846**	**0.015**	**0.917**
Normal	**1**	**0**	**1**
Average	**0.897**	**0.017**	**0.911**

The proposed method begins by performing training on few sets of tumorous and non-tumorous images based on some parameters.

Table 2. Parameters designed for obtaining segmentation

Parameters	Set Values	Obtained Values
Total Segments	5	5
Solution	0	0
Tolerance	-	-
Population Size	16	16
Maximum Generation	1000	1
Maximum Time(sec)	60	0.2990

It has explained in Table 1. that five segments are used with population size of 16 maximum generation used is 1 out of 1000 in maximum time of 0.2990 sec with solution tolerance 0.

Table 3.Parameter values obtained when MRI applied 50 times

Parameters	Mahalanobis Distance	Proposed Method
Training Time(sec)	0.038981	0.056411
Matching Time	0.0128832	0.024134
True Positive	0.7845	0.9867
True Negative	0.9034	0.9799
False Positive	0.0964	0.0201
False Negative	0.2153	0.0133
Accuracy	0.8258	0.9897
Precision	0.8913	0.9866
Recall	0.7845	0.9865
F-measure	0.8155	0.9865

The Table 2. shows the parameters used to determine the efficiency of the proposed method with the Mahalanobis Distance. It has been cleared from the table that the proposed method gives 17.38% accuracy and 8.42% precision then the Mahalanobis Distance.

Table 4.Average 6 fold cross validation test accuracies with brain tumor images only

Model Details				Per Image Accuracy			Per Patient Accuracy		
Image Size	Preprocessing	Network	Epochs	Last	Best	Best-PD	Last	Best	Best-PD
256 x 256	Vanilla	CNN	100	89.95	90.26	89.69	**91.43**	89.52	**91.43**
256 x 256	Vanilla	FCNN	100	87.30	87.32	87.46	86.67	85.71	86.67
256 x 256	Vanilla	ConcatNN	100	84.62	86.09	84.30	86.67	86.67	87.62
256 x 256	Tumor Locations	ConcatNN	100	85.66	85.96	85.80	87.62	87.62	89.52
207 x 312	Tumor Zoomed	CNN	100	88.99	88.16	88.99	88.57	88.57	88.57
69 x 69	Vanilla	CNN	100	81.70	82.46	81.44	79.05	82.86	79.05
45 x 45	CO	CNN	500	83.67	81.72	82.75	81.90	84.76	85.71
64 x 64	Vanilla	CNN	100	83.83	84.52	82.10	82.86	82.86	82.86
64 x 64	Vanilla	FCNN	100	80.86	80.43	81.30	77.14	76.19	77.14
196 x 196	Crop Averaging	CNN	100	86.77	87.65	88.16	82.86	83.81	84.76

Table 5. Average six-fold Cross Validation Test Accuracies with Brain Tumor and tumorless

Model Details				Per Image Accuracy			Per Patient Accuracy		
Image Size	Preprocessing	Network	Epochs	Last	Best	Best-PD	Last	Best	Best-PD
256 x 256	Vanilla	CNN	100	88.59	**89.13**	88.78	85.71	89.52	88.57
64 x 64	Vanilla	CNN	100	85.06	82.69	83.21	84.76	82.86	84.76
64 x 64	Vanilla	FCNN	100	84.51	86.30	84.05	82.86	84.76	81.90

The last layer of this path and the last fully connected layer from CNN were then concatenated together and connected to one last fully connected layer with 800 neurons before reaching the soft max layer from CNN. We will refer to this neural network as ConcatNN in this deep learning approach.

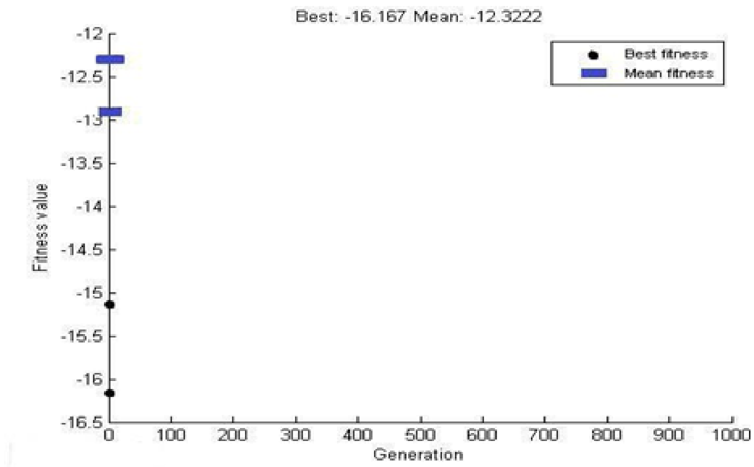


Figure 5 .Best and Mean fitness value

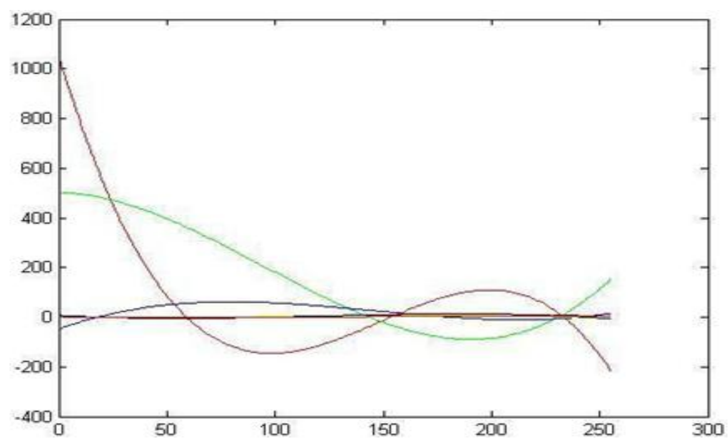


Figure 6. Curves obtained on Segmentation

The proposed method has been compared with the previous method using Mahalanobis Distance on the basis of few parameters on the Tumor images 50 times which has optimized the results. 16.39% accuracy and 9.53% precision has been obtained on tumor images when applied 50 times. This result shows that the proposed method proves to be highly beneficial for detection of tumor.

CONCLUSIONS

Training convolutional neural networks to de- tect types of tumors in brain images improves classification accuracy and provides initial steps into introducing deep learning into medicine. Not only does this method produce equal and better results when compared to

Cheng et. al.'s initial work, but neural networks also utilize a more general methodology requiring only an image to understand brain tumor types. Furthermore, the accuracy per patient metric consistently remained at the levels of per image accuracy results, implying the neural network is providing consistent predictions for patient images. To extract and segment the tumor we used different techniques such as SOM Clustering, k-mean clustering, Fuzzy C-mean technique, curvelet transform. It can be seen that detection of Brain tumor from MRI images is done by various methods, also in future work different automatic methods achieve more accuracy and more efficient. Improving performance on smaller images can have great benefits in training and assisting doctors in treatment of patients. Dealing with noisy, smaller images can help generalize neural networks to understand more complex brain images which in turn can help doctors in their diagnosis.

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