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Classification of Tumors in Brain MRI Images With Hybrid of Global and Local DWT Features using Decision Tree

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Abstract*: Automated brain tumor identification and classification is still an open problem for research in the medical image processing domain. Brain tumor is a bunch of unwanted cells that develop in the brain. This growth of a tumor takes up space within skull and affects the normal functioning of brain. Automated segmentation and detection of brain tumors are important in MRI scan analysis as it provides information about neural architecture of brain and also about abnormal tissues that are extremely necessary to identify appropriate surgical plan. Automating this process is a challenging task as tumor tissues show high diversity in appearance with different patients and also in many cases they tend to appear very similar to the normal tissues. Effective extraction of features that represent the tumor in brain image is the key for better classification. In this paper, we propose a hybrid feature extraction process. In this process, we combine the local and global features of the brain MRI using first by Discrete Wavelet Transformation and then using texture based statistical features by computing Gray Level Co-occurrence Matrix. The extracted combined features are used to construct decision tree for classification of brain tumors in to benign or malignant class.

Keywords*: Brain Tumor, MRI, Segmentation, DWT, GLCM, Decision Tree.

I. INTRODUCTION

Brain tumor is an unwanted collection of cancerous cells that develop in the brain beyond the natural cell cycle. These tumors may be benevolent, usually termed as benign, or malevolent, referred to as malignant. The benign tumors contain non-active cancer cells and many a times have uniform structures where as malignant tumors contain active cancer cells that may stretch to other body parts. Also, the malignant tumors mostly have non-uniform structures. Magnetic Resonance imaging is a non radio-active imaging technique used for study of internal organs to envisage high resolution images of the internal body parts, their structure and functions.

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With MRI doctors can visualize both surface and deep structures with a high degree of anatomical details and they can detect the occurrence of minute changes in these structures. Early detection of tumors increases the chances of better planning of treatment and hence better chances of survival of the patient. Automating this process is a challenge as tumors tend to develop in diverse shape, size and position and in some cases they exhibit appearance similar to the normal tissues.

Medical Image Analysis involves processing of image at various stages. First, the Pre-processing is done to enhance the image quality where we remove the noise components, boost the image intensity and prepare the image for further processing [2]. In Segmentation stage the specific region of interest in the image is identified through one or combination of many intelligent methods [3] to obtain determinant characteristics of tumors from medical images. Feature selection is the general term to represent the methods used for constructing the combination of variables that describe the data effectively [4]. It is the technique of obtaining a subset of highly relevant variables by eliminating irrelevant and redundant variables to build appropriate learning models. Accurate tumor classification is possible with more accurate feature selection techniques. Classification is a phase of analysis where we compute the numerical properties of given image features so that the image can be placed into one of the many categories. Classification is achieved by employing two processing phases: decision tree construction phase and testing phase. In tree construction phase, optimal decision tree with unique descriptions of each category of classification is computed using the labeled training samples. In testing phase we use the decision tree to classify the unique descriptions of the test image [5].

In this paper we propose an automated method for tumor classification with two class labels namely benign and malignant. We propose a hybrid feature extraction method to get the better representation of image samples by combining local and global wavelet coefficients obtained from DWT and texture based statistical features obtained by computing GLCM. This approach is motivated by the fact that both the local and global features are experimentally found to be uncorrelated and hence upon combining can give enhanced statistical details. This paper is organized into 5 sections. In section II we have summarized related works by various researchers in the field of brain image tumor classification. Section III gives the details of proposed work.

The outcomes of the proposed work and evaluation with other benchmarks are discussed in Section IV. Section V has concluding remarks and discusses future enhancement options for this work.

II. RELATED WORK

Many articles have been published by the researchers in the recent years on methods for classification of tumors from MRI images.

Ayush Arora et al [6] suggested a method where the image was segmented using the popular segmentation techniques like thresholding followed by morphological operations. The features ware extracted from the segmented image using DWT. Using principal component analysis the high dimensional features were reduced to computationally convenient lower dimension without losing much of the classification information. Then, k-NN classification was used to decide if the tumor is benevolent or malevolent.

A scheme for brain tumor identification and further classification from MRI images by probabilistic neural network is suggested by Shree and Kumar [4]. They have used DWT to decompose the images into horizontal, vertical and diagonal components followed by textural image features extraction by computing GLCM. PNN classifier was used for the categorization of tumors.

Adhi Lakshmi et al [7] suggested techniques for tumor analysis. In this method image pre-processing was done with Distribution based Adaptive Mean Filtering and Adaptive Threshold based Edge Detection. Segmentation was achieved by using connected component analysis with Cellular Automata and Multi-angle Cellular Automata. The most representing features were obtained using a method called Dynamic Angle Projection Pattern. Those features optimized with Cockoo Search Optimization and such selected features were passed to SVM with Pointing Kernel Classifier.

A comparative analysis of various feature extraction algorithms is published by El-Gayer et al [8]. They have compared the performances of FAST, SIFT, PCA-SIFT, F-SIFT and SURF algorithms with respect to scaling, rotation, illumination change and other transformations.

Image processing techniques for brain tumor analysis is published by Hemanth and Anitha [2] where they have conducted a survey of many techniques for pre-processing, feature extraction, classification. They have proposed a method where pre-processing was done with connected component analysis. Eight textural features namely Correlation, Contrast, Entropy, Variance, Angular Second Moment (A measure of Uniformity), Skewness (A measure of symmetry), Inverse Difference Moment (A measure of homogeneity) and Kurtosis (A Measure of data distribution) are extracted and these features were used for classification.

Stationary Wavelet Transformation (SWT) which has superior wavelet coefficients as compared to DWT in terms of translation invariant property is proposed by Zhang et al [9]. Those features were reduced with PCA and Fisher Discriminant Analysis (FDA) was used to categorize brain into benevolent or malevolent.

Daljit Singh and Kamaljeet Kaur [5] have observed that GLCM features and classified using SVM with any of the RBF, Linear and Quadratic kernel functions will also yield better classification. They have compared GLCM with PCA for feature extraction.

GLCM features were extracted from the fuzzy clustering based segmented images is proposed by B. Thamaraichelvi and G. Yamuna [10]. Entropy, Correlation, Energy, Contrast, Mean, Standard Deviation and variance features were extracted. SVM with RBF kernel was used to classify brain tumors with an accuracy of 98%.

Using deep learning methods a survey on segmentation of MRI-based brain tumors is published by Işın et al [11]. They have effectively highlighted the challenges in manual, semi-automatic and fully automatic segmentation methods.

III. PROPOSED METHODOLOGY

From the literature Survey we conclude that accurate brain diagnosis can be done by developing more effective and accurate techniques in feature extraction and classification. Literature survey motivated us to look into methods for extracting more meaningful features from the MR Images. In this work, we propose a method for extracting the features as shown in figure 1. First, the image samples are prepared for segmentation. This pre-processing and segmentation stages are described in sub-sections A and B respectively. We extract the local features from the segmented image and global features from the original but enhanced image. The details are discussed in sub-sections C, D and E. We were motivated to use a hybrid of local and global features of the image, after closely examining the local and global image features. We found that both the features are not correlated. Hence we hypothesize that use of hybrid features can give better description of the area of interest. These feature vectors obtained from DWT were reduced using PCA and further by computing GLCM, 13 statistical features were computed from them namely, Energy, Contrast, Mean, Correlation, Standard Deviation, Homogeneity, RMS, Entropy, Skewness, Inverse Difference Movement (IDM), Variance, Kurtosis and Smoothness. Using these statistical features the decision tree classifier was modeled as discussed in sub-section F. The classifier efficiency was found using test images.

A. Preprocessing

Brain MRI Image data set is obtained from the online repository of IMAGE & DATA ARCHIVE (IDA), University of Southern California [1]. The dataset contains RGB MRI FLAIR image slices with matrix size of 256 x 256, all with axial perspective. Results of various pre-processing stages are shown in figure 2. The images are first converted to gray scale and then enhanced by median filter (Figure 2a).

B. Segmentation

The emphasis was on the removal of skull tissues and text in the MRI. Image was segmented using a Dynamic thresholding technique (Figure 2b) along with suitable morphological operations to filter out those undesired pixels (Figure 2c). Filling and Erosion are the two main morphological operations that are performed on binarized image to highlight the area of interest and generate the mask as shown in figure 3b. The original image is fused with the segmented image to get the masked image as shown in Figure 3c.

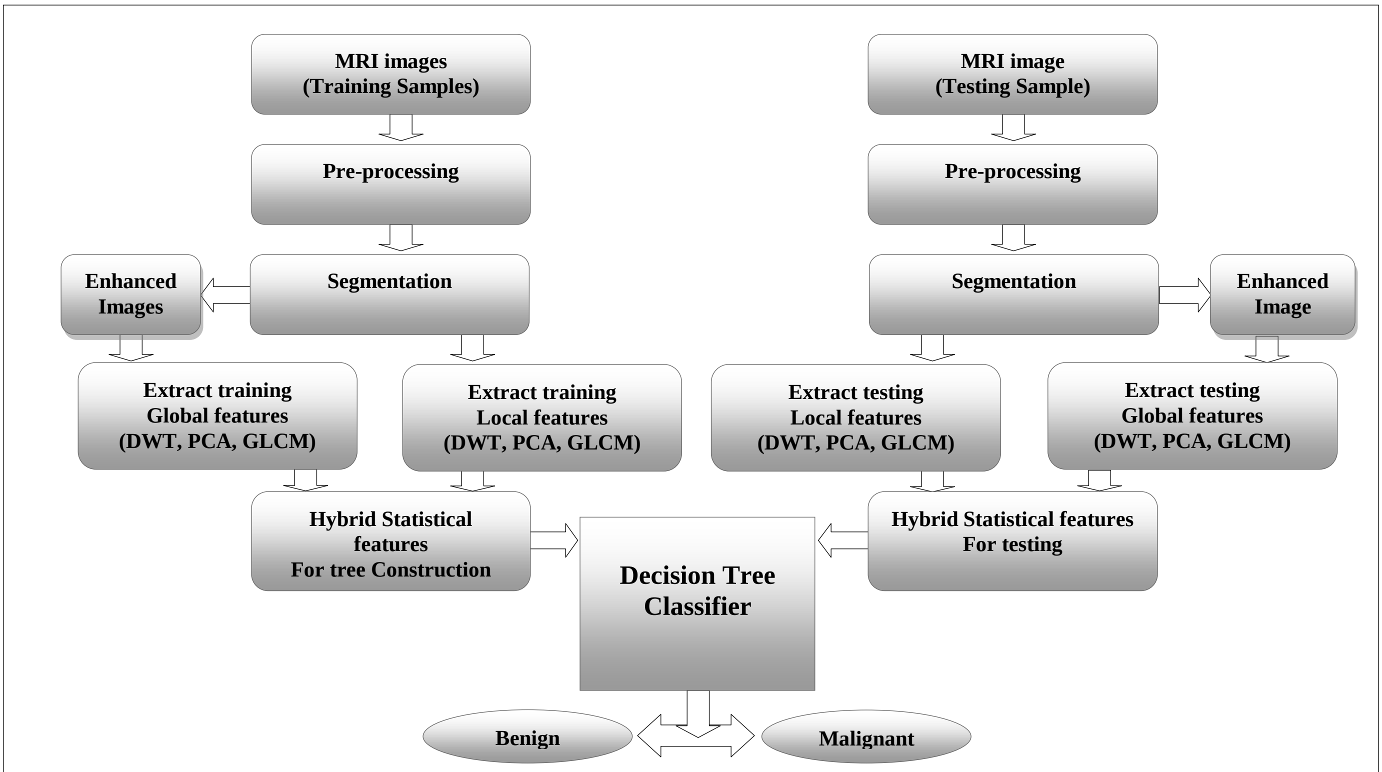

Figure 1. Schematic diagram of the proposed tumor classification

Figure 2 a) Color to Gray Conversion and Enhancement with median filter **2b) Dynamic Thresholding** **2c) After flood Fill**

Figure 3a) Original Image **3b) Segmented Image** **3c) Masked Image**

C. Discrete Wavelet Transformation

MRI image is decomposed using discrete wavelet transform with four sub regions. These regions are called approximate component region and three high-frequency regions, namely horizontal component, vertical component, and diagonal component. Theoretically the approximate component region is obtained by using two successive low-pass filters. The horizontal component is obtained by a pair of high-pass and low-pass filter. The vertical component is filtered using a pair of low-pass and high-pass filter. The diagonal component is created by two successive high-pass filters.

2D discrete wavelet transform was applied with the two-level wavelet decomposition. With the increase in number of levels more detailed information will emerge. At the same time this will affect the classification model stability and hence reduce the computing efficiency. By trial and error method (as shown in features table below) we have found that at second level all but particularly the diagonal component information is maximized and also features become more discriminating and hence we have chosen second level of Haar wavelet decomposition. 30 MRI images are used to extract the features as training samples with 10 of them belonging to benign class and 20 belonging to malignant class. The masked images (as shown in Figure 3c) are used to compute DWT coefficient vectors of all the four components.

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These global features are the input for PCA for further feature reduction. Output of such an image sample is shown in figure 4a. The segmented images (shown in Figure 3b) are used to compute DWT coefficient vectors which are the local features. DWT coefficients of segmented image sample are shown in figure 4b.

D. PCA and GLCM

For feature dimensionality reduction PCA is one of the most commonly used technique. PCA technique preserves the variance of the given input data and finds the linear lower-dimensional closest representation of that data by using orthogonal transformations. It transforms a large set of correlated points into set of principal components. This reduced feature set of all the components are used to compute GLCM. GLCM is a statistical procedure to tabulate how often different combinations of pixel intensity levels co-occur in an image. Every element in the ith row and jth column of the GLCM is an indicator of how many times a pixel with a specific intensity i occurs in relation with other pixel with intensity j. Two GLCMs are computed, one for local DWT coefficients and the other one for global DWT coefficients.

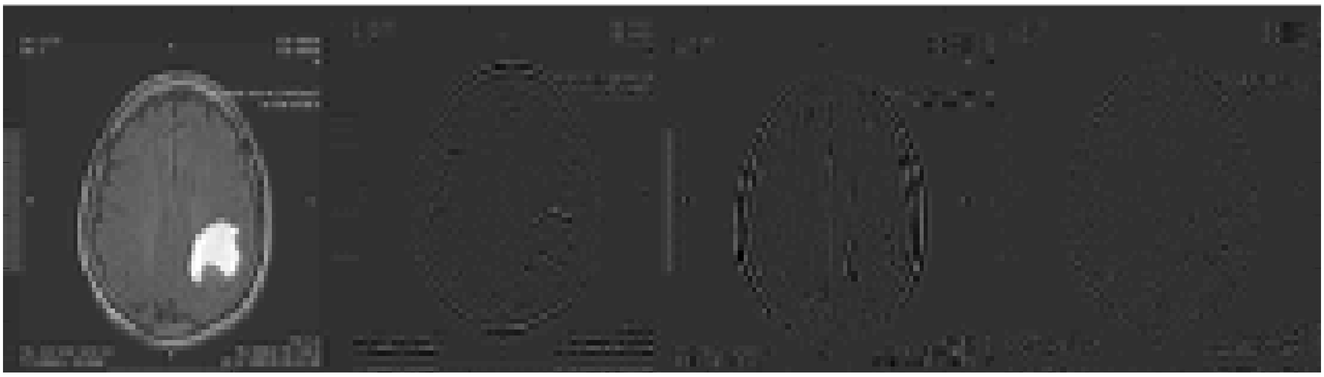

Figure 4a) DWT Coefficients of the image after applying the mask

Figure 4b) DWT Coefficients of the segmented Image

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E. Statistical features

13 statistical features [12] namely Inverse Difference Movement, Skewness, Kurtosis, Smoothness, Variance, RMS, Entropy, Standard Deviation, Mean, Homogeneity, Energy, Correlation and Contrast are computed from both local and global GLCM. A set of 26 features extracted using different DWT decomposition levels from the training sample image are shown in the following table.

Features	DWT L1		DWT L2		DWT L3	
	Original Image (Global Feature)	Segmented Image (Local Feature)	Original Image (Global Feature)	Segmented Image (Local Feature)	Original Image (Global Feature)	Segmented Image (Local Feature)
Contrast	14.31	54.53	26.75	69.88	44.20	54.53
Correlation	0.93	0.89	0.89	0.87	0.80	0.89
Energy	0.91	0.35	0.86	0.18	0.84	0.35
Homogeneity	0.97	0.79	0.95	0.66	0.94	0.79
Mean	1.63	9.19	3.09	17.80	5.57	9.19
Standard Deviation	21.03	32.13	40.61	61.31	76.32	32.13
Entropy	0.28	3.78	0.48	2.97	0.87	3.78
Root Mean Square level (RMS)	6.80	18.67	13.06	35.63	25.16	18.67
Variance	388.97	597.88	1456.9	2139.8	5200.4	597.88
Smoothness	1.00	1.00	1.00	1.00	1.00	1.00
Kurtosis	174.99	39.45	185.38	42.65	200.16	39.45
Skewness	12.88	5.03	13.20	5.27	13.48	5.03
Inverse Difference Movement (IDM)	25057.46	53648.58	24096.03	52146.33	22322.51	53648.58

F. *Classification with Decision Tree*

In this paper we have modeled Decision Tree as the classifier. We build the classifier by constructing the decision tree from the training feature set.

Decision tree algorithm is a data mining induction technique that recursively partitions a data set of records using depth-first greedy approach or breadth-first approach until all the data items belong to a particular class. A decision tree structure is made of root, internal and leaf nodes. The tree structure is used in classifying unknown data records. At each internal node of the tree, a decision of best split is made using impurity measures. Decision tree classification technique is performed in two phases [13]: Tree building and Tree pruning. Tree building is done in top-down manner. During this phase that the tree is recursively partitioned till all the data items belong to the same class label. It is very tedious tasking and computationally intensive as the training data set is traversed repeatedly. Tree pruning is done in bottom-up fashion. It is used to improve the prediction and classification accuracy of the algorithm by minimizing over-fitting.

The key idea of decision tree construction is to find, repeatedly, the one most promising feature at a time, that can divide the data, with lowest possible impurity and maximum information gain until we run out of all features or some tolerable percentage of homogeneity is achieved.

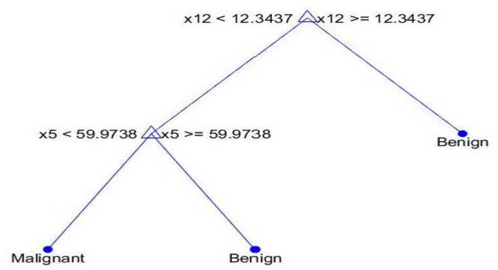
The information Gain of an attribute n is given by:

Information Gain (n) = Entropy (x) - ([Homogeneity ratio] * entropy (children of x))

where, Entropy is computed as: $H = -\sum p(x)\log p(x)$

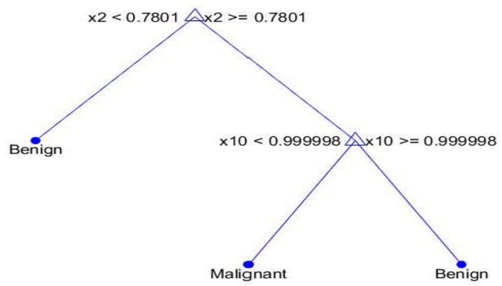
1) Decision tree for classification (13 Global Features):

1 if x12<12.3437 then node 2 elseif x12>=12.3437 then node 3 else Benign
2 if x5<59.9738 then node 4 elseif x5>=59.9738 then node 5 else Malignant
3 class = Benign
4 class = Malignant
5 class = Benign



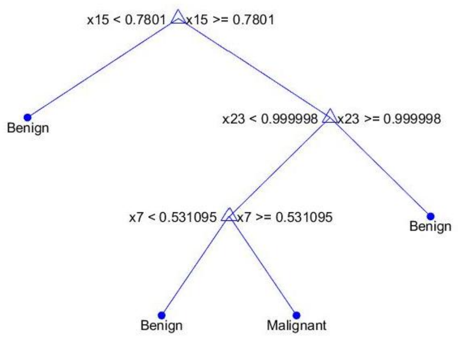
2) Decision tree for classification (13 Local Features):

1 if x2<0.7801 then node 2 elseif x2>=0.7801 then node 3 else Benign
2 class = Benign
3 if x10<0.999998 then node 4 elseif x10>=0.999998 then node 5 else Malignant
4 class = Malignant
5 class = Benign



3) Decision tree for classification (26 Hybrid Features):

1 if x15<0.7801 then node 2 elseif x15>=0.7801 then node 3 else Benign
2 class = Benign
3 if x23<0.999998 then node 4 elseif x23>=0.999998 then node 5 else Malignant
4 if x7<0.531095 then node 6 elseif x7>=0.531095 then node 7 else Malignant
5 class = Benign
6 class = Benign
7 class = Malignant



IV. RESULT ANALYSIS

The performance measure, Accuracy is computed as the probability of correctly classifying the samples. We compute accuracy as:

$$\text{Accurcy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP is True Positive, the number of correctly classified benign tumors; TN is True Negative, the number of correctly classified malignant tumors; FP is False Positive, the number of incorrectly classified benign tumors and FN is False Negative, the number of incorrectly classified malignant tumors. The experimental results are tabulated as follows:

DWT decomposition Level	Features used for classification	Accuracy (Rounded)
L1	Local	62%
	Global	60%
	Proposed Hybrid Method	**73%**
L2	Local	67%
	Global	63%
	Proposed Hybrid Method	**87%**
L3	Local	60%
	Global	67%
	Proposed Hybrid Method	**80%**

V. CONCLUSION

In this paper we have shown implementation of our proposed method, a hybrid of local and global feature selection with statistical features extracted from the Brain MR Images. They were reduced using PCA and GLCM was computed. Those local and global features were combined to form a set of 26 features are used to model the decision tree classifier. After successful implementation of this model we have tested the model with test image samples. As listed above, found that hybrid features with decision tree classifier method is having a maximum accuracy of 87% when we decompose the image with two levels of DWT. There may be many possibilities to improvise this method in future. Different feature selection techniques may also be employed to obtain the hybrid feature set and investigate for even better accuracy over larger datasets. This method can also be employed in analysis of other disease MRI for the purpose of diagnosis.

REFERENCES

1. LONI IDA, "LONI Image and Data Archive."
2. D. J. Hemanth and J. Anitha, "Image pre-processing and feature extraction techniques for magnetic resonance brain image analysis," presented at the International Conference on Future Generation Communication and Networking, 2012, pp. 349–356.
3. V. P. Gladis Pushpa Rathi, "A Novel Approach for Feature Extraction and Selection on MRI Images for Brain Tumor Classification," in Computer Science & Information Technology (CS & IT), 2012, pp. 225–234.
4. N. V. Shree and T. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network," Brain Inform., vol. 5, no. 1, pp. 23–30, 2018.
5. D. Singh and K. Kaur, "Classification of abnormalities in brain MRI images using GLCM, PCA and SVM," Int. J. Eng. Adv. Technol. IJEAT, vol. 1, no. 6, pp. 243–248, 2012.
6. A. Arora, "k-NN Based Classification of Brain MRI Images using DWT and PCA to Detect Different Types of Brain Tumour," p. 6, 2017.
7. A. Lakshmi, T. Arivoli, and M. P. Rajasekaran, "A Novel M-ACA-Based Tumor Segmentation and DAPP Feature Extraction with PPCSO-PKC-Based MRI Classification," Arab. J. Sci. Eng., vol. 43, no. 12, pp. 7095–7111, 2018.
8. M. M. El-gayar, H. Soliman, and N. meky, "A comparative study of image low level feature extraction algorithms," Egypt. Inform. J., vol. 14, no. 2, pp. 175–181, Jul. 2013.
9. Y. Zhang, S. Wang, Y. Huo, L. Wu, and A. Liu, "Feature extraction of brain MRI by stationary wavelet transform and its applications," J. Biol. Syst., vol. 18, no. spec01, pp. 115–132, 2010.
10. B. Thamaraichelvi and G. Yamuna, "Gray level co- occurrence matrix features based classification of tumor in medical images," vol. 11, no. 19, p. 12, 2016.
11. A. Işın, C. Direkoğlu, and M. Şah, "Review of MRI-based brain tumor image segmentation using deep learning methods," Procedia Comput. Sci., vol. 102, pp. 317–324, 2016.
12. Namita Aggarwal and R.K. Aggarwal, "First and Second Order Statistics Features for Classification of Magnetic Resonance Brain Images," J. Signal Inf. Process. 2012 3 146-153.
13. Sujatha and Dr. K Usha Rani, "Evaluation of decision tree classifier on tumor dataset" International Journal of Emerging trends & technologies in Computer Science, Volume 2, Issue 4, July – August 2013

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