

Classification of Brain Tumor using GLCM and SVM from MRI Images

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Abstract: This paper primarily focuses to deal a textural approach to classify the brain tumor. Tumor is an uncontrolled enlargement of tissues in any portion of the human body. Tumors are of several types and have some different characteristics. According to their characteristics some of them are avoidable and some are unavoidable. Brain tumor is serious and life threatening issues now days, because of today's hectic life style. Medical imaging play important role to diagnose brain tumors .In this study a automated system has been proposed to detect and classify the tumor ,whether it is avoidable or not. For proposed system the experiment carried out with 150 T1 weighted MRI images. Supervised classification has applied for classification, so that training set is created using the texture feature, that are extracted with GLCM and DWT methods, for feature selection principle component analysis have used. The experimental results show KSVM ,RBF Kernel gives 94% accuracy to classify the brain tumor and find the accuracy and specificity to get the classification accuracy.

Keywords: MRI, KSVM, GLCM, DWT.

1. Introduction

Abnormal development of tissues in the brain causes the Brain tumor. Basically BRAIN in the human body is core part ,in the human body, every part have different cells and all cells have their own capabilities, some cell grows with their own functionality and some lose their capability and resist and grow aberrant. These mass collections of the cells form the tissue which is called as "tumor". Among those cells some are cancerous or some are non-cancerous. Based on those cells, the tumor can defined in two categories Benign and Malignant. Central Brain Tumor Registry of the United States (CBTRUS) in December 2015 published a report, according to this statistical report brain tumor is the second leading cause of death in children and Leukemia is first.[] Basically Brain tumor categorized into two parts: Benign and Malignant. The World Health Organization (WHO) had classified tumor into 4 Grades, Grade I to IV. Grade I and Grade II are Low Grade which represents Benign Tumor. Grade III and Grade IV are High Grade which represents Malignant Tumor. [1] Many different imaging modalities are used in the last two decades to identify and locate the anatomical structure such as X-Ray, CT scans and MRI.[5] But due to the change in time the high quality images are used to determine tumor, which is known as MRI(Magnetic Resonance Image).T1 weighted and T2 weighted images are part of the MRI[2].Anatomic behavior of brain is shown through the MRI. MRI is also used for the study the internal structure of the human body. Radiologist visualizes and analyzes those images. MRI techniques completely based on Magnetic Field. [3]. In MRI electromagnetic waves are used and these waves are transmitted in the human brain and signal are recorded and reconstructed on images and these images are analyzed by computer programmers.

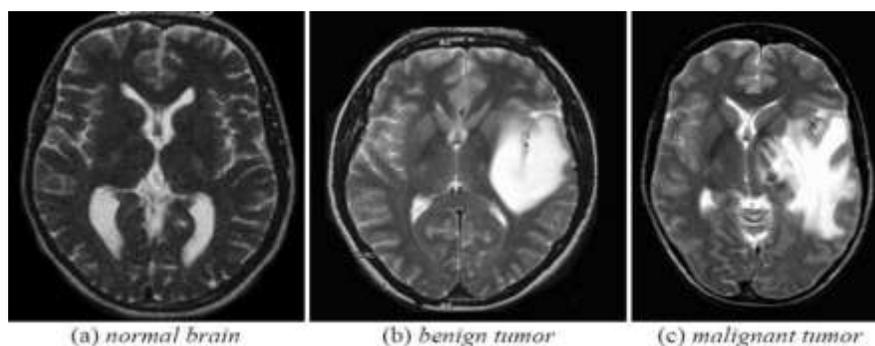


Fig. 1:Types of Tumor

In medical image processing, Segmentation plays an important role for modelling of brain and construct Brain atlases. It's a challenging task for us to segment proper region because DICOM image have a variety of information, such are location, shape, intensity, etc. so that it is a tedious task to segment region of interest. For segmentation, medical imaging has different segmentation approaches, like edge based, threshold base, region growing etc. [4]

2. Proposed Work

The proposed work as illustrate in Fig2 is based on the following techniques, Gray Level Co-occurrence Matrix (GLCM),the “principal components analysis (PCA)”and Support Vector Machine (SVM). The methodology contains mainly three stages: - feature extraction, feature selection and classification. The Brain tumor dataset containing 3064 T1-weighted contrast-enhanced images of 233 patients with two kinds of brain tumor.The Experiment is carried out with 150 T1 weighted MRI images.

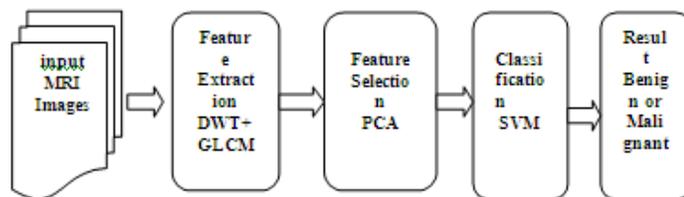


Fig. 2:- Process of Brain tumor extraction and Classification

In this paper, we proposed a system that could extract and classify the tumor from MRI images. All experimental work is done with MRI images and MATLAB. The following steps are used to detect and segment the tumor.

Algorithm

- Input MRI image.
- Convert image into gray image using **rgb2gray** function in MATLAB for segmentation.
- In the third step remove all small connect object those are have fewer than pixel P from binary image using a **bwareaopen** function in MATLAB.
- In the fourth step Suppress light structures connected to image border with **imclearborder** function.
- In the fifth step, For gradient of the image using **Sobel Operator**.
- In sixth step **threshold segmentation** is applied to extract different pixels from the background for segmentation and detection.
- In the seventh step, texture feature will extract using **GLCM and DWT** methods.
- In the next step we train our system with those texture features which are extracted from GLCM and DWT.
- In the last step **SVM** is applied to classify the tumor whether it is Benign and Malignant tumor.
- After that we measure the performance of SVM with different parameters like **Specificity, Sensitivity and Accuracy**.

3. Feature Extraction[4858]

When the input data is excessively huge to be processed and alleged to be unneeded, then the data is transformed into a compact set of feature representations. The method of change the input data into a set of features is called feature extraction. Features include in order to relative information like color, shape, texture or context. Basically image data are analyzed for examining the specific purpose. Generally, the unprocessed data of a set of images are analyzed to get close problem, and how these features are useful to get the desired result. Feature extraction is an essential step, which is a unique form of dimensionality reduction. The first order of statistical image features like skewness, kurtosis, entropy, mean and variance and second order of statistical image feature like contrast, homogeneity and energy. GLCM (Gray Level Concurrence Matrix) is used to extract second order image features.

The first-order histogram P(I) is defined as:

$$P(I) = \frac{\text{number of pixel with gray level } I}{\text{Total number of pixels in the region}} \tag{1}$$

The second order Gray Level Co-occurrence Matrix, P(X,Y) is defined as follows.

$$P_{\Delta x \Delta y}(X,Y) = \begin{cases} 1, & \text{if } \text{Img}(i,j) = X \text{ and } \text{Img}(i + \Delta x, j + \Delta y) = Y \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Here image intensity values are i and j, the spatial position of an image is X and Y in the image ,Img and the offset (Δx, Δy) rely on the way used and the distance at which the matrix is computed.[9]

GLCM technique is used to extract textural features of an image in the above equation we use following notations;-[10]

G:- number of gray levels

μ:-mean value of p

μ_x, μ_y:-means of P_x and P_y

σ_x , σ_y:-Standard Deviation

The following features are used:

- Homogeneity, Angular Second Moment (ASM) :

$$\text{Homogeneity} = \sum_{i,j} \frac{1}{1+(i-j)^2} P(i,j) \tag{3}$$

Homogeneity is far above the ground when image pixels are incredibly related Angular Second Moment is also known as Homogeneity. Homogeneity is measured by the sum of squares of the entries at the GLCM Angular Second Moment. [11]

- Contrast

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \{ \sum_{i=1}^G \sum_{j=1}^G p(i,j) \} |i-j| - n \tag{4}$$

- Inverse Difference Moment(IDM)

$$\text{IDM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i,j)^2} P(i,j) \tag{5}$$

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is homogeneous and contrary GLCM is high.

- Entropy

$$\text{Entropy} = - \sum_{i,j} P(i,j) \log P(i,j) \tag{6}$$

When the image is compressed amount of information is lost, to measure the how much information is lost when the signal is transmitted [20]

- Correlation

$$\text{Correlation} : - \sum_{i,j} \frac{(i-\mu)(j-\mu)}{\sigma^2} P(i,j) \tag{7}$$

- Variance

$$\text{Variance} = \sum_{i,j} (i-\mu)^2 P(i,j) \tag{8}$$

- Average

$$\text{Average} = \sum_{i=0}^{G-1} i P_x + y (i^2) \tag{9}$$

TABLE I: GLCM feature

Texture Image Features	Image1	Image2	Image3	Image4	Image5	Image6	Image7	Image8	Image9	Image10
Contrast	0.3850	0.3741	0.3010	0.2506	0.3242	0.37690	0.3481	0.3050	0.4453	0.2329
Correlation	0.1528	0.1826	0.1681	0.1271	0.1238	0.1173	0.0880	0.1689	0.1160	0.1485
Energy	0.9129	0.9076	0.8754	0.8149	0.8659	0.8895	0.8089	0.8622	0.9001	0.8448
Homogeneity	0.9727	0.9712	0.9629	0.9488	0.9592	0.9662	0.9600	0.9601	0.9689	0.9567
Mean	0.0036	0.0035	0.0038	0.0031	0.0041	0.0048	0.0095	0.0043	0.0053	0.0023
Standard Deviation	0.0821	0.0821	0.0821	0.0853	0.0816	0.0821	0.0821	0.0800	0.0844	0.0800
Entropy	1.1930	1.0585	1.7236	2.9517	1.8589	1.5563	2.3302	1.7891	1.1242	2.558
Variance	0.0068	0.0068	0.0068	0.0069	0.0066	0.0069	0.0068	0.0064	0.0071	0.0064
Kurtosis	54.043	53.8762	27.4228	17.6255	29.2878	48.6370	32.7170	35.0670	59.5910	2.3909
skewness	4.2179	4.6017	2.2223	1.4460	2.3562	3.9226	2.9634	2.8917	5.1537	1.6205

For the texture feature extraction we have one more another method to extract the feature DWT . Basically to state the 2D images with different levels of resolutions DWT is used. DWT decomposes the images with different levels. As the decomposition level is greater than before, compressed and obscure estimated coefficients can be accomplished. In this paper, single level decomposition of Daubechies wavelet is apply for the feature extraction.

The following diagram show the decomposition process for images:

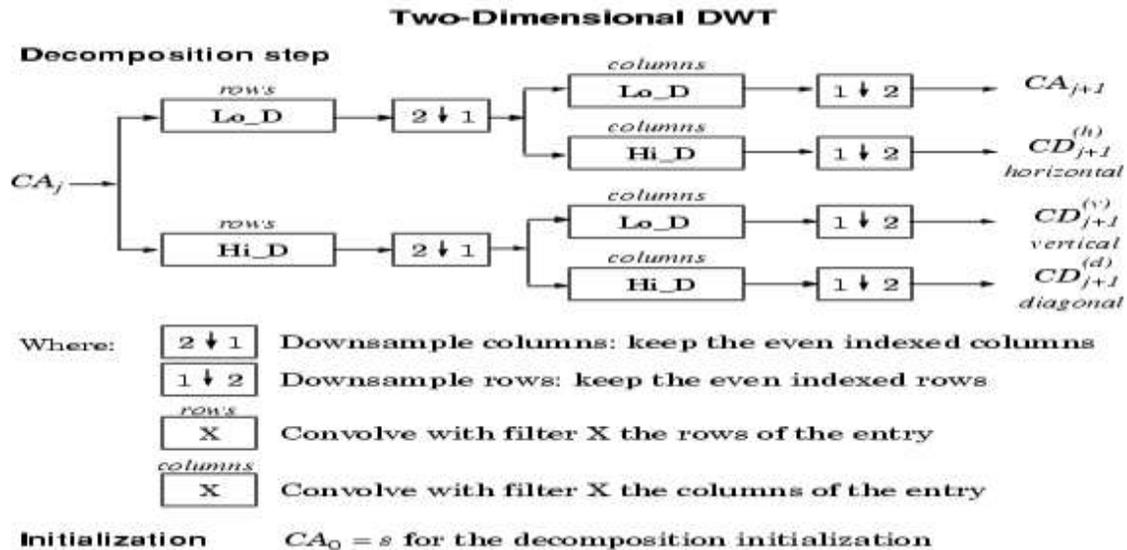


Fig. 3. 2D Discrete Wavelet Transformation

4. Feature Selection

One of the main ordinary forms of feature selection is “principal components analysis. For feature selection and reduction PCA use feature vector that calculated from wavelets. Through the feature vector PCA selects the features for efficient classification using supervised approach .So; the major initiative behind by the PCA method is to lessen the dimensionality of the wavelet coefficients.[12] It is essential to diminish the amount of features to drop off the computation time and the necessary storage. Principal component analysis (PCA) is an excellent technique used for modifying input feature into a novel one through inferior dimension.PCA uses the major eigenvectors of the correlation matrix to restructure features according to their divergences [8].

5. Classification

In our proposed method, we incorporate the last step classification. Here we make use of the “Kernel based Support Machine (SVM)” classifier to classify the tumors [11]. “Support Vector Machine (SVM)” classifier is one of the finest classifier to categorized brain tumor through MR images.[11]. For the pattern recognition technique Support Vector Machine plays an important role. The central idea of using classifier for classification

problems can be affirmed shortly as follows: a) Greatly change the input space to advanced dimensional feature space through a non-linear mapping function”and b) Build the extrication hyperplane with greatest expanse from the neighboring points of the training set. In linear separable data”case, the SVM tries to locate along with all hyper planes that reduce the training inaccuracy, the one that divides the prepared data with the greatest distance from their neighboring positions[7]

$$W \cdot x + b = 0$$

With w and b are weight and bias parameters respectively.[2]

(LK): $k(x_i, x_j) = x_i \cdot x_j$

(QK): $k(x_i, x_j) = (x_i \cdot x_j + 1)^2$

(PK): $k(x_i, x_j) = (x_i \cdot x_j + 1)^n$

(RBFK): $k(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / \sigma)$ [13]

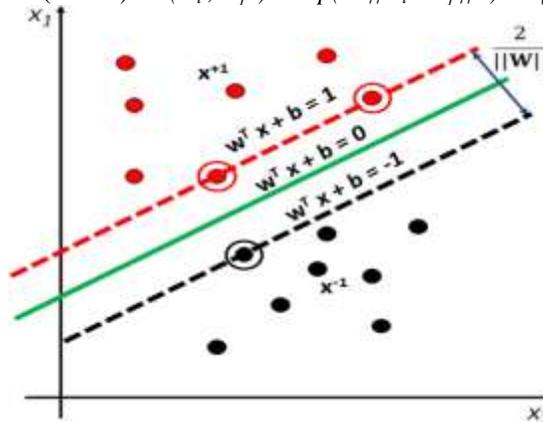
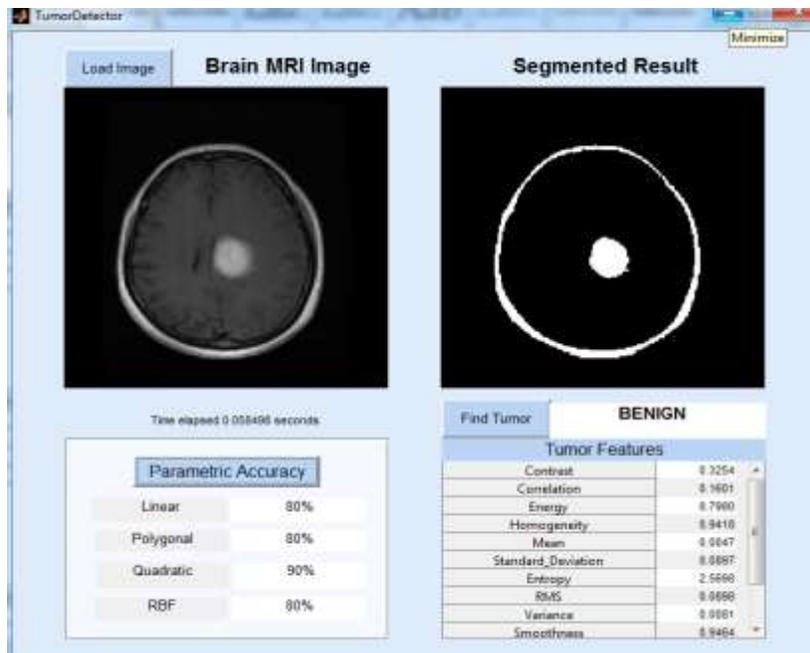


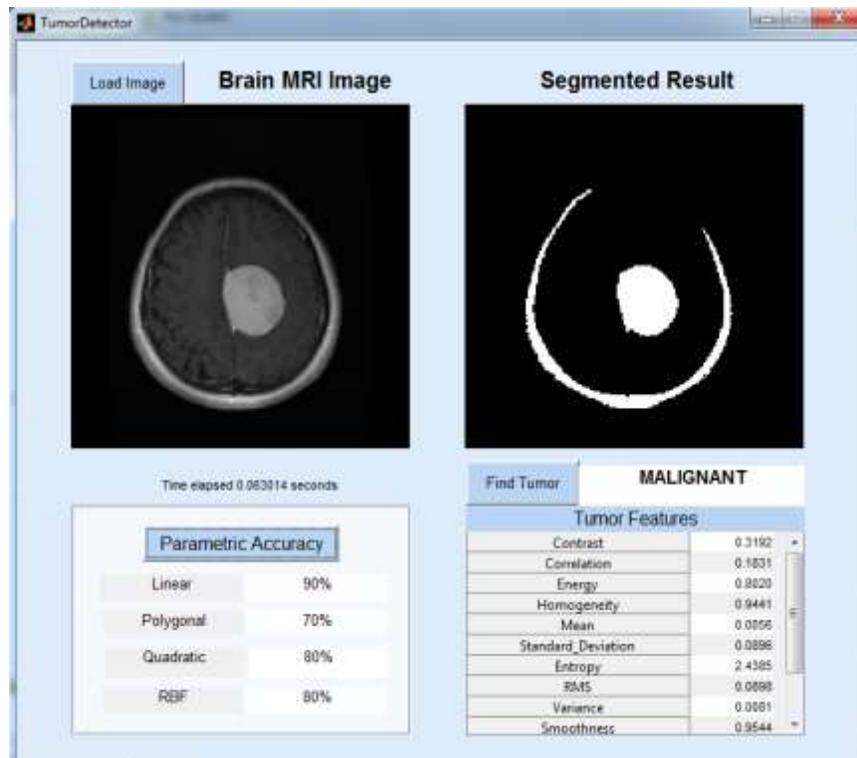
Fig. 4 Support Vector Machine Linear Classifier

6. Experiment and Result

For Brain tumor detection, segmentation, and classification a Graphical user interface (GUI) system has been developed. The system is designed to process MRIs different formats like tiff, jpg, png and bmp. In Fig 5(a) and (b) overview of GUI is displayed .The interface consists three buttons as; LOAD IMAGE is used to select the target MRI image. A FIND TUMOR, button classifies the input MRI as a normal or abnormal image. The GUI displayed the SVM kernel parameter and GLCM textural features.



(a)



(b)

Fig. 5.(a),(b) Malignant and Benign Tuumor Classification

In this paper ,we have extracted the different Textural feature using GLCM and DWT methods. After getting all Texural features we train our system using those features, for supervised classification. Kernel based SVM is used for classification. There are the main parameters to measure the performance of classifiers; Sensitivity, Specificity and Accuracy. the following formulas shows the metrics for those parameters:-

$$\text{Sensitivity} = \frac{TP}{TP+TN} * 100 \tag{10}$$

$$\text{Specificity} = \frac{TN}{TP+FN} * 100 \tag{11}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100 \tag{12}$$

Where FP, FN, TP, TN are:-

False Positive (FP):- Normal images classified as abnormal.

False Negative (FN):- Abnormal images classified as normal.

True Positive (TP):- Abnormal images classified correctly.

True Negative (TN):- Normal images classified correctly.

TABLE II: Performance Analysis of SVM classification

Parameters	RBF	LINEAR	QUADTRATIC
Sensitivity	90%	76%	98%
Specificity	98%	58%	88%
Accuracy	94%	64%	92%

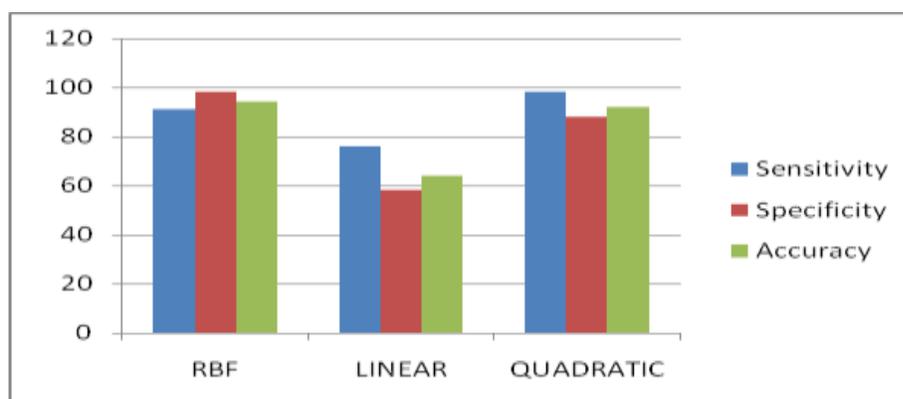


Fig. 6 Performance Analysis of SVM Classification

TABLE III Classification of MRI images using SVM Kernel

Kernel Used	No. of Images	Classified Images		
		Normal	Benign	Malignant
Linear	150	15	98	16
Quadratic	150	17	103	12
RBF	150	18	107	17

The above results shows RBF kernel gives the more accuracy. The Table3 shows the classification of images. The experiment done with 150 images, with the help of RBF kernel we get 18 normal brain images, 107 Benign Brain images and 17 Malignant Brain Images. The Result shows most of the patients have Benign tumor. The RBF kernel gives highest accuracy 94% as compared to Quadratic Kernel.

7. Conclusion

In this paper we have discussed different approaches to detect and classify the Brain tumor. The system is designed to detect existence of Brain tumor or not, then we classify the tumor in two classes “Benign” and “Malignant”. All the experiments are done with 150 T1 weighted MRI images of patients. First, we extract the different textural feature of MRI images using GLCM and DWT at 2level method, for feature reduction and selection PCA (Principal Component Analysis) are used. From those features we train our system to perform supervised classification, SVM. The above result shows RBF and Quadratic Kernel gives more accuracy. The experiment done with 150 images, with the help of RBF kernel we get 18 normal brain images, 107 Benign Brain images and 17 Malignant Brain Images. The Result shows most of the patients have Benign tumor. The RBF kernel gives highest accuracy 94% as compared to Quadratic Kernel.

In the future work we propose a new system to find tumor area and thickness of tumor to get the patients critical state and stage of tumor, which might be helpful for the radiologist.

8. References

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