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Classification of Brain MRI using Wavelet Decomposition and SVM

Pravada Deshmukh
Department of
Electronics Engineering,
Walchand Institute of Technology,
Solapur

P. S. Malge
Department of
Electronics Engineering,
Walchand Institute of Technology,
Solapur

ABSTRACT
Automated classification of brain MRI is important for the analysis of tumor. In this paper brain MRI are taken for the classification and detection of tumor .It consists of four stages, discrete wavelet transform (DWT), texture feature extraction, Classification by support vector machine and last segmentation. Due to the structure of the tumor cells, its detection became a challenging problem. Segmentation is used to extract tumor region in brain, which is carried out by fuzzy c-means clustering algorithm. The features are extracted from horizontal (LH) and vertical (HL) sub bands of the wavelet transform.The system gives better performance as compared to LL sub band because LH and HL sub bands can effectively encode the selective features of normal and abnormal images.Based on standard methods the system was evaluated and validated

Keywords
MRI, DWT, texture feature, SVM, segmentation

1. INTRODUCTION
Tumor is an unusual growth of cells within the brain and it is one of the most important reasons of death among societies. It is important that, it can be detected and classified in early stage in clinical practice. There are many diagnostic techniques can be performed for the before time detection of brain tumor such as Computed Tomography (CT) and

Magnetic Resonance Imaging (MRI). MRI is effective in the application of brain tumor detection and identification as compared to all other imaging methods because of its high contrast of soft tissues and its high spatial resolution. MRI does not produce any harmful radiation [3]. Various researchers have suggested different systems for the classification of tumor based on various sources of information. Brain tumors can be cancerous or non- cancerous [6].This paper presents a classification of brain MRI that it is normal or abnormal. From abnormal MRI the detection of tumor is carried out by clustering. Clustering is suitable method for medical image segmentation as the numbers of cluster are generally known to detect tumor. For the classification different types of non-linear SVM kernel tricks are used, from all of them SVM-polynomial gives better performance. There is comparison between all SVM-kernel functions and also extraction of features using LL-sub band. This paper organized in six sections, section 1 gives introduction of overall system. Section 2 describes the related work done on this topic. In Section 3 overall methodologies. Section 4, 5 give the results and implementation. Finally, Section 6 concludes the paper.

2. RELATED WORK
Various research works have been done in classifying MR brain images into normal and abnormal. Classification of brain MRI is a critical task. Ahmed kharrat et al. [5] presented their work on classification of brain MRI using genetic algorithm and SVM. They concluded that, Gabor filters give poor performance due to absence of orthogonality that result in redundant features at dissimilar scales or channels. Therefore wavelet transform and GLCM give better performance in representing textures at the most suitable scale. Classification of brain MRI using the LH and HL wavelet sub-bands was performed by Salim Lahmiri [2].There system shows that feature extraction from the vertical LH (Low-High) and horizontal HL (High-Low) sub-bands using first order statistics has higher performance than features from LL (Low-low) bands. In paper proposed by Alan Jose it was suggested to do clustering for segmenting tumor and to use fuzzy c-means clustering for calculation of area. Fuzzy c means gives superior performance than other clustering algorithm. In segmentation by Thresholding technique, segmented image ignores tumor cells. Segmentation by region growing is effective method but not fully automatic as it requires user interface. Clustering is suitable method for medical image segmentation. In clustering method the numbers of clusters are usually known to detect tumor accurately. Fuzzy c-means gives accurate prediction of tumor cells which are not predicted by K-means [12]. Pratap.S present a system in that haar wavelet is used for filtering the MRI. Then those images are given to the principal component analysis. FP-ANN classifier is used to classify the images as a normal or abnormal. The accuracy of the system using FP-ANN algorithm is found to be 90% [4].

3. METHODOLOGY
The system consists of a) Discrete Wavelet transform b) Texture feature extraction from horizontal(LH) and vertical(HL) sub bands using GLCM(gray level co-occurrence Matrix c)SVM classification. d)Segmentation.

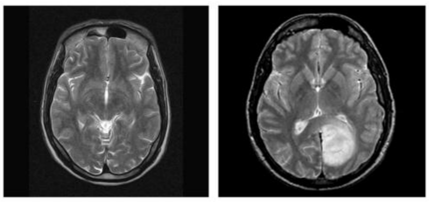

Figure 1: Input normal and abnormal MRI.

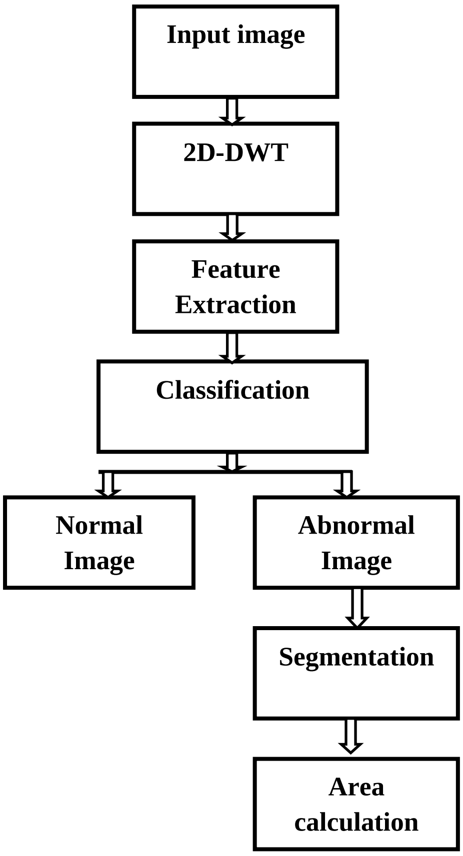

Figure 2: Flow of system

3.1 Discrete Wavelet Transform

The Discrete Wavelet Transform is built on sub-band coding. The wavelet is good for feature extraction and has been used for extracting the wavelet coefficients from MR images. In this system a 4- level decomposition using Daubechies (db1) wavelet was calculated and the features extracted from LH and HL sub bands. By filtering it gives time-scale representation of the signal [1]. The basic fundamental of DWT is given as, Suppose x (t) is a square- integral function then relation of continuous wavelet transform of x (t) to a given wavelet Ψ (t) is gives

$W(a, b) = \int_{-\infty}^{\infty} x(t)\Psi a, \mathrm{b}\,(t)\, \mathrm{d}t$......... (1)

Into a set of basic functions, it decomposes a signal. These basic functions are called wavelets. It is given as

$\Psi_{a,b}(t)=\frac{1}{\sqrt{a}}\,\Psi\,(\frac{t-a}{b})$.................(2)

Where, a represent scaling parameter and b represent the shifting parameter.

3.1.1 2-D DWT

Two dimensional DWT gives four sub bands that are LL (low-low), LH (low-high), HL (high-low), HH (high-high) at every scale. Sub band LL is the approximation band which is used for further decomposition up to four levels by Daubechies mother wavelet.

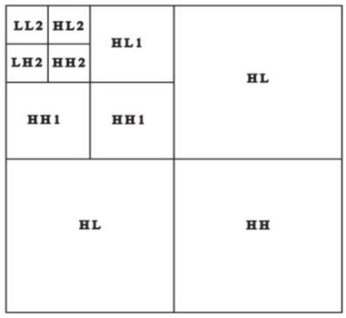

Figure 3: DWT decomposition

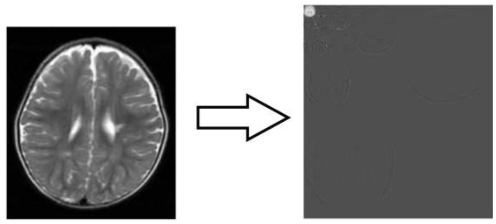

Figure 4: 4-level wavelet decomposition

3.2 Texture feature extraction

Procedure of finding higher-level information of an image such as colour, shape and texture called feature extraction. Its analysis makes difference between normal and abnormal tissue easy. Texture shows its characteristics both by pixel co-ordinates and pixel values. For texture feature extraction there is well-known statistical method called Gray-Level Co-occurrence Matrix (GLCM) is [3]. The GLCM is the two dimensional matrix with joint probabilities p (i, j) between pairs of pixels which are parted by a distance'd' in a direction 'θ '.It calculate how often a pixel having intensity i, occurs in relation with another pixel j at a distance d and direction θ. In this system total 14 features are extracted, out of that 7 features from LH and 7 from HL sub bands of the fourth level of wavelet decomposition.

First order statistics: Mean and standard variation these two features are extracted.

Second order statistics: These statistics are related to the co-occurrence of two pixels at specific relative positions.

1) **Contrast:** Contrast measures the local variation present in an image.

   $\sum_{i,j}(i-j)^{2} P_{d,\theta}(\mathrm{i, j})$........... (3)

2) **Correlation:** Correlation measures how a pixel is correlated to its neighbourhood pixel

   $\sum_{i,j} \frac{(i-\mu_x)(j-\mu_y)P_{d,\theta}(i,j)}{\sigma_x \sigma_y}$........ (4)

3) **Homogeneity:** It gives the similarity of pixel.

   $\sum_{i,j} \frac{P_{d,\theta}(i,j)}{1+|i-j|^2}$.................... (5)

4) **Entropy:** It measure of randomness of intensity image.

   $\sum_{i,j} Pd\,,\theta log_2[(P_{d,\theta}(\,i,\ j)]$....(6)

5) **Energy:** It returns the sum of squared elements in the gray level co-occurrence matrix.

$\sum_{i,j} (P_{d,\theta}\ (i,j))^2$ ……………..….. (7)

These 14 statistical features are given as input to SVM classifier.

3.3 Classification

SVM is based on supervised leaning, it is a binary classifier. By creating a hyperplane in high dimensional feature space SVM classifies between two classes. Hyperplane is represented by equation.

-w.x+b=0……………..……….. (8)

w represent weight vector and x normal to hyperplane. B gives bias or threshold. SVM consist of nonlinear transformation with kernels called 'kernel tricks' [8]. Some classification problems do not have a simple hyperplane as a suitable separating criterion. For those problems, there is a different mathematical approach that holds nearly all the simplicity of an SVM separating hyperplane [7]. Training vectors x_i, x_j are mapped into a higher dimensional space by the function ϕ.K (x_i, xj) $=\phi(x_i)^T\phi(x_j)$ is called the kernel function.

1. Polynomial:

   $K(x_i, x_j) = (\gamma x_i^T x_j) + r)^d \ ,\gamma > 0$……....(9)

2. Radial basis function (Gaussian):

   $K(x_i,x_j) = \exp(-\gamma||x_i-x_j||^2),\ \ \gamma > 0$…..(10)

3. Quadratic

   $K(x_i x_j) = (x_i^T x_j)^2$……..……………. (11)

Where,γ is a hyper parameter (also called the Kernel bandwidth) and r, d are the kernel parameters [8].SVM classifies between two classes as normal or abnormal (tumor affected).MRI classification is done by using these three kernel functions from which polynomial kernel gives better performance than other.

3.4 Segmentation

If the input image is classified as abnormal then it goes to segmentation for segmenting tumor. Fuzzy C means is overlapping clustering algorithm. It is based on minimization of the following objective function:

$$j_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m\ ||x_i - c_j||^2 \text{…….} (12)$$

Where (the fuzziness exponent) is any real number which is greater than 1, *N* represent the number of data, number of clusters C, u_{ij} gives the degree of membership of x_i in the cluster j, x_i is the i[th] of d-dimensional measured data, the d-dimension center of the cluster given by c_j, and $||*||$ is any norm expressing the relation between any measured data and the center[9].In this work number of cluster(C) are taken as 4 for T2 weighted MRI. In T2 weighted MRI there are 4 clusters classified on base of intensity values of pixels. These clusters are white matter (WM), cerebrospinal fluid (CSF),gray matter (GM)and background of MR image[11].Fuzzy partitioning is done through an iterative optimization of the$j_m$with the update of membership u_{ij} and the cluster centres c_j by

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\cdot\left\{\frac{||x_i-c_j||}{||x_i-c_k||}\right\}^{\frac{2}{m-1}}} \text{……….……} (13)$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_j}{\sum_{i=1}^{N} u_{ij}^m} \text{……..……..….} (14)$$

The algorithm of fuzzy c-means as follow

1. Initialize U=[u_{ij}] matrix, $U^{(0)}$
2. At k-step centres vectors are calculate $C^{(k)}=[c_j]$ with $U^{(k)}$

   $$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_j}{\sum_{i=1}^{N} u_{ij}^m}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

   $$u_{ij} = \frac{1}{\sum_{k=1}^{C}\cdot\left\{\frac{||x_i-c_j||}{||x_i-c_k||}\right\}^{\frac{2}{m-1}}} \text{……...} (15)$$

4. If $\left|\left|U^{(k+1)} - U^{(k)}\right|\right| < \epsilon$ then stop otherwise return to step 2.

Where,ϵ is a termination criterion between 0 and 1 and are the iteration steps [9]. Fuzzy clustering gives accurate detection of tumor cells from abnormal images.

3.5 Area calculation

Binarization method is used to calculated area of tumor. Area estimates the objects in binary image. Binary image have only two values either black or white (0 or 1) [10]. The binary image can be represented as

$I=\sum_{W=0}^{255}\sum_{H=0}^{255}[\ f(0) + f(1)]$…………..... (16)

Pixels = Width (W) X Height (H) = 256 X 256

f (0) = white pixel (digit 0)

f (l) = black pixel (digit 1)

No of white pixel P = $\sum_{W=0}^{255}\sum_{H=0}^{255}[f(0)]$

The area calculation formula is

Size of tumor= $[((\sqrt{P}) * 0.264]mm^2$ ...(17)

Where

P = number of white pixels in tumor region.

1 Pixel = 0.264 mm.

3.6 Performance measure

In order to estimate the performance of the classifier the performance measures are calculated. These performance measures are Sensitivity, Specificity, and Accuracy. Before calculating these measures one should know few important parameters and their descriptions which are standards for calculating the performance measures [11].

True positives (TP): Brain tumor (abnormal) images are correctly recognized.
False positives (FP): Non-Brain tumor (Normal) images are incorrectly recognized. Simply healthy persons incorrectly recognized as sick.
True negatives (TN): Normal MRI is correctly recognized as they do not have brain tumor.
False negatives (FN): Brain tumor (abnormal) images are incorrectly recognized. Sick persons incorrectly recognized as healthy.

Accuracy (%) $=\frac{TP+TN}{TP+TN+FP+FN}$ *100.... (18)

Specificity (%) $=\frac{TN}{TN+FP}$ *100…..……. (19)

Sensitivity (%) $=\frac{TP}{TP+FN}$ *100……..… (20)

4. EXPERIMENTAL RESULTS

The result was carried out on total 135 MRI images. For training purpose 90 images are taken and 45 images are for testing. Classification is done by using SVM kernel functions. Table 1 shows the result of testing images when SVM polynomial kernel function applied.

Table 1. Result of test images

Testing(45)	Normal	Abnormal
Normal(23)	22	1
Abnormal(22)	2	20

The important parameters which are standards for calculating the performance measures are obtained from table 1.Table 2 shows the parameter values obtained from table 1.Table 3 shows performance measures obtained by SVM polynomial kernel function

Table 2

TP(true positive)	20
FP(false positive)	1
TN(true negative)	22
FN(False negative)	2

Table 3.Performance measures

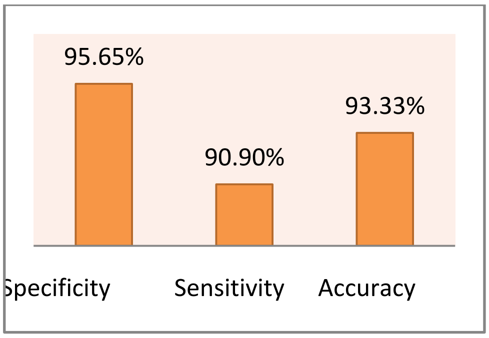

Table 4 shows Performance comparison of LH-HL (Horizontal-Vertical) sub bands versus LL (Approximation) sub band based classification using polynomial kernel functions

Table 4 .Performance comparison of LH-HL and LL sub band

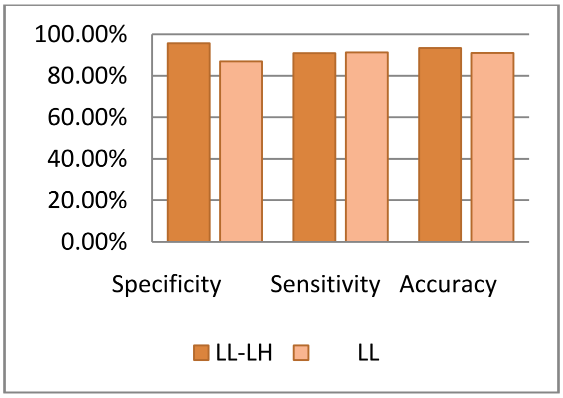

Table 5 shows performance comparisons between the different methods used for classification. SVM polynomial kernel function gives more accuracy than the Rbf and quad kernel function.

Table 5.Performance comparison between different methods

Methods	Classification Accuracy (%)
DWT(LH-HL)+Feature+ SVM(Polynomial)	93.33%
DWT(LHHL)+Feature SVM(Radial basis function)	89.00%
DWT(LH-HL)+Feature+ SVM(quadratic)	91.00%
DWT(LL)+Feature+ SVM(Polynomial)	91.00%

Table 5shows that the features extracted from horizontal (LH) and vertical (HL) sub bands of the wavelet transform gives better result as compared to LL sub band because LH and HL sub bands can effectively encode the selective features of normal and abnormal images.

5. IMPLEMENTATION AND DETECTION

From the classification of image as normal or abnormal, if it is abnormal then it goes to segmentation for segmenting tumor. Fuzzy C means is used for segmentation of tumor. Figure 5 shows the output of Fuzzy C-Means algorithm with four clusters.

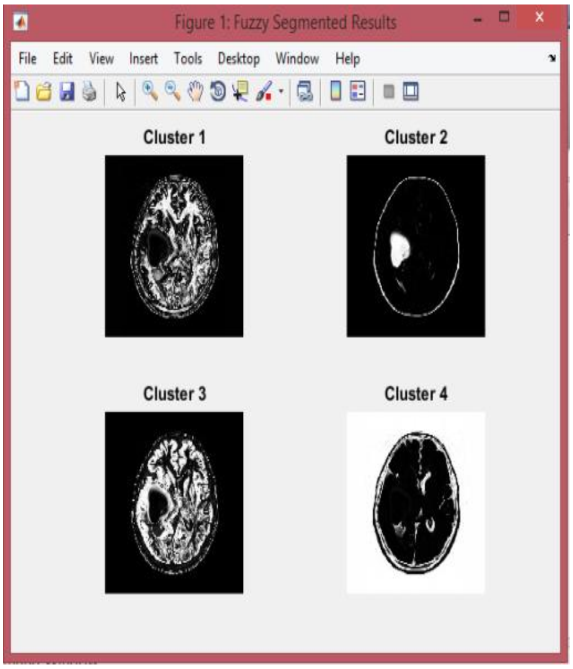

Figure 5.output of Fuzzy C-Means

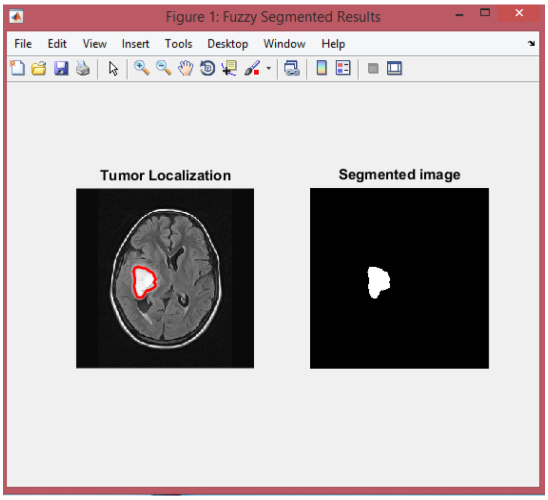

Figure 6.Segmentation of tumor

Figure.6 shows the output image for Fuzzy C means it gives tumor localization and segmentation of tumor region. Tumor part in brain is highlighted in the image and segmented. It is mainly developed for the accurate prediction of tumor cells. 8.53mm^2 tumor area of this test image is obtained.

6. CONCLUSION

The developed algorithm provides an efficient method to classify MRI and detect tumor from MRI image. For the system 45 images are considered for testing and 90 for training. The overall accuracy of the system is 93.33%.The experimental results are compared with other algorithms. In this paper, four different approaches are proposed and studied to classify the images as normal or abnormal. The aim was to find the best approach so that an efficient system is developed.SVM polynomial kernel function gives more accuracy than the Rbf and quad kernel functions. The classifiers categorize the image as normal and abnormal and detect the location of tumor by fuzzy clustering. The area of tumor is calculated. The system gives better performance as compared to LL sub band because LH and HL sub bands can effectively encode the selective features of normal and abnormal images. Based on standard methods the system was evaluated and validated. The future work will be extended for classification of more types of brain tumors and also for the identification of other brain disorders.

7. REFERENCES

[1] Yudong Zhang ,Zhengchao Dong "A hybrid method for MRI brain image classification".0957-4174 www.elsevier.com/2011 ELSEVIERLtd.

[2] Salim Lahmiri and Mounir Boukadoum,, "Classification of Brain MRI using the LH and HL Wavelet Transform Sub-bands," IEEE Transaction,2011.

[3] Pauline John "Brain Tumor Classification Using Wavelet and Texture Based Neural Network" International Journal of Scientific & Engineering Research Volume 3, Issue 10, 2012 1 ISSN2229-5518.

[4] Vrushali S. Takate1andPratap S.Vikhe "Classification of MRI Brain Images using FP_ANN" © ELSEVIER, 2013

[5] Ahmed kharrat, Karim Gasmi, et.al, "A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and SVM" Leonardo Journal of Sciences, pp.71-82,2010.

[6] Dimple Chaudhari "Classification of Brain Tumor Using Discrete Wavelet Transform, Principal Component Analysis and Probabilistic Neural Network" VOLUME-1, ISSUE-6, NOVEMBER-2014IJREST.

[7] Saurabh Shah, and N.C. Chauhan "Classification of Brain MRI Images using Computational Intelligent Techniques "International Journal of Computer Applications (IJCA) (0975 – 8887) Volume 124 – No.14, August 2015.

[8] Chih-Wei Hsu and Chih-Chung Chang, "A Practical Guide to Support Vector Classification" Department of Computer Science National Taiwan University,106, Taiwanhttp://www.csie.ntu.edu.tw/~cjlin .April 15, 2010.

[9] JAMES BEZDEK,ROBERT EHRLICH "FCM-FUZZY CMEANSCLUSTERINGALGORITHM"www.researchgate.net/publication/222868331.vol.10. no2-3 pp.191-203.

[10] V.Sowjanya"Investigation on Abnormal tissues detection methods for MRI images"1877-0509. © ELSEVIER, 2016.

[11] K. SUDHARANI, Dr.T.C. SARM "Advanced morphological technique for automatic brain tumor detection and evaluation of statistical parameters"2212-0173 © 2015 Published by Elsevier Ltd.

[12] Jay Patel1 and KaushalDoshi "A Study of Segmentation Methods for Detection of Tumor in Brain MRI" Advance in Electronic Engineering.volume4, Number3 (2014), pp.279284©ResearchIndia. Publication&V10, No. 2-3BEZDE JAMES C. BEZDEK