BRAIN TUMOR DIAGNOSIS ON FUSED IMAGE USING SVM CLASSIFIER

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ABSTRACT-Image fusion is a method of combining two images of different modalities in order to obtain the corresponding details from both the images with less loss. This increases the human visual perception on the corresponding images. This work gives wavelet transform on the given set of source images here CT and MRI. CT provides huge information on the hard tissues like bones and MRI provides information on the soft tissues like muscles. Therefore, fusing the CT and MRI images, the resultant image gives information on both hard and soft tissues. The fusion can be done with the help of fusion rules such as meanmax and maximum selection rule. Segmentation of the fused image is proposed by using K-means clustering before that binarization of the image by Otsu's thresholding is achieved. Extract the features using DWT. PCA is applied to reduce the extracted features. Texture analysis can be done with the help of GLCM and the properties such as contrast, correlation, energy, homogeneity and mean are taken as features. These features are given to SVM classifier in order to classify whether it is normal or abnormal.

Keywords: **Discrete wavelet transform, Computed tomography, Magnetic resonance imaging, Principal component analysis, Gray level co-occurance matrix, Support vector machine.**

1. INTRODUCTION

Medical imaging of different modalities facilitates the human visual perception for different diseases. Different imaging modalities includes Radiography, Magnetic Resonance Imaging(MRI), Nuclear medicine, Ultrasound, Elastography, Echocardiography, Magnetic Particle Imaging etc., Today Computed Tomography(CT), Magnetic Resonance Imaging(MRI), Positron Emission Tomography(PET), Single Photon Emission Computed Tomography(SPECT) plays a vital role in the diagnosis of any malfunctioning in our body and especially the growth of Tumorous and Cancerous cells. Different modality medical images would have different information about the human body. For example, CT highlights information on hard tissues like bones whereas MRI highlights information on soft tissues. So it is indispensable to combine different modality images to single image pertaining identical information from the source images which would ease the doctors for crystal clear diagnosis.

Three levels of image fusion methods are available: Pixel level, Decision level and Feature level. Pixel level image fusion has shown notable achievements in remote sensing, medical imaging and night vision application. Pixel level fusion method is categorized in two domains: Spacial domain and Transform domain. At present, Discrete Wavelet Transform (DWT) has been well used for image fusion applications. Here image fusion of CT and MRI has been achieved. In this work, segmentation of fused images by thresholding followed by feature extraction for classification is proposed. Otsu thresholding is employed here. K-means clustering algorithm is used to find the groups which have not been explicitly labeled in the data. It uses iterative refinement to produce a final result. The algorithm inputs are the number of clusters k and the data set. The data set is the collection of features for each data point. The vector which defines the hyperplane is said to be Support Vector. Support Vector Machine (SVM) classifier has been used to classify whether the given set of images are normal or abnormal.

2.WAVELET TRANSFORM

The repeated regular disturbance that moves through an intermediate agency from one place to next place is called wave. Small waves are said to be wavelets also defined as a wave of short period. Wavelet Transform is of two types Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Division of continuous time function into small waves can be done by using CWT. Any signal can be represented in the form of time frequency this is possible with the help of CWT that gives proper frequency localization and better time, not like Fourier transform. Wavelet transform have the properties of separability, scalability, translatability, multiresolution compatibility, orthogonality.

3. DISCRETE WAVELET TRANSFORM BASEDIMAGE FUSION

When sampling of the image is done discretely then the transform is said to be discrete wavelet transform. 'h' and 'l' in the Fig 1 is said to be highpass and lowpass filter respectively followed by downsampling. Here downsampling is carried out by a factor of 2. First highpass and lowpass filtering is done along rows and then followed by columns. This operation together combined to form a simple analysis filter of DWT.

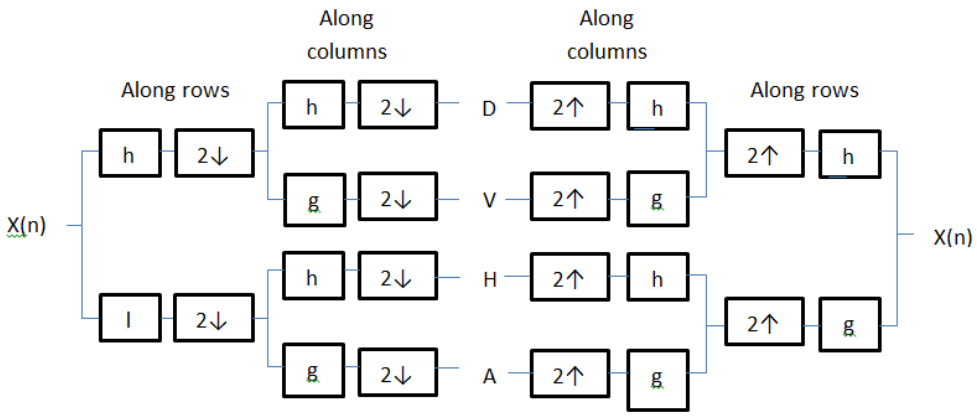

Fig 1:2D DWT filter bank

The outcome of analysis filter is wavelet coefficients. The obtained wavelet coefficients are approximation, horizontal, vertical and diagonal.

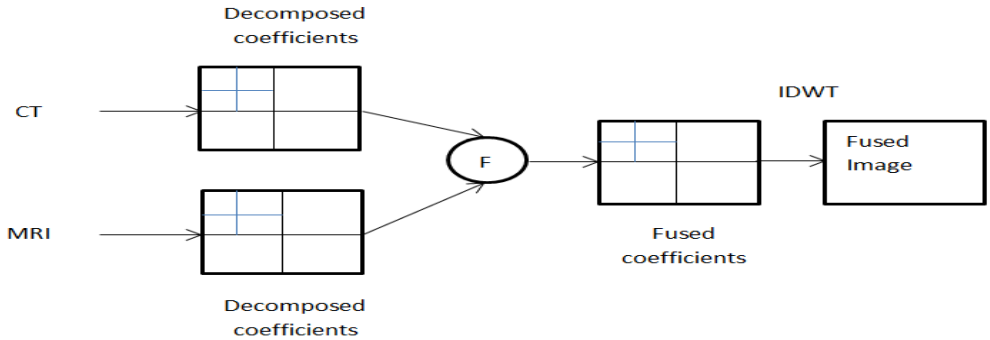

Fig 2 : Image fusion scheme for DWT

The result of two lowpass filtering is approximation coefficients, two highpass filtering is diagonal coefficients, one lowpass followed by another highpass is horizontal coefficients, and one highpass followed by another lowpass is vertical coefficients. This can be simply denoted as 'LL','HH','LH','HL' subbands. These outputs are given as subsequent inputs to the synthesis filter which is completely the inverse of analysis filter produces the original input at the output. Thus the perfect reconstruction is obtained.

In the Fig 2, two images of different modalities CT and MRI is taken as inputs. Discrete wavelet transform is employed on both the images so that each image is divided as four subbands of approximation, horizontal, vertical and diagonal. the subbands of CT image is 'LL', 'LH', 'HL', 'HH' and the subbands of MRI image is 'LL1', 'LH1', 'HL1', 'HH1'. The corresponding subbands for example 'LL' and 'LL1' is fused. Similarly, all other corresponding subbands are fused together in order to form a fused coefficients as shown in the Figure 2. The fusion rule used here is meanmax and maximum selection rule. On employing inverse discrete wavelet transform to the fused coefficients the fused image is obtained.

4. PROPOSED SYSTEM

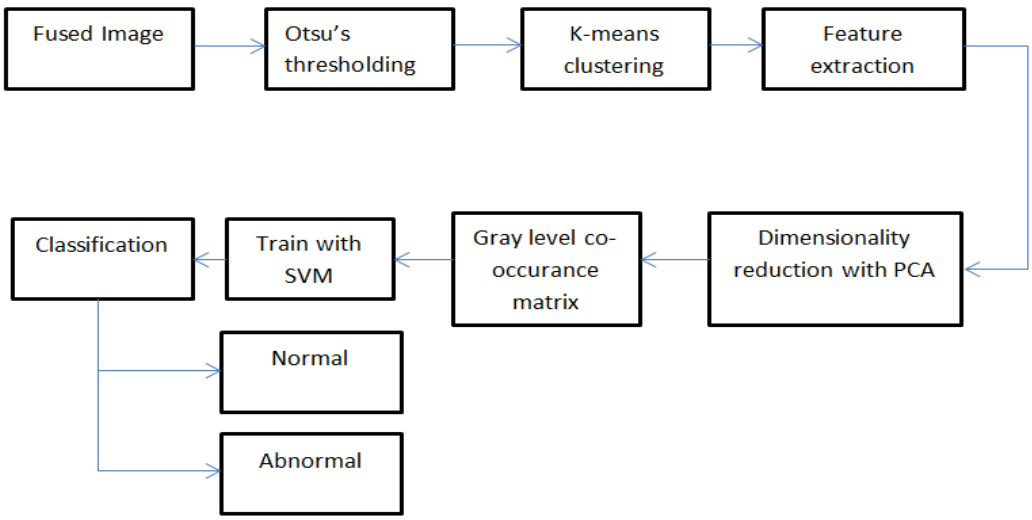

Fig 3. Overall proposed system

5. SEGNENTATION USING OTSU'S THRESHOLDING

Monochrome images are converted to gray scale images using many binarization methods. Nobuyuki Otsu is one who invented the Otsu's method of binarization algorithm. A binary image of range [0, 1] is obtained by converting the gray scale images by using Otsu's binarization method. This binary range is explained by the following equation,

$$k(x,y) = \begin{cases} 1, & g(x,y) \geq T \\ 0, & g(x,y) < T \end{cases} \quad (1)$$

Where T is a threshold, g(x, y) is the pixel value at each location of an image, K(x, y) is the resulted Otsu's binarized image.

6. K-MEANS CLUSTERING

Clustering divides the given dataset into n number of clusters based on the identical and non-identical properties. The samples within each cluster must be same but the samples between each cluster must be far from each other. According the K-means algorithm classification of N samples results in K groups or clusters. K= $\{K_1, K_2, \ldots, K_j\}$. The samples within each cluster would more same but the samples between the clusters have more dissimilarity. If u= $\{u_1, u_2, \ldots, u_j\}$ are j classes within the centroid where u_j is the mean sample in the K_j-th cluster. Division of samples can be done with the help of minimum squared error function. The function is given as follows:

$$A(X,K) = \sum_{j=1}^{J} \sum_{y_i \in K_j} \|y_i - u_j\|^2 \quad (2)$$

The distance between K_j and u_j is very minimum. It can be explained in the below formula

$$K_j = \{y_i \in (X|J) = \underset{l \in \{1,2,..,j\}}{argmin} \|y_i - u_j\|^2\} \quad (3)$$

$$u_j = \frac{\sum_{y_i \in k_j} y_i}{|K_j|} (4)$$

7. FEATURE EXTRACTION

Now on applying DWT to the segmented image, produces Approximated, Horizontal, Vertical, and Diagonal details were obtained. Take the Low-Low (LL), Low-High (LH), High-Low (HL), High-High (HH) subbands as DWT features. Contrast, correlation, homogeneity, energy and mean are taken as given from the segmented image obtained by above process. The above haralick features represent the texture features of an image.

8. PRINCIPAL COMPONENT ANALYSIS

PCA is a mathematical tool which is usually used for data reduction or dissection. For example, here PCA is indispensable for the reduction of total number of features. PCA is most commonly used in signal processing especially for two dimensional signals. This two dimensional images is said to have rows and columns. Rows of the images correspond to the observations and the columns of the images correspond to the variables. It uses singular value decomposition algorithm by default.

8.1 SINGULAR VALUE DECOMPOSITION

Centering of features in PCA is achieved with the help of Singular Value Decomposition. SVD decomposes a matrix A whose rows are M and columns are N into three individual matrices. This can be explained in formula as follows,

$A = U\mathcal{E}V^T$(5)

U represents the MxM orthogonal matrix which is given as follows,

$U = AA^T$(6)

$\mathcal{E}$is a diagonal matrix

V^Trepresents the NxN orthogonal matrix which is in the form of Eigen vector is as follows,

$$V^T = A^T A \quad (7)$$

To find the Eigen values of the matrix AA^T use the following equation

det $(\lambda I - AA^T)$=0 (8)

9. GRAY LEVEL CO-OCCURANCE MATRIX

The most famous second order statistical features are texture feature and also co-occurance matrix established by Haralick. There are two steps found by Haralick for textural feature extraction. The first step is to figure out the co-occurance matrix and second step is to estimate texture feature in reference to the co-occurance matrix. This technique is used for the application of image processing and biomedical etc.

9.1WORKING OF GLCM

Consideration of relation between two neighbouring pixel in one excess level is the basic of GLCM texture. The gray level values are converted to co-occurance matrix space by matrix kernel mask 5x5, 7x7 and forth. The neighbouring pixels are selected in one of the eight directions 0°,45°,90°,135°,180°,225°,270°,315° usually four directions are used 0°,45°,90°,135° and the negative directions are also taken into considerations. The Gray level co-occurance matrix, (a,b) represents the location of gray level intensity values where 'a' represents the gray level intensity value of row and 'b' represents the gray level intensity value of column. Calculation can be done by noting down how much the gray level intensity values 'a' is adjacent to the gray level intensity values 'b'.

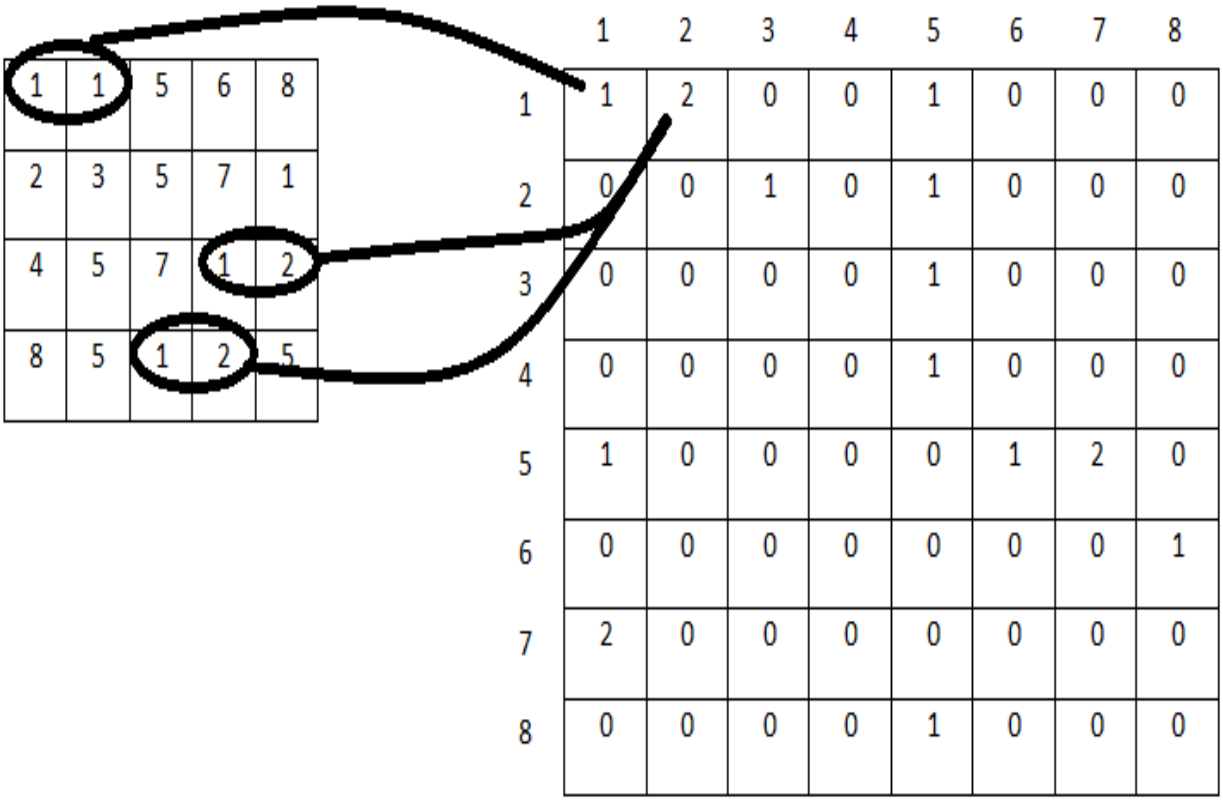

Fig 4. Creation GLCM from image matrix

Every element (a,b) in the matrix of GLCM represents the number of times the pixel value 'a' occurs with respect to the neighbouring pixel value 'b'. For example in the Fig 4 the element (1,1) have the value of 1 because the value one with the neighbouring pixel value 1 is present with only one instance. The element (1,2) have the value of 2 since the value 1 with neighbouring pixel value 2 is present two times in the GLCM matrix.

10. HARALICK TEXTURAL FEATURES

Haralick proposed thirteen textural features from GLCM matrix of an image. Some of the important textural features used for the analysis of tumor is contrast, correlation, energy, homogeneity and mean.

10.1 CONTRAST

Contrast in the image processing is defined as the difference in the intensity value of neighbouring pixel values. It is defined by using the following equation,

$$C = \sum_{a=0}^{N-1} \sum_{b=0}^{M-1} (a-b)^2 \, M(a,b) \quad (9)$$

10.2 CORRELATION

Correlation is a measure of how closely a pixel in an image is related to the neighbouring pixel. It ranges between -1 to 1. It is mathematically represented as,

$$Cor = \sum_{a=1}^{k} \sum_{b=1}^{k} \frac{(a-m_r)(b-m_c)}{\mu_r \mu_c} \quad (10)$$

Where $\mu_r \neq 0, \mu_c \neq 0$

10.3 ENERGY

Energy is a measure of squared element in GLCM matrix. It has a value 1 for constant image. It ranges from [0 1].Its corresponding equation is,

$$Energy = \sum_{a=1}^{k} \sum_{b=1}^{k} M(a,b) \quad (11)$$

10.4 HOMOGENEITY

Homogeneity is a measure of closeness of distributed elements in GLCM matrix to the diagonal element in the GLCM whose value ranges from 0 and 1.

$$Homogeneity = \sum_{a=1}^{k} \sum_{b=1}^{k} \frac{M(a,b)}{1+|a-b|} \quad (12)$$

10.5 MEAN

Mean is the representative value of a large dataset that describes the center or middle value. Mean is the measure of the group contributions per contributor which is conceived to be the same as the amount contributed by each 'n' contributors if each were to contribute equal amounts,

$$Mean = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (13)$$

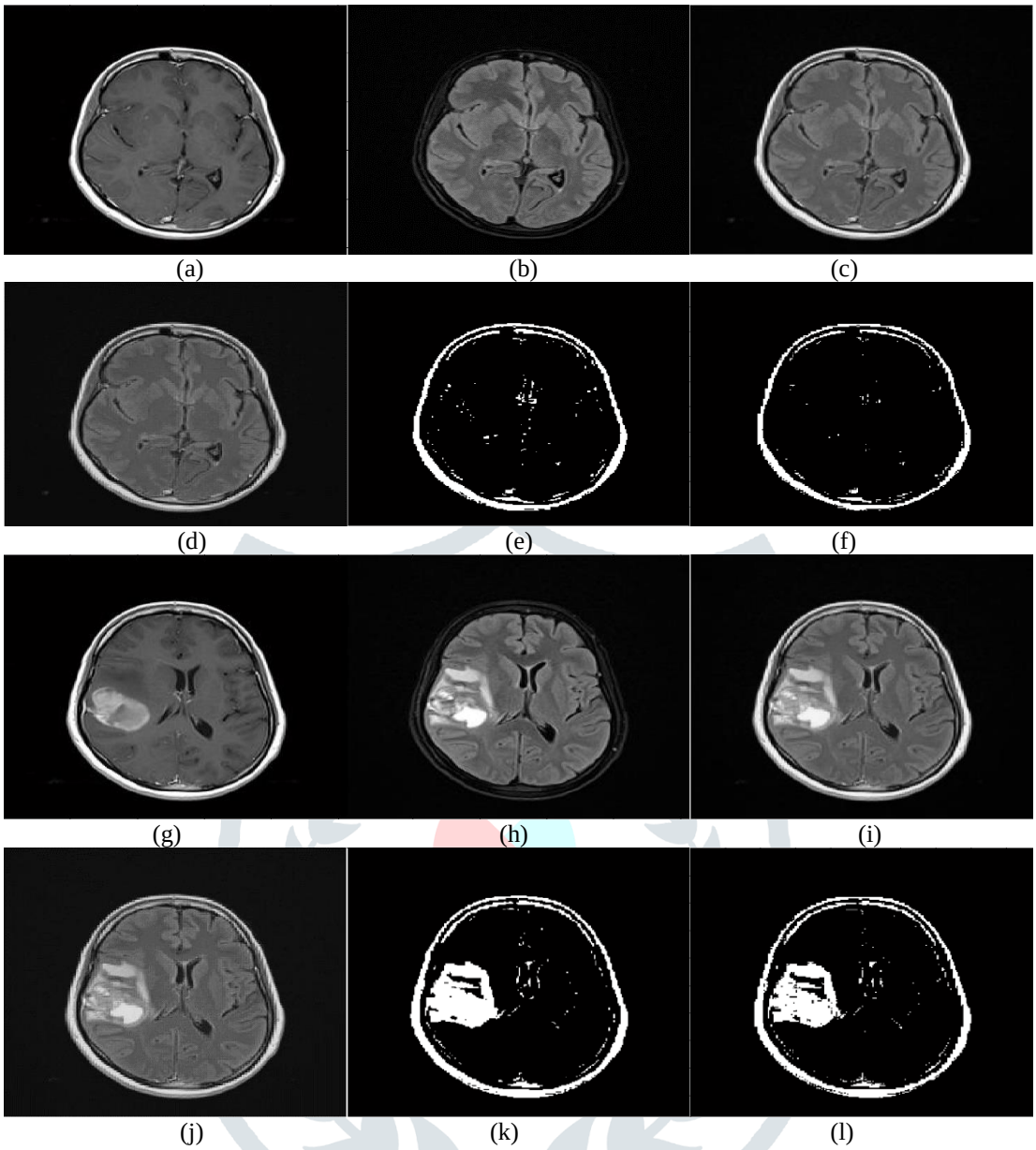

Fig 5. (a) Normal CT input image (b)Normal MRI input image (c) fused image using meanmax fusion rule of normal images (d) fused image using maximum fusion rule of normal images (e) segmented image of meanmax fused normal image (f) segmented image of maximum fused normal image (g) Abnormal CT input image (h) Abnormal MRI input image (i) fused image using meanmax fusion rule of abnormal images (j) fused image using maximum fusion rule of abnormal images (k) segmented image of meanmax fused abnormal image (l) segmented image of maximum fused abnormal image.

Table 1. DWT fusion results

PARAMETER	DWT FUSION	
	MEANMAX	MAXIMUM
PSNR (dB)	22.3312	23.2454
SSIM (no units)	0.2161	0.2051

The result in the Table 1 shows that the fusion is done with the transform called discrete wavelet transform and the fusion rule used here is meanmax fusion rule where average is taken for high frequency subband and maximum selection rule is applied for low frequency subband and the another fusion rule is maximum selection rule which is applied to both high frequency coefficients and low frequency coefficients.Structural similarity index (SSIM) actually measures the perceptual difference between two similar images. The parameters used for evaluations are Peak-signal to noise ratio (PSNR) and Structural Similarity Index (SSIM). Thus, the PSNR must be high and SSIM must be low enough to say the scheme is efficient**.**

PSNR is defined through MSE,

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (14)$$

$$PSNR = 10\ \log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (15)$$

Structural similarity index (SSIM) is used to calculate the intuitive difference among same images. It is a multiplication of three terms namely the contrast, the structural and the luminance terms.

$SSIM(a,b) = [c(a,b)]^x.[s(a,b)]^y.[l(a,b)]^z$ (16)

Where

$$c(a,b) = \frac{2\sigma_a\sigma_b + C_1}{\sigma_a^2 + \sigma_b^2 + C_1} \quad (17)$$

$$s(a,b) = \frac{\sigma_{ab} + C_2}{\sigma_a\sigma_b + C_2} \quad (18)$$

$$l(a,b) = \frac{2\mu_a\mu_b + C_3}{\mu_a^2 + \mu_b^2 + C_3} \quad (19)$$

11. CLASSIFICATION OF SEGMENTED FUSED IMAGE USING SVM

Support Vector Machine (SVM) is a biased classifier. It is defined with the help of separating hyperplane. The distance between the closest data point and the hyperplane is said to be margin shown in the Fig 6. The pros of SVM are it performs well with good separation margin; it is active where number of samples is lesser than the number of dimensions, it is memory efficient since uses support vectors. The cons of SVM are it does not works well, when the dataset is large and also when noise is present in the dataset because time taken for training is high and overlapping of target class respectively. The SVM is used in handwritten digit recognition, text categorization, image based gender identification.

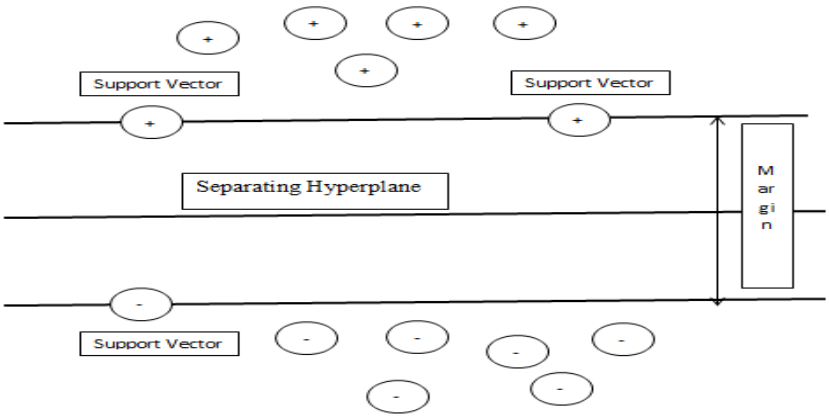

Fig 6. Hyperplane separation

12. TESTING

The inputs to the testing process are fused images. The fused images have their own features. When it is given to the trained classifier the features of test fused images get mapped with the features that are already trained. The process of mapping compares the features of one image with the entire trained image features and then classifies whether the image is normal or abnormal.

Fig 7. Testing phase

13. SVM CLASSIFIER

Training and classification are the two basic steps used in classifier. Training is the process of fetching subject that is belonging to specified classes and creating a classifier on the reference of that known subject. Training is an iterative process where there is a possibility of building best classifier. Extract the features for 80% of fused dataset and also extract the features for 20% of test images. Train the data set as 1 for normal and 0 for abnormal by labeling the dataset.

Table 2. Table of Accuracy

Types of classifier	MRI input accuracy	Fused input accuracy
Linear SVM	75.0%	71.2%
Quadratic SVM	82.7%	78.8%
Cubic SVM	94.2%	96.2%
Medium Gaussian SVM	76.9%	75.0%
Coarse Gaussian SVM	76.9%	71.2%

Kernel used here is Cubic SVM since its prediction speed is fast for binary and flexible. 80% of 65 images (i.e), 52 images are taken as input for training in which normal images are 37 and abnormal images are 15. 37 out of 37 are classified as normal while 13 out of 15 are classified as abnormal remaining two images are misclassified. The total accuracy obtained for fused input is 96.2% in cubic kernel when compare to all other kernel as shown in Table 2 because it is more flexible and easy to interpret and the total accuracy obtained for MRI input is 94.2%. Therefore, it is proven that accuracy increases for the fused input type.

14. CONCLUSION

In this paper, a method of introducing a fused image for segmentation and for further classification is proposed. The proposed approach gives increased accuracy than the other existing methods. Usually the tumor diagnosis is done with the help of MRI images not with CT images because MRI gives more information on tumor. Image fusion technique owns both the information from CT and MRI. On using the result of image fusion as an input, more information is given as input obviously this increases the accuracy. The advantage of the proposed technique is more accurate, robust, easy to interpret. The limitation of this approach is still accuracy is not 100 percentage lags by some percentage from hundred.

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