International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 6 (2015) pp. 14669-14687

http://www.ripublication.com

A Novel Method of Feature Extraction from MRI Brain Nuclei to Diagnose Brain Disorders

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Abstract

Feature extraction is an important component for MRI (Magnetic Resonance Imaging) brain image classification. This paper presents a new approach of feature extraction from the normal (Cerebrospinal, Gray matter, White Matter) and pathological tissues (Cyst, tumour, edema) segmented from the input MRI brain image. The statistical features like Mean 'M', Variance 'σ^2', Entropy 'E_n'and Energy '$E_{(H,V,D)}$' functions like horizontal, vertical and diagonal are chosen in the proposed framework. The feature extraction process is carried out with some initial pre-processing. Each segmented tissue image is divided into a limited number of blocks of size 4x4 and the feature values are calculated for every block. Then all these feature values can be stored in a vector and fed as an input to the classifier to detect brain disorders.

Keyword- Feature Extraction, MRI Brain, Schizophrenia, Alzheimer, Texture Analysis, Brain nuclei

I. INTRODUCTION

MRI is an important diagnostic imaging technique for the detection of brain abnormalities [1], [2], [3]. To represent an image, large amount of data is required which occupies large amount of memory and time. In order to reduce the amount of data, memory and time, the features are extracted from an image. The extracted features contain the relevant information of an image. It can be used as an input to the classifier for image classification. The type of features extracted from an image is classified as: Intensity based features, texture based features and shape based features. The intensity features such as mean, median, mode, skewness, kurtosis, energy, entropy are considered. Texture is a characteristic of an image that provides higher order description of an image and includes information about the spatial distribution of tonal variations or grey tones. The texture extraction defines the homogeneity or similarity between regions of an image. Shape provides the geometrical information of an object in an image. The shape features such as centroid, eccentricity, area, perimeter, circularity, shape index, solidity, orientation, euler number are considered.

Features are extracted from the segmented normal (CSF, WM, GM) and pathological tissues (tumour, edema and cyst). There are several approaches to Brain MR image segmentation: discriminant analysis [4], [5], neural networks [7], [8], clustering [6], brain atlases [9], knowledge-based techniques [10], shape-based models [11], [12], morphological operators [13], multivariate principal component analysis [14], pixel based models Expectation Maximization Algorithm [15], Multi-resolution edge detection [7] and statistical pattern recognition [16], to name a few.

Supervised segmentation methods have exhibited problems with reproducibility, due to significant intra and inter-observer variance introduced over multiple trials of training. Further they consume more time and needs domain expertise. So, supervised methods are unsuitable for clinical use. These limitations suggest the need for a fully automatic method for segmentation and classification. In unsupervised methods instead of feeding the input as raw image, features of the image are calculated and later it can be fed as input to the classifier so that the time consumption and storage space can be reduced. The success of classification depends up on the effective extracted features.

Intensity based features are most widely used. But due to the complexity of the brain tissues, intensity based features alone cannot achieve acceptable result so, texture features are calculated along with intensity features. Co-occurrence matrix and wavelet based texture features are used to achieve promising results. In this paper, we have utilized the brain tissues segmented using the segmentation technique that we have proposed in our previous research paper [17], [18]. In this proposed work, three intensity features (mean, variance, standard deviation) and two texture features (Entropy, Energy) are calculated.

The rest of the paper is organized as follows. In section 2, the features extracted from MRI brain image by various feature extraction methods are reviewed. In section 3, the proposed feature extraction method from segmented MRI brain tissue images is discussed. Section 4 discusses the results and their analysis. In this section, the results are also compared with the conventional method. Conclusion is presented in the last section.

II. REVIEW OF PREVIOUS WORK ON MRI BRAIN IMAGE FEATURE EXTRACTION

Various MRI brain image feature extraction methods are listed in this section. The next step in the automated brain image segmentation and classification method is feature extraction. Feature extraction is the technique of extracting specific features from the pre-processed images. Various feature extraction methods have been cited in the literature for improving feature extraction process from MRI brain image.

Arivazhagan and Ganesan [19] used 2D wavelet transform based textural features for classification. In their work, initially basic statistical features are used and then co-occurrence based textural features are used to improve the accuracy. An improved version based on wavelet packet decomposition is implemented by [21]. Their results revealed that the packet decomposition technique is more efficient than the 2D wavelet transform.

Ryszard [20] extracted features from local region apart from extracting the features from the whole image, which is used for image segmentation. They revealed that the entropy is the most dependable feature among the textural features.

Kadam et. al. Kadam et. al. have used eight textural features: angular second moment, contrast, inverse difference moment, sum variance, sum entropy, entropy, and difference entropy and information measure of correlation to train the MLP network in segmenting brain tumor. Although the proposed method improves segmentation results, the qualitative and quantitative results given are inadequate.

Guler et. al. [27] presented an image segmentation system to automatically segment and label brain MR images to show normal and abnormal brain tissues using self-organizing maps (SOM) and knowledge-based expert systems. The feature vector is used as an input to the SOM. SOM is used to over segment images and a knowledge-based expert system is used to join and label the segments. Spatial distributions of segments extracted from the SOM are also considered as well as gray level properties. Segments are labeled as background, skull, white matter, gray matter, cerebrospinal fluid (CSF) and suspicious regions.

Mishra [28] has developed an efficient system, where the Brain Tumor has been diagnosed with higher accuracy using artificial neural network. After the extraction of features from MRI data by means of the wavelet packets, an artificial neural network has been employed to find out the normal and abnormal spectra. Normally, the benefit of wavelet packets is that it gives richest analysis when compared with the wavelet transforms and thus adding more advantages to the performance of their proposed system. Moreover, two cancer detection approaches have been discussed. The neural network system has been trained using the Error Back Propagation Training Learning rule.

In [24], a fuzzy kohonen neural network is implemented for brain MR image segmentation. The technique used features like area, entropy, mean and standard deviation to segment tumor from brain MR image but did not use any preprocessing, for instance, noise removal to improve the extraction of these features. In addition, the qualitative and quantitative analyses of the proposed method are inadequate.

Joshi jayashri and phadke [26] proposed a method for segmenting tumour based on statistical structure analysis. The structural analysis was done for both tumour and normal tissues. The texture features have been extracted using co-occurrence matrix. Fuzzy c-means and an artificial neural network are used for classification. They proposed this method to examine the differences of texture features between macroscopic lesion white matter (LWM) and normal appearing white matter (NAWM) in magnetic resonance images with tumour and normal white matter (NWM)

Nandita ibraheem jabbar [25] proposed a technique for segmenting tumour, edema, white matter, gray matter and cerebrospinal fluid from FLAIR MRI brain images. In addition to tumour, they segmented edema as a separate class. In their technique, MRI brain images are segmented into 5 classes using k-means algorithm and calculated texture properties and features of wavelet energy function. They extracted the feature vectors from all the 5 segmented images by dividing the image into small blocks of size 4x4 pixels. The block feature vectors of all the segmented images are given as input to an artificial neural network using back propagation algorithm for classification.

III. PROPOSED BLOCK BASED FEATURE EXTRACTION FROM SEGMENTED IMAGES

The block diagram of the proposed method for feature extraction is shown in figure 1. In the proposed method, the segmented normal brain tissues such as gray matter, white matter, cerebrospinal fluid and pathological tissues (tumor) from our previous work [17], [18] are divided into 'N' number of blocks which is represented as B = {bn}; n = 1, 2, 3, ... N, as shown in figure 2. We have 128 blocks of size 4 x 4 as shown in figure 3, because the size of input MRI brain image is 512 x 512 pixels.

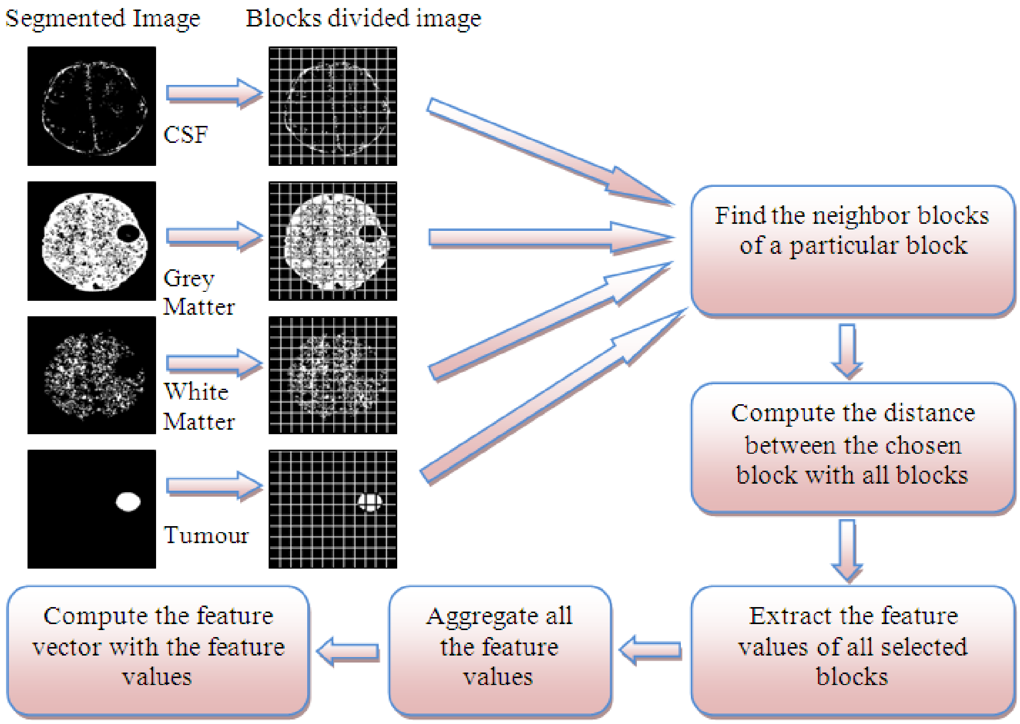


Fig. 1. Block diagram of proposed Feature Extraction Method

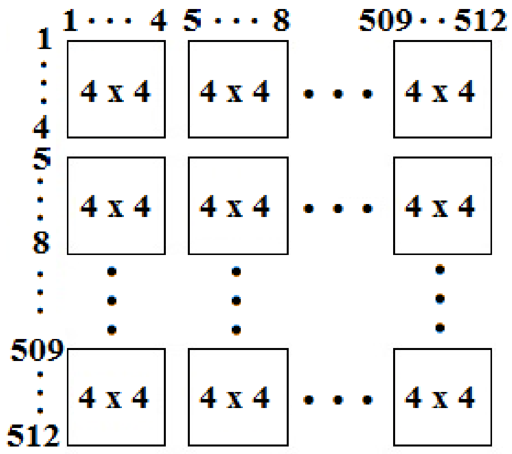


Fig. 2. Segmented image (512 x 512) broken down in to smaller blocks of size 4x4

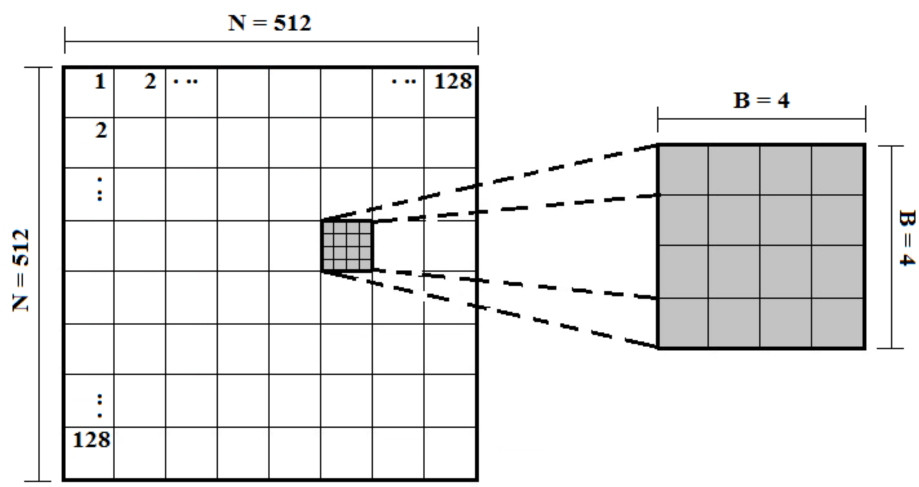


Fig. 3. Segmented Image (512 x 512) broken down in to 128 smaller blocks of size 4x4

For feature extraction process, we have taken a block b_n and checked this block with the neighbour blocks. If the entire neighbour block value is zero then these blocks are not considered for feature extraction process or else the distance between the chosen block and the neighbour block is determined by exploiting euclidian distance. $D_{nl} = b_n - b_l$; $l = 1, 2, 3, \ldots\ldots N$ $(n \neq l)$

The distance value of each block D_{nl} is compared with the threshold value 't_1'. During the comparison, if the distance value D_{nl} of all blocks is less than the defined threshold value t_1, then it is adequate to store one block instead of storing all the blocks or else store the block's values individually. The obtained block values are stored in a variable $B_s = \{n'\}$; $n' = 1, 2, \ldots N'$ and the feature extraction process is carried out only for these stored blocks 'B_s'. The initial steps are as follows [22], [23]:

1. Find the neighbor blocks of the entire divided blocks.
2. Find the distance between all the neighbor blocks.
3. Compare the distance value of each block with threshold value.
4. Store all the blocks whose distance value is less than threshold value in a separate variable.
5. Find the feature values of all the blocks stored in a variable.
6. Find the average value of all the computed blocks' distance.
7. Store all the features in a vector and fed as an input to the classifier.

Features can be extracted from the matrix to reduce feature space dimensionality and the formal definitions of chosen features from the matrix are done. The statistic feature's formula is depicted as below from equations (1) to (7).

Mean, $$M = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{m} x(i,j) \tag{1}$$

A. ***Variance***

The variance is a parameter describing in part either the actual probability distribution of an observed population of numbers, or the theoretical probability distribution of a not-fully-observed population of numbers.

Variance, $$\sigma^2 = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j) - M)^2 \tag{2}$$

B. ***Entropy***

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as,

Entropy (E), $$E = -\sum_i\sum_j x(i,j)\log x(i,j) \tag{3}$$

C. ***Wavelet based Energy function***

The feature vectors of the three energy functions of high frequency horizontal, vertical and diagonal sub-bands of the wavelet transform are extracted, since it reflects the texture properties.

Energy, $$E_{(H,V,D)} = \sum_i\sum_j x(i,j)^2 \tag{4}$$

In order to obtain the three wavelet energies, the Haar wavelet transform is applied to each blocks of brain MRI image. A Haar wavelet is the simplest type of wavelet. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. The Haar transform serves as a prototype for all other wavelet transforms. Haar transform can be used for compressing image, signals and for removing noise. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two subsignals of half its length. One subsignal is a running average or trend and the other subsignal is a running difference or fluctuation.

The first trend subsignal, $a^1 = (a_1, a_2, \ldots\ldots a_{N/2})$ for the signal 'f' is computed by taking a running average in the following way. Its first value, 'a_1' is computed by taking the average of the first pair of values of f: $(f_1 + f_2)/2$ and then multiplying it by $\sqrt{2}$. i.e., a1 = $(f_1 + f_2)/\sqrt{2}$, continuing in this way all of the values of a^1 are produced by taking averages of successive pairs of values of 'f' and then multiplying these averages by $\sqrt{2}$. A precise formula for the values of a^1 is,

$$a_m = \frac{f_{2m-1} + f_{2m}}{\sqrt{2}}\,; \text{for} \quad m = 1, 2, 3, \ldots\ldots \frac{N}{2} \tag{5}$$

The first fluctuation of the image f, which is denoted by $d^1 = (d_1, d_2, \ldots\ldots d_{N/2})$ is computed by taking a running difference in the following way. Its first value, 'd_1' is computed by taking the half the difference of the first pair of values of f: $(f_1 - f_2)/2$ and then multiplying it by $\sqrt{2}$. i.e., d1 = $(f_1 - f_2)/\sqrt{2}$, continuing in this way all of the values of d^1 are produced by taking running difference of successive pairs of values of 'f' and then multiplying these averages by $\sqrt{2}$. A precise formula for the values of d^1 is,

$$d_m = \frac{f_{2m-1} - f_{2m}}{\sqrt{2}}\,; \text{for} \quad m = 1, 2, 3, \ldots\ldots \frac{N}{2} \tag{6}$$

Haar transform can be used in image compression. The following denotation is used; 'A' is the approximation area that includes information of the average of the image, 'H' is the horizontal area that includes information about the vertical edges / details in the image, 'V' is the vertical area that includes information about the horizontal edges / details in the image and 'D' is the diagonal area that includes information about the diagonal details. After Haar transform, the approximation component contains most of the energy and the diagonal component contains less energy. So, excluding the approximation area will result in biggest distortion to the compressed image and excluding the diagonal area will result in least distortion to the compressed image.

Thus the 1-level Haar transform has kept the energy constant. After a one level wavelet transform, a 4×4 pixel block is decomposed into four frequency bands of 2×2 coefficients as shown in figure 4. For example, the coefficients in horizontal band of one block are H_1, H_2, H_3, H_4, in vertical band V_1, V_2, V_3, V_4 and in diagonal band D_1, D_2, D_3 and D_4. Then horizontal energy E_H, vertical energy E_V and diagonal energy E_D are combined to attain the feature value of the energy.

A_1	A_2	H_1	H_2
A_3	A_4	H_3	H_4
V_1	V_2	D_1	D_2
V_3	V_4	D_3	D_4

Fig. 4. 4×4 pixel block is decomposed into four frequency bands of 2×2 coefficients

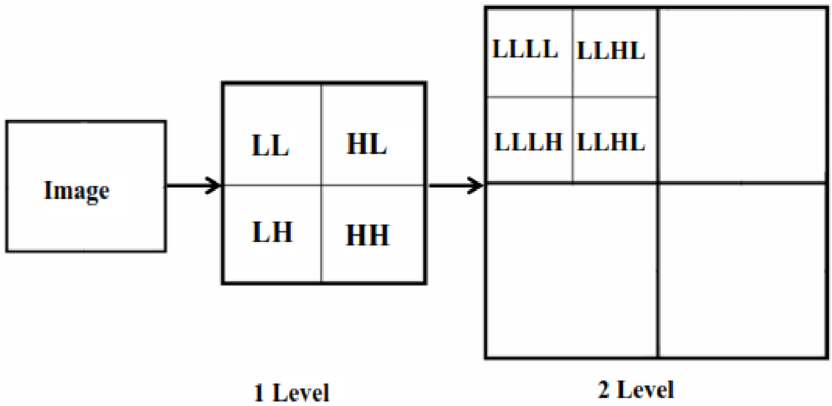


Fig. 5. 2D DWT for image

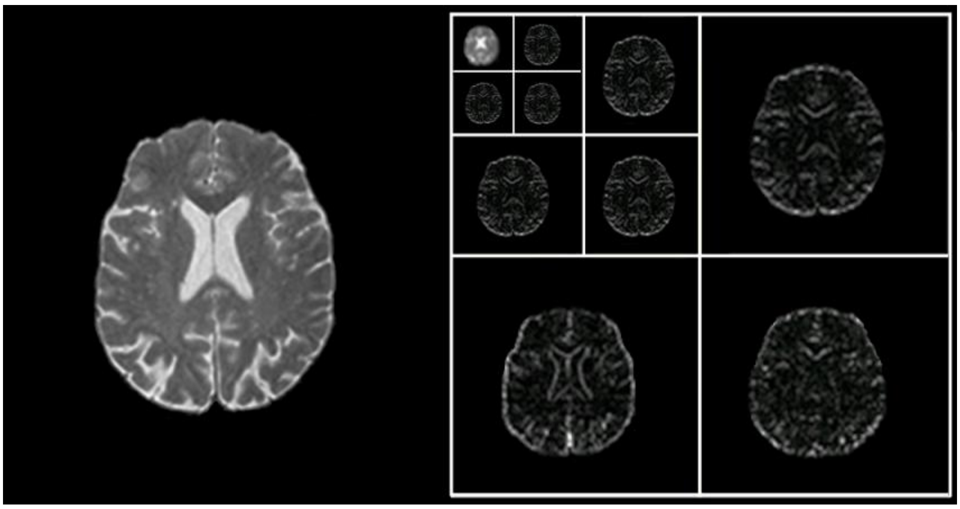


Fig. 6. 2D DWT for normal brain MR image

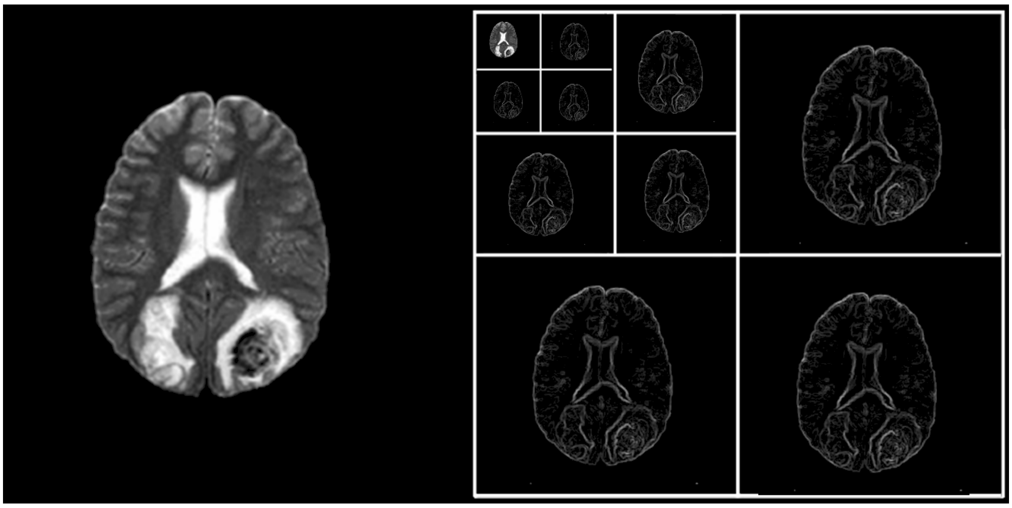


Fig. 7. 2D DWT for abnormal brain MR image

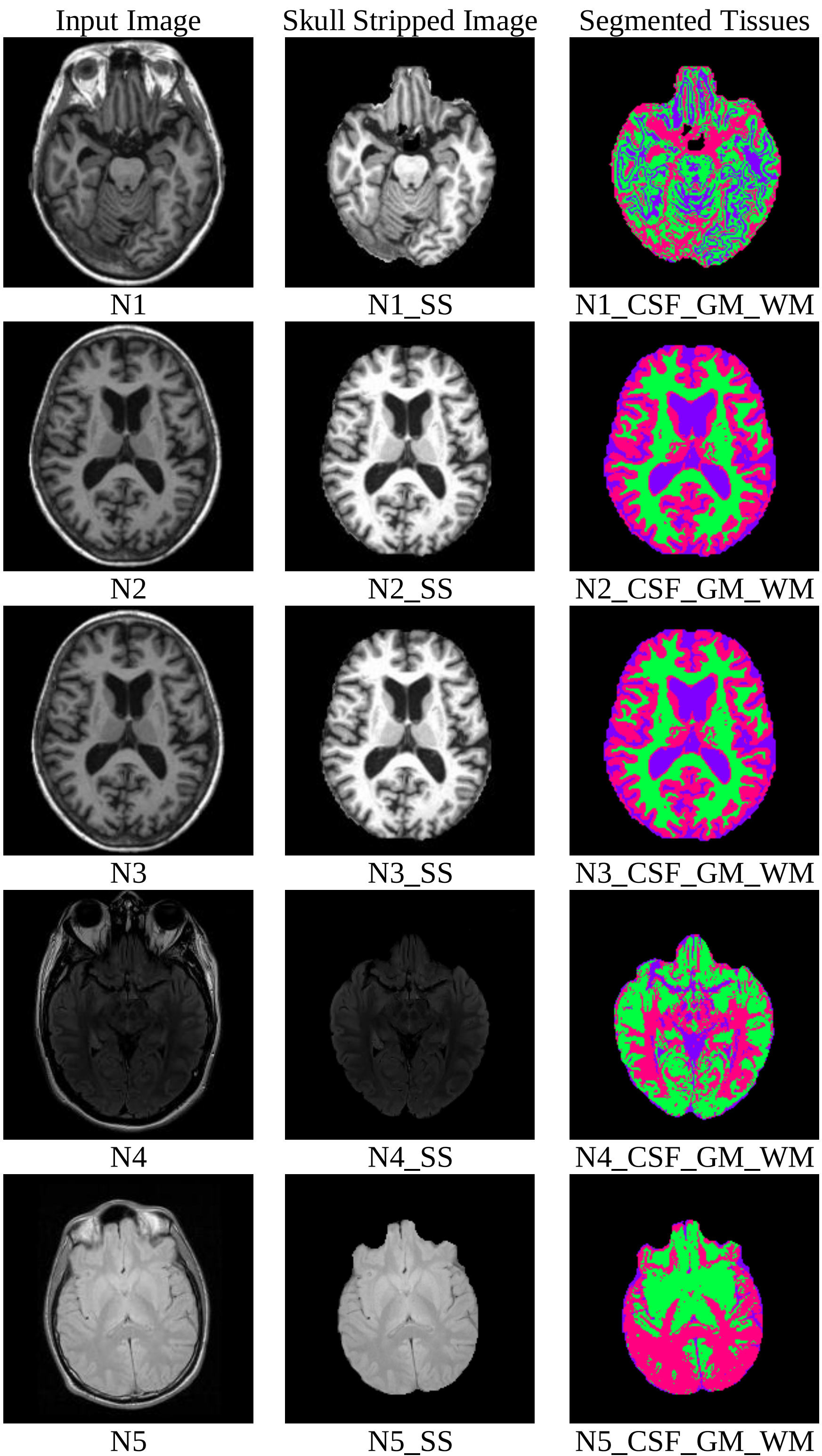
Sub band image LL is used only for DWT calculation at the next scale. To compute the wavelet features in the first stage, the wavelet coefficients are calculated for the LL sub band using haar wavelet function. Figure 5 illustrates 2D DWT schematically. 2D wavelet decomposition of normal and abnormal brain MR images are shown in Figure 6 and Figure 7 respectively.

After haar transform, the approximation component contains most of the energy and the diagonal component contains less energy. So, excluding the approximation area will result in biggest distortion to the compressed image and excluding the diagonal area will result in least distortion to the compressed image. Then horizontal energy E_H, vertical energy E_V, and diagonal energy E_D are combined to attain the feature value of the energy. The training feature vector 'Fv' is defined by Equation (7) by combining all the extracted features like mean M, variance σ2, entropy E and the energy E (H, V, D).

$$Fv = [f(M), f(\sigma^2), f(E), f(E_H), f(E_V), f(E_D)] \quad (7)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section illustrates the experimental results of our proposed feature extraction technique using brain MRI images with and without tumors. Our proposed approach is implemented in MATLAB environment on Core i5, 1.8 GHZ processor installed with MATLAB 7.13. The MRI image dataset that we have utilized in our proposed technique is taken from diagnostic centers and publicly available sources. This image dataset contains 200 brain MRI images with and without tumor. Fig. 5 and Fig. 6 shows the input MRI brain image datasets of normal (N) and abnormal images (AN). The Fig. 7 and Fig 8. shows the segmented tissues of some of the sample MRI normal and abnormal brain images and Tables I to IV shows the extracted feature values of segmented tissues of sample normal and abnormal MRI brain images.


Input Image
Skull Stripped Image
Segmented Tissues
N1
N1_SS
N1_CSF_GM_WM
N2
N2_SS
N2_CSF_GM_WM
N3
N3_SS
N3_CSF_GM_WM
N4
N4_SS
N4_CSF_GM_WM
N5
N5_SS
N5_CSF_GM_WM

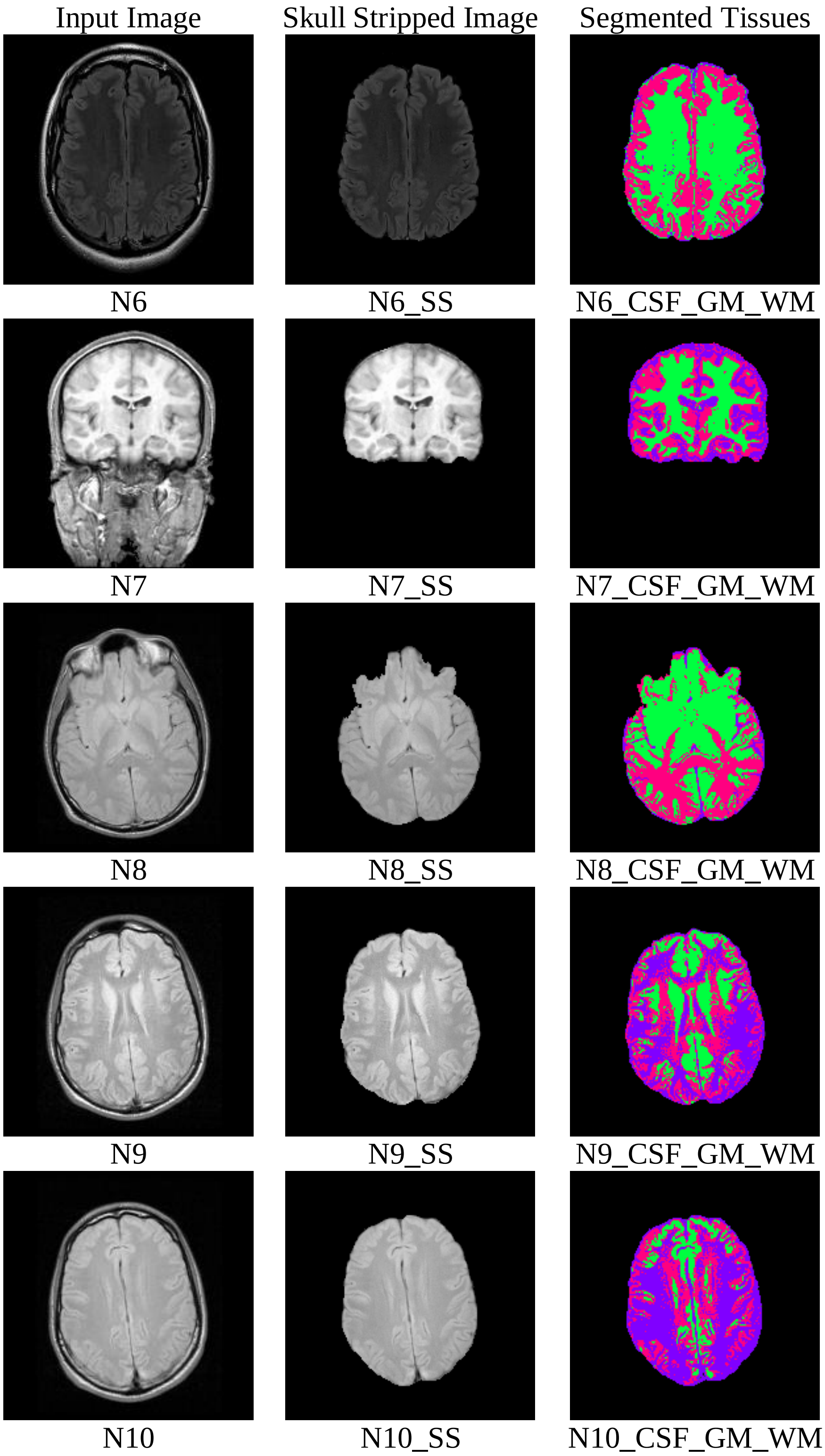
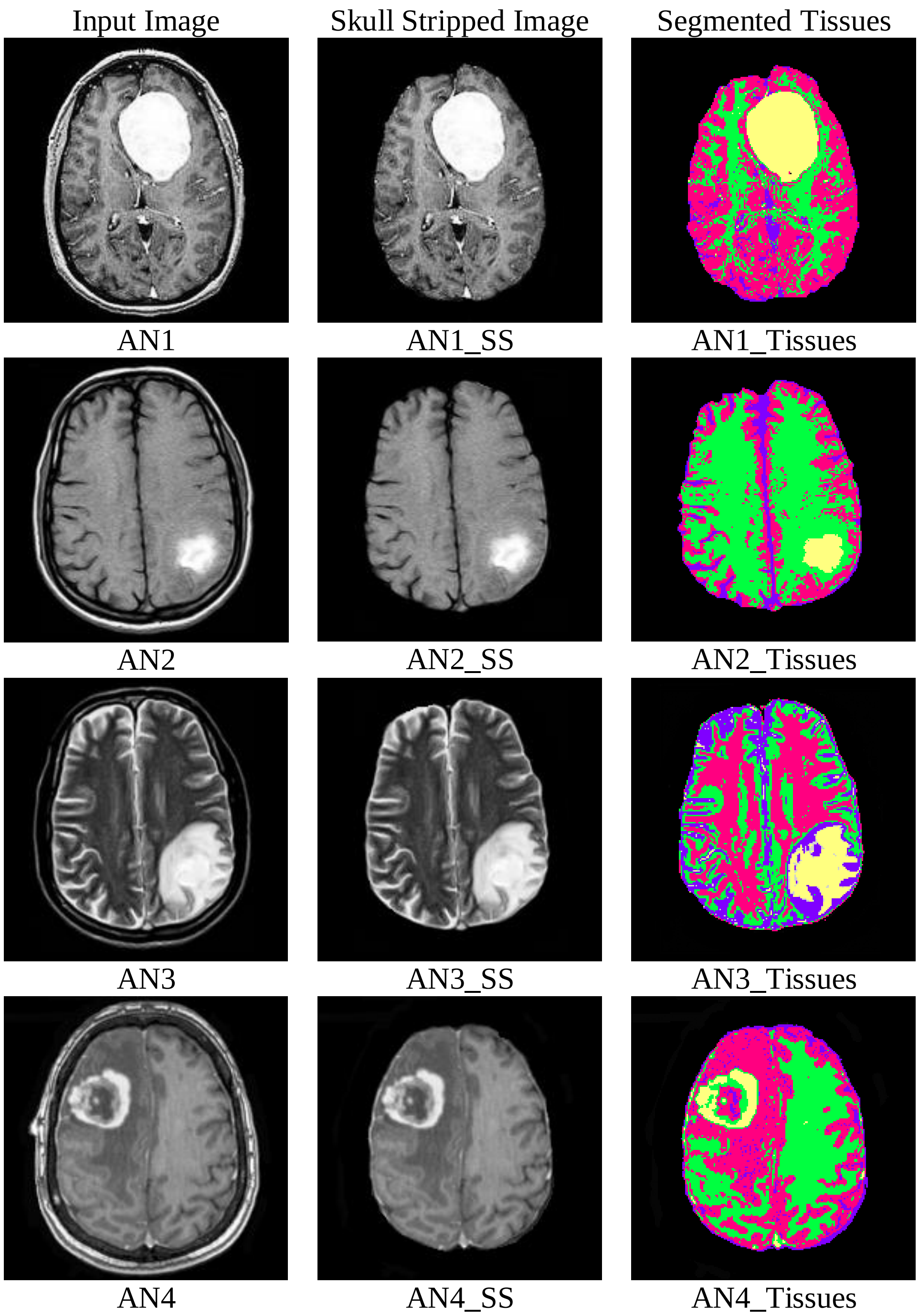
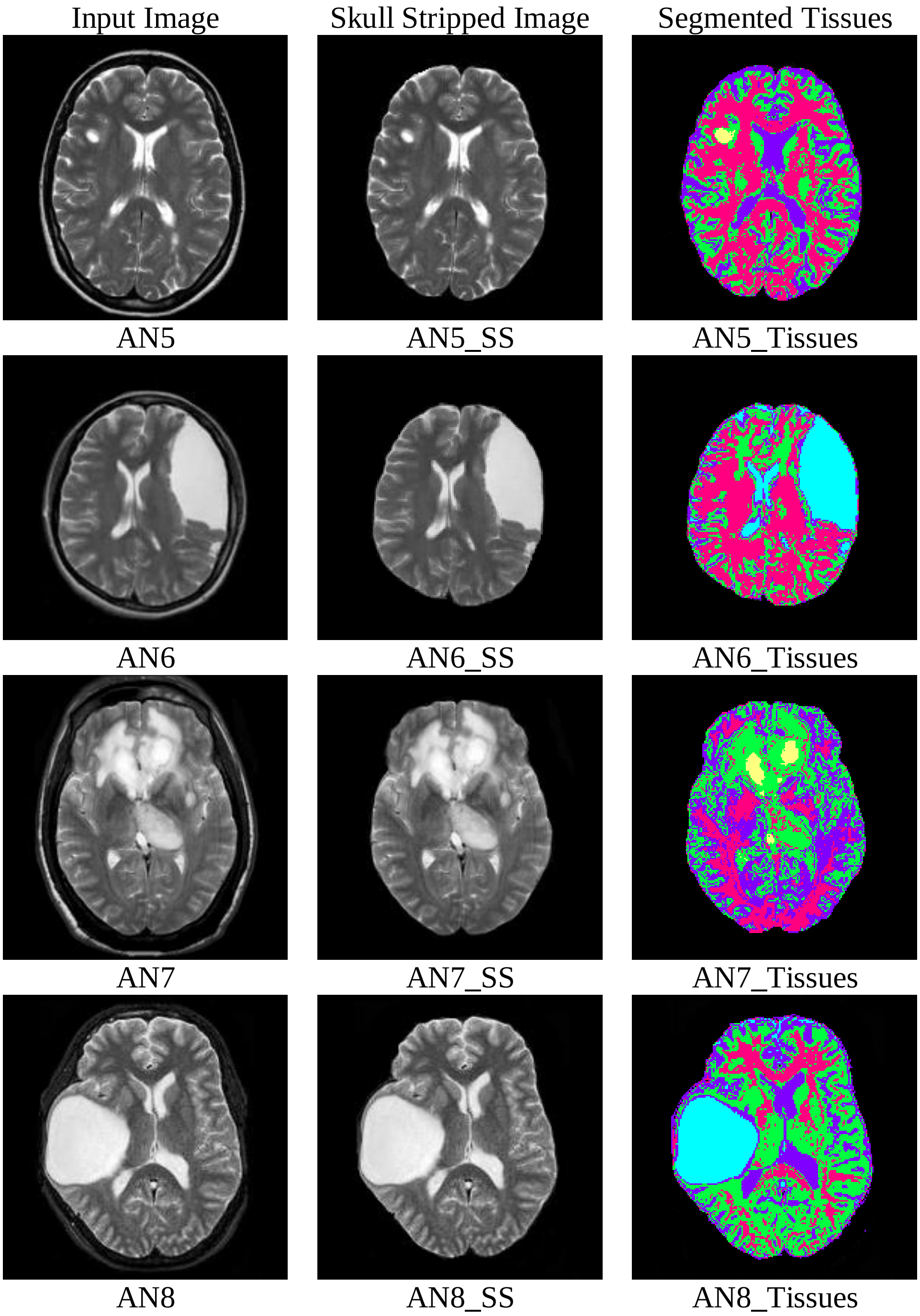


Fig. 5 Input normal MRI brain image database along with segmented tissues (CSF, GM, WM)


Input Image
Skull Stripped Image
Segmented Tissues
AN1
AN1_SS
AN1_Tissues
AN2
AN2_SS
AN2_Tissues
AN3
AN3_SS
AN3_Tissues
AN4
AN4_SS
AN4_Tissues


Input Image
Skull Stripped Image
Segmented Tissues
AN5
AN5_SS
AN5_Tissues
AN6
AN6_SS
AN6_Tissues
AN7
AN7_SS
AN7_Tissues
AN8
AN8_SS
AN8_Tissues

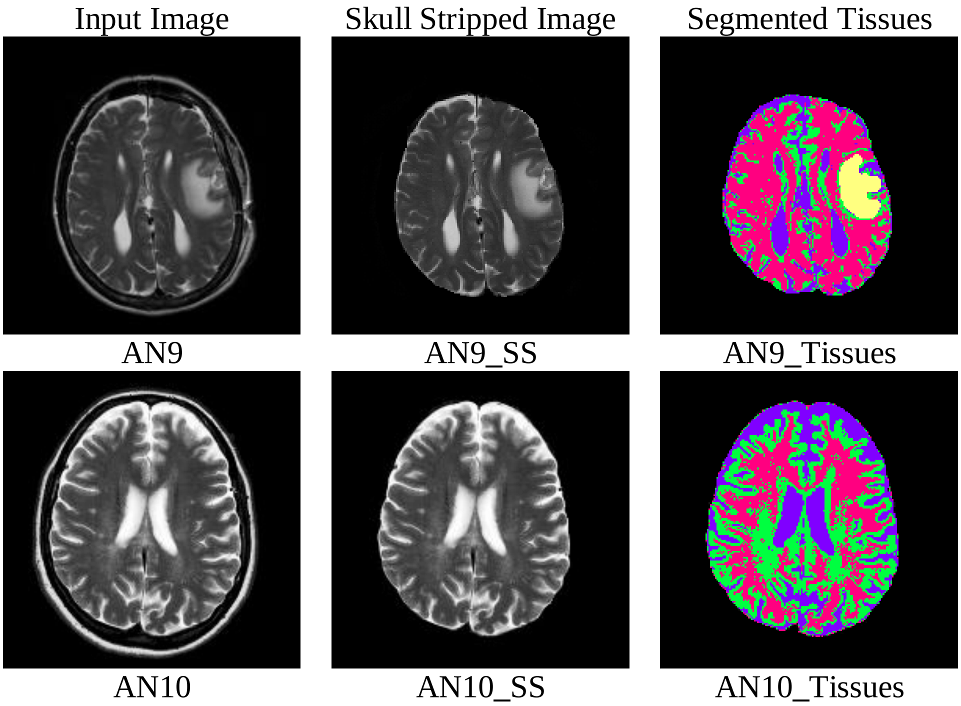


Fig. 6 Input Abnormal MRI brain image database along with segmented tissues (CSF, GM, WM and tumour)

CSF GM WM Tumour Cyst

An MR image is initially segmented by the method proposed in our previous work [17][18]. The obtained experimental results from the proposed technique are shown in figure 5 and figure 6. In figure 5 and figure 6, the segmented normal tissues (CSF, WM, GM) and pathological tissues (tumour) of MRI brain image with and without tumor is shown. In these figures blue colour indicates cerebrospinal fluid, Rose colour indicates gray matter, Green indicates white matter, yellow indicates tumour and cyan indicates cyst. The feature values calculated for these segmented tissues using block based feature extraction method is tabulated in Table I to Table III.

TABLE I. MEAN AND VARIANCE VALUE OF NORMAL AND ABNORMAL BRAIN IMAGES

Images	CSF		WM		GM		Tumour	
	M	σ^2	M	σ^2	M	σ^2	M	σ^2
P1_1	0.345	0.425	44.87	1330.91	72.30	871.18	171.27	955.87
P1_2	0.375	0.450	37.96	1342.53	65.93	869.24	172.50	927.36
P1_3	0.306	0.375	36.25	1318.41	66.51	896.69	183.02	851.29
P1_4	0.310	0.425	39.13	1354.26	72.21	831.40	176.71	847.75
P1_5	0.351	0.372	36.68	1346.19	72.67	820.41	184.93	913.41
P1_6	0.475	0.337	40.54	1317.67	67.16	887.42	170.55	830.85

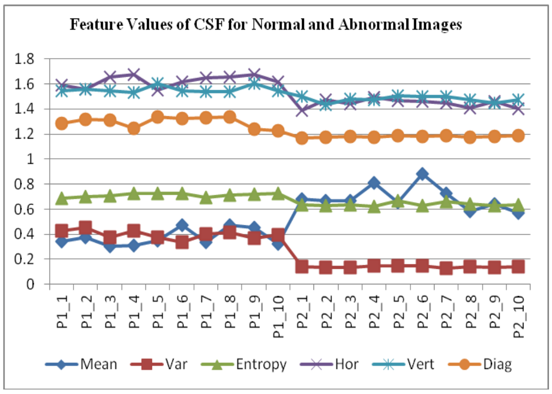
Images	CSF		WM		GM		Tumour	
	M	σ^2	M	σ^2	M	σ^2	M	σ^2
P1_7	0.336	0.398	41.62	1353.68	72.68	862.74	184.57	843.17
P1_8	0.473	0.414	37.74	1330.58	68.09	898.38	175.46	992.11
P1_9	0.456	0.368	44.18	1313.19	65.24	844.67	176.90	1025.40
P1_10	0.324	0.395	38.47	1353.45	68.76	889.32	161.75	932.44
P2_1	0.678	0.144	22.53	946.02	44.99	402.88	16.21	3188.81
P2_2	0.668	0.134	21.92	880.29	54.50	383.46	18.33	3189.51
P2_3	0.665	0.134	17.16	767.34	56.90	385.07	17.97	2491.40
P2_4	0.813	0.147	18.10	904.86	55.85	400.46	10.38	2756.09
P2_5	0.655	0.147	15.57	793.97	46.73	414.39	19.67	3437.42
P2_6	0.882	0.148	19.30	1030.11	40.53	399.63	13.25	2315.57
P2_7	0.729	0.126	28.84	914.60	54.71	429.82	12.03	2354.53
P2_8	0.584	0.140	23.59	978.62	48.59	412.54	13.12	3333.34
P2_9	0.642	0.134	15.96	1011.78	57.49	384.66	13.22	2218.55
P2_10	0.571	0.143	23.14	836.84	41.19	407.52	13.03	3519.86

TABLE II. ENTROPY AND HORIZONTAL ENERGY VALUE OF NORMAL AND ABNORMAL BRAIN IMAGES

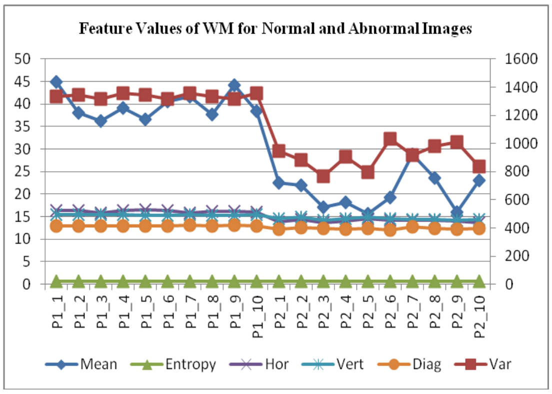
Image	CSF		WM		GM		Tumour	
	E	E_H	E	E_H	E	E_H	E	E_H
P1_1	0.689	1.592	0.737	16.389	0.432	13.426	0.425	12.462
P1_2	0.698	1.560	0.735	16.352	0.427	13.314	0.384	12.467
P1_3	0.707	1.658	0.734	15.783	0.404	13.442	0.387	12.288
P1_4	0.729	1.677	0.732	16.403	0.441	12.900	0.373	12.474
P1_5	0.725	1.551	0.740	16.471	0.420	13.613	0.278	12.575
P1_6	0.726	1.619	0.736	16.411	0.424	12.684	0.408	12.296
P1_7	0.693	1.649	0.739	15.772	0.417	13.056	0.339	12.674
P1_8	0.713	1.659	0.733	16.173	0.469	12.650	0.515	12.426
P1_9	0.718	1.676	0.737	16.181	0.424	13.154	0.383	12.085
P1_10	0.724	1.619	0.739	15.938	0.404	13.882	0.376	12.370
P2_1	0.638	1.392	0.730	13.872	0.317	10.768	0.627	21.666
P2_2	0.631	1.471	0.724	14.433	0.282	10.275	0.705	21.753
P2_3	0.634	1.439	0.730	13.677	0.275	10.384	0.623	21.748
P2_4	0.625	1.496	0.728	13.954	0.305	10.721	0.669	23.053
P2_5	0.670	1.468	0.727	14.619	0.298	10.594	0.704	21.224
P2_6	0.629	1.458	0.724	14.226	0.314	10.479	0.685	21.397
P2_7	0.662	1.451	0.725	14.181	0.352	10.355	0.682	22.844
P2_8	0.641	1.410	0.730	14.158	0.308	10.446	0.668	23.018
P2_9	0.630	1.464	0.730	14.002	0.264	10.674	0.629	22.316
P2_10	0.632	1.402	0.721	13.628	0.308	10.623	0.678	23.195

TABLE III. VERTICAL AND DIAGONAL ENERGY VALUE OF NORMAL AND ABNORMAL BRAIN IMAGES

Image	CSF		WM		GM		Tumour	
	E_V	E_D	E_V	E_D	E_V	E_D	E_V	E_D
P1_1	1.544	1.288	15.526	12.970	12.040	9.844	12.836	12.125
P1_2	1.560	1.320	15.560	13.022	12.017	9.860	12.408	7.493
P1_3	1.547	1.312	15.449	12.927	12.143	9.901	11.635	8.227
P1_4	1.532	1.247	15.499	13.036	12.184	10.024	12.904	7.931
P1_5	1.605	1.339	15.269	13.025	12.275	9.651	12.779	12.478
P1_6	1.543	1.325	15.377	12.992	12.390	9.940	12.307	8.062
P1_7	1.542	1.331	15.493	13.042	12.441	9.946	12.879	8.521
P1_8	1.540	1.335	15.286	12.911	12.439	9.886	13.917	9.819
P1_9	1.602	1.238	15.317	13.047	12.109	9.789	13.951	10.733
P1_10	1.547	1.225	15.392	13.014	12.482	9.640	13.465	12.171
P2_1	1.500	1.170	14.569	12.237	10.573	7.649	21.316	18.962
P2_2	1.437	1.173	14.898	12.654	10.519	8.472	18.811	18.220
P2_3	1.483	1.182	14.178	12.462	11.020	9.178	20.658	14.683
P2_4	1.475	1.173	14.662	12.214	10.946	7.939	21.448	17.393
P2_5	1.506	1.187	14.853	12.492	10.566	9.142	18.992	18.558
P2_6	1.498	1.183	14.517	11.980	11.083	8.066	17.633	14.681
P2_7	1.501	1.185	14.439	12.678	11.167	9.011	18.253	14.972
P2_8	1.473	1.172	14.432	12.394	10.648	9.016	19.670	15.889
P2_9	1.449	1.181	14.161	12.189	10.733	8.604	16.636	14.528
P2_10	1.472	1.190	14.383	12.329	10.681	8.448	18.378	15.565

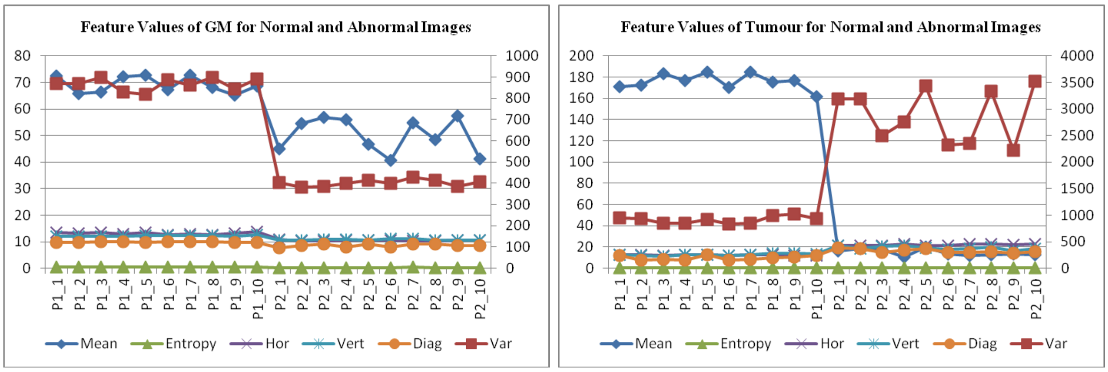


(a)



(b)

Fig. 9 (a) Feature values of CSF for normal and abnormal brain images and (b) Feature values of WM for normal and abnormal brain images



(a) **(b)**

Fig. 10 (a) Feature values of GM for normal and abnormal brain images and (b) Feature values of Tumour for normal and abnormal brain images

V. CONCLUSION

In this paper, the features values are extracted based on block extraction method instead of extracting the features values for the entire image. So, the computation time can be reduced by calculating the feature values only for the selective blocks. Next in this paper instead of calculating all feature values, only selective feature values which is enough to give promising result is calculated. Intensity based features like mean, variance and texture based features like entropy and energy is calculated. Haar wavelet transform is used to obtain the horizontal, vertical and diagonal energy. From the graphs (Figures 9 to 10), it was found that the feature values (mean, variance, entropy, horizontal energy, vertical energy, and diagonal energy) for normal and abnormal images could be easily distinguished. It was also found that considering only the feature values of segmented gray matter and white matter, the diseases like Alzheimer due to white matter and schizophrenia due to gray matter can be easily detected using a proper classifier.

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