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Ensemble Classifications of Wavelets based GLCM Texture Feature from MR Human Head Scan Brain Slices Analysis

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Abstract—This paper presents an automatic image analysis of multi-model views of MR brain using ensemble classifications of wavelets based texture feature. Primarily, an input MR image has pre-processed for an enhancement process. Then, the pre-processed image is decomposed into different frequency sub-band image using 2D stationary and discrete wavelet transform. The GLCM texture feature information is extracted from the above low-frequency sub band image of 2D discrete and stationary wavelet transform. The extracted texture features are given as an input to ensemble classifiers of Gentle Boost and Bagged Tree classifiers to recognize the appropriate image samples. Image abnormality has extracted from the recognized abnormal image samples of classifiers using multi-level Otsu thresholding. Finally, the performance of two ensemble classifiers performance has analyzed using sensitivity, specificity, accuracy, and MCC measures of two different wavelet based GLCM texture features. The resultant proposed feature extraction technique achieves the maximum level of accuracy is 90.70% with the fraction of 0.78 MCC value.

Keywords- *Magnetic Resonance Imaging (MRI); discrete wavelet transform; stationary wavelet transform; Grey Level Co-occurrence Matrices (GLCM); ensemble classifiers; Otsu thresholding.*

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I. INTRODUCTION

The extraction of a feature from an image is a form dimensionality reduction, which represents the most effective features of the certain image. As this way, texture feature based pattern recognition techniques have an important role to develop the image processing based application domain areas such as satellite imaging, medical imaging, content based image retrieval, document processing etc. [1] . The discrete wavelets based GLCM texture feature has extracted from an LH and HL subbands images and classified with PNN to recognize the brain image samples [2]. The combination of SOM-clustering, proximal SVM classifier has deliberated to detect the brain abnormality depend on the PCA with use of GLCM features [3]. Berkeley transform based GLCM texture feature with use of SVM classification had suggested of an automatic analysis and extract the tumor portions from an image [4]. The DWT texture features of non-stationary wavelet signals and PCA based KNN classification has introduced for an MR brain image diagnosis [5]. A new method, histogram equalization technique has used as pre-processing. And the discrete wavelet based texture features with PCA reduction of KNN and ANN classification methodology was discussed for an automatic image analysis normal and abnormal image samples [6]. Another automated and accurate classification of MR image analysis, PCA feature reduction based DWT features are applied with use of RBF-SVM Kernel classifier has suggested [7]. An ensemble method is a supervised learning approach, to combine the more than one learning algorithms to generate a strong learner and better predictive model which performance is higher than other integrated learning algorithms [8-10].

In this paper, the ensemble classifications of wavelets based GLCM texture features based approach has introduced for an automatic image analysis of MR brain images. The prominent outcome of this proposed approach has compared with an existing feature extraction techniques and the conventional algorithm of GLCM technique.

II. MRI BRAIN IMAGE DATASET

An input MR DICOM multi-model view of brain images at the size of 1105×650 pixel by pixels in two image sample of normal and abnormal are taken from the two different image sets as training and testing sets which had together of Madurai Rajaji Government Hospital, and KG Advanced scan center, Madurai, Tamil Nadu, India named as MDU-Hs. Totally, 328 images are collected. From this 60% and 40% of image data's are assigned to the training and testing set respectively. The sample images of two different normal and abnormal samples are shown at Figure 1.

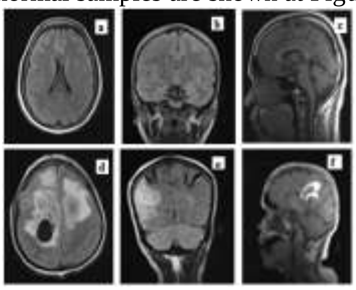

Figure 1. Normal and Abnormal MR imaging samples: (a) and (d) are axial view; (b) and (e) are coronal view; (c) and (f) are sagittal view

And another some set of axial view of MR brain images were gathered from an online free open dataset, in different brain disease and normal images at different size from the available online sources as OASIS dataset (URL: http:// www.oasis-brains.org/), Harvard Medical School (URL:http://med.harvard.edu/AANLIB/), BRATS, and BRAINIX(URL:http://www.osirixviewer.com/resources/dico

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m-image-library/). There are 200 images had taken from this above mentioned link named as OpenDataset, from this 125 images are allocated to the training set and 75 has given for testing set.

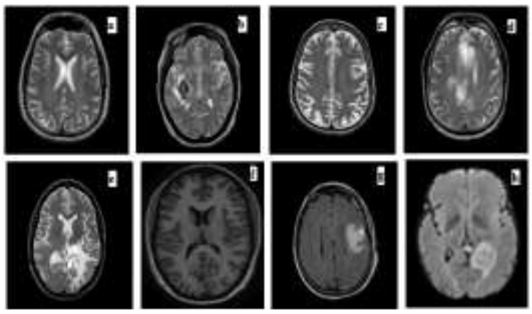

Figure 2. Sample MRI axial view of the brain in different disease from online image dataset at normal and abnormal images: (a) Normal (b) Brain stroke (c) Degenerative disease (d) Inflammatory disease (e) Neoplastic tumor (f) Alzheimer (g) and (h) are a brain tumor.

III. Research Methodology

The wavelets based GLCM texture feature extraction has different phases as,

1. Pre-processing
2. Hybrid approach of discrete wavelet based GLCM and stationary wavelet based GLCM texture feature extraction and image recognition
3. Multi-threshold based abnormality detection and extraction and
4. Tumor area calculation.

The overall process flow diagram of this proposed approach of wavelets based GLCM feature extraction and recognition approach has illustrated at Figure 3.

A. Pre-processing

A given set of brain images are pre-processed by means of two processes as, (i) image standardization, and (ii) grayscale conversion. The collection of acquired brain images from various resources has different from one to another their resolution and size. Because of this sense, the requirement of image standardization is an important one. Then these images are converted to a grayscale image to reduce the much amount of storage area while maintaining the images at image dataset. And these factors are also helpful to further subsequent process of image segmentation, feature extraction, and classification.

B. Texture feature extraction and recognition

The pre-processed MR brain images from the MR image dataset, are decomposed into four different frequency sub-band images like LL (low-low), LH(low-high), HL(high-low), and HH(high-high) are generated using two different two-level discrete and stationary wavelet decomposition. The LL (low-low) frequency sub-band image generates the high detailed approximation of scaling information about an image at each level of image decomposition. So, that the low-frequency subband image of discrete and stationary wavelet has taken as an input to the texture feature extraction technique.
From this low-frequency sub band image, the GLCM texture features are extracted. The extraction of GLCM texture features process has separated into two main steps of (i) Computation of GLCM Matrix, and (ii) texture feature calculation. Here, contrast, correlation, energy, entropy, and homogeneity features are computed from co-occurrence matrices of each two-level decomposition discrete and stationary wavelet transform. Therefore, DW based GLCM and SWT based GLCM texture features are extracted. These extracted features are fed into ensemble bi-classifications of Gentle Boost and Bagged Classifier to classify or recognize the appropriate testing image samples of normal and abnormal for each MR image datasets.

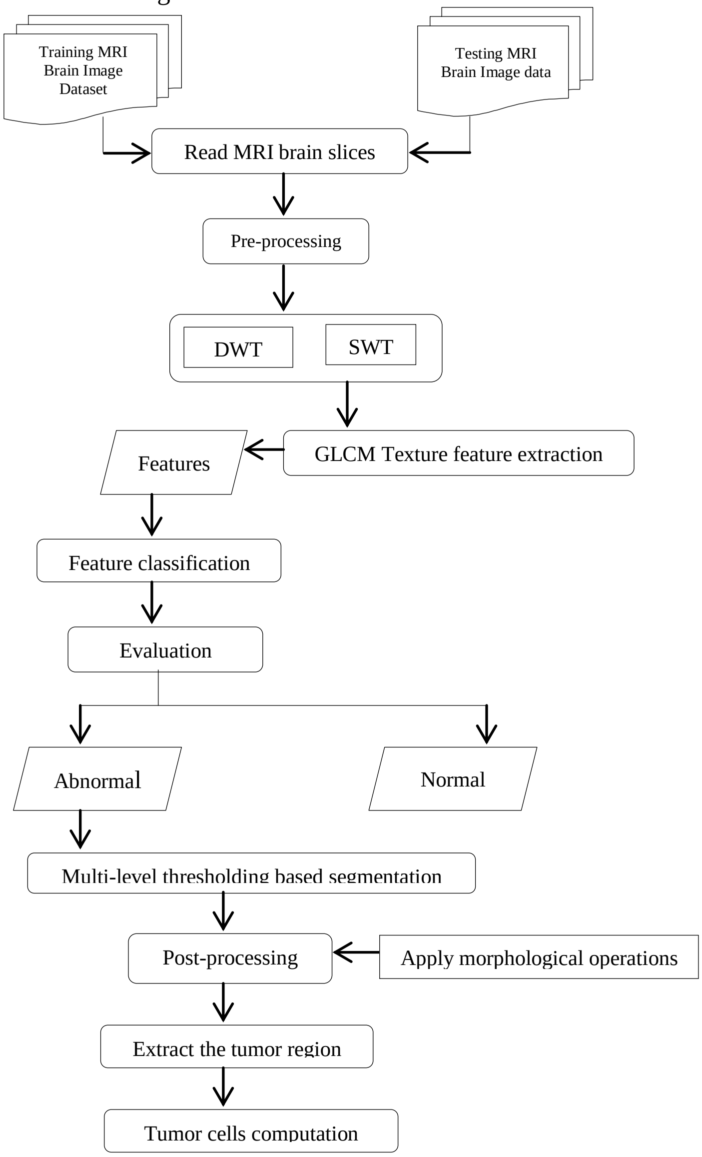

Figure 3. Process flow diagram for an automatic image diagnosis of wavelets based GLCM feature extraction and image recognition

C. Multi-threshold based abnormality detection

The multi-level Otsu thresholding technique has used to differentiate the abnormal tissues from normal tissues. For real-world images, Otsu thresholding method provides better threshold value selection [11, 12]. The best threshold value that maximizes two class variances of two regions such as background and object [13]. Firstly, the threshold value has desired for each abnormal sample of testing images using Otsu thresholding. Then the image is quantized into two regions as normal tissues and abnormal tissues to extract abnormality of an image. The skull portion is along with abnormal tissues of brain image have occurred while image segmentation process. The morphological operation erosion is deliberated for post-processing, which shrinks the image boundary based on the structural element to extract the tumor regions.

D. Tumor area calcultation

From the extracted tumor region, the total number of affected abnormal cells is computed with the use of steps as, (i) the extracted tumor regions are converted into logical type array of tumor image from the numerical type of array. (ii) Calculate the available number of channels and these size like 0 (zero) or 1 (non-zero) at the logical type of binary image. (iii)Then search and calculate the total number of the non-zero pixels at the pixel position of (i, j) at the binary image of I_b (x, y). (iv) Lastly, the total number of non-zero pixels has multiplied with the value of 0.264 (where 1-pixel size= 0.264 mm approximately) to generate the total number of affected brain cells.

IV. RESULTS AND DISCUSSION

The hybrid approach wavelet based texture feature extraction and classification of different image datasets of different resources are real MR hospital image dataset MDU-Hs and different disease of brain image from online images OpenDataset are analyzed using the performance measures of sensitivity, specificity, accuracy, and MCC [14, 15]. The classification results of normal and abnormal samples of two different datasets are computed using 2×2 confusion matrix as,

TABLE I. CONFUSION MATRIX FOR BI-CLASSIFIER MODEL

Actual class	Predicted class	
	Positive image class	*Negative image class*
Positive image class	True Positive	False Negative
Negative image class	False Positive	True Negative

The TP (True Positive) happens when the number of testing images in class positive truly classified by the system. And TN (True Negative) follows when the number testing negative image samples well classified by the system model. Then FP (False Positive) arises when the number of testing image samples of negative class incorrectly classified as positive class. As well as, FN (False Negative) occurs when the number of testing image samples of positive class untruly classified by the system model as negative class.

An ability to measure the abnormal image samples of sensitivity is defined by the equation of,

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (1)$$

An ability to identify the normal testing image samples of specificity has expressed by the formula as,

$$Sepecificity = \frac{TN}{TN+FP} * 100 \quad (2)$$

The mathematical expression of correct classification rate or accuracy can be calculated using

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} * 100 \quad (3)$$

The proficiency of compute the quality of binary image classification system measured by the expression of,

$$MCC = \frac{((TP \times TN)-(FP \times FN))}{\sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}} \quad (4)$$

The table 2 depicts the DWT based GLCM and SWT based GLCM features based ensemble classification of Gentle boost outcomes sensitivity (Sen.), specificity (Spe.), and accuracy (CCR) in percentage.

Texture Feature Extraction Techniques based Gentle Boost classifier						
Image Dataset	**DWT based GLCM**			**SWT based GLCM**		
	Sen.	*Spe.*	*CCR*	*Sen.*	*Spe.*	*CCR*
MDU-Hs	88.76%	65.00%	81.40%	89.89%	65.00%	82.17%
OpenDataset	82.00%	72.00%	78.67%	96.00%	76.00%	89.33%
Texture Feature Extraction Techniques based Gentle Boost classifier						
MDU-Hs	88.76%	57.50%	79.07%	96.63%	77.50%	90.70%
OpenDataset	92.00%	80.00%	88.00%	96.00%	68.00%	86.67%

TABLE II. THE DIFFERENT WAVELET BASED TEXTURE FEATURE EXTRACTION AND CLASSIFIC CATION

As contained in table 2, DWT based GLCM has the lowest percentage of accuracy in the gentle boost classification of MDU-Hs and OpenDataset and bagged tree classification of MDU-Hs dataset rather than SWT based GLCM feature extraction techniques. Then the gentle boost classification outcomes of two different wavelet-based texture features are compared with the graphical representation of Figure 4 as,

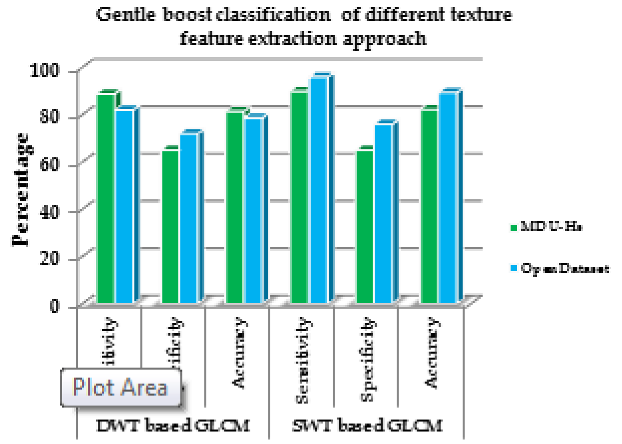

Figure 4. Comparison of two different wavelet based texture feature extraction approach

Similarly, the bagged tree classification of DWT based GLCM and SWT based GLCM texture feature extraction technique has compared and that is illustrated in Figure 5.

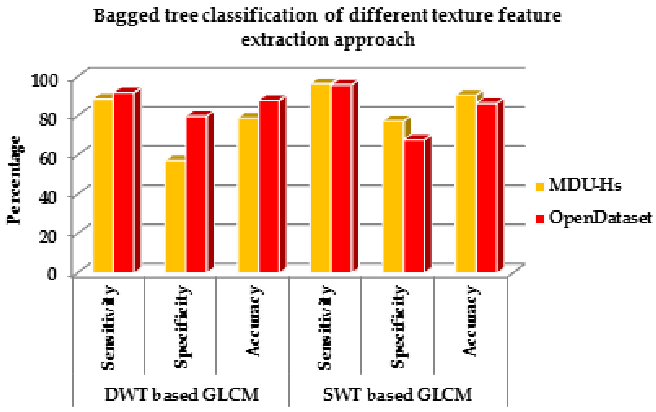

Figure 5. Comparison of two different wavelet based texture feature extraction approach based on the bagged tree classifier

From this table 2, the two ensemble classifications of SWT based GLCM has an overall performance of the prediction of a positive and negative class of testing samples as with highest rate of accuracy rather than DWT based GLCM that is illustrated and highlighted at Fig.4 and Fig.5. Then the quality of these two feature based classification techniques is also has analyzed and reported in table 3.

TABLE III. FRACTION OF IMAGE QUALITY ANALYSIS FOR CLASSIFICATION OF PROPOSED FEATURE EXTRACTION TECHNIQUES

Performance measures of MCC		
Feature Extraction techniques	*MDU-Hs*	*OpenDataset*
	Bagged Tree (BT)	
DWT based GLCM	0.49	0.73
SWT based GLCM	**0.78**	0.69
	Gentle Boost (GB)	
DWT based GLCM	0.55	0.53
SWT based GLCM	0.57	**0.76**

Table 3 describes the highest quality of image bi-classification based on the proposed texture feature extraction techniques. From these two techniques, SWT based GLCM provides better outcomes, the fraction of 0.78 and 0.76 for MDU-Hs and OpenDataset respectively, which has highlighted in table 3. After the image recognition task, the prediction of abnormal tumor images is segmented using multi-level Otsu thresholding algorithm which has depicted at Figure 6 as,

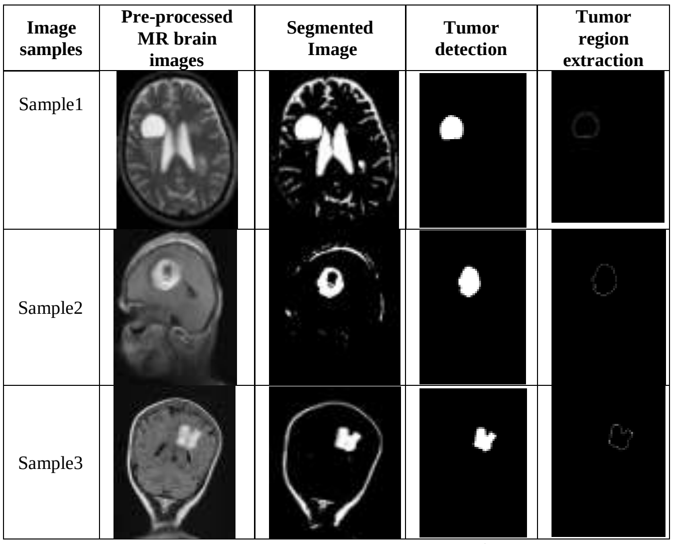

Figure 6. The tumor or abnormal tissue extraction of sample MR multi-model view of brain images

From this extracted tumor image regions, the total number of affected brain cells are computed for sample multi-model view of different brain images and which is placed at the Table4.

TABLE IV. TOTAL NUMBER OF AFFECTED CELLS IN A SAMPLE BRAIN OF DIFFERENT VIEWS

Image Samples	**View of MRI Brain image**	**Number of cells in Affected brain area**
Sample1	Axial	2876
Sample2	Sagittal	4995
Sample3	Coronal	2858

Finally, the highest pre-eminent results of SW based GLCM feature has compared with another existing approach, and conventional GLCM methods in the measurement of sensitivity, specificity, and accuracy that is represented at Table 5 and 6.

TABLE V. COMPARISION OF DIFFERENT TEXTURE FEAURE EXTRACTION TECHNIQUES

MDU-Hs MRI Brain Dataset			
Feature Extraction Approach	***Sensitivity***	***Specificity***	***Accuracy***
3DWT+PCA+FDA [16]	67.42%	40.00%	58.91%
3DWT+PCA+KNN [6]	74.16%	47.50%	65.89%
3DWT+PCA+SVM [7]	87.64%	52.50%	76.74%
GLCM + Bagged Tree	89.89%	70.00%	83.72%
SWT based GLCM	96.63%	77.50%	**90.70%**

TABLE VI. COMPARISION OF DIFFERENT TEXTURE FEAURE EXTRACTION TECHNIQUES FOR AXIAL VIEW OF OPEN BRAIN IMAGE DATASET OF ONLINE IMAGES

MRI Axial view of Online Image set			
Feature Extraction Approach	***Sensitivity***	***Specificity***	***Accuracy***
3DWT+PCA+FDA	86.00%	60.00%	77.33%
3DWT+PCA+KNN [6]	94.00%	76.00%	88.00%
3DWT+PCA+SVM [7]	84.00%	72.00%	80.00%
GLCM + Bagged Tree	96.00%	72.00%	88.00%
SWT based GLCM	96.00%	76.00%	**89.33%**

From these comparisons, stationary wavelet based GLCM texture feature extraction has highest percentage of accuracy 90.70% for MDU-Hs and 89.33% for different disease of brain image dataset of OpenDataset.

The graphical representation of different feature extraction techniques accuracy for various MR image dataset has illustrated at Figure 7.

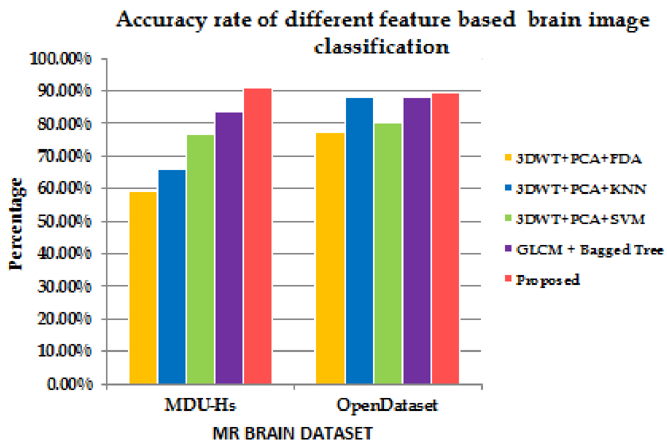

Figure 7. Image classification rate of different feature based classification of two different MR image brain image dataset.

V. CONCLUSION

This paper proposed a hybrid approach of wavelets based texture feature extraction technique has compared with a use of different ensemble classifications of gentle boost and bagged tree classifier to recognize the normal and abnormal image samples. This proposed approach has compared with another existing approach using the performance measures of

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sensitivity, specificity, accuracy, and MCC. The recognized abnormality brain image is segmented to extract the tumor portion of an image. Finally, the tumor portion is detected and extracted, and then the total number of affected tumor cells is calculated. The future work is to improve the quality of classification rate, and accuracy rate with effective feature extraction technique.

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