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AN INTELLIGENT HYBRID APPROACH FOR BRAIN PATHOLOGY DETECTION IN MRI IMAGES

[1]B.Deepa and [2]M.G.Sumithra

[1]Department of ECE, Jayaram College of Engineering & Technology, Trichy, India
cool.deeps.143@gmail.com
[2]Department of ECE , Bannari Amman Institute of Technology, Erode, India
mgsumithra@rediffmail.com

ABSTRACT

Medical Image Processing is a complex and challenging field nowadays. Processing of MRI Images is one of the parts of this field for efficient brain pathology detection like tumor, asymptomatic unruptured aneurysms, Alzheimer's disease, vascular dementia, cerebral microbleeds in brain and multiple sclerosis (MS) in magnetic resonance (MR) images. The methodology used in this paper for brain pathology detection consists of the following steps: The first step includes pre-processing by a Wavelet Transform (WT) for removal of noises like Salt and Pepper noise, Gaussian, Speckle and Brownian noise, without affecting the image quality. The second step is to extract the features from the pre-processed image. The process of feature extraction is carried out by a Walsh- Hadamard Transform (WHT) methodology. The final step involves the detection of abnormality by segmenting the abnormal tissues using a combined methodology called Modified Fuzzy C-Means Clustering (MFCM) followed by Level Set (LS). The performance measure of proposed system is evaluated both by objective and subjective method. Feature extraction and segmentation is evaluated objectively by using confusion matrix and by measuring Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Positive Rate (FPR) or Over Segmentation(OvS), False Negative Rate (FNR) or Under Segmentation(UnS), and Total False Rate or Incorrect Segmentation(InS). Subjective evaluation is done by taking the opinion of 35 expert radiologists that is average mean opinion score to corroborate the results of proposed method. From the obtained results it is understand that the proposed new amalgam technique is giving 95% accurate results for detecting abnormality in MRI brain images when compared to other hybrid methodology.

Keywords- Accuracy, Level Set, MFCM, NPV, PPV, Sensitivity Selectivity ,Wavelet transform, Walsh-Hadamard Transform.

I. INTRODUCTION

In recent years, brain tumour is found as one of the major diseases leading to death of human beings. The MRI is widely used by most of the physicians to identify the brain pathology in the present days. Identification of the tumour regions accurately from the MRI images is considered to be a challenging job for the physicians. Moreover it is difficult for radiologist to make a diagnostic when he is tired or there are injuries which need a lot of time to make a decision, it will be very helpful if exists a tool for decision's support to avoid the problems above, for which the works like [1], [2] try to resolves some problems on the segmentation of MR image processing. Then works like [3], [4] try to make a segmentation of MR brain images using a combination of pre-processing and feature extraction. CBIR (Content-based image retrieval) systems appear in the 80's, where one of the first implementation was the QBIC (Query by image content). At the last decade, CBIR systems become one of the most interesting topics in computer vision [5], to resolves the problem of index data by similarity image measures. This work includes an intelligent hybrid approach for brain pathology detection in MRI Images by undertaking three steps namely pre-processing, feature extraction and segmenting the affected region from MRI brain images.

II. METHODOLOGY

The proposed hybrid method is shown in Fig.1.It includes three steps, first pre-processing (Denoising) by WT, second feature extraction by WHT and final step is image segmentation by combining MFCM and LS. Denoising and Feature Extraction can be done in both spatial domain and frequency domain. The methodology used in each step has been discussed in the following sections.

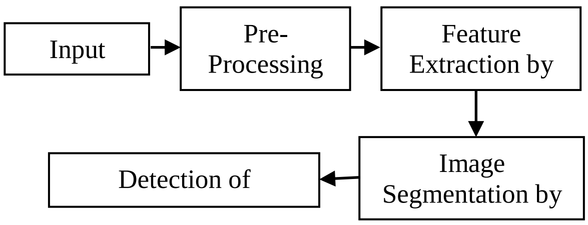

Fig .1 Proposed Methodologies

III. PRE-PROCESSING BY WAVELET TRANSFORM

Image denoising is devised as a regression problem between the noise and signals; finally, it is solved by using Wavelet Transform [6]. It is one of the promising methods of image denoising. The conventional wavelet transform decomposes the low frequency components to obtain the next level's approximation and detail components; the current level of the detail components remains intact. The algorithm is very simple to implement and computationally more efficient. It has following steps:

- Perform multistage decomposition of the image corrupted by various noises using wavelet transform.
- Estimate the noise variance σ^2 by

$$\hat{\sigma}^2 = \left[\frac{median(|Y_{ij}|)}{0.6745}\right]^2, \; Y_{ij} \text{ € Sub band } HH_1 \qquad (1)$$

- For each level, compute the scale parameter β by

$$\beta = \sqrt{\log\left(\frac{L_k}{J}\right)} \qquad (2)$$

L_k is the length of the sub band at k^{th} scale.

- For each sub band (except the low pass residual), compute the standard deviation σ_y, threshold T_N using,

$$T_N = \frac{\beta \hat{\sigma}^2}{\hat{\sigma}_y} \qquad (3)$$

and then apply soft thresholding to the noisy coefficients.

- Invert the multiscale decomposition to reconstruct the denoised image $\hat{f}$.

IV. FEATURE EXTRACTION TECHNIQUES

A. Gray Level Co-Occurance Matrix(GLCM)

Gray Level Co-occurrence Matrix (GLCM) is one of the most popular ways to describe the texture of an image. The extracted ROI can be distinguished as either cancerous or not using their texture properties. A GLCM denote the second order conditional joint probability densities of each of the pixels, which is the probability of occurrence of gray level among a given distance 'd' and on the direction 'θ'. The matrix can be found by measuring area, mean, energy, contrast, homogeneity etc, some of them are given below,

- **Mean:** It's the proportion of the pixels within the convex hull that also within the ROI.

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(p_{i,j}\right) \qquad (4)$$

- **Energy:** It's the summation of square parts within the GLCM and its price ranges between zero and one.

$$E = \sum_{K=0}^{N} p^2(i,j) \qquad (5)$$

- **Contrast:** It's the live of distinction between N intensity of constituent and its neighboring pixels over the total ROI, where N is the variety of various gray levels.

$$C = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad (6)$$

B. Fluid Vector Flow(FVF)

The FVF feature extraction process is a two-step process which consists of:

- **Vector flow initialization:** The contour must be initialized to initialize the external force field. The initial contour can be inside, outside or overlapping the target objects. Contour C can be represented as:

$$C(i) = (x_i, y_i), \text{ i €[0,1,....P-1]} \qquad (7)$$

where P is the number of points on the contour. An external energy function is defined as:

$$E_e(x,y) = \chi\left(f_x + \delta\cos\theta, f_y + \delta\sin\theta\right) \qquad (8)$$

Where χ is a normalization operator and $\delta = \pm 1$

- **FVF Computation and Contour Extraction:** FVF has directional and gradient forces. The directional force attracts the evolving contour towards the control points even for control points in a concave region. When the contour is close to the object, the gradient force fits the contour onto the object. A parameter δ is used to manage the selection of control point. Once the control point moves to its new location it generates new external force field for further evolution of contour until convergence is achieved [7,8].

C. Gabor Filter(GF)

The Gabor filter is used to extract the texture features from the pre-processed image. The coding is implemented using the Matlab. The 2D Gabor filter constitutes a sinusoidal plane of specific frequency and modulated Gaussian.

$$G(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right) \qquad (9)$$

The Gabor filter will extract the texture features and the various orientations of the images are taken along with the max, min, mean, median.

D. Walsh-Hadamard Transform(WHT)

The Walsh–Hadamard transform returns sequency values.

Sequency is a frequency notion and defined as one half of average number of zero-crossings per unit time interval. The Walsh functions in the matrix are not arranged in increasing order of their sequencies or number of zero-crossings

$$H_N = \frac{1}{\sqrt{2}}\begin{vmatrix} H_{N-1} H_{N-1} \\ H_{N-1} - H_{N-1} \end{vmatrix} \qquad (10)$$

Additionally, the WHT was advantageous due to the following reasons: (a) it has a real nature and (b) only additions and subtractions are needed to compute coefficients.

V. SEGMENTATION TECHNIQUES

After feature extraction process, in-order to identify the abnormal regions in brain we present a new hybrid method to segment it by using Modified Fuzzy C-Means clustering followed by level sets algorithm [9]. The most widely used segmentation methodology is described below,

A. K Means Method (KM)

It is also one of the clustering methods and is very famous because it is simpler and easier in computation. It is the simplest unsupervised learning algorithms that solve the well known clustering problem. It classifies the input data points into multiple classes based on their intrinsic distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The algorithm which follows for the k-means clustering is given below: The cluster centres are obtained by minimizing the objective function

$$x_i \varepsilon s_i$$

- Initialize the centroids with k random values.
- Repeat the following steps until the cluster labels of the image do not change anymore.
- For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster

$$C(i) = \arg\min \left\| x(i) - \mu_j \right\|^{\wedge} 2 \qquad (11)$$

- If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster. If the data point is already closest to its own cluster, we will not shift it.
- Compute the new centroid for each of the clusters. Where k is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the in-tensities, j iterates over all the centroids and μ_j are the centroid intensities.

B. Modified Fuzzy C Means(MFCM)

MFCM gives three clusters viz WM, GM, and CSF of brain MRI described by the following steps 10:

- Set the number of clusters c and the parameter m in

$$J_m(u,v) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^m d^2(x_j, v_i) \qquad (12)$$

where $X=(x_1, x_2, \ldots x_j, \ldots x_n)$ is a data matrix with size pXn, x_j-feature vector , v_i-fuzzy cluster , d-distance metric.

- Initialize the fuzzy cluster centroid V= [v_1, v_2,..vc] randomly and set ε=0.01
- Compute u_{ij} by

$$u_{ij} = \left(\sum_{k=1}^{c} \left(\frac{d(x_j, v_i)}{d(x_j, v_k)} \right)^{\frac{2}{m-1}} \right)^{-1} \qquad (13)$$

- Compute v_i

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \qquad (14)$$

- Update u_{ij} by, $$u_{ij} = \frac{u_{ij}^m s_{ij}^m}{\sum_{k=1}^{c} u_{kj}^m s_{kj}^n} \qquad (15)$$

where $s_{ij} = \sum_{k \in N(x_j)} u_{ik}$ called the spatial function and N (x_j) represents a squared window centered on pixel x_j in spatial domain.

- Update v_i from above equation
- Repeat the last two updating function until the following the following criteria is satisfied,

$$\left| v_{new} - v_{old} \right| \leq \varepsilon \qquad (16)$$

C. Level Set Method (LS)

The main idea of Level set method is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred to as the level set function, and to evolve the level set function according to a partial differential equation (PDE). The evolution equation of the level set function ϕ is given by,

$$\frac{\partial \phi}{\partial t} + F\left|\nabla \phi\right| = 0 \qquad (17)$$

called the level set equation. F represents the speed function and it depends on image data and level set function. The parameters controlling level set segmentation are: controlling the spread of Gaussian smoothing function, controlling the gradient strength of initial level set function, regulator for dirac function. The method has overcome manual intervention and improved segmentation.

D. Mean Shift Method (MS)

Mean shift approach is a non-parametric technique for the analysis of a complex multi-modal feature space and identification of feature clusters [11]. The only free parameters of the mean shift process are the size and shape of the region of interest, i.e, multivariate density kernel estimator satisfying the following condition

$$K(x) = ck\left(\left\|x\right\|^2\right) \qquad (18)$$

where c is a strictly positive constant that makes it to integrate to one. Using multiple initializations by covering the entire feature space, mean shift method is employed to identify the stationary points of multivariate kernel density estimator. Reduce these points to retain the local maxima corresponding to density modes.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The implementation of proposed method has been carried out using MATLAB. Here the images considered are MRI Brain images taken from the databases namely MR-TIP, NCIGT, BraTS, BITE and TCIA and in total 200 gray scale images are considered [12] [13]. The images are pre-processed for noise removal, and the features are extracted for segmentation of abnormality. The performance of the proposed hybrid algorithms is estimated and compared with various hybrid techniques. First, denoising is done by wavelet transform (WT) for removing noises like salt and pepper, Gaussian, Speckle and Brownian noise at 5dB noise level. Second, features are extracted by Walsh-Hadamard Transform (WT) and its performance is evaluated by confusion matrix. Finally segmentation of abnormal region is done by combining MFCM and LS method and it is evaluated both objectively and subjectively.

Figure 1 indicates denoising by Wavelet Transform (WT) for removing various noises at 5 dB noise level without disturbing the image quality and thereby image borders, and its shape is maintained.

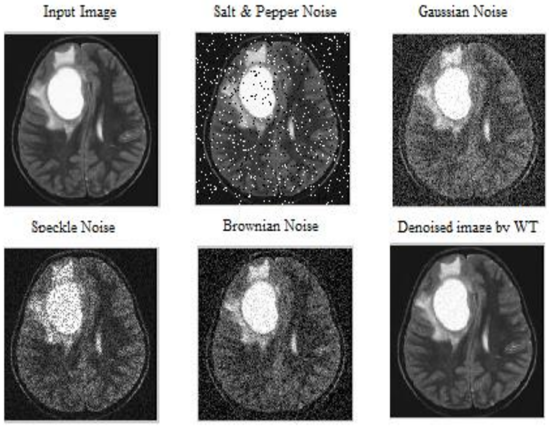

Fig .1 Denoising by WT for various noises at 5 dB noise level for image 1

Figure 2 and 3 shows the abnormality detection using proposed method for image 1 and image 2.Initially the input image is clustered by using MFCM as grey matter (GM), white matter (WM) , cerebrospinal fluid (CSF) and tumor affected region. By using Modified Fuzzy C Means (MFCM) the boundaries of clusters are not well defined, so level set (LS) algorithm is introduced to define it. Level set method is used after MFCM for detecting the abnormality with well defined boundaries. Hence when compared to MFCM, MFCM+LS is giving better results.

Figure 4 implies the comparison of various segmentation techniques for detecting tumor region. From the obtained results it is seen that proposed hybrid technique is giving better results when compared to other hybrid methods.

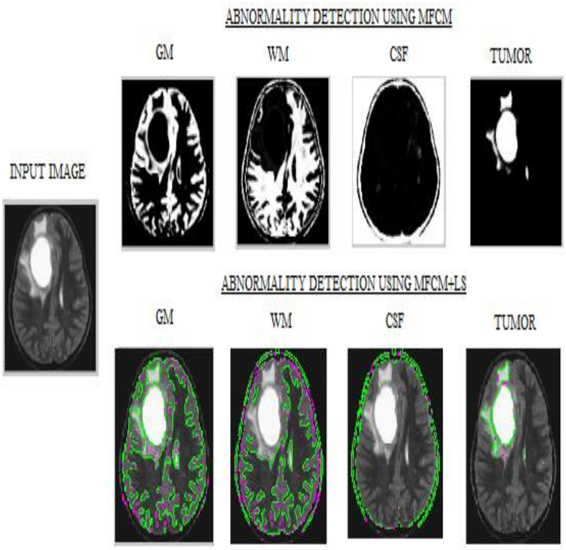

Fig .2 Abnormality detection using MFCM and MFCM+LS for image 1

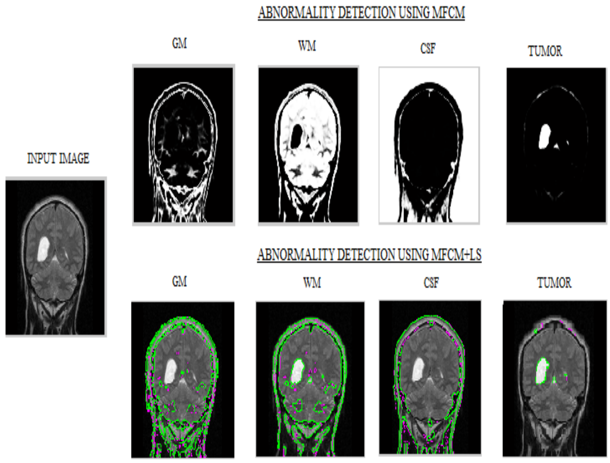

Fig .3 Abnormality detection using MFCM and MFCM+LS for image 2

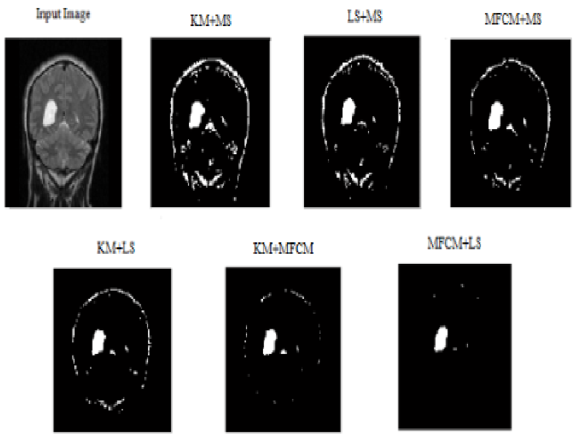

Fig .4 Comparisons of various hybrid segmentation techniques for image 2

A. *Confusion Matrix*

Table I shows a confusion matrix that is often used to describe the performance of a classification model on a set of test data for which the true values are known.

TABLE I. CONFUSION MATRIX

	P (Predicted)	**n (Predicted)**
P (Actual)	True Positive(Tp)	False Negative(Fn)
n (Actual)	False Positive(Fp)	True Negative(Tn)

It contains information about actual and predicted classifications done by a classification system.

B. *Sensitivity*

Sensitivity is the probability of positive for a diagnostic test. It is also termed as true positive fraction.

$$Sensitivity = \frac{Tp}{Tp + Fn} * 100\% \qquad (19)$$

Where Tp is the True positive and Fn is the False negative.

C. Specificity

Specificity is the probability of negative for a diagnostic test. It is also termed as true negative fraction.

$$Specificity = \frac{Tn}{Tn + Fp} * 100\% \quad (20)$$

Where Tn is the True negative and Fp is false positive.

D. Accuracy

Accuracy is the probability that a diagnostic test is correctly performed. It is calculated by

$$Accuracy = \frac{Tp + Tn}{Tp + Fn + Tn + Fp} * 100\% \quad (21)$$

E. UnS, OvS, InS Estimation

UnS, OvS and InS are the parameters related to segmentation which is given by,

$$UnS = \frac{N_{fp}}{N_n} \; ; \; OvS = \frac{N_{fn}}{N_p} \; ; \; InS = \frac{(N_{fp} + N_{fn})}{N_n} \quad (22)$$

Where N_{fp} represents the pixels that are segmented wrongly, N_{fn} represents the pixels that are not segmented into cluster, N_p is the number of pixels in the cluster, N_n represents the number of pixels that are not in cluster.

F. Positive Predictive Value(PPV)

PPV is the ratio of pixels classified as tumour pixels that have been correctly classified. It is calculated by

$$PPV = \frac{Tp}{Tp + Fp} * 100\% \quad (23)$$

G. Negative Predictive Value(NPV)

NPV is the ratio of pixels classified as background pixels that are correctly classified. It is calculated by

$$NPV = \frac{Tn}{Tn + Fn} * 100\% \quad (24)$$

H. Subjective Evaluation

The subjective evaluation was done by taking the opinion of 35 expert radiologists to corroborate our results. The results are validated by radiologists as 'Average mean opinion score'.

Table II indicates the evaluation of confusion matrix for various feature extraction algorithm interms of confusion matrix. The total images taken are 200, among them true positive value is seen high and false negative is seen low while using Walsh-Hadamard transform (WHT).

TABLE II. EVALUATION MATRIX FOR FEATURE EXTRACTION

Feature Extraction Methods	Total number of Images	Tp	Fn	Tn	Fp
GLCM	200	143	11	17	9
FVF	200	148	9	18	5
GF	200	154	6	16	4
WHT	200	160	5	13	6

Figure 5 shows the performance measure of various hybrid segmentation techniques for detecting the abnormality. Accuracy, Sensitivity and Positive Predictive Value is seen high while combining MFCM +LS when compared to other hybrid methodology. Worst performance is seen while combining KM and MS. It is understanding from Fig 6 that incorrect segmentation results is seen high while combining KM and MS, whereas under segmentation, over segmentation and incorrect segmentation is found to be negligible while combining MFCM and LS.

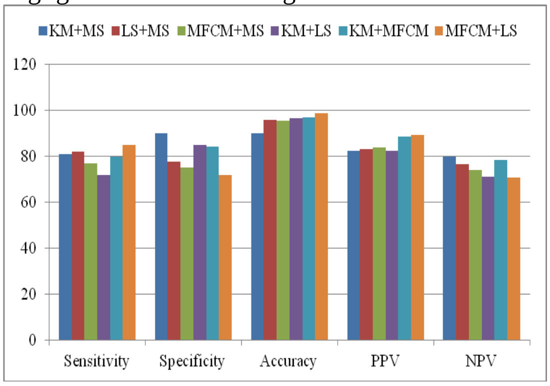

Fig .5 Performances of various hybrid segmentation techniques for image 1

The subjective measurement results are shown in Fig.7. Here the opinion of about 35 radiologists is taken into account. Average mean opinion score is rated high for the proposed hybrid method that is WT followed by WHT and MFCM + LS when compared to other techniques.

Table III shows the overall performance of the proposed method. In Feature extraction step WHT is performing better whereas in segmentation step a hybrid combination of MFCM and LS is giving good results. The accuracy and sensitivity results is seen better for following process, i.e, preprocessing by WT, feature extraction by WHT and segmentation by MFCM+LS in order to detect the abnormality.

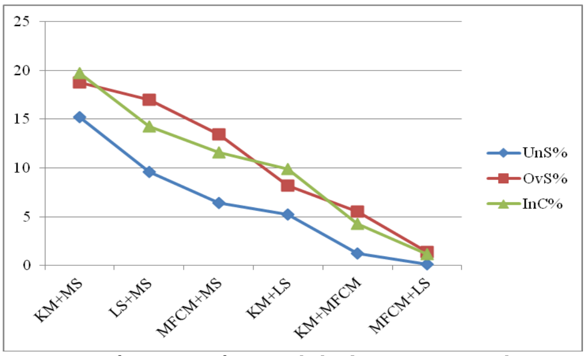

Fig .6 Performances of various hybrid segmentation techniques for image 2

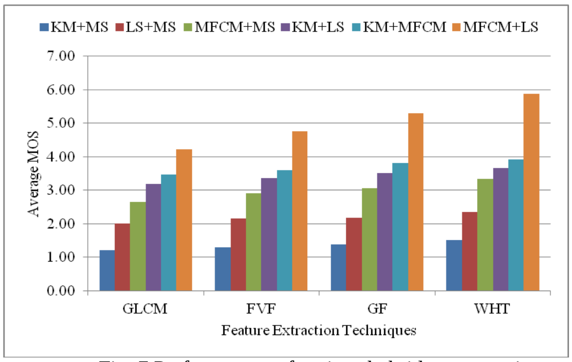

Fig .7 Performances of various hybrid segmentation techniques for image 2

TABLE III. EVALUATION MATRIX FOR FEATURE EXTRACTION

Denoising Methods	Feature Extraction	Segmentation	Accuracy	Sensitivity	Specificity
WT	GLCM	KM+MS	71.34	68.42	64.76
		LS+MS	73.56	68.83	67.45
		MFCM+MS	75.23	67.43	66.32
		KM+LS	76.44	68.65	68.23
		KM+MFCM	77.11	69.38	68.94
		MFCM+LS	78.02	70.48	69.34
	FVF	KM+MS	80.12	71.32	69.34
		LS+MS	81.55	71.89	70.65
		MFCM+MS	82.37	72.62	73.73
		KM+LS	83.56	73.42	74.41
		KM+MFCM	84.72	74.36	74.95
		MFCM+LS	85.23	75.52	75.00
	GF	KM+MS	86.42	76.38	75.28
		LS+MS	85.44	78.63	77.74
		MFCM+MS	87.21	79.72	76.47
		KM+LS	87.94	80.52	78.43
		KM+MFCM	88.23	81.73	80.86
		MFCM+LS	89.41	82.83	81.74
	WHT	KM+MS	90.23	83.54	82.38
		LS+MS	90.78	84.78	83.43
		MFCM+MS	91.34	85.52	84.74
		KM+LS	92.45	86.74	85.31
		KM+MFCM	93.56	87.44	85.98
		MFCM+LS	95.32	88.56	87.34

VII. CONCLUSION

The proposed system includes pre-processing by WT and feature extraction by WHT and segmentation by MFCM+LS. In first step, WT is used to remove noises like salt and pepper, Gaussian, speckle and Brownian noise at 5 dB noise level. In second step, better features are extracted by using WHT compared to other methods by having high true positive value as 160 among the database of 200 considered. False negative value is seen high while using GLCM and seen low while using WHT. Finally, segmentation of abnormal region is done by using MFCM+LS with high accuracy and sensitivity results than by using other hybrid techniques.

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