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Development of Novel CAD System for the Detection of Abnormality in MRI Brain Images

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Abstract— **Computer Aided Diagnosis (CAD) systems assists neuroradiologists by giving a second opinion to improve the accuracy in detection of brain diseases like tumor, asymptomatic unruptured aneurysms, Alzheimer's disease, vascular dementia, cerebral microbleeds in brain and multiple sclerosis (MS) in magnetic resonance (MR) images. In this paper a new amalgam (hybrid) technique in CAD system is proposed for efficient detection of brain abnormality (tumor). The first step includes pre-processing by a hybrid process called WTHE (Wavelet Transform and Histogram Equalization) for removal of noises 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 mixture of GF (Gabor Filter) and WHT (Walsh- Hadamard Transform) methodology. The final step involves the detection of abnormality by SVM (Support Vector Machine) having Gaussian radial basis kernel function. Among the performance measure of proposed CAD system, the first step (preprocessing) is evaluated by peak signal to noise ratio (PSNR), root mean square (RMSE), universal quality index (UQI) and picture quality scale (PQS). Feature extraction and SVM is evaluated by using confusion matrix and by measuring accuracy, sensitivity, selectivity, positive predictive value (PPV) and negative predictive value (NPV). From the obtained results it is understand that the proposed new amalgam technique is giving 88% good accuracy results for detecting abnormality in MRI brain images when compared to other hybrid methodology in CAD systems.**

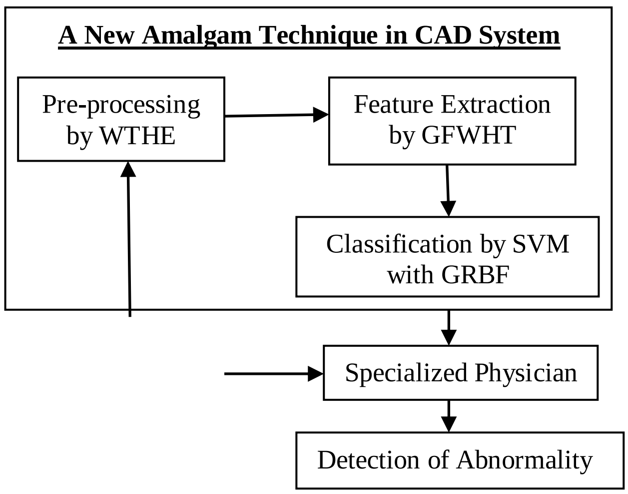
Keywords- CAD, confusion matrix, PSNR, PQS, RMSE, , UQI, accuracy,sensitivity,selectivity,PPV,NPV.

I. Introduction

In recent years, brain tumor 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 tumor in the present days. Identification of the tumor 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, works likes [1], [2] try to resolves some problems on the classification of MR image processing. Then works likes [3], [4] try to make a classification of MR brain images using a combination of feature extractor and classifiers. 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], works likes [6]–[8] use CBIR techniques to resolves the problem of index data by similarity image measures. This work shows the development of a computer aided medical diagnosis tool by hybrid techniques which includes various steps like pre-processing, feature extraction and Support Vector Machine for classification process.

II. Methodology

The proposed hybrid method in CAD System is shown in Fig.1.It includes three steps, first pre-processing (Denoising), second feature extraction and final step is image classification. 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.



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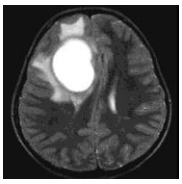

Fig .1 Proposed CAD Systems

III. PRE-PROCESSING

Image denoising is devised as a regression problem between the noise and signals; finally, it is solved by using many algorithms. Accordingly, noises are detected with surrounding information and are removed in both spatial domain and frequency domain without affecting the image quality and strengthen the smoothness of the image taken for analysis [9].

A. Median Filter(MF)

The best-known order-statistic filter in digital image processing is the median filter. Median filter is of nonlinear class that easily removes impulse noise while preserving edges. The median filter plays a key role in image processing and vision. In comparison with basic version of the other filters, median has better corner preserving characteristics. This filter is defined as

$$g(p) = avg\left\{ \begin{array}{l} avg\left\{ \begin{array}{l} f(p),\ p \in N_4(p) \\ f(p),\ p \in C_4(p) \end{array} \right. \\ f(p) \end{array} \right\} \quad (1)$$

These filters are yet to be applied by researchers to remove the Gaussian noise in the medical images.

B. Weiner Filter(WF)

It incorporates both the degradation function and statistical characteristics of noise into the restoration process. The method is founded on considering images and noise as random processes and the objective is to find an estimate $\hat{f}$ of the uncorrupted image f such that the mean square error between them is minimized and the error measure is given by,

$$e^2 = E\left\{ \left(f - \hat{f} \right)^2 \right\} \quad (2)$$

Where E(.) is the expected value of the argument. It is assumed that noise and the image are uncorrelated; that one or the other has zero mean; and that the gray levels in the estimate are a linear function of the levels in the degraded image.

C. Wavelet transform(WT)

Wavelet transform 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

$$\hat{\sigma}^2 = \left[\frac{median\left(\left|Y_{ij}\right|\right)}{0.6745} \right]^2, \ Y_{ij} € \text{ Sub band } HH_1 \quad (3)$$

- For each level, compute the scale parameter β by

$$\beta = \sqrt{\log\left(\frac{L_k}{J}\right)} \quad (4)$$

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,

$$T_N = \frac{\beta \hat{\sigma}^2}{\hat{\sigma}_y} \quad (5)$$

and then apply soft thresholding to the noisy coefficients.

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

D. Histogram Equalization(HE)

Histogram manipulation can be effectively used for image denoising for the gray levels in the range [0, L-1]. Considering the transformations of the form

$$S = T(r) \qquad 0 < r < 1 \quad (6)$$

which should satisfy the following

- T(r) is single valued and monotonically increasing in the interval 0< r <1 and
- 0< T(r) <1 for 0< r <1.

A transformation function that is not monotonically increasing could result in at least a section of the intensity range being inverted, thus producing some inverted gray levels in output image.

Let f(x,y) represent the value of an image pixel at any image coordinates (x,y) and let g(x,y) represent the corresponding enhanced pixel at those coordinates, then

$$g(x,y) = \{E.f(x,y), \text{ if } m_{s_{xy}} \le k_o M_G \ \& \ k_1 D_G \le \sigma_{s_{xy}} \le k_2 D_G \quad (7)$$

else $g(x,y) = f(x,y)$, where E, k_o, k_1 and k_2 are specified parameters, M_G is the global mean of the input image and D_G is its global standard deviation.

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.

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(p_{i,j}\right) \tag{8}$$

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

$$E = \sum_{K=0}^{N} p^2(i,j) \tag{9}$$

- **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.

$$C = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{10}$$

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:

$$C(i) = (x_i, y_i)\ ,\quad i \text{ €}[0,1,\ldots.P-1] \tag{11}$$

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

$$E_e(x,y) = \chi\left(f_x + \delta\cos\theta,\ f_y + \delta\sin\theta\right) \tag{12}$$

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

- **FVF Computation and Contour Extraction:** FVF has directional and gradient forces. The directional force attracts the evolving contour toward 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 [10].

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.

$$G(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right) \tag{13}$$

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

$$H_N = \frac{1}{\sqrt{2}}\begin{vmatrix} H_{N-1} & H_{N-1} \\ H_{N-1} & -H_{N-1} \end{vmatrix} \tag{14}$$

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. CLASSIFICATION BY SUPPORT VECTOR MACHINE(SVM)

After feature extraction process, in-order to detect the presence of the tumor in the input, we perform the final classification step. Here we use the Support Vector Machine classifier to classify the image into tumorous or not. SVM basically tries to divide the given data into decision surface. Decision surface is a hyper plane which divides the data into two classes. Training points are the supporting vector which defines the hyper plane. The training classifiers are supported by many functions like polynomial functions, radial basis functions, neural networks etc [11].Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs. A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high. The kernel function H (xi, xj) is defined by:

Linear kernels are:

$$H(x_i, x_j) = x_i^T x_j \tag{15}$$

Polynomial kernels are:

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$$H(x_i, x_j) = (\alpha x_i^T x_j + 1)^d \quad \text{, d is an integer.} \tag{16}$$

Gaussian Radial based function kernel (GRBF) are:

$$H(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \tag{17}$$

σ is an adjustable parameter. It is a non-linear kernel and is very sensitive to noise.

Exponential Radial based function kernel (ERBF kernel) are:

$$H(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{2\sigma^2}\right) \tag{18}$$

ANOVA Radial based function kernel (ARBF kernel) are:

$$H(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \tag{19}$$

γ is positive parameter for slope control.

Multilayer Perceptron kernel (MPK) are:

$$H(x_i, x_j) = \tanh\left(\gamma x_i^T x_j + r\right), \tag{20}$$

γ is the slope and r is the intercept constant.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The implementation of a new amalgam technique in CAD systems has been carried out using MATLAB. Here the images taken into account are MRI Brain images taken from the databases namely MR-TIP, NCIGT, BraTS, BITE and TCIA. The images are pre-processed for noise removal, and the features are extracted for classification of abnormality. The performance of the proposed hybrid algorithms in CAD systems is estimated and compared with various hybrid techniques. First, denoising is done by combining wavelet transform and histogram equalization (WTHE), affected by noises like salt and pepper, speckle, Gaussian and Brownian noise and its result are evaluated and compared with other hybrid methods like WFMF, WFWT, WFHE, MFWT, MFHE. Second, features are extracted by combining Gabor filter and watershed transforms (GFWST) and its performance is compared with other amalgam methods like GLCM+FVF, GCM+GF, GLCM+WHT, FVF+GF, FVF+WHT. Finally classification is done by SVM with GRBF kernel function and its performance is also evaluated.

A. PSNR AND RMSE RATIO

$$PSNR = 20\log_{10}\left(\frac{255}{RMSE}\right) \tag{21}$$

$$RMSE = \sqrt{\frac{\sum (f(i,j) - g(i,j))^2}{mn}} \tag{22}$$

Here f (i,j) is the original medical image with impulse noise , g(i,j) is an enhanced image and m and n are the total number of pixels in the horizontal and the vertical dimensions of the image.

B. UQI AND PQS ESTIMATION

It measures image similarity across distortion types. Distortions in UQI are measured as a combination of three factors; Loss of correlation, Luminance distortion and Contrast distortion. Let $\{x_i\}$ and $\{y_i\}$ =1, 2,...,N be the original and the test image signals. The UQI is given by

$$UQI = \frac{4\sigma_{xy}\bar{X}\bar{Y}}{\left[\sigma_x^2 + \sigma_x^2\right]\left[\left(\bar{X}\right)^2 + \left(\bar{Y}\right)^2\right]} \tag{23}$$

The most commonly used subjective test is the picture quality scale (PQS) which is used to evaluate the user's acceptance of an image output system. For these observing tests, thirty subjects are surveyed and asked to rate the denoised image for quality, using a PQS scale.

Figure 2 shows the PSNR and PQS estimation for MRI images affected by salt and pepper and Gaussian noise. It is inferred from the result that a hybrid combination of WT and HE is giving enhanced output when compared to other hybrid combination like WF and MF, WF and WT, WF and HE, MF and WT, MF and HE. The largest PSNR value is seen for WTHE and low value for WFHE.

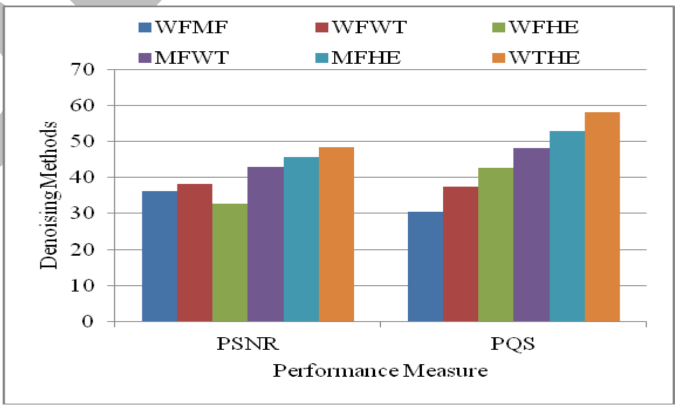

Fig .2 Performances of various hybrid denoising algorithms for MRI Images affected by salt & pepper and Gaussian noise

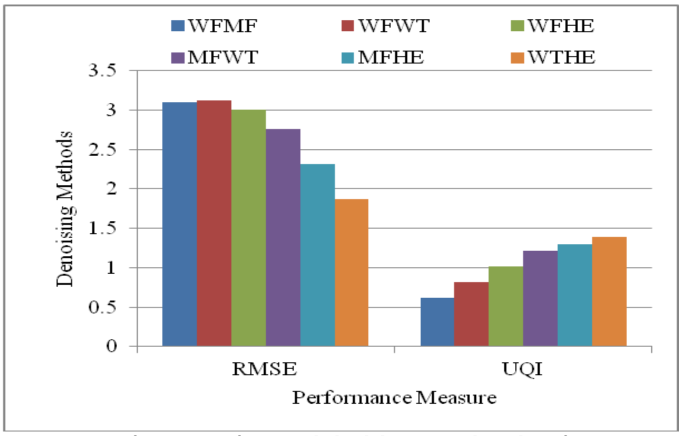

Fig .3 Performances of various hybrid denoising algorithms for MRI Images affected by speckle and Brownian noise

The similarity measure and RMSE estimation for MRI images affected by Speckle and Brownian noise is indicated in Fig.3. From the obtained result it is seen that proposed amalgam algorithm is having minimum mean square error value and high similarity index when compared to other hybrid methods.

C. 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.

D. SENSITIVITY

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

$$Sensitivity = \frac{Tp}{Tp + Fn} * 100\% \qquad (24)$$

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

E. SPECIFICITY

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

$$Specificity = \frac{Tn}{Tn + Fp} * 100\% \qquad (25)$$

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

F. ACCURACY

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

$$Accuracy = \frac{Tp + Tn}{Tp + Fn + Tn + Fp} * 100\% \qquad (26)$$

G. POSITIVE PREDICTIVE VALUE(PPV)

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

$$PPV = \frac{Tp}{Tp + Fp} * 100\% \qquad (27)$$

H. NEGATIVE PREDICTIVE VALUE(NPV)

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

$$NPV = \frac{Tn}{Tn + Fn} * 100\% \qquad (28)$$

TABLE II. EVALUATION MATRIX FOR FEATURE EXTRACTION

Feature Extraction Methods	**Total number of Images**	**Tp**	**Fn**	**Tn**	**Fp**
GLCM+FVF	180	130	12	23	15
GLCM+GF	180	133	13	18	16
GLCM+WHT	180	143	11	17	9
FVF+GF	180	148	9	18	5
FVF+WHT	180	154	6	16	4
GF+WHT	180	160	5	13	6

Table II indicates the evaluation of confusion matrix for various hybrid feature extraction algorithm interms of confusion matrix. The total images taken are 180, among them true positive value is seen high and false negative is seen low while combining Gabor filter and Walsh-Hadamard transform.

Figure.4 shows the performance of support vector machine with various kernel functions. It's observed from the result that Gaussian radial basis kernel function (GRBF) is giving better result when compared to other kernel functions. Poor performance is seen while using MP kernel.

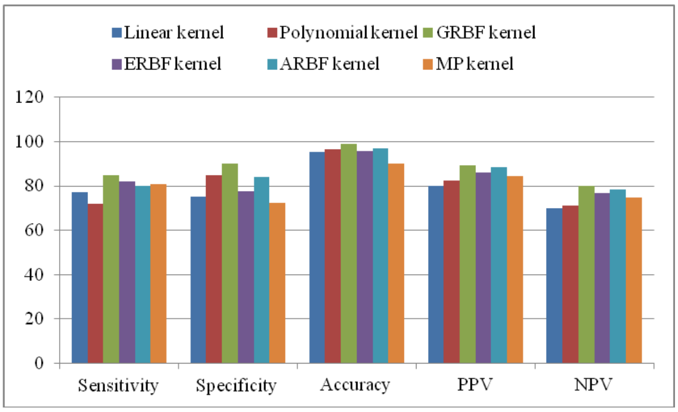

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Fig .4 Performance of SVM with kernel function

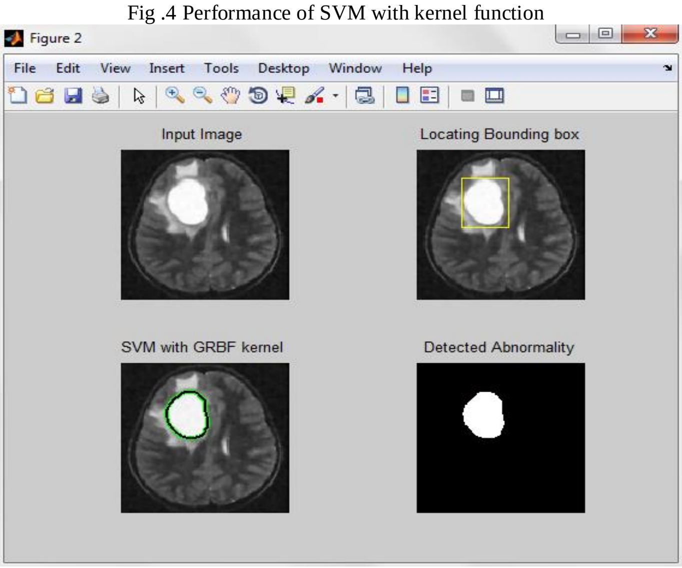

Fig .5 Detection of abnormality by SVM Classifier for MRI brain tumor image1

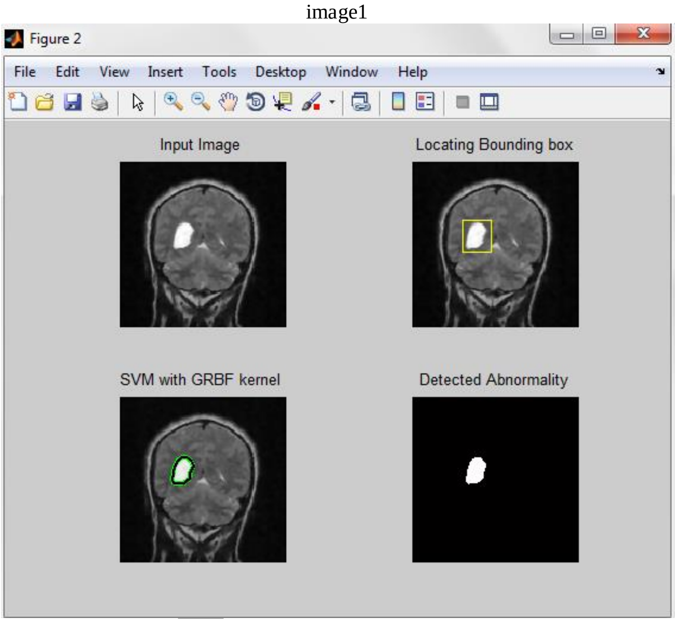

Fig .6 Detection of abnormality by SVM Classifier for MRI brain tumor image2

Fig.5 and Fig.6 implies the output result of detected abnormality for various MRI brain tumor images. Gaussian radial basis kernel function is giving accurate result when compared to other kernel function while using with SVM classifier.

TABLE III. EVALUATION MATRIX FOR FEATURE EXTRACTION

Methodology in CAD System			Performance Measure		
Denoising Methods	Feature Extraction	SVM with GRBF	Accuracy	Sensitivity	Selectivity
WFMF	GLCM+FVF	SVM with GRBF	56.43	57.24	56.33
	GLCM+GF		57.34	58.22	57.21
	GLCM+WHT		57.88	59.74	58.22
	FVF+GF		58.33	59.32	60.32
	FVF+WHT		58.21	60.12	58.44
	GF+WHT		58.89	59.43	59.37
WFWT	GLCM+FVF		60.23	61.23	60.43
	GLCM+GF		62.67	62.76	61.65
	GLCM+WHT		63.21	63.56	62.72
	FVF+GF		65.61	64.53	63.12
	FVF+WHT		68.34	65.42	64.78
	GF+WHT		69.27	67.43	63.16
WFHE	GLCM+FVF		71.34	68.42	64.76
	GLCM+GF		73.56	68.83	67.45
	GLCM+WHT		75.23	67.43	66.32
	FVF+GF		76.44	68.65	68.23
	FVF+WHT		77.11	69.38	68.94
	GF+WHT		78.02	70.48	69.34
MFWT	GLCM+FVF		80.12	71.32	69.34
	GLCM+GF		81.55	71.89	70.65
	GLCM+WHT		82.37	72.62	73.73
	FVF+GF		83.56	73.42	74.41
	FVF+WHT		84.72	74.36	74.95
	GF+WHT		85.23	75.52	75.00
MFHE	GLCM+FVF		86.42	76.38	75.28
	GLCM+GF		85.44	78.63	77.74
	GLCM+WHT		87.21	79.72	76.47
	FVF+GF		87.94	80.52	78.43
	FVF+WHT		88.23	81.73	80.86
	GF+WHT		89.41	82.83	81.74
WTHE	GLCM+FVF		90.23	83.54	82.38
	GLCM+GF		90.78	84.78	83.43
	GLCM+WHT		91.34	85.52	84.74
	FVF+GF		92.45	86.74	85.31
	FVF+WHT		93.56	87.44	85.98
	GF+WHT		95.32	88.56	87.34

VII. CONCLUSION

The proposed CAD system includes pre-processing by WTHE and feature extraction by GFWHT and SVM by GRBF. In first step, the performance of WTHE is better than WFMF by 42% and WFWT by 34.55% and WFHE by 32.11% and MFWT by 26% and MFHE by 24.21%. In second step, better features are extracted by using GFWHT compared to other hybrid methods by having high true positive value as 160 among the database of 180 considered. False negative value is seen high while using GLCMGF and seen low while using GFWHT and FVFWHT. Finally SVM classification is used with six kernel functions, where by the GRBF is giving higher accuracy and sensitivity results than by using other kernel function.

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