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Analysis of the Performance of Classifiers on Wavelet Features with PCA and GA for the Detection of Breast Cancer in Ultrasound Images

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Abstract : *Breast cancer is the most commonly diagnosed life threatening cancer in women worldwide. Breast cancer is the leading cause of cancer death among women. Early detection is of great significance and essential to the treatment of breast cancer. Ultrasonography is one of the most widespread imaging modality used to detect and classify abnormalities of the breast. This paper proposes the use of wavelet transform and its coefficients as texture features for the detection of abnormalities in the breast. Gray level co-occurrence matrix is computed from wavelet coefficients at two levels. Principal component analysis and genetic algorithms are used for feature reduction and selection. Support vector machine (SVM) and Naïve Bayes (NB) are used to differentiate benign and malignant lesions. Their performances are evaluated using diagnostic accuracy, sensitivity, specificity, positive predictive value, negative predictive value and Mathew's correlation coefficient. The proposed method results in high classification accuracy of 98.57% in a data set containing 70 (30 benign and 40 malignant) breast ultrasound images. Results indicate that the proposed features can effectively characterize the properties of breast lesions in ultrasound images.*

Keywords*: Breast lesion, Genetic algorithm, Principal component analysis, Ultrasonography, Wavelet transform.*

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I. Introduction

Cancer is one of the most leading causes of morbidity and mortality all over the world. Breast cancer is the most common cancer and is the second leading cause of death in women. It is estimated that approximately 250000 cases of breast cancer will be diagnosed in 2017 in United States [1]. Breast cancer is the number one cancer among women in India with the rate as high as 25.8 per 100,000 women [2]. Ultrasonography (US) has been playing an important role in the clinical diagnosis of breast cancer [3]. It is useful in the evaluation of palpable masses that are mammographically concealed during the evaluation of clinically suspected breast masses in women younger than 30 years of age. Benign masses have hyperechogenecity, ellipsoid shape and macro lobulations and malignant masses have speculated contour, taller than wide , marked hypoechogenecity, microlobulations and posterior acoustic shadowing. It is important to note that a lesion with a single malignant US characteristic, in spite of the presence of multiple benign characteristics prevents a benign classification and requires biopsy. Hence ultrasound classification of a lesion should be based on the most suspicious finding. However, the interpretation of the breast ultrasound image is operator-dependent and varies based on the skill and experience of the radiologist. To overcome this computer aided diagnosis (CAD) systems have been developed to analyze breast ultrasound images and assist the radiologist with a second opinion to improve the diagnosis accuracy and reduce the effect of operator dependency.

Several studies have shown the significance of textural and morphological features of breast ultrasound images in the characterization of the breast mass. H.D. Cheng et al. [4] reviewed CAD systems for breast cancer detection and classification in ultrasound images, D.R Chen et al. [5] have presented a method to differentiate benign and malignant lesions using self organizing map based on textural features. Carima et al. [6] have used only morphological features for tumor classification using NNs and SVM, where as Yamni Su et al. [7] and Wu et al. [8] used both textural and morphological features for classification. Bagging ensemble classifier and SVM are used by Wahdan et al. [9] for the differentiation of the tumors. Histogram oriented feature metric with textural and morphological features are proposed by Radhika et al. [10]. Kim et al. [11] have come out with histogram based features. Gomez et al. [12] used Fisher linear discriminant analysis with texture features for differentiation of breast lesions ,wavelet transform based texture features are used in [4,13,14] for

characterization of breast lesion. Shearlet transform [15] based features are also used for detection and classification of breast tumors. C.D. Katsis et al. [16] developed a system for early detection of breast cancer using multimodal (mammography, ultrasonography and contrast-enhanced magnetic resonance imaging tomography (CE-MRI) extracted features. From the literature review it is found that the performance of the classification algorithms highly depends on features extracted from breast lesion since they are used to train the classifier. Further large number of features present redundant information to the classifiers which in turn decreases the classification accuracy and increases the computational complexity. Hence in this study attempt has been made to characterize the breast lesion in ultrasound image with minimum number of features based on wavelet transform.

II. Image Database

Breast ultrasound images used in this study are obtained from the publicly available database of ultrasound images of breast cancer provided by the department of radiology of Thammasat University and Queen Sirikit Center of breast cancer of Thailand [17]. In this study 70 BUS images (30 images containing benign and 40 containing malignant) are used.

III. Proposed Method

Steps involved in the detection of the breast cancer is as shown in Fig.1. Breast ultrasound images are preprocessed using anisotropic diffusion filtering and the region of interest is extracted from each image. Wavelet decomposition is done at two levels and co occurrence matrix of all the sub bands are calculated. Using these matrices the features are extracted. These features are used for classification of breast lesions using support vector machine and Naïve bayes.

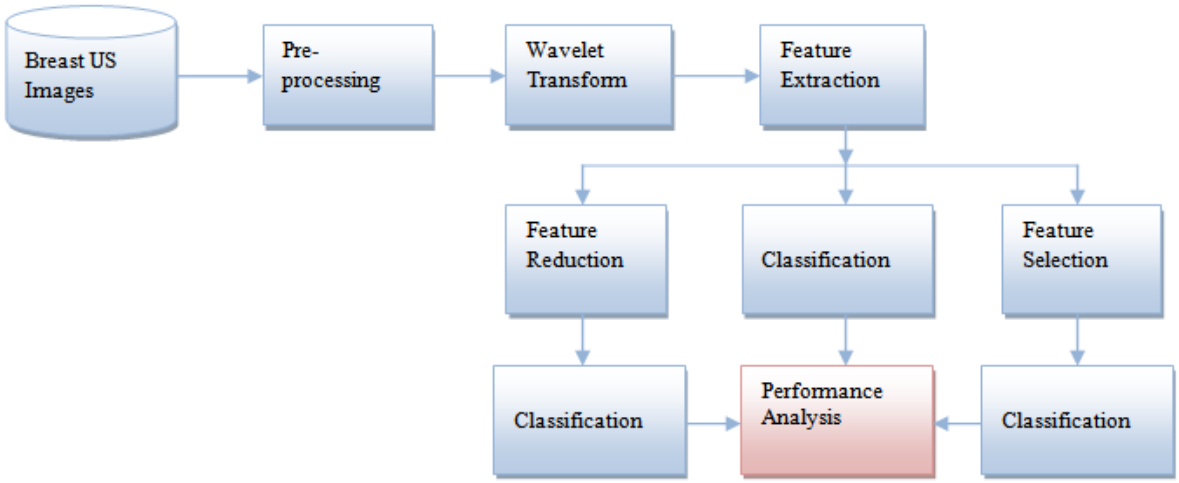

Fig. 1 : Block Diagram of the Proposed Method

3.1 Preprocessing

Speckle is an intrinsic artifact in breast ultrasound images mainly responsible for their poor resolution and degraded borders. In this work anisotropic diffusion filter is used to reduce the speckle in breast ultrasound image. Region of interest (ROI) is selected to reduce the computational complexity. The extracted ROI consists of a rectangular region which includes the tumor area.

1.2 Discrete Wavelet Transform

Discrete wavelet transform (DWT) is a most frequently used technique in image processing because of its time-frequency resolution properties. DWT uses filter banks to decompose signals into low and high pass components. The low pass component carries the information about the slow varying characteristics of the signal and high pass components carries information about sudden changes in the signal.

The multiresolution analysis of an image using DWT is carried out by applying low pass and high filter to both rows and columns of the image iteratively. The following filter functions through the multiplication of separable scaling and wavelet functions in horizontal and vertical directions are used.

$$\varphi(m,n) = \varphi(m)\,\varphi(n) \quad (1)$$

$$\psi^{H}(m,n) = \psi(m)\,\varphi(n) \quad (2)$$

$$\psi^{V}(m,n) = \varphi(m)\,\psi(n) \quad (3)$$

$$\psi^{D}(m,n) = \psi(m)\,\psi(n) \quad (4)$$

where $\varphi(m,n)$, $\psi^H(m,n)$, $\psi^V(m,n)$ and $\psi^D(m,n)$ represents the approximated image, image with horizontal details, image with vertical details and image with diagonal details respectively. Decomposition stages are shown in Fig.2.

Filtering in each direction follows down sampling by a factor of 2, so that each of the four subbands corresponding to filter outputs contain one-fourth of the number of samples, compared to the original image.
The output of filter banks are discrete wavelet transformed (DWT) coefficients. The bands $\varphi(m,n)$, $\psi^H(m,n)$, $\psi^V(m,n)$ and $\psi^D(m,n)$ are also referred to as LL, LH,,HL and HH respectively where the first letter indicates the type of the filter used along the columns (vertical direction) and the second letter indicates the type of the filter used along the rows (horizontal direction). The LL subband at each level can be used for next level decomposition and this can be extended to multiple levels to get more frequency resolution. Fig.3 shows two level decomposition of an image.

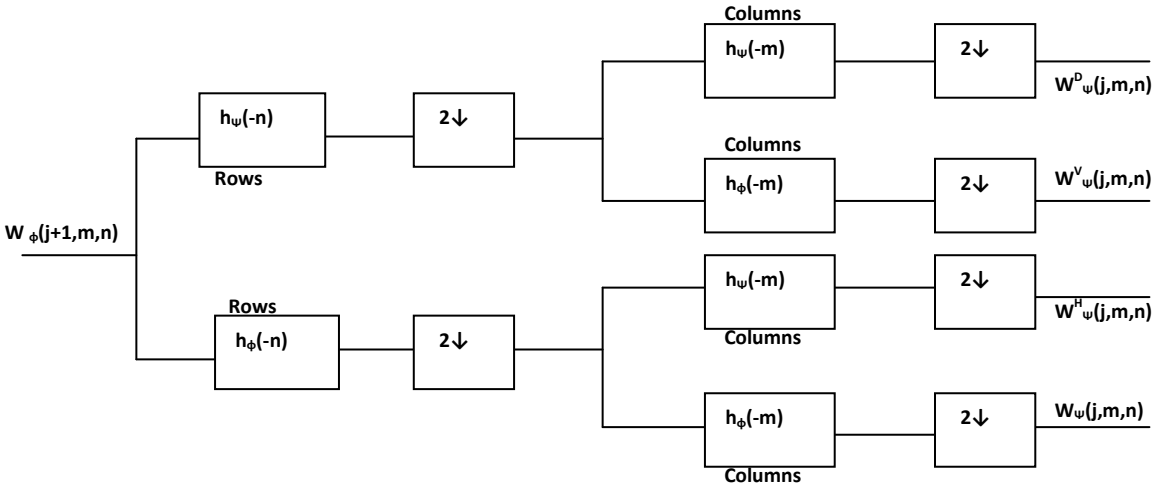

Fig. 2 Decomposition of an Image through Scaling and Wavelet functions

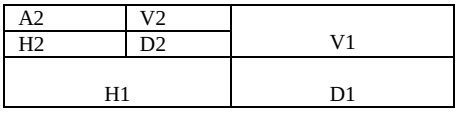

Fig. 3 Two level wavelet decomposition of an image

In this work four wavelet families, Daubechies 4 (db4), Biorthogonal 3.7 (bior3.7), symlet 5 and coiflet 2 are used to obtain wavelet coefficients. Daubechies wavelets are compactly supported orthogonal wavelets which preserves energy. Symlets are the symmetrical wavelets having least symmetry and maximum number of vanishing moments for a given compact support. Coiflet is near symmetric and biorthogonal wavelets have the property of linear phase.

3.3 Feature Extraction

Gray level co occurrence matrix (GLCM) is most widely used for texture analysis, due to its ability to capture the spatial dependence of gray level values within an image. Multiresolution analysis helps to obtain information about the lesion at different scales. The lesion can then be characterized by the statistical textural properties of the multiscale representation. In this work DWT is applied to extracted ROI using db4, bior3.7, symlet 5 and coiflet 2 as the mother wavelets with two levels. Co occurrence matrix of each sub band is computed. Second order statistical textural features are extracted from the co occurrence matrix of all the sub bands at each level in order to characterize the nodule. Five features that are extracted from each subband are energy, contrast, cluster prominence, cluster shade and dissimilarity and their implementation details are as follows.

Energy : Is a measure of uniformity of gray levels in an image.

$$\text{Energy} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)^2 \quad (5)$$

Contrast : Is a measure of local variations in an image.

$$\text{Contrast} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} |i-j|^2\, p(i,j) \tag{6}$$

Cluster prominence (CP) : Is a measure of asymmetry in an image.

$$\text{Cluster Prominance} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \left(i+j-\mu_x-\mu_y\right)^4\, p(i,j) \tag{7}$$

Cluster shade (CS) : Is a measure of skewness in an image.

$$\text{Cluster Shade} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \left(i+j-\mu_x-\mu_y\right)^3\, p(i,j) \tag{8}$$

Dissimilarity : Is a measure of variations of gray level pairs in an image.

$$\text{Dissimilarity} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} |i-j|\, p(i,j) \tag{9}$$

where p(i,j) is the normalized co occurrence matrix obtained from the wavelet coefficients, μ_x and μ_y are the means of p_x and p_y respectively.

3.4 Classification

In this work classification of breast lesions as benign or malignant is carried out using SVM and Naïve Bayes classifier.

3.4.1 Support Vector Machine

SVM is the supervised learning technique which produces a model to predict the target values of the test data given only the test data attributes. Given a training set of instance-label pairs (x_i,y_i), I = 1,…..,N, where $x_i \in R^n$ and $y \in \{1,-1\}^N$, the SVM [18] requires the solution of the following optimization problem,

$$\underset{w,b,\zeta}{min}\ \ \frac{1}{2}w^T w + C\sum_{i=1}^{N}\zeta_i \tag{10}$$

subject to

$$y_i(w^T\emptyset(x_i)+b) \geq 1-\zeta_i \quad \zeta_i \geq 0 \tag{11}$$

where $\zeta_i's$ are slack variables which allow misclassification in the set of inequalities and C is a tuning parameter. Training vectors x_i are mapped into a higher dimensional space by the function ∅. SVM finds a linear separating hyperplane with maximal margin in this higher dimensional space.

3.4.2 Naïve Bayes

Naïve Bayes (NB) classifier is a probabilistic classifier based on the Bayes theorem with the consideration that all features independently contribute to the probability of certain decision [19]. It learns the conditional probability of each variable X_k given the class label C from the training data. Consider a simple classification learning in which the goal is to predict the class $c \in C = \{c_1, c_2, \ldots..c_m\}$ of a query input $x = \{a_1, a_2, \ldots. a_n\}$ given a training data of pre classified examples. Instances are characterized in terms of an attribute value representation and a_i is the value of the i^{th} attribute. Classification procedure consists of the following steps.

1. The class c will be the class with maximum posterior probability $\max_{ci \in C} P(c_i|x)$.
2. To identify this class, the posterior probabilities $P(c_i|x)$ must be estimated using $P(c_i|x) = \frac{P(x|c_i)P(c_i)}{P(x)}$
3. The probability $P(x|ci)$ can be estimated as, $P(x|ci) = \prod_{j=1}^{n} P(a_j|c_i)$
4. Estimate the probabilities for $P(c_i)$ and $P(a_j|c_i)$ using the training data set.

To quantitatively evaluate the performance of classification results with various features and classifiers, six common performance measures are used namely accuracy sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and Mathew's correlation coefficient (MCC). Their definitions are,

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \text{ x } 100 \tag{12}$$

$$Sensitivity = \frac{TP}{TP+FN} \text{ x } 100 \quad (13)$$

$$Specificity = \frac{TN}{TN+FP} \text{ x } 100 \quad (14)$$

$$PPV = \frac{TP}{TP+FP} \text{ x } 100 \quad (15)$$

$$NPV = \frac{TN}{TN+FN} \text{ x } 100 \quad (16)$$

$$MCC = \frac{(TP\ X\ TN - FP\ X\ FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (17)$$

where
TP : Correct classification rate of malignant nodules
FN : Misclassification rate of malignant nodules
TN : Correct classification of benign nodules
FP : Misclassification rate of benign nodules

Sensitivity refers to the proportion of cases with disease with a positive result, while the specificity is the proportion of cases without disease with a negative result. PPV is defined as the percentage of cases with a positive result with disease and NPV indicates the percentage of cases with a negative result without disease. MCC is the correlation coefficient between observed and predicted classifications, which takes the value between -1 and +1. MCC of +1 represents a exact prediction, 0 denotes a uniform random prediction and -1 indicates a inverse prediction. Here it is represented in terms of percentage.

3.5 Feature Reduction

With many features extracted, the critical task is to find an optimum set of features. Appropriate selection of optimum features is an important task since their dimension directly affects the performance of the classifier and computation time. In this work two methods, principal component analysis (PCA) and genetic algorithm (GA) are used to find the optimum set of features.

3.5.1. Principal component analysis

The most popular method for feature reduction is principal component analysis. It combines correlated features and creates new features ie., principal components, superior to original features [20]. Hence it reduces high dimensional feature space to low dimensional feature space. The first principal component accounts for as much of the variability in the feature set as possible and each succeeding principal component accounts for as much of the remaining variability as possible. PCA involves the calculation of eigen values of the data covariance matrix, usually after mean centering the data for each feature.

3.5.2 Genetic algorithm

Genetic algorithm is a heuristic search algorithm based on the evolutionary ideas of natural selection and natural genetics [21]. Initially GA randomly create individuals (initial population) and the fitness of every individual in the population is evaluated. Based on their fitness, multiple individuals are randomly selected from the current population and modified (crossover and mutation) to form a new population. The algorithm stops, when either the satisfactory fitness level for the population has been reached or a maximum number of generations has been produced.

IV. Results And Discussion

In this study a total of 70 breast ultrasound images (including 30 benign lesions and 40 malignant lesions) are used. Since local texture characteristics are well reinforced by wavelet transform the distribution of wavelet coefficients can be utilized for differentiating malignant lesions from benign lesions. The selection of wavelets plays a major role and it depends on the characteristics of ultrasound image. In this study experimentation has been carried out with different wavelet families. The better features are obtained with db4, bior3.7, symlet5 and coiflet2. Hence two level decomposition of enhanced ROI sub images using db4, bior3.7,

symlet 5 and coiflet 2 is done. Five features energy, contrast, cluster prominence, cluster shade and dissimilarity are computed from all the subbands at each level. Hence a total of 40 features are obtained. Then the optimum set of features are obtained using both PCA and GA. These optimum features are further given as the inputs to both SVM and Naïve Bayes classifiers and their performances are compared.

During classification, 10-fold cross validation scheme is employed. 70 images are equally divided into 10 segments. 63 images are used in the training phase while remaining 7 images are used for testing. This approach is iterated 10 times by shifting the test data. The performance metrics accuracy, sensitivity, specificity, PPV, NPV and MCC are evaluated in each iteration. Finally the performances recorded in all the 10 iterations are averaged and considered as the overall performance of the classifier.

Table 1 lists the performances of SVM and NB with db4 (a) approach with all wavelet features. (b) approach with GA feature selection. (c) approach with PCA feature reduction. The classification accuracies of approaches (a) – (c) with SVM are 94.28%, 95.71% and 98.57% respectively and 87.14%, 88.57% and 98.57% respectively with NB. It is clear that the highest classification accuracy of 98.57% is obtained with PCA feature reduction approach with both the classifiers. It is also observed that this approach results in 100% sensitivity with NB and 100% specificity with SVM. It also results in 100% positive predictive value and 96.67% negative predictive value. High PPV and NPV imply that the number of biopsies for benign lesions can be reduced. This approach further results in a very good MCC of 0.97 or in terms of percentage it is 97.5%.

Performances of SVM and NB with bior3.7 are tabulated in Table 2. Bio3.7 wavelet is also resulting in the same highest accuracy of 98.57% with PCA feature reduction approach. Table 3 shows the performances of classifiers with symlet5. The accuracies of SVM with three approaches are 91.42%, 92.86% and 97.14% respectively and that of NB are 85.71%, 87.14% and 97.14% respectively. Both the classifiers are performing with higher accuracy of 97.14% with PCA feature reduction. Similarly Table 4 reports the performances of the classifiers using coiflet2.

Table 1. Performance of SVM and Naïve Bayes using db4.

db4	**SVM**			**Naïve Bayes**		
	All features	**With GA**	**With PCA**	**All features**	**With GA**	**With PCA**
Accuracy	94.28	95.71	98.57	87.14	88.57	98.57
Sensitivity	96.00	96.00	98.00	92.50	89.33	100.00
Specificity	95.00	97.50	100.00	80.00	96.00	96.67
PPV	95.00	97.50	100	92.5	95.00	100
NPV	93.33	93.33	96.67	80.00	80.00	96.67
MCC	89.60	92.10	97.30	76.90	79.51	97.30

Table 2. Performance of SVM and Naïve Bayes using bior3.7

bior3.7	**SVM**			**Naïve Bayes**		
	All features	**With GA**	**With PCA**	**All features**	**With GA**	**With PCA**
Accuracy	88.57	90.00	98.57	87.14	88.57	98.57
Sensitivity	94.00	93.00	100.00	87.50	94.00	97.50
Specificity	88.50	88.33	96.67	86.67	88.50	100.00
PPV	87.50	90.00	100	87.50	87.50	97.50
NPV	90.00	90.00	96.67	86.67	90.00	100.00
MCC	79.89	80.64	97.30	77.19	79.89	97.50

Table 3. Performance of SVM and Naïve Bayes using symlet5.

symlet5	**SVM**			**Naïve Bayes**		
	All features	**With GA**	**With PCA**	**All features**	**With GA**	**With PCA**
Accuracy	91.42	92.86	97.14	85.71	87.14	97.14
Sensitivity	96.00	97.50	100.00	85.00	94.00	97.5
Specificity	91.00	89.17	95.00	86.67	85.00	96.67
PPV	90.00	90.00	95.00	85.00	85.00	97.5
NPV	93.33	96.67	100.00	86.67	90.00	96.67
MCC	85.08	86.67	95.00	74.79	76.91	94.80

Table 4 . Performance of SVM and Naïve Bayes using coiflet2

Coiflet2	SVM			Naïve Bayes		
	All features	With GA	With PCA	All features	With GA	With PCA
Accuracy	90.00	91.42	97.14	82.85	88.57	97.14
Sensitivity	94.00	93.50	97.50	80.00	93.00	97.50
Specificity	90.00	91.67	96.67	86.67	85.83	96.67
PPV	90.00	92.50	97.50	80.00	87.50	97.50
NPV	90.00	90.00	96.67	86.67	90.00	96.67
MCC	81.91	83.77	94.80	68.97	78.13	94.80

The graphical representation of classification accuracies of SVM and NB for the wavelet db4, bior3.7, symlet5 and coiflet2 with all the three approaches are shown in Fig. 4 and Fig. 5 respectively.

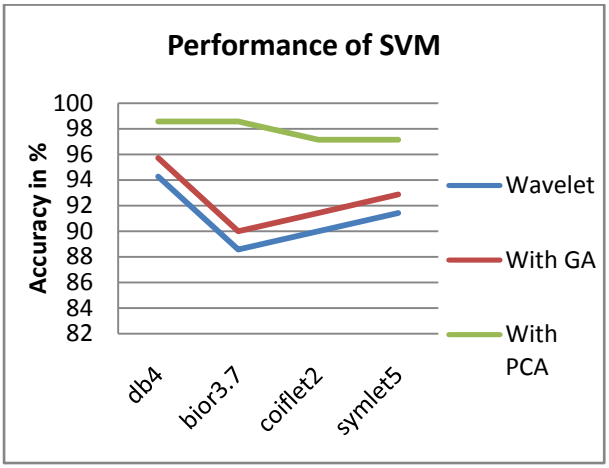

Fig. 4 Comparison of accuracies of SVM

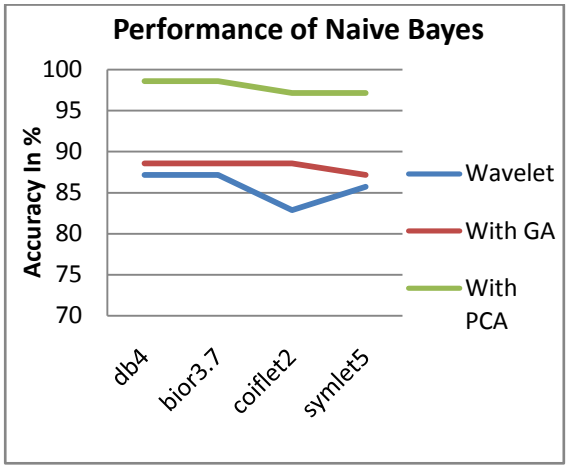

Fig. 5 Comparison of accuracies of NB

Mathew's correlation coefficients obtained from SVM and NB with wavelet families db4, bior3.7, symlet5 and coiflet2 for the three approaches are plotted in Fig. 6 and Fig. 7 respectively.

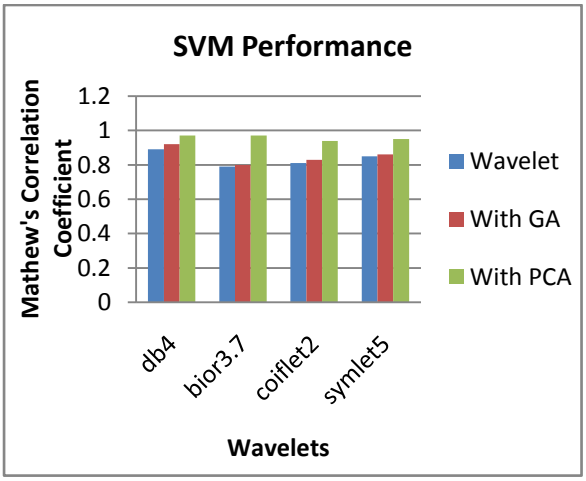

Fig. 6 MCC's obtained from SVM for various wavelets

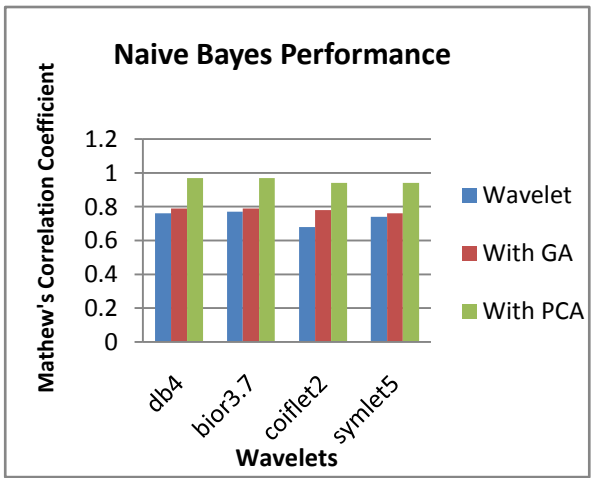

Fig. 7 MCC's obtained from NB for various wavelets

Reduction in the accuracy of the classifier when the features were selected using GA may indicate that there are less redundancy in the number of features extracted. Further, it can be seen that creating new features by combining all the extracted features using PCA leads to higher accuracy.

Table 5 lists the performance of the approaches reported in the literature and also the performance of the proposed method. Direct comparison of the performances is not possible as the image databases used in these studies are obtained from different population with different image quality.

Table 5. Classification performance of the proposed work and other classification approaches from literature.

Sl. No.	Author and year	No. of Images	Nature of features extracted	Classifiers	Performance (Accuracy/AUC)
1	Kim et al. (2014) [11]	69 (42B/27M)	Histogram based features	SVM	Acc : 82.67%
2	Gomez et al. (2012) [12]	633 (219b/217M)	Textural features	Fishers linear discriminant analysis	AUC : 0.87
3	Shichong et al. (2013) [15]	200 (100B/100M)	Shearlet features	SVM	Acc: 91%
4	Su et al. (2011) [7]	132 (67B/65M)	Textural and morphological features	ANN	Acc : 93.18%
5	Wu et al. (2012) [8]	210 (120B/90M)	Textural and morphological features	SVM with GA	Acc: 95.25%
6	Proposed work	70 (30B/40M)	GLCM based Wavelet features	SVM with PCA	Acc : 98.57%

V. Conclusion

In this paper, the wavelet transform based co occurrence matrix feature has been proposed for the characterization of breast lesions in ultrasound images. Four wavelet families db4, bior3.7, symlet5 and coiflet2 are used to derive the texture features. The performances of SVM and Naïve Bayes are compared considering all the features, features selected by genetic algorithm and features with principal component analysis. Experimental results indicate that wavelet features using db4 and bior3.7 with PCA could more effectively characterize breast lesions in ultrasound image than features selected using genetic algorithm.

Hence the highest classification accuracy of 98.57% is obtained when PCA is used with both SVM and Naïve Bayes for db4 and bior3.7 wavelets. The results obtained using the method proposed in this paper encourages us to further continue the study using a large dataset in order to establish its clinical applicability as a supplement to assist doctors in breast lesion classification.

References

[1] R. L. Siegel, K. D. Miller, A. Jemal, Cancer statistics, 2017, *Cancer J. Clin., 67(1)*, 2017, 7–30 .
[2] Malvia, S., Bagadi, S. A., Dubey, U. S. and Saxena, S, Epidemiology of Breast Cancer in Indian Women, *Asia-Pac J Clin Oncol, 13(4)*, 2017, 289–295.
[3] C.M.Sehgal, S.P. Weinstein, P.H. Arger, E.F. Conant, A Review of Breast Ultrasound, *Journal of Mammary Gland Biology and Neoplasia, 11(2)*, 2006, 113-123.
[4] H.D.Cheng, J.Shan, W. Ju, y. Guo, L. Zhang, Automated breast cancer detection and classification using ultrasound images: A Survey, *Pattern Recognition, 43(1)*, 2010, 299—317.
[5] D.R. Chen, R.F. Chang, Y.L. Huang, Breast Cancer Diagnosis using Self Organizing Map for Sonography, *Ultrasound Med. Biol. 26(3)* , 2000, 405–411.
[6] C.D.L Nascimento et. al, Breast Tumor Classification in Ultrasound Images using Support Vector Machines and neural networks, *Research on Biomedical Engineering, 32(3)*, 2016, 283-292.
[7] Y. Su, Y. Wang, J. Jiao, Y. Guo, Automatic Detection and Classification of Breast Tumors in Ultrasonic Images using Texture and Morphological Features, *Open Med. Inform. J. 5(1)*, 2011, 26–37.
[8] W.J. Wu, S.W. Lin, W.K. Moon, Combining Support Vector Machine with Genetic Algorithm to Classify Ultrasound Breast Tumor Images, *Comput. Med. Imaging Graph. 36(8)*, 2012, 627–633.
[9] Passant Wahdan, Amani Saad, Amin Shoukry, Automated Breast Tumour Detection in Ultrasound Images Using Support Vector Machine and Ensemble Classification, *Journal of Biomedical Engineering and Bioscience, 3*, 2016, 4-11.
[10] Radhika V Menon et. al, Automated Detection and Classification of Mass from Breast Ultrasound Images, *Fifth National Conference on Computer Vision, Pattern recognition, Image Processing and graphics*, 2015, 1-4.
[11] J.H. Kim, J.H. Cha, N. Kim, Y. Chang, M.S. Ko, Y.W. Choi, H.H. Kim, Computer Aided Detection System for Masses in Automated Whole Breast Ultrasonography: Development and Evaluation of the Effectiveness, *Ultrasonography , 33(2)*, 2014, 105–115.
[12] W. Gomez, W.C.A. Pereira, A.F.C. Infantosi, Analysis of co-occurrence texture statistics as a function of gray-level quantization for classifying breast ultrasound, *IEEE Trans. Med. Imag. 31(10)*, 2012, 1889–1899.
[13] D.R. Chen, R.F. Chang, W.J. Kuo, M.C. Chen, Y.L. Huang, Diagnosis Of Breast Tumors With Sonographic Texture Analysis Using Wavelet Transform And Neural Networks, *Ultrasound Med. Biol. 28(10)* , 2002, 1301–1310.
[14] H.W. Lee et. al, Breast Tumor Classification of Ultrasound Images using Wavelet based Channel Energy and imageJ, *IEEE Journal of Selected Topics in Signal Processing, 3(1),* 2009, 81-93.

[15] Shichong Zhou, Jun Shi, Jie Zhu, Yin Cai, Ruiling Wang, Shearlet- based Texture Feature Extraction for Classification of Breast Tumor in Ultrasound Image, *Biomedical Signal Processing and Control, 8(6)*, 2013,688-696.
[16] C.D.Katsis et. al, Using Artificial Immune Recognition Systems in Order to Detect Early Breast Cancer, *International Journal of Intelligent Systems and Applications, 5(2)*, 2013, 34-40.
[17] Rodtook, A and Makhanov S.S. , Multi-Feature Gradient Vector Flow Snakes for Adaptive Segmentation of the Ultrasound Images of Breast Cancer, *Journal of Visual Communication and Image Representation, 24(8)*, 2013, 1414-1430.
[18] C Cortes, V Vapnik. "Support-Vector Networks", *Machine Learning, 20(3),* 1995, 273-297.
[19] D. Lowd, P. Domingos, Naive Bayes Models for Probability Estimation, *Proceedings of the 22th International Conference on Machine Learning*, 2005, 529-536.
[20] Shiens J , A Tutorial on Principal Component Analysis, Center for Neural Science, New York University, 22nd, version3.0l, (2009).
[21] John McCall, Genetic Algorithms for Modeling and Optimization, *Journal of Computational and Applied Mathematics, 184(1),* 2005, 205–222.

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