

DETECTION OF BREAST CANCER IN MAMMOGRAMS THROUGH A NEW FEATURES AND DECISION TREE BASED, CLASSIFICATION FRAMEWORK

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ABSTRACT

This research proposes a new framework for detection of breast cancer. Currently, mammography is the primary tool for early detection and diagnosis. The use of computer systems to assist clinicians in digital mammography image screening has advantages over traditional methods. Computer-aided techniques can enhance the appearance of the mammogram images and highlight suspicious areas. Also it extracts certain dynamic features to distinguish between benign and malignant mammograms. Although great efforts have been made to come out with effective methods, their performances especially in terms of accuracy are fallen short due to poor image resolution, noise, and distinction between cancerous and non-cancerous tumours is very subtle. Thus, this study presents an automatic classification scheme to classify breast cancer into normal, benign and malignant, which covers background detection, image enhancement, pectoral muscles separation, selected features and classification processes. To this aim, this framework uses set of various techniques. First step we have achieved improvement on mammogram to improve the image accuracy based on this framework, after new method has been used for features extraction. A new method named Weighted Sparse Principal Component Analysis (WSPCA) is applied to select the distinctive features of the images of mammogram. The analysed mammograms of images are then identified as benign or malignant through decision tree by comparing the performance of Decision Tree with Support Vector Machine (SVM) and Bayesian classification on the MIAS data set. Decision Tree classifier is chosen to classify the mammograms using the above features as its input. The evaluations are carried out on the entire Mammography Image Analysis Society (MIAS) standard dataset. The proposed framework tested on MIAS data set achieved an overall accuracy of 90% with Decision Tree classifier and the perform accuracy of 97.8% using WSPCA features with Decision Tree classifier for sequential selection of benign versus malignant mammograms. Suggested method achieves good results when we have verified on various mammograms.

Keywords: *Chest Cancer, Mammograms, Feature Extraction, Weighted Features, Classification Techniques*

1. INTRODUCTION

Breast cancer is the most common malignancy and cause many deaths among women. The early detection is the only way to shun mastectomy, increase survival probability, and decrease mortality rate. Mammography is the most efficient way of screening for breast cancer patients which can diagnose a malignancy (cancer) up to two years before a lump can be aroused. Mammography cannot stop or decrease breast cancer but is helpful only in the early detection in order to reduce mortality rate (DeSantis et al., 2011).

There are a number of renowned and probable causes for chest cancer. These can be splitted into

(7) broad classes: hormonal factors, age, proliferate chest disease, family history of chest cancer, lifestyle factors and irradiation of the breast region at an early age [2][3][4][5][6]. Estimates show that between 10 and 30 percent of breast cancers are missed by radiation during routine screening. Defect of mammography errors in malignant or benign classification is very large. Statistics show that only 20% to 30% of chest biopsy cases are cancerous. Even though mammography facilitated with more precise breast diseases diagnostic [7], there are still 10-30% of malignant cases which are not identified due to different causes such as procedural issues in the imaging process, radiologists inefficiency in detecting abnormalities,

and misinterpreted abnormalities [8]. With the development of technology, Computerized enhancement, segmentation and detection of lesions (benign or malignant) are also being done for mammograms with high precision. Various computer-aided techniques are being developed for the enhancement and diagnosis of breast cancer as well as for assessing the breast cancer threat. Computerized examination in screening mammography has already produced promising results. People become more aware of computer applications in medical imaging. In this paper, enhanced Principle Component Analysis (PCA) was used to extract features. Although PCA has been widely applied in the area, but the features considered in this study have not been extracted before [9]. Further, these extracted features are reduced to the best features only. Features selection, that have been investigated and used for classification include but are not limited to Discrete Cosine Transform (DCT) (Kendall and Flynn, 2014) features, etc. Principal component analysis (PCA) (Bichen Zheng et al., 2014) is used to reduce the dimensionality of extracted features by removing the redundant ones. After features extraction and selection, next step is to fuse them in order to obtain the best features set. This process is accomplished by two variations of PCA as Sparse Principle Component Analysis (SPCA) [12] and Weighted Sparse Principle Component Analysis (WSPCA). The choice of the (ideally "small") number of principal components (PCs) to include into the description of the information without losing too much information was somewhat arbitrary [12]. In automatic classification of breast cancer, it is important to decide which parameters give the best differentiation between categories such normal, benign and malignant. The objective of the study is to create entirely automated techniques for image enhancement, pectoral muscle separation and classification of mammogram images into normal, benign (harmless) and malignant (cancer) categories on the basis of proposed features. An experiment is performed to judge the classification accuracy in the presence/absence of quantum noise. Some Discrete Cosine Transform (DCT) features are extracted and classified by using well known classifiers such as Decision Tree, support vector machine (SVM) and Bayesian [13][14]. The results show that there is a significant improvement in the classification accuracy rate after selected features. This study introduces (WSPCA) features used to classify mammograms into normal and abnormal categories in order to minimize false-positive result. Project is

ordered as follows: Introduction is displayed in stage first. stage second presents related work. stage third defines the suggested method. stage forth contains experimental outcomes and conclusion is presented in stage fifth.

2. BACKGROUND OF THE STUDY

Numerous classification schemes have been designed in literature [15][16][17][18] for characterization of malignant and benign breast lesions but tragically couldn't achieve the encouraging results due to their incompetence either in removing noise or lack of robust and differentiating features or selection of misfit classifier [19]. High detection rate is mainly depends upon proper and state-of-the-art pre-processing techniques (noise restoration, exclusion of non-breast areas, and visual enhancement due to poor quality images), discriminating features and sophisticated classifier harmonized with the nature of data to detect cancer in order to avoid misclassification problems [16]. Several studies (Liu et al., 2010) have been conducted in the literature to rule out the malignancy from mammographic images and unfortunately couldn't acquire the desired results. The possible reason for not attaining higher detection accuracy rate is the possibility of standard pre-processing techniques for enhancement, features selection and inclusion of unnecessary parts from breast such as pectoral muscles. Most of the researchers used already available techniques for preprocessing, they mainly focused on features extraction, selection and classification. It seems their lack of interest in preprocessing steps [21][22], while preprocessing bring the image to that standard where it can be best suitable for further processing such as features extraction and classification into normal, benign and malignant cases. Some of them used one type of transform based or shape features [23], rest did not check the various classifiers to select the best one according to available features, and they just used any one of those such as SVM or KNN [24][25][26]. Due to aforementioned reasons they were unable to achieve the higher accuracy rate in classifying mammograms into normal, benign and malignant cases. Hence, only a classification scheme with state-of-the-art pre-processing techniques, discriminating features with a suitable classifier can achieve higher classification accuracy rate that was the missing part in the literature [27][28]. Segmentation of breast area is significantly very important in automated examination of mammogram images [29]. The

main aim of segmentation in mammograms is to separate the breast tissue and unwanted regions from breast part (which are not part of breast and have no utility in breast cancer detection) in order to limit the area of interest. Only useful, correct and most discriminating extracted features from the mammogram images can produce better results for the diagnostic of abnormality and provide higher classification accuracy rate. Redundant, insignificant and non-representative features given to classifier as an input carry no weight in terms of accuracy rate and may yield misleading results [30]. The classification process is mainly depends on correct feature extraction methods. The extracted features should be capable to differentiate between normal, benign and malignant masses [31][32]. It is a demanding job for automatic techniques to extract good features set for classification in order to achieve promising results because malignancy detection depends upon the most representative and robust features [21]. The selection of suitable classifier according to nature of input features is the task of utmost importance at classification stage that may deliver state-of-the-art performance in classifying mammograms into normal, benign and malignant categories with higher accuracy rate. tables.

3. PROPOSED TECHNIQUE

The projected method is splitted into (4) major phases as presented in Figure 1: Enhancement by applying Histogram Equalization, Feature Selection, Tree Classifier. Every part of these four phases is defined below one after another.

3.1 Improvement for Image

In this phase, Histogram Equalization method has been used. The improvement is focused in flat regions of the image, which avoid over development of noise. It also decreased influence of edge shadowing.

3.2 Features Extraction

Features performed an important role in CAD environment. We have applied DCT feature for our projected method.

3.2.1 Discrete cosine transform (DCT)

Features Discrete cosine transform (DCT) is applied for converting the signal into its frequency parts. In image processing DCT attempts

to de-correlate the image information [33]. DCT has the ability to pack the image data into as few DCT coefficients as possible without any distortion [34]. DCT has the property of separability and symmetry. 2-Dimensional DCT of the input is presented by the following equation:

$$C(u,v)=\alpha(u)\alpha(v) \tag{1}$$

$$\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos \left[\frac{\pi(2x+1)u}{2N} \right] \cos \left[\frac{\pi(2y+1)v}{2N} \right]$$

Where $0 \leq u \leq N$, & $0 \leq v \leq N$, and

$$\alpha(u)\alpha(v) = \begin{cases} \frac{1}{\sqrt{N}} & \text{for } u \neq 0 \\ \frac{2}{\sqrt{N}} & \text{for } u = 0 \end{cases}$$

3.3 Feature Selection

In the past, researchers used to reduce the dimensions apply PCA here. Each PCs is basically a linear amalgamation of all the original features. This makes the results difficult to Explanation [35]. Various approaches have been attempted to overcome this problem. We present a novel technique called WSPCA applying LASSO (elastic net) to generate adjusted PCs with sparse loadings. Important features are selected based on their weights. The aim behind is to use WSPCA to construct a regression basis in which PCA is reconstructed and use LASSO to construct modified PCs with sparse loadings. Then important features are selected with adaptive feature’s weights to find the best loading vector corresponding the features to achieve high accuracy. The uncorrelated linear combinations are called principal components, which express maximal variations in the data. This provided the researchers with a method of transforming the original high-dimensional dataset into one of the much lower dimension. This method was devised inevitably at the cost of some information loss (variance) and limited ability to interpret new variables and analysis. SPCA can successfully derive sparse loadings. Despite of its positive aspects, SPCA is not efficient in identifying important features with high accuracy. It also lacks a better steps to choose its regulation parameter [9]. WSPCA uses strict criterion and flexible control for selected the important features. To fit our WSPCA models for both features weights expression arrays and regular multivariate features, an efficient

algorithm is proposed. In addition, we propose a novel form to calculate the total difference of the modified PCs. Further, the algorithm for WSPACA in parallel to PCA and SPCA is presented in detail with example: Let DCT features (variables) $F = (F_1, F_2, \dots, F_p)$ represent a p-dimensional random vector with a multivariate normal distribution. It is possible that some features correlate with one another. For instance, if the variables F_1 and F_2 are highly correlated, such that the correlation index between F_1 and F_2 approaches 0.9, then either F_1 or F_2 could be eliminated from the analysis as its role is duplicated by the other. By doing this, the basis of the original features is altered to a more efficient set by using linear combinations. In the general p-dimensional case, this leads to a candidate set of new features. The explained steps are presented in Algorithm 1.

Algorithm 1

Step 1: Suppose A beginning at V [1: k], the loadings of the headmost k (PCs).

Step 2: Assumed a constant $A = [\alpha_1 \dots \alpha_k]$, fix the next elastic net issue

$$X_w = \sum_{j=1}^n W_j X_j \quad j=1, \dots, n \quad (2)$$

Step 3: $B_{WSPACA} = \left(\left| \alpha_j^T X_w^T X_w \right|^{\frac{\lambda_j}{2}} \right) + \text{Sign}(\alpha_j^T X_w^T X_w) \quad , j=1, \dots, k \quad (3)$

Step 4: For a fixed $\beta_j = [\beta_{SPCA1}, \dots, \beta_{SPCK}]$, PCA can be found via compute the SVD of the features matrix, Calculate the

$$\text{SVD of } X_w^T X_w = UDV^T, \quad (4)$$

Then update $A_w = UV^T. \quad (5)$

Step 5: reiterate Steps 4-5, until concurrence.

Step 6: Normalization: $\tilde{V} = \frac{\tilde{W}_{WSPACA}}{\tilde{W}_{WSPACA}} \quad (6)$

In step 1. the presented PCs are the linear combinations of all original features, V is the response vector (non-zero components) and it is less than or equal to k, given an integer k with $1 \leq k \leq p$. In Step 2, A is a vector matrix. In Step 3, assumed variables of X are presented in (nxp) matrix, where n rows represent an independent feature from features (number of observations) and p is the number of variables (dimensions), where is spare coefficients, j be the predictors

for nonzero entries, is feature vector, $X^T X$ is represent (covariance matrix) transpose for vector matrix by row vector of features, where represents the norm in the constraint.

In the current research, in order to find the best number of features, λ is penalty by directly imposing a constraint on PCA and $\lambda_{1,j} = 0$ call SPCA criterion r. $B = (\beta_0, \beta_1, \beta_2, \dots, \beta_k)^T$ where its regression coefficients represent the optimal minimizing. In Step 4, SVD is a singular value decomposition, UD are PCs, the columns of V^T are the congruoung loading of the PCs eigenvectors, V diagonalizes the covariance matrix $X^T X$, U are called Eigen values of the covariance matrix, D is the diagonal matrix, which has the eigenvalues of covariance matrix. $X^T X$ and V are the Eigen – genes, which represent the sparse loading of feature matrix. In Step 6, W_j is weighted features, and, $\beta_j = [\beta_{SPCA1}, \dots, \beta_{SPCAj}]$. Then (X_w) was calculated, which represents weighted feature matrix. Where X is a new feature matrix of SPCA and represents 8 types of features.

Coefficients for WSPACA technique were obtained by minimizing both SPCA and weighted feature matrix. In Step 7, represents highly correlated by weighted features among all features, is penalty by directly imposing an constraint on PCA and $(\lambda_{1,j} = 0)$, represents to exclude redundant features with very little variation from other features that sufficiently represents it. This is where adaptive weights were used for penalizing different coefficients in the 1 penalty, Here, we can ignore the penalty part in calculating Step 8. Then, $A_w = UV^T$ was updated where PCs were selected for displaying the selected features. Thus, a large dimensionality decrease was realized. Then after (V_j) Normalization was calculated for approximated weighted sparse principal components.

Step 9 was where β_{WSPACA} was the WSPACA coefficient. Therefore, WSPACA gives more accuracy for important features than SPCA as shown in Figure 2. WSPACA represents advantages in a number of aspects, including calculation efficiency, high interpreted difference, and capability in high accuracy identifying significant for DCT features.

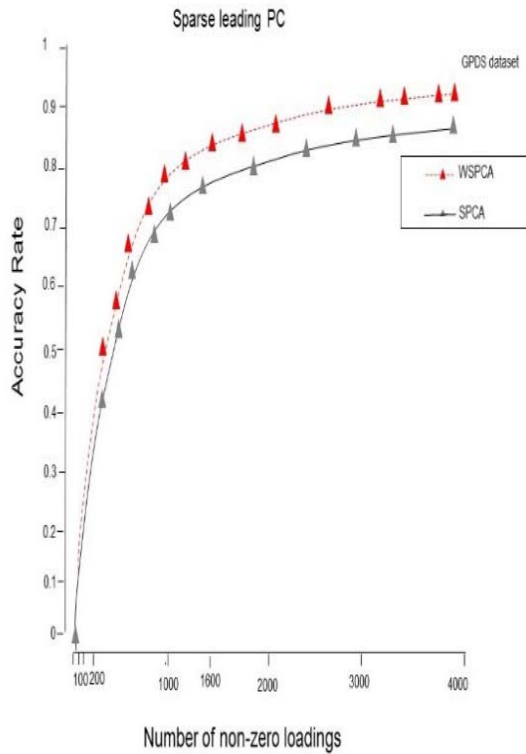
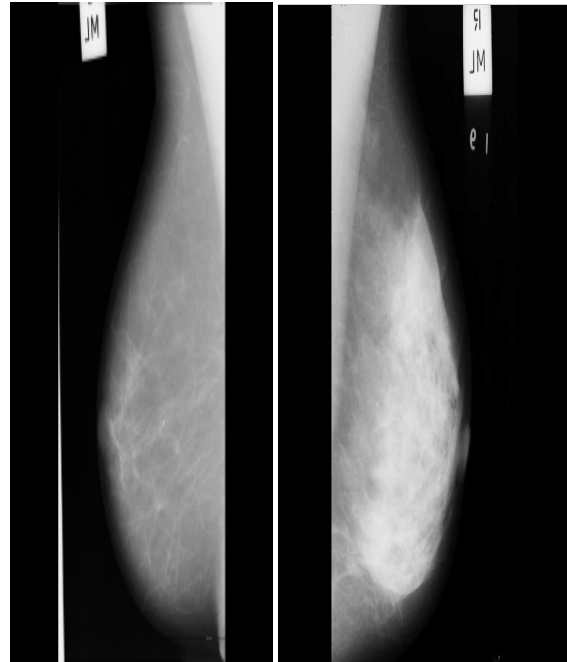


Figure 2: Scatter plot for DCT Features with WSPCA Applied to Find Leading PC

69 mammograms were diagnosed as being benign, 54 malignant as shown in Figure 4 and 207 normal as presented in Figure 5.

Improvement has been done by histogram equalization [37]. Outcomes have been display in Figure 6.



(a) Right view (mdb009) (b) Left view (mdb004)

Figure 3: Examples of mammogram images from MIAS Dataset

4. OUTCOMES AND DISCUSSION

We have applied widely presented datasets MIAS. The database is taken from the Mammographic Institute Society Analysis (MIAS) [36]. Each image of mammogram is of size 1024 x 1024 pixels, and resolution of 200 microns as shown in Figure 3. There are 322 mammograms of right and left chest of 161 patients in this database.

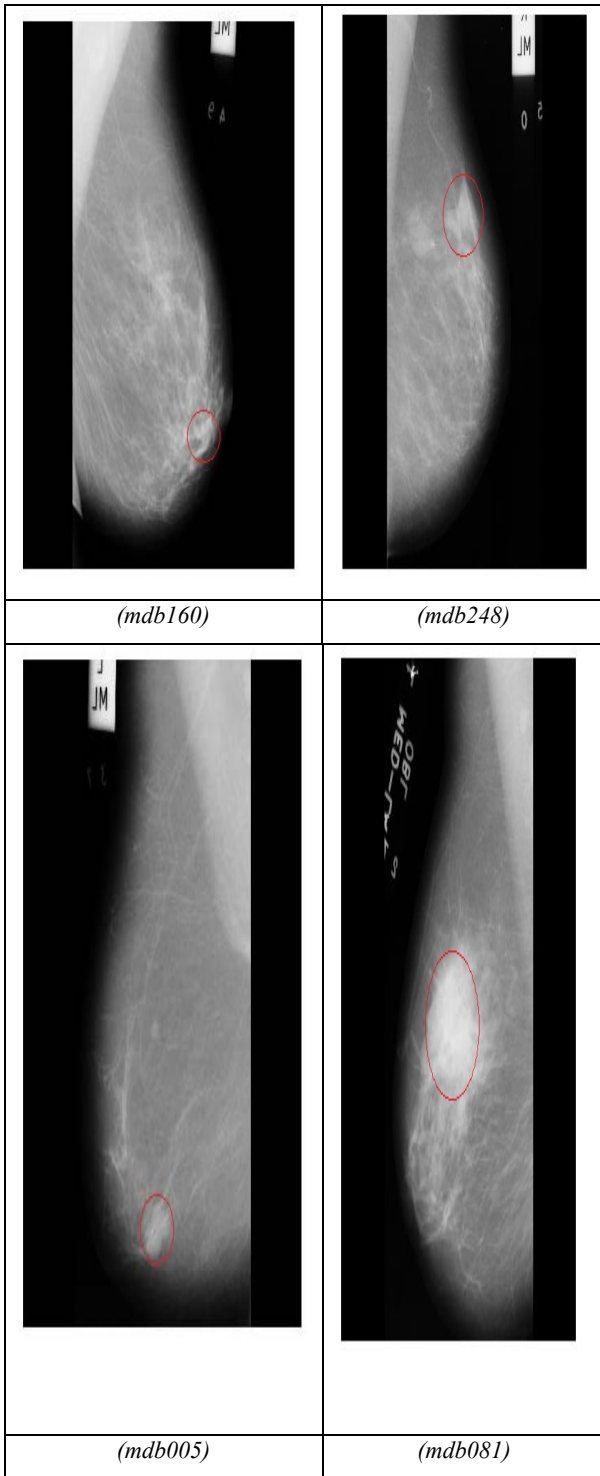


Figure 4: Benign mammogram images

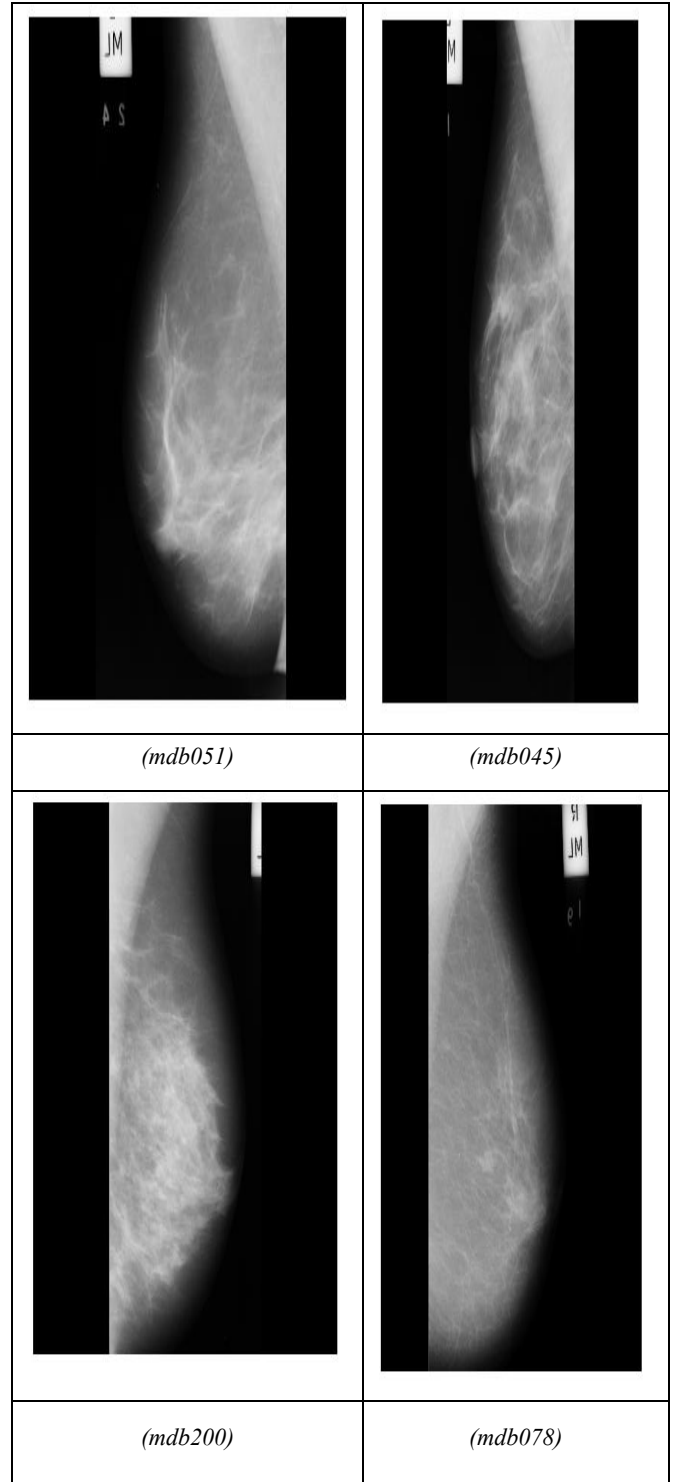


Figure 5: Normal mammogram images

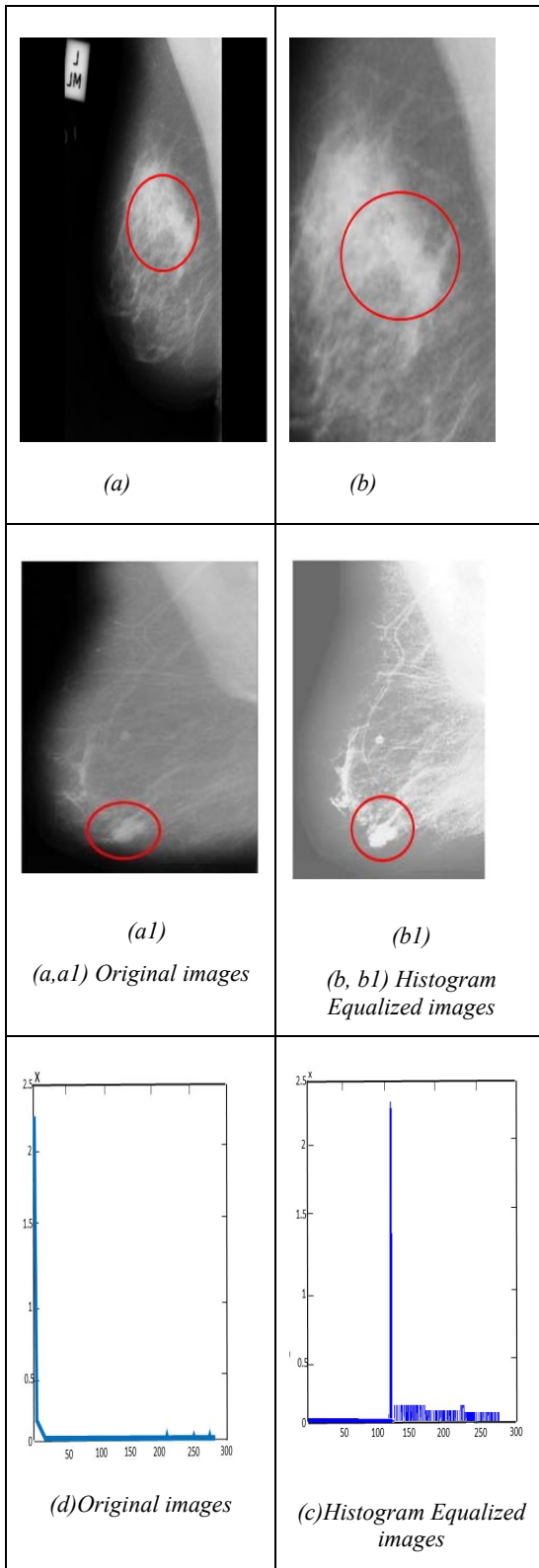


Figure 6: Show The Results by Histogram Equalization

We have verified the achievement of the Decision Tree by computing and examination of accuracy, specificity and sensitivity for malignancy discovery [38]. achievement of classifiers is computed by the next achievement measures. Features of the object is seem independent of each other in Decision Tree classifier [39][40]. In Decision Tree classifier database is split. various classifier outcomes with MIAS dataset and, various classifier outcomes using WSPCA features with MIAS dataset are displayed in Table 1 and Table 2.

5. COMPARISON WITH STATE-OF-THE-ART TECHNIQUES

This is a rigid task to critically compare proposed work with various existing methods in the literature due to certain reasons such as various mammographic databases, various samples within same datasets, sample size, different training and testing ratio. However, the main aim is to have common trends of performance comparison and proposed technique is compared with other existing techniques on the basis of performance measures such as accuracy. Results in Table 3. have clearly shown that the proposed method outperformed other existing techniques in accuracy. This excellent performance is due many factors, among others: enhancement, pectoral muscle separation, features selection and classification.

6. CONCLUSION

Suggested method is improved for test the breast cancer from mammograms. This technique achieves this testing in multiple stages. The preprocessing stage on image is done to improve image accuracy. Then features extraction and features selection has been achieved. Decision Tree has been applied for classification. All proposed methods are developed properly to attain the best possible results. MIAS dataset have been used for experimentation purpose. Performance measures are used to evaluate the capacity of proposed techniques and tools.

Screening mammography has two major concerns which are false-positive results and false-negative results. These both concerns are managed by developing a new classification scheme that accomplishes this task through proposed state-of-

the-art features, using empirically selecting suitable classifier and along with well contribution on newly proposed pre-processing techniques.

The Decision Tree classifier is implemented into two steps: mammograms are first classified as normal or abnormal, then the abnormal mammograms are further classified into benign and malignant. This study discussed the Fuzzy logic to enhancements technique to enhance image foreground. Segmentation of pectoral muscle is also introduced to extract the breast part from the mammographic image. This research also discussed in great length about new selected features (WSPCA) features along with their analysis. The sensitivity of mammography screening process is usually influenced by quality of image and radiologist's expertise level since the majority of screening mammograms are benign, hence the proposed classification scheme can help a radiologist by handling this issue as well. All tests display that the projected method provides especially perfect outcomes.

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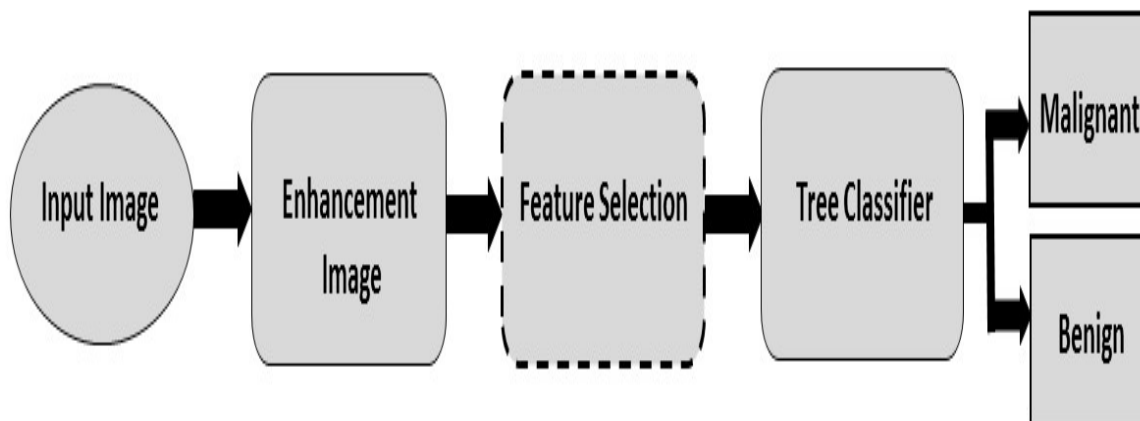


Figure 1: Projected Technique

Table 1: Comparison of Achievement Measurement of Various Classifiers of MIAS dataset

Methods	Accuracy	Sensitivity	Specificity
SVM	87	87.3	87.5
Bayesian	87.5	89.5	90
Decision Tree	90	90.3	90.7

Table 2: Comparison of Achievement Measurement of Various Classifiers using (WSPCA) features from MIAS dataset

Classification Methods using (WSPCA) Features	Accuracy	Sensitivity	Specificity
SVM	95	93	98.5
Bayesian	93.5	91.3	96
Decision Tree	97.8%	95%	100

Table 3. Comparison with state-of-the-art techniques

Author(s)/Year	Features/Classifiers	Accuracy
(Tahmasbi et al., 2011)	Shape and Margin features / Multi-Layer Perceptron classifier	93.6%
(Salve and Chakkarwar, 2013)	Discrete Wavelet Transform / Support Vector Machines	89%
(Serifovic-Trbalic et al., 2014)	Shape and Margin features / Back propagation neural network	90.4%
(Vaidehi and Subashini, 2015)	Automatic Characterization of Benign and Malignant Masses in Mammography/	93.7%
(Proposed Method, 2017)	(WSPCA Features) / Decision Tree classifier	97.8%