

## **Classification of mammograms for breast cancer detection using fusion of discrete cosine transform and discrete wavelet transform features.**

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### **Abstract**

**Radiologists mainly depend upon computer aided detection/diagnosis (CAD) in order to rule out the indirect symptoms of malignant cells such as microcalcifications, architectural distortion and ill-defined masses in digital mammograms. A mammogram is low-contrast image whose quality needs to be enhanced for clarity and better interpretation. For this purpose, Genetic Programming (GP) based filter is proposed, while the fusion of Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) features is also proposed which is used as an input to classifier. The proposed scheme accomplishes 96.97% accuracy, 98.39% sensitivity and 94.59% specificity for classifying mammograms into normal and abnormal (cancer) categories using SVM (Support Vector Machine) classifier and MIAS (Mammographic Institute Society Analysis) dataset.**

**Keywords:** Mammograms, Breast cancer, Enhancement, Micro-calcifications, Fusion, DCT, DWT.

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### **Introduction**

Breast cancer is the frequently diagnosed cancer, other than skin cancer, amongst females in U.S [1,2]. It is also forecasted that the breast cancer can be the foremost cause of casualties during forthcoming decades [3,4]. Various studies have demonstrated that early detection and proper treatment of breast cancer may diminish the mortality rate [5,6]. Mammography cannot stop or decrease breast cancer but are supportive only in detecting the breast cancer at early stages to increase the survival rate [2,6]. Regular screening can be a successful strategy to identify the early symptoms of breast cancer in mammographic images [7].

Enhancement of digital images is the foremost challenging task in computerized diagnosis of breast cancer using mammographic images [8,9]. Because of low contrast results [10], it is complicated to handle two major concerns namely; false-positive interpretations [11] and false-negative results [12]. False-positive results lead to surgeries with benign (non-cancerous) conditions. False-negatives let the early stage disease to develop to a more complicated stage with fewer rates of survival. Recently, an assortment of computer-aided methods have been examined and yielded different levels of success for the analysis of digital mammograms. They aim at highlighting to areas of interests like lesions, masses, etc, making them visible to the radiologists which are helpful in increasing the likelihood of early detection of breast cancer from mammographic images.

For noise restoration from mammograms, a method has been introduced by Naveed et al. [13] which are supposed to address this problem by combining various filters and neural network

based noise detection. An adaptive technique based on wavelet transform was proposed by Scharcanski [14] in order to restore the noise from mammograms; a mammogram image is decomposed into many scales and at each scale, coefficients related to noise are modeled by generalized Gaussian random variables and the shrinkage function at successive scales are combined and wavelet coefficients are applied. Langarizadeh et al. [15] used Histogram Equalization stretching and median filters equalization for the diagnostic of masses and micro-calcifications for the detection of breast cancer. Other findings also revealed that the quality of image is improved relatively by using selected techniques. The second pre-processing task is segmentation that is performed to delineate the unwanted regions from the mammograms which contains background removal and pectoral muscles separation [16]. An enormous part of mammogram carries background which is nothing to do with breast cancer detection so it is pertinent to remove it to restrict the region of interest where the tumor normally exists in order to obtain the better classification accuracy rate.

Texture features perform a significant task in CAD environment. DWT is a linear transformation where mammographic image information is divided into detailed and approximation parts. Detail components carry information of vertical, horizontal and diagonal sub-bands of the mammogram. These parts can be achieved by implementing the high pass and low pass filters on the mammogram respectively. DCT is used to convert the signal into its frequency parts. In image processing DCT is intended to decorrelate the image data. DCT features have been used for the recognition of face and some coefficients are selected to form feature vectors [17]. To reduce the dimensionality of features,

Principal Components Analysis (PCA) is applied. Park et al. [18] implemented PCA to reduce the features dimensions which are fed to a classifier. PCA attempts to reduce the huge data saving time and efforts for further image processing with no loss of significant information. It is necessary that the resultant features restrain the utmost information of input image data.

Numerous methods have been created to classify masses into benign and malignant categories. Lahmiri and Boukadoum [19], proposed a supervised learning technique for classification using SVM classifier with DCT features in order to classify mammograms into normal and cancer images with an accuracy of around 92.98%. Another study tested the robustness of extracted DCT features to discriminate between normal and suspicious of mammograms. They implemented KNN classifier achieving the sensitivity of 98% and specificity of 66% using the MIAS [20].

Zakeri et al. [21] used the shape and texture features for classification of mammograms into benign and malignant classes. They applied SVM classifier and achieved 95.00% accuracy, 90.91% sensitivity, 97.87% specificity, 96.77% positive predictive value (PPV), 93.88% negative predictive value (NPV), and 89.71% Matthew's correlation coefficient (MCC). In another research, the authors used the Bayesian Neural Network for the classification of

mammograms into normal, benign and malignant mammograms with accuracy rate of about 86.84%. The experiments were conducted using a total of 218 tissues samples including 99 normal, 68 benign and 51 malignant [22].

In this paper, a new GP based enhancement technique is introduced for noise restoration. Then region of interests (ROIs) are extracted by implementing background and pectoral muscles removal techniques. Subsequently, DCT and DWT features are extracted from the ROIs and are fused to get unique features set. Finally these features set are given to the SVM classifier to classify mammograms into normal and abnormal (either benign or malignant) mammograms.

## Material and Methods

MIAS dataset is used for experimentation purpose in this study which is a standard and publicly available dataset. The size of each mammogram is  $1024 \times 1024$  pixels and 200 micron resolution. MIAS contains a total of 322 mammograms of both breasts (left and right) of 161 patients. Out of which 61 are labeled as benign, 54 as malignant and 207 are normal mammogram [23]. The complete scheme in this study was implemented using the Image Processing Toolbox in MATLAB 8.0. The whole methodology comprised of the four sequential steps as shown in figure 1.

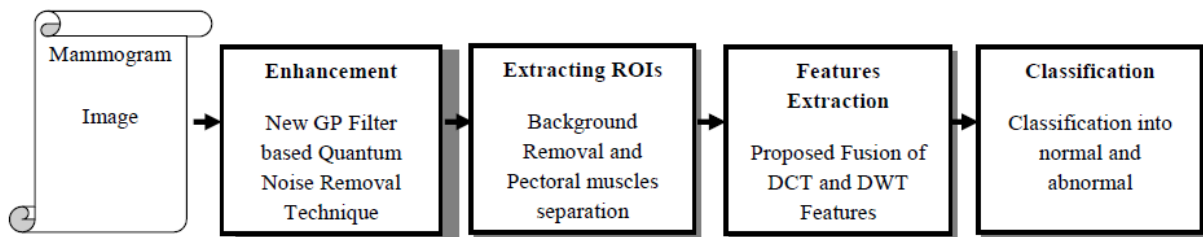


Figure 1. The schematic diagram of methodology.

### Genetic programming (GP) based quantum noise removal filter

GP is a machine learning procedure which optimizes a population of computer programs in order to perform a particular assigned computational job. The best optimal solution in the numerical function form is generated through GP evolution cycle. For the proposed filter, GP is supposed to create a numerical optimal evolved expression for mammogram image restoration that optimally combines and exploits dependencies among features of the degraded/blurred mammogram image. To develop such type of function, at first stage, a set of feature vectors is generated by taking a small neighbourhood around each pixel. Then, at second stage, the estimator is trained and produced through GP procedure which has an automatic way of selecting and combining the beneficial feature information under a fitness criterion. These are the same features which make the feature vector at first level. Finally, the created function (equation 1) is used to estimate the mammogram image pixel intensity of the degraded

mammographic images. The performance of the filter function is estimated using various degraded mammogram images. The proposed filter effectively removes the noise and enhances the mammograms for further processing. The newly proposed technique is divided into three parts which are described above and shown in Figure 2, Table 1 and Equation 1 respectively.

- Features Extraction Module
- Evaluating Optimal Function using Genetic Programming
- Estimation of Restored Value

### Extracting ROIs

After the noise removal from all mammograms, now they are fit for further processing so the next step is to extract ROIs. A mammogram contains background (black portion) and pectoral muscles which are not part of breast so it is necessary to remove these unwanted regions in order to focus on region of ROIs only where the probability of cancer exists. Removal of these extra regions not only increases the performance but also decreases the complexity of a classifier. The background is

removed by implementing the technique used by Nagi et al. [24] and pectoral muscles are separated by using the method of Naveed et al. [13]. Now the resultant mammogram image is the breast part (ROI), this is used to extract the features in forthcoming section.

Parameters set,  $\theta = \{ \text{Functions set, Constants set} \}$   
 Constants set: random constants are in the range of [0-1]

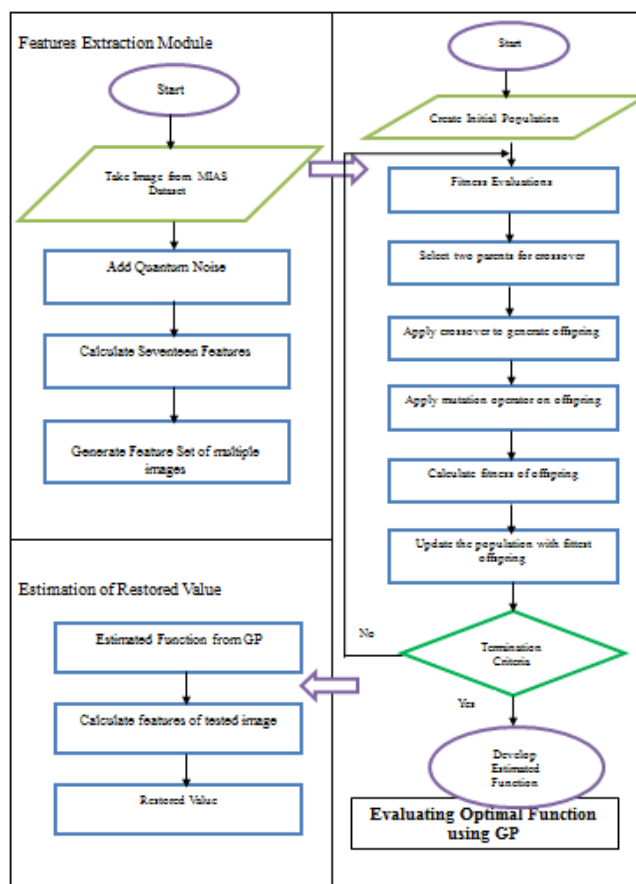


Figure 2: The GP filter mechanism.

Table 1. GP parameters setting under minimum Root Mean Square.

Parameters	Set values
Fitness criterion	Minimization of RMSE $RMSE = \sqrt{\frac{1}{L \times J} \sum_{i=1}^L \sum_{j=1}^J (f(ij) - \hat{f}(ij))^2}$
Selection method	Roulette Wheel
Population size	400
Generations	3000
Population Initialization	Ramped half and half with maximum depth 5
Operators probabilities	Variable crossover/mutation ratio
Crossover Probability	0.5
Mutation probability	0.25
Reproduction Rate	0.25
Function set	+ , - , * , / , ^ , log , sin , cos , exp
Terminals/non-terminal set	Variable set of feature vectors, $x = (x_1, \dots, x_{17})$

Error (RMSE) fitness criterion

$$F(x_1, \dots, x_{17}) = x_7 + \sin(x_2 + x_6 + x_{10} + x_{19}) + 0.352 \times (x_{17} + \cos(x_{12} + ((x_{13} \times (x_{15} + x_{13} + x_9 + x_2)) \times x_1) + ((x_5 \times x_6) \times \sin(x_8) \times x_9) \times 0.419) + \sin(x_{11} + x_7) \times 5(x_7 + x_8) / x_9 + (0.502 \times ((x_5 + x_9) + 0.312)) \times (x_8 + (x_7 + (x_{17} \times (0.102 \times x_5))) \times (x_2 + (x_{13} / \sin(\exp(x_7 + x_9))) + x_2) + 0.243) + (\log(x_6) + ((x_{13} + (x_{12} + x_6))) \times x_{14})) + \sin(x_{11} + x_5) \times 4(x_6 + x_2) / x_{11} + (0.73 \times ((x_4 + x_1) + 0.816))(1)$$

**Features extraction**

The accurate classification and diagnostic rate is mainly depends upon robust features, particularly while dealing with mammograms. DWT and DCT are applied on mammographic images. Then twelve (12) DCT and eight (8) DWT features have been experimentally selected using principal component analysis (PCA). This set of 20 features has been fused (combined) to form a single vector which is fed to SVM classifier. Similarly features of all images have been extracted which are given to the classifier in order to distinguish between normal and abnormal mammograms in the subsequent section.

**Classification**

The process of classifying features into their respective classes, such as normal and abnormal or benign and malignant, is known as classification. In binary classification problems like normal/abnormal, SVMs perform better comparatively. SVM is implemented in this paper using hold-out technique for splitting the entire dataset into training and testing components, where 70% of the mammograms are allocated to the training set and the remaining 30% to the testing set from both classes. The results are presented in the upcoming section.

**Experimental Results**

The proposed GP filter effectively restores the noise from mammograms which is beneficial in getting higher diagnostic rate (differentiation between normal and abnormal mammograms). The images shown in figure 3 (a-b) however, are the original noise-free images and their respective noisy images are shown in figure 3 (a1-b1) where quantum noise is manually added using Matlab 8.

There does not exist such dataset that carry this kind of noise [24-27]. It is observable that Poisson noise has been eliminated effectively and the sharpness of the images are preserved-the images almost look like their original (Figures 3, a2-b2). This shows the efficacy of the proposed GP filter in noise removal.

In order to reaffirm the performance of the proposed GP filter, some further experiments were conducted. The classification accuracy in the presence/absence of quantum noise is computed using DCT features by using some famous classifiers like SVM, ANN (Artificial Neural Networks), k-NN (k-nearest neighbourhood) and Bayesian.

The results shown in table 2 and figure 4 have demonstrated that the proposed GP filter has successfully enhanced the classification accuracy rate by more than 6%.

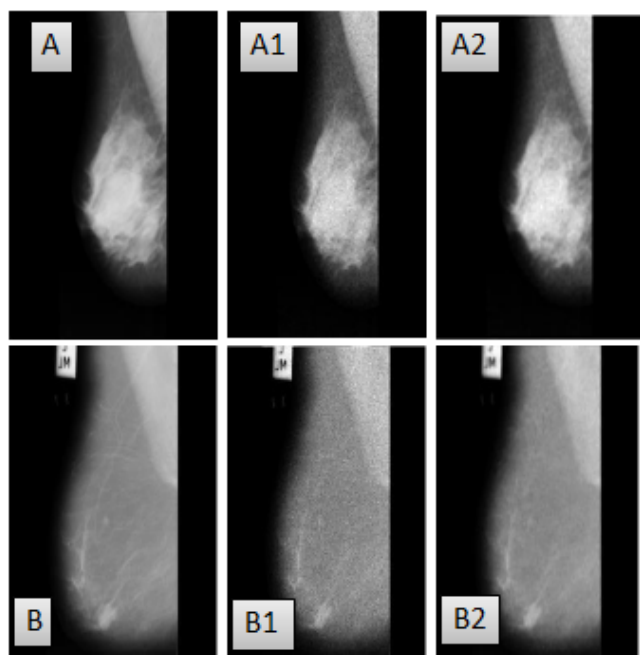


Figure 3. Noise removal: (a-b) Original images (a1-b1) Noise added images and (a2-b2) Filtered images.

Table 2. Classification accuracy (%) of proposed GP based noise removal filter using DCT features.

Classifiers	Accuracy (%)	
	Without noise removal	With noise removal
NN	82.31	88.65
Bayesian	83.87	87.99
KNN	79.05	85.56
SVM	86.29	93.89

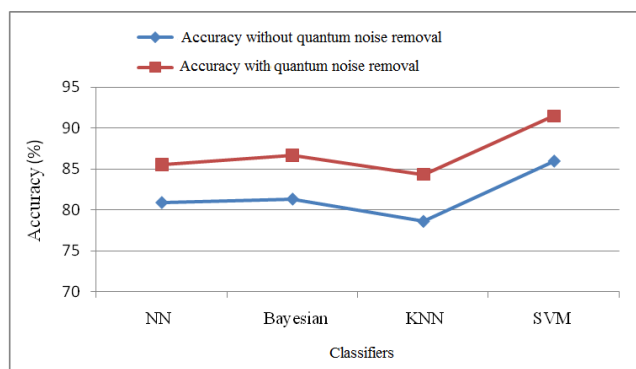


Figure 4. Classification accuracy of proposed GP based noise removal filter using DCT features.

This substantial improvement proved the supremacy of GP noise removal filter and as well as SVM classifier. It is also

demonstrated that the removal of noise is very important before classification into normal and abnormal mammograms.

After the noise removal, the background of the image is removed which contains annotations and black portion. Once the background is removed, then the pectoral muscles have been removed since they are not part of breast.

Now the resultant mammogram image is the part which contains only the breast region where the probability of cancer exists. The proposed fused (DCTODWT) features from this part are extracted and fed to SVM. The results are shown below in table 3.

Table 3. Classification accuracy of normal and abnormal mammograms Using fusion of (DCTODWT) features.

Index	SVM
Accuracy	96.97%
Sensitivity	98.39%
Specificity	94.59%

The above Table depicts the overall accuracy rate of SVM classifier with 10-fold cross validation technique to distinguish between normal and abnormal mammograms. The promising results revealed that the newly proposed features are discriminating.

### Conclusion

The produced classification results are very much promising with 96.97% accuracy, 98.39% sensitivity and 94.59% specificity. Such type of encouraging results are the indicative of the state-of-the-art newly proposed GP based noise removal technique and best performance of proposed fusion of (DCTODWT) features in order to differentiate between normal and abnormal mammograms with higher accuracy rate.

The proposed method may provide an adequate support to the radiologists in differentiating between normal and abnormal mammograms, as a second opinion. The algorithm successfully differentiates normal and abnormal mammograms with high accuracy, sensitivity and specificity.

### Discussion

In the present paper, a fully computerized classification scheme is proposed which focuses on identifying normal and abnormal mammograms. The main contribution of this paper is the newly proposed GP filter which addresses the major problem of mammograms, which is removal of noise. Then, the second contribution is the proposed fusion of (DCTODWT) features.

These fused features proved highly fruitful results in differentiating between normal and abnormal mammograms with higher accuracy rate. The notable advantage of this proposed classification scheme can also be the reduction in false positive rate. The limitations of this work includes the large amount of time required to train GP filter, once it is

trained properly then it works efficiently and produces better results.

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