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Mammogram Analysis using League Championship Algorithm Optimized Ensembled FCRN Classifier

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Abstract

An intelligent mammogram diagnosis system can be very helpful for radiologist in detecting the abnormalities earlier than typical screening techniques. This paper investigates a new classification approach for detection of breast abnormalities in digital mammograms using League Championship Algorithm Optimized Ensembled Fully Complex valued Relaxation Network (LCA-FCRN). The proposed algorithm is based on extracting curvelet fractal texture features from the mammograms and classifying the suspicious regions by applying a pattern classifier. The whole system includes steps for pre-processing, feature extraction, feature selection and classification to classify whether the given input mammogram image is normal or abnormal. The method is applied to MIAS database of 322 film mammograms. The performance of the CAD system is analysed using Receiver Operating Characteristic (ROC) curve. This curve indicates the trade-offs between sensitivity and specificity that is available from a diagnostic system, and thus describes the inherent discrimination capacity of the proposed system. The result shows that the area under the ROC curve of the proposed algorithm is 0.985 with a sensitivity of 98.1% and specificity of 92.105%. Experimental results demonstrate that the proposed method can form an effective CAD system, and achieve good classification accuracy.

Keywords*: Computer-Aided Detection, mammograms, League Championship Algorithm, Fully Complex valued Relaxation Network*

1. Introduction

Breast cancer is a fatal disease that originates from breast tissue. It causes more deaths than any other cancer among women. It is a progressive disease. The screening is very important, because the disease is easily detectable, if the tumor is found early and the quality of the patient's life will not be affected due to its non-invasive diagnosis. In India, 37 per 1 lakh women population are vulnerable for breast cancer. India sees 4.6 lakh women have breast cancer annually. Digital mammography has been shown to be an effective tool for early detection of breast cancer [1]. However, it is insufficient for detecting non-calcified small cancers hidden within the dense fibro-glandular tissue [2].

Computer-aided methods make easy to localize the suspicious tumor area and it aids the radiologists to have a second opinion on their results. Hence, Computer-Aided Detection (CAD) systems and the related techniques have been attracting the attention of both researchers and radiologists [3, 4]. In a CAD system, feature extraction and selection of prominent features is an important step. The features of digital images are extracted directly from the spatial data or from a different space. Special data transforms such as wavelet or curvelet are employed to extract specific characteristics from the data. Donoho [5] framed a new multi-scale transform called, curvelet transform. It is more powerful for representing the boundaries and other singularities along curves than the other conventional transforms. It provides constant, efficient and near-optimal depiction. Mohamed Meselhy Eltoukhy, et al., [6] compared the wavelet and curvelet transform for diagnosing the breast cancer and have demonstrated the superior performance of curvelet transform. The fractal concept was framed by mandelbrot [24]. Saraswathi D, et al., [18] proposed a high sensitivity CAD system to detect calcifications in mammograms and have achieved 98.18% classification accuracy using curvelet fractal textures and ensembled FCRN classifier. A limitation of this work is choosing the appropriate number of hidden neurons. It is addressed in this work by optimizing the number of hidden neurons in ensembled FCRN classifier using League Championship Algorithm (LCA).

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Extracting the prominent features is an important step in the classification task. A great deal of research work has happened towards extracting the features and selecting the prominent among them from microcalcification clusters using various techniques [7-13]. Also, optimization of a suitable classifier plays a vital role in increasing the accuracy. The League Championship Algorithm (LCA) is a recently proposed algorithm for global optimization, which mimics the championship process in sport leagues [14]. It is a sport-inspired optimization algorithm, introduced by Ali Husseinzadeh Kashan in 2009. Since then, it has drawn enormous interest among the researchers due of its potential efficiency in solving several optimization problems and real-world applications. Wei Xu, et al., [15] proposed an improved league championship algorithm with free search strategy. They have shown that this algorithm is superior in respect of global searching performance and convergence speed.

This paper, describes an LCA optimized ensembled FCRN classifier, suitable for diagnose the abnormalities in digital mammograms by extracting the curvelet fractal textures. LCA is used for optimizing the number of neurons in the hidden layers of ensembled FCRN classifier. The performance of the proposed classifier has been extensively evaluated and the results obtained are presented. The paper is organized as follows. A complete CAD System for breast cancer diagnosis is described in Section II. Section III presents the results and discussions in detail. Section IV concludes the work.

2. CAD System

The proposed CAD system for mammogram diagnosis is shown in Figure 1. First, breast mammograms are preprocessed using DCT sharpening. Features are extracted from the enhanced images using discrete curvelet transform. Prominent features are selected from the curvelet layers using fractal measures. These selected features are used to train the proposed League Championship Algorithm Optimized Ensembled Fully Complex valued Relaxation Network (LCA-FCRN) classifier for abnormality detection.

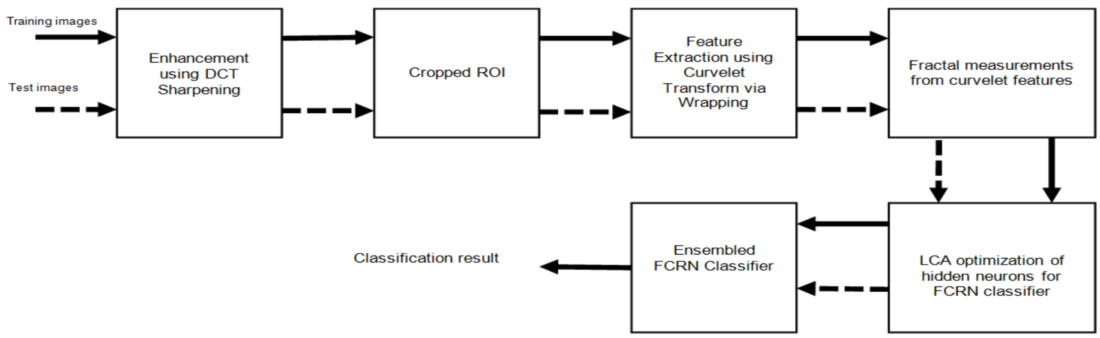


Figure 1. Proposed CAD system for Mammogram Diagnosis

2.1. Image Database

MIAS Database consisting of 322 images has been used for this work. Mammographic Image Analysis Society (MIAS) is an organization of UK research groups interested in the understanding of mammograms and it has created a database of digital mammograms [16]. The distribution of cases in the MIAS dataset is summarized in Table 1.

Table 1. The distribution of cases from the MIAS dataset

Class	Benign	Malignant	Total
Microcalcification	12	13	25
Circumscribed mass	19	4	23
Spiculated mass	11	8	19
Ill-defined mass	7	7	14
Architectural distortion	9	10	19
Asymmetry	6	9	15
Normal	0	0	207
Total	64	51	322

2.2. Preprocessing

The mammogram images from MIAS database are pre-processed using DCT sharpening. Most of the coefficients in the DCT domain are small and they are quantized to zero. As a result, manipulating the data in the DCT domain is an efficient way to save the computer resources. The DCT sharpened images, shown in Figure 2, can be noted to be better in terms of contrast enhancement.

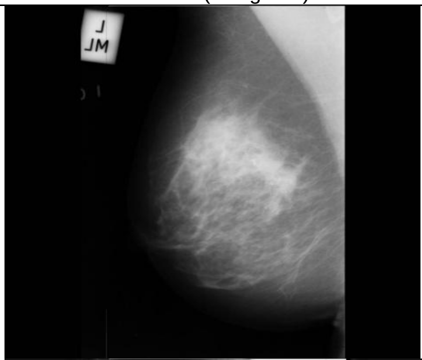
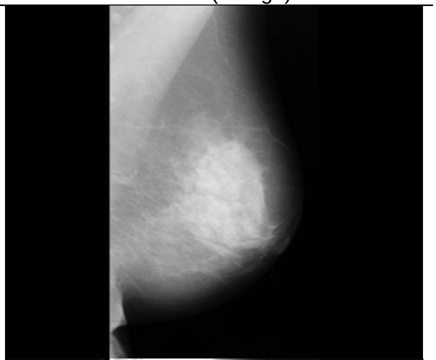
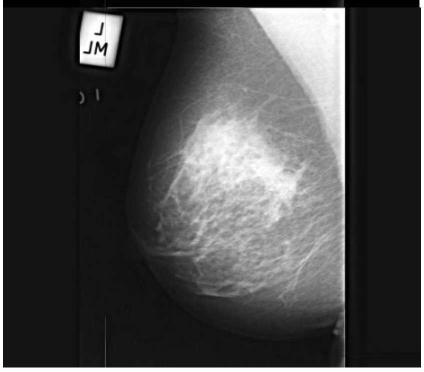
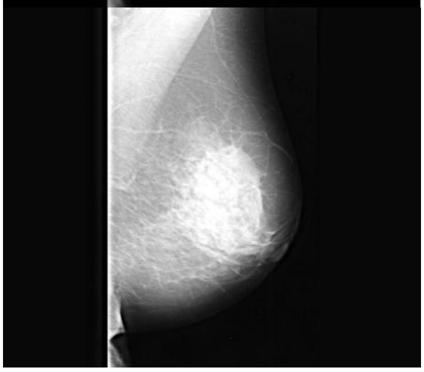
Type of Image	mdb209 (Malignant)	mdb212 (Benign)
Original Image		
Preprocessed Image by DCT Sharpening		

Figure 2. Comparison of original image with preprocessed Image

2.3. Feature Extraction

Feature extraction defines a set of features which, most efficiently, represent the information that is important for analysis and classification. The authors in [17], used five different types of features, namely, Binary Object Features, RST Invariant Features, Histogram Features, Texture Features and Spectral Features for mammogram classification. Texture features capture the granularity and repetitive patterns of regions within an image.

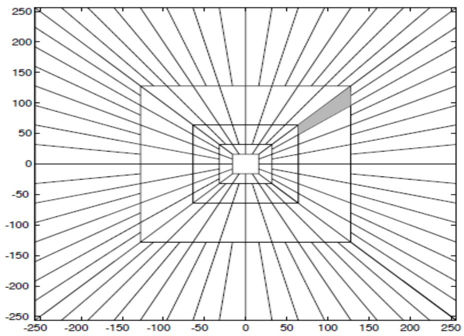


Figure 3. Curvelet tiling, the shaded region represents the wedge shape layer

In this work, texture features are extracted from mammograms in the curvelet domain. Fractal measurements are made from each of the curvelet scale layers and then the feature vector is obtained to be given as input to the classifier [18]. Fast Discrete Curvelet transform was introduced by Candes and Donoho [19], using a “wrapping” algorithm which is simpler, faster, and less redundant than the existing transforms.

Figure 3 presents the curvelet analysis method. Conceptually, the curvelet transform is a multiscale pyramid with many directions and positions at each length scale, and needle-shaped elements at fine scales. However, this pyramid is nonstandard. The approximate scales and orientations are supported by a generic ‘wedge’. Two parameters are involved in the digital implementation of the curvelet transform: number of resolutions (scales) and number of angles (orientations) at the coarsest level. The image is decomposed into subbands at different scales. This results in multiresolution subbands comprising of curvelet coefficients. An increase in scale and/or orientation results in more subbands that may carry redundant information. Hence, it is necessary to select the significant subbands for extracting features.

The ROI (Region of Interest) is cropped from the enhanced image and decomposed using curvelet transform at different levels of scales and orientations. Decomposed curvelet layers have one approximate subband and a specified number of detail coefficient subbands (equal to number of orientations). The approximate subband contains the low-frequency components and the rest capture the high-frequency details along different orientations. Maximum variance criterion is used to select the optimum subband for feature extraction.

Procedure to obtain curvelet coefficients is given below:

1. Apply 2D FFT and obtain Fourier samples $\hat{f}[n_1, n_2]$, $\frac{-n}{2} \le n_1, n_2 < \frac{n}{2}$.

2. For each scale *j* and angle *l* , form the product $\tilde{U}_{j,l}[n_1, n_2].\hat{f}[n_1, n_2]$ where $\tilde{U}$ is the “Cartesian” window.

3. Wrap this product around the origin and obtain $\hat{f}_{j,l}[n_1, n_2] = W\left(\tilde{U}_{j,l}\,\hat{f}\right)[n_1, n_2]$ where the range for n_1 and n_2 is $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$; (for angle in the range $\left(-\frac{\pi}{4}, \frac{\pi}{4}\right)$).

4. Apply the inverse 2D FFT to each $\hat{f}_{j,l}$, to obtain the discrete curvelet coefficients C.

The number of curvelet coefficients obtained is extremely large. If all the coefficients are used, the classification algorithm becomes too complex. The computational complexity becomes high. Fractal dimension (FD) measurements are used to estimate and quantify the complexity of the shape or texture of objects. Hence, fractal measurements are calculated from the curvelet coefficients. The authors in [18], have reported an increased classification accuracy with curvelet fractal features.

2.4. LCA optimized FCRN Classifier
2.4.1. League Championship Algorithm

LCA is a newly proposed stochastic population based algorithm for continuous global optimization which imitates a championship situation, where synthetic football clubs participate in an artificial league for a number of weeks. A number of individuals making role as sport teams compete in an artificial league for several weeks (iterations). Based on the league schedule in each week, teams play in pairs and their game outcome is determined in terms of win or loss, given the known playing strength (fitness value) along with the particular team formation/arrangement (solution) followed by each team. Keeping track of the previous week events, each team devices the required changes in its formation (a new solution is generated) for the next week contest and the championship goes on for a number of seasons (stopping condition). The way in which a new solution is associated with a LCA team, is governed via imitating the match analysis process followed by coaches to design a suitable arrangement for their forthcoming match. In a typical match analysis, coaches will modify their arrangement on the basis of their own game experiences and their opponent’s style of play [20].

The following pseudo-code describes in detail, the steps of the LCA algorithm.

1. Initialize the league size (L) and the number of seasons (S); week (t) = 1;
2. Generate a league schedule;
3. Initialize team formations (generate a population of L solutions) and determine the playing strengths F(X)) along with them. Let the initialization be also the teams' current best formation;
4. While t = S (L−1).
5. Based on the league schedule at week t, determine the winner/ loser among every pair of teams using a playing strength based criterion;
6. t = t + 1;
7. For i = 1 to L.
8. Devise a new formation for team i for the forthcoming match, while taking into account the team's current best formation and previous week events. Evaluate the playing strength of the resulting arrangement;
9. If the new formation is the fittest one (that is, the new solution is the best solution achieved thus far for the ith member of the population), then choose the new formation as the team's current best formation;
10. End for
11. If mod(t, L−1) = 0.
12. Generate a league schedule;
13. End if
14. End while.

There are two key steps when applying LCA to optimization problems: the representation of the solution and the fitness function. The searching is a repeat process, and the stop criterion is either the maximum iteration number or the minimum error condition. The League Championship Algorithm is illustrated in Figure 4.

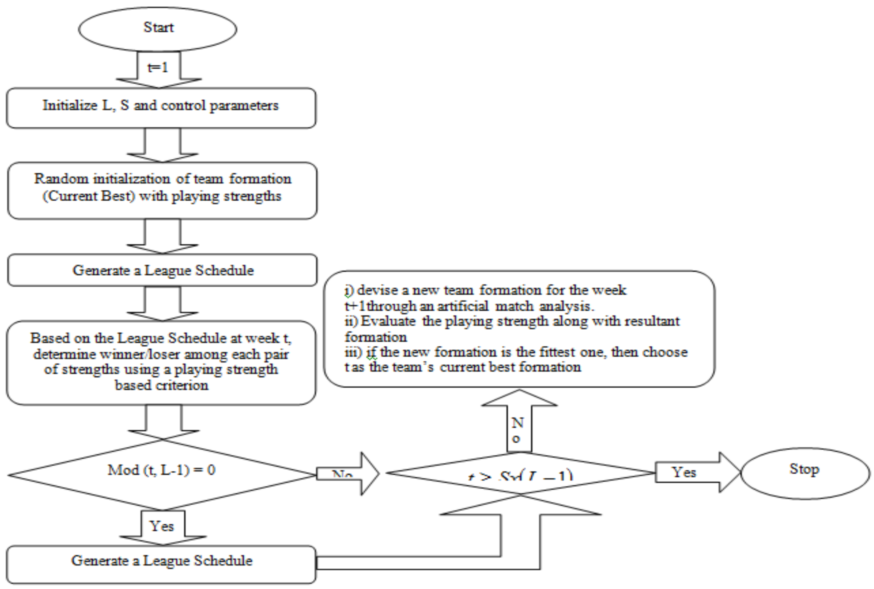


Figure 4. League Championship Algorithm

2.4.2. LCA Optimized FCRN Classifier

Fully Complex-valued Relaxation Network (FCRN) is a single hidden layer feed forward network. FCRN network is a complex-valued network used for approximating both the magnitude and phase of the complex-valued signals accurately. Hence, the error function J can be represented in terms of both the magnitude and the phase of the complex-valued error, of the form:

$$J = \left[\ln\left(\frac{M^t}{\hat{M}^t}\right)^2 + \left(\phi^t - \hat{\phi}^t\right)^2 \right]$$

Which can also be written as:

$$J = \left[\ln\left(\frac{y^t}{\hat{y}^t}\right) . \ln\left(\frac{y^t}{\hat{y}^t}\right)' \right] \quad (1)$$

Where M^t and ϕ^t are the true/target magnitude and phase of the *t*-th sample and $\hat{M}^t$ and $\hat{\phi}^t$ are the predicted magnitude and phase of the *t*-th sample. $\ln\left(\frac{y^t}{\hat{y}^t}\right)'$ is the complex conjugate of $\ln\left(\frac{y^t}{\hat{y}^t}\right)$ in equationn (1).

In this work, fully connected feed forward FCRN network is used. The optimal network architecture is obtained by optimizing the weight error in the hidden layer using LCA algorithm. Let the input layer neurons are represented by n_i and the output layer neurons are represented by n_o. For the entire configuration in the network architecture, fixed number of neurons is used in the input and output layer.

The predicted output $\hat{y}^t$ of FCRN with k hidden neurons is given by:

$$\hat{y}^t = \exp\left(\sum_{j=1}^{k} w_{kj} h_t^j\right); \; k = 1,2,....n$$

Where $h_t^j = \operatorname{sech}\left[v_j^T \left(z^t - u_j\right)\right]; \quad j = 1,2,.........K$

h_t^j is the response of the *j*-th hidden neuron for the given input z^t, v_j^T is the complex-valued scaling factor and u_j is the complex valued center of the hidden neurons. Hyperbolic secant activation function is used in the hidden layer and exponential activation function is used in the output layer as in eqn. (2). In order to optimize the error weights, Mean Square Error (MSE) is used as fitness function in LCA as in equationn (3).

$$MSE = sum(t\arg et output - actual\, output)^2$$

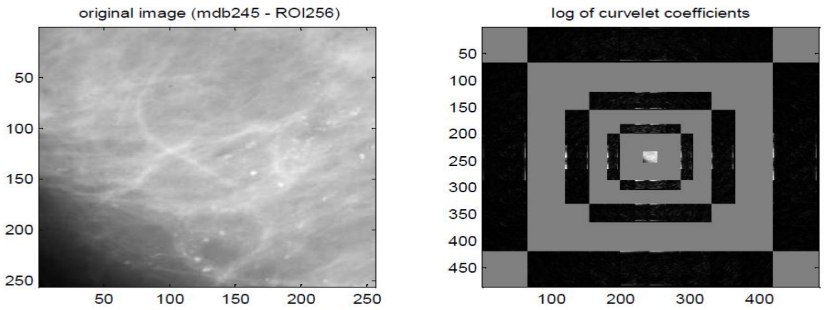
$$MSE = \sum_{t \in T} \sum_{k=1}^{n_0} \left(y_k^t - \hat{y}_k^t\right)^2 \quad (3)$$

The best solution is evolved using this fitness function of LCA-FCRN algorithm. The optimally designed LCA-FCRN has three-layer feedforward architecture: an input layer, hidden layer and an output layer. The number of input layer neurons is equal to the number of extracted curvelet fractal texture features. The number of hidden layer neurons is optimally added to the FCRN. The output layer has one neuron which classifies the input mammogram image as normal or abnormal.

Ensembled FCRN has been shown as a good classifier for mammogram analysis [17]. In this work, two LCA-FCRNs have been used. Therefore, the input data can produce diverse FCRN neural network classifiers, which are combined using hierarchical fusion (majority vote algorithm). The optimal hidden neurons are used in these two FCRNs and the parameters of each LCA-FCRN classifier are different, then each classifier will represent that knowledge in a slightly different way and that will create diversity. The classifiers with such diversity allow for the learning of different characteristics in digital mammograms. These networks provide different decisions for the same input data and combining them improves the performance in terms of accuracy and consistency. Suspicious areas in digital mammograms have different characteristics and therefore, an optimized ensemble will learn and generalize better than an individual classifier.

3. Results and Discussions

MIAS dataset images are used to evaluate the performance of the proposed CAD system. Figure 5 shows the cropped input image and its curvelet layers.



(a) (b)

Figure 5. (a) Cropped input image and (b) curvelet layers (4-scale and 16-orientation curvelets)

For example, mdb245 MIAS image is a malignant image of size 1024×1024. It is enhanced using DCT sharpening. The enhanced image is cropped and sized to 256×256. Utmost care has to be taken while cropping the abnormal image; else, the tumor tissues are likely to be missed out, which in turn will increase the False Negatives. Input image can be resized to 256×256, but the problem is, it may affect the resolution. Cropping retains the same resolution as that of the input image. Curvelet coefficients are extracted from the cropped image. On decomposition, the curvelet consists of one approximate band of size 21×21 real values of low frequency coefficients and other subbands of high frequency coefficients. The outer most layer is the highest frequency coefficient layer of size 256×256.

Table 2 summarizes the curvelet coefficients cell structure for an image. The number of curvelet coefficients obtained is extremely large for a single image. If all these coefficients are used, the classification algorithm becomes too complex. Hence, the fractal measurements are made and 24 optimal features are computed for each image. These features are given to the optimized ensembled LCA-FCRN classifier to classify whether the input image is normal or abnormal. MIAS database consists of 322 images. Among these, 50% of the images (161) used for training and 30% of the images (97) used for testing and the remaining 20% (64) images used for validation. Cross-validation is another method for training process. It controls the error on an independent set of data and stops training when this error begins to increase. In this work, 10-fold cross validation is performed and average classification accuracy is calculated.

Parameters used in LCA optimization: League size, L=161(same as the number of input feature vectors); Number of seasons, S=1000; ψ_1 =2; ψ_2 =2; p_c=0.7 (preserving diversity among solutions generated), Team size=1x161, initial population will be of size 161x24.

A Particle Swarm Optimization (PSO) based ensembled FCRN classifier is also built for comparison. The parameters used for PSO optimization: Inertia weight = 0.1 to 0.9 (varies linearly with the iterations); Number of particles=161; Learning factors φ_1 and φ_2 = 2; Maximum iteration number=1000 (yielding the total number of 10000 function evaluations).

Comparison is done between two optimization algorithms such as LCA and particle swarm optimization (PSO) algorithm [21]. The results show that LCA-FCRN classifier with curvelet fractal features input yields higher classification accuracy compared to PSO-FCRN classifier. This increased accuracy is due to the fact that the LCA has the capability to select the optimal number of hidden neurons through a number of iterations.

Table 2. The curvelet coefficients cell structure

Cropped Input image	256x256				
Curvelet coefficients cell structure	1x5 cell				
	1x1	1x16 cell	1x32 cell	1x32 cell	1x1
Curvelet decomposition (scale-4 & orientation-16)	441 real values (21x21)	5984 complex values	22880 complex values	90144 complex values	65536 complex values (256x256)
Total coefficients	184985 (Complex values)				
After wrapping	236196 (Complex values) (486x486)				
Curvelet Fractal feature vectors	1x24				

3.1. Performance measures

Table 3 shows the decision matrix which includes True Negative (TN), False Positive (FP), False Negative (FN) and True Positive (TP). Sensitivity and specificity are statistical performance measures. Sensitivity measures the proportion of actual positives which are correctly identified when the mammogram contains cancer tissues in it. Specificity measures the proportion of negatives which are correctly identified when cancer is not present in the mammogram. Sensitivity and Specificity are defined as follows:

$$Sensitivity = \frac{TP}{TP+FN} \tag{5}$$

$$Specificity = \frac{TN}{TN+FP} \tag{6}$$

A Receiver Operating Characteristic (ROC) curve is a graph that plots the true positive rate (Sensitivity) in function of the false positive rate (Specificity) at different cutoff points. Medcal version 12 [34] is a statistical software used in this work to plot and analyze the ROC. Figure 6 presents the ROC values for the proposed ensembled LCA-FCRN Classifier, ensembled FCRN classifier and FCRN classifier with ten-fold cross validation for comparison. For this ROC analysis, 200 samples were taken in which 100 were tumor samples and 100 were normal samples.

Table 3. Decision Matrix

		Predicted	
Actual	Healthy	True Negative	False Positive
	cancer	False Negative	True Positive

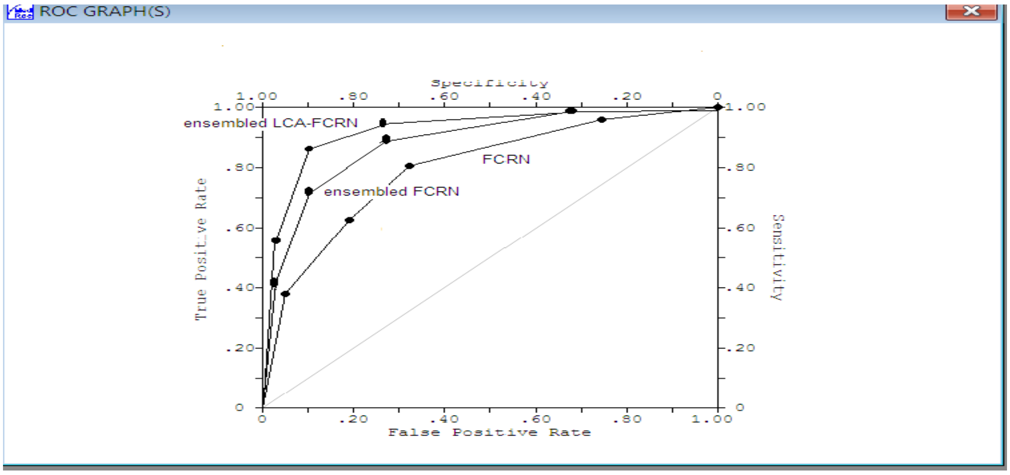


Figure 6. Comparison of the ROC curves for various classifiers

The results presented in Table 4 show that the proposed LCA optimized ensembled FCRN classifier yields better performance than its PSO counterpart. Optimal number of hidden neurons are 90 FCRN1 and 120 for FCRN2. It can be observed that the proposed ensembled LCA-FCRN classifier outperforms its competitive counterparts. This is consistent with the fact that optimization is useful in initial parameter setting of the network.

Table 4. Classification accuracy with different combinations of hidden layer neurons

No. of hidden neurons		Classification accuracy %		
FCRN1	FCRN2	Curvelet fractal features + ensembled FCRN classifier	Curvelet fractal features + ensembled PSO-FCRN classifier	Curvelet fractal features + ensembled LCA-FCRN classifier
79	103	81	89.63	90.42
85	115	83	90.72	93.63
90	120	84	95.6	98.22
97	139	80	92.8	94.25
103	151	81	93.9	94.8

Table 5. Performance measures

Classifier Metrics	FCRN	Ensembled FCRN	Ensembled LCA-FCRN
Sensitivity (%)	90.984	98	98.1
Specificity (%)	86.111	92	92.8
Accuracy (%)	89.873	98.18	98.22
AUC	0.91382	0.98	0.985
Youden's index	0.77095	0.8205	0.882
Misclassification rate	0.10127	0.07	0.052

Table 5 summarizes the attributes including the Area under the curve, Youden index and Optimal Criterion. Ensembled LCA-FCRN classifier achieves a significantly higher accuracy of 98.22%. The proposed ensembled LCA-FCRN classifier based CAD system outperforms the other classifiers in terms of all metrics. As part of future work, it is proposed to segment the classified tumor part in an efficient way to aid the radiologists for locating the tumor tissues easily. In such a scenario, no patient will experience a false prediction of breast cancer.

The ROC curves for FCRN, ensembled FCRN and ensembled LCA-FCRN classifiers are presented in Figure 6 for comparison. The best area under the ROC curve is found to be 0.985 for the ensembled LCA-FCRN classifier. Besides it yields a sensitivity of 98.1% and a specificity of 92.8%. The misclassification rate is found to be 0.052 which is less than that of other classifiers. With an optimized learning, a high classification accuracy of 98.22% is achieved. Therefore, ensembled LCA-FCRN classifier is a promising choice for automatic detection of abnormalities in mammograms.

4. Conclusion

A LCA optimized ensembled FCRN classifier for mammogram analysis for early detection of breast cancer is presented in this paper. LCA-FCRN classifier based CAD system built in this work classifies mammograms into normal and abnormal. MIAS database images are used for training and testing the proposed CAD system. First, the input mammogram image is enhanced by DCT sharpening and the ROI of the image is chosen and cropped. The curvelet fractal texture features are extracted and classified using ensembled LCA-FCRN. The LCA optimized FCRN based classifier provides a high classification accuracy of 98.22% by reducing the false positives and false negatives.

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