# Least-Squares Support Vector Machine for Characterization of Clusters of Microcalcifications

Baljit Singh Khehra, Amar Partap Singh Pharwaha

Abstract-Clusters of Microcalcifications (MCCs) are most frequent symptoms of Ductal Carcinoma in Situ (DCIS) recognized by mammography. Least-Square Support Vector Machine (LS-SVM) is a variant of the standard SVM. In the paper, LS-SVM is proposed as a classifier for classifying MCCs as benign or malignant based on relevant extracted features from enhanced mammogram. To establish the credibility of LS-SVM classifier for classifying MCCs, a comparative evaluation of the relative performance of LS-SVM classifier for different kernel functions is made. For comparative evaluation, confusion matrix and ROC analysis are used. Experiments are performed on data extracted from mammogram images of DDSM database. A total of 380 suspicious areas are collected, which contain 235 malignant and 145 benign samples, from mammogram images of DDSM database. A set of 50 features is calculated for each suspicious area. After this, an optimal subset of 23 most suitable features is selected from 50 features by Particle Swarm Optimization (PSO). The results of proposed study are quite promising.

*Keywords*—Clusters of Microcalcifications, Ductal Carcinoma in Situ, Least-Square Support Vector Machine, Particle Swarm Optimization.

#### I. INTRODUCTION

**B**REAST cancer is the major occurrence of cancer among women in both developed and developing countries. Still, there is no known way of preventing it but early detection of breast cancer is the key to improving breast cancer prognosis. Mammography is one of the most effective tools in early detection of breast cancer [1]. It is reliable, low cost and highly sensitive method. Mammography offers high quality images at low x-rays radiation doses. Mammography uses low energy x-rays that pass through the compressed breast of patient and are absorbed by film during an examination. Mammography is the only widely accepted imaging method for routine breast cancer screening. It is recommended that women at the ages of 40 or above should have a mammogram every one to two years [2]. Although mammography is widely used around the world for breast cancer detection, there are some difficulties when mammograms are searched for signs of abnormality by expert radiologists. One of the difficulties is that some anomalies may be missed due to human error or as a result of fatigue. This is one of the main reasons of false

positive and false negative readings of mammogram. False positive detection causes unnecessary biopsy. It has been estimated that only 15-30% of breast biopsy cases are proved to be cancerous [3]. On the other hand, in a false negative detection, an actual tumor remains undetected. Retrospective studies [4] have shown that 10-30% of the visible cancers are undetected. So, false positive and false negative have caused a high proportion of women without cancer to undergo breast biopsies or miss the best treatment time. Thus, there is a significant necessity to improve the correct diagnosis rate of cancer. Several solutions were proposed in the past to increase accuracy and sensitivity of mammography and reduce unnecessary biopsies. Independent double reading of mammograms by two radiologists is one of the solutions and has proved effective in significantly increasing the sensitivity of mammographic screening [5]. The basic idea of independent double reading is for the mammograms to be read by two radiologists independently. However, this solution is both highly costly and time consuming. Instead of double reading, radiologists have an opportunity to improve their diagnosis with the aid of computer system. It might provide a useful second opinion to radiologists during mammographic interpretation.

The classifier plays an important role in the implementation of Computer-Aided Diagnosis (CAD) of mammography. It is last phase of a CAD scheme that is aimed at assisting radiologists in making more accurate diagnosis of breast cancer on mammograms [6]. The classifier makes the decision regarding the region of suspicion. The aim of the classification stage of CAD system is the characterization of each cluster as malignant or benign using the selected features. To evaluate the performance of classifier for classifying MCCs as benign and malignant, confusion matrix and Receiving Operating Characteristics (ROC) analysis are used.

A number of classifiers have been proposed for CAD system to classify MCCs as benign or malignant. Kramer and Aghdasi [7] used K-Nearest Neighbor (KNN) classifier to classify MCs in digitized mammograms using multi-scale statistical texture analysis. Bruce and Adhami [8] used Linear Discriminant Analysis (LDA) to classify mammographic masses into three classes: stellate, nodular and round. Bottema and Slavotinek [9] used decision trees for classification of lobular and DCIS (small cell) MCs in digital mammograms. In 2007, Nicandro et al. [10] used Bayesian network classifiers for the diagnosis of breast cancer. Hassanien [11] used fuzzy rough sets hybrid scheme for breast cancer detection. Artificial Neural Networks (ANNs) have also been widely used for classification of MCs as benign or malignant [12]–[14]. SVM

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is a supervised learning two-class classifier derived from statistical learning theory. It is developed by Vapnik [15]. It is based on the principle of structural risk minimization. SVM has been most recently used in many applications [16]–[20]. LS-SVM is a variant of the standard SVM. It is proposed by Suykens and Vandewalle [21]. In the proposed research work, LS-SVM is explored for classifying MCCs as benign or malignant task from various kernel function point of view.

# II. DESCRIPTION OF LS-SVM FOR CLASSIFICATION OF MCCS

When SVM is used for classification of the two-class pattern classification problem, the aim is to find the optimal separating hyperplane that separates these two classes [22]. Classification of MCCs as benign or malignant is a two-class pattern classification problem. To begin, let  $\{(X_i, Y_i), i=1, 2, ..., i=1, ...,$ ...., L} be a set of L training data samples, where  $X_i$  $\in \mathbb{R}^d$  are L data points, each of which belong to class  $Y_i \in$ {+1, -1}. In classification of MCCs as benign or malignant problem, vector  $X \in \{x_i, i=1, 2, \dots, n\}$  denotes a cluster of MCs to be classified, where  $\{x_i, i=1, 2, \dots, n\}$  denotes a set of *n* features of the cluster of MCs, and  $Y \in \{+1, -1\}$ denotes its class label i.e. '+1' denotes malignant cluster of MCs and '-1' denotes benign cluster of MCs. An optimal separating hyperplane is a hyperplane that correctly separates the positive and negative classes. An optimization problem for optimal separating hyperplane can be formulated as

Objective function: Minimize 
$$\frac{w^T w}{2}$$

Subject to the constraints:

$$Y_{j}\left(w^{T}X_{j}+b\right) \geq 1 \quad for \quad \forall j$$

where  $w^T X$  denotes dot product between w and X; parameter w is the norm to the hyperplane;  $\frac{|b|}{||w||}$  is the perpendicular

distance from the hyperplane to the origin and ||w|| is the Euclidean norm of w. Hence, the goal is to find w and b such that  $\frac{w^T w}{2}$  is minimized and  $Y_j (w^T X_j + b)$  is greater than or equal to 1 for all j. The optimal solution  $w^*$ ,  $b^*$  enables classification of a test example Z as follows:

class (Z) = sign 
$$\left(w^{*T}Z + b^*\right)$$
 (1)

The above said optimization problem is a Quadratic Programming (QP) optimization problem with linear constraints. To solve this, it is necessary to switch on Lagrangian formulation of the problem [23] because when constraints are replaced by constraints on the Lagrange multipliers, then it is much easier to handle. To obtain Lagrangian formulation of the problem, first take positive Lagrange multipliers  $\alpha_{j}$ ,  $j=1,2,\ldots,L$ . After this, the constraint equations are multiplied by positive Lagrange

multipliers and subtracted from the objective function. Thus, the following objective function is obtained:

$$L_{P} = \frac{1}{2} w^{T} w - \sum_{j=1}^{L} \alpha_{j} Y_{j} (w^{T} X_{j} + b) + \sum_{j=1}^{L} \alpha_{j}$$
(2)

Objective function: Minimize  $L_P$  w. r. t w, b

Subject to the constraints:

(a) Derivatives of  $L_P$  w. r. t all  $\alpha_j$  vanish

(b)  $\alpha_j \ge 0$ 

Dual problem can be formulated from the above primal problem as follows:

Objective function: Maximize  $L_P$ 

Subject to the constraints:

(a) Gradient of  $L_P$  w. r. t w and b vanish

(b)  $\alpha_i \ge 0$ 

Now, Gradient of  $L_P$  w. r. t w and b vanish gives the following conditions:

$$w = \sum_{j=1}^{L} \alpha_{j} Y_{j} X_{j}$$
(3)

$$\sum_{j=1}^{L} \alpha_{j} Y_{j} = 0 \tag{4}$$

By substituting (3) and (4) into (2), the following equation is obtained:

$$L_{D} = \sum_{j=1}^{L} \alpha_{j} - \frac{1}{2} \sum_{j=1}^{L} \sum_{i=1}^{L} \alpha_{j} \alpha_{i} Y_{j} Y_{i} X_{j}^{T} X_{i}$$
(5)

In this case, the problem is formulated as Objective function: Maximize  $L_D$ Subject to the constraints:

(a).  $\sum_{j=1}^{L} \alpha_{j} Y_{j} = 0$ 

(b).  $\alpha_j \ge 0$ 

Thus, the goal is to find  $\alpha_i$ ,  $\alpha_2$ ,..., $\alpha_L$  such that  $L_D$  is maximized along with  $\sum_{j=1}^{L} \alpha_j Y_j$  is equal to zero and  $\alpha_j$  is greater than or equal to 0 for all *j*. For non-zero  $\alpha_j^*$ ,  $j = 1, 2, \dots, L_s$ , the optimal values of  $w^*$  and  $b^*$  are obtained as follows:

$$w^{*} = \sum_{j=1}^{L_{s}} \alpha^{*}_{j} Y_{j} X_{j}$$
(6)

$$b^{*} = Y_{j} - \sum_{j=1}^{L_{s}} \alpha_{j}^{*} Y_{j} X_{j}^{T} X_{j}$$
(7)

where non-zero Lagrange multipliers,  $\alpha_{j}^{*}$ ,  $j = 1, 2, \dots, L_{s}$ , indicate their corresponding support vectors  $S_{j} \in (X_{j}, Y_{j})$ . Thus, classification of a test example Z is done as

class (Z) = sign 
$$\left(\sum_{j=1}^{L_s} \alpha_j^* Y_j X_j^T Z + b^*\right)$$
 (8)

# A. Soft-Margin SVM

For soft-margin classification [24], slack variables  $\zeta_j$  can be added to allow misclassification of difficult or noisy examples. Thus, modified formulation of the primal problem is as follows:

Objective function: Minimize 
$$\frac{1}{2} w^T w + C \sum_{j=1}^{L} \zeta_j$$

Subject to the constraints:

$$Y_j(w^T X_j + b) \ge 1 - \zeta_j \quad for \quad \forall j \text{ and } \zeta_j \ge 0$$

where C is a soft-margin parameter that controls the penalty for misclassifying the training samples. Now, modified formulation of the dual problem is as follows:

Objective function: Maximize  $L_D$ Subject to the constraints:

(a)  $\sum_{j=1}^{L} \alpha_{j} Y_{j} = 0$ (b)  $0 \le \alpha_{j} \le C$  for  $\forall \alpha_{j}$ 

Similarly as mentioned in the dual problem, now, the goal is to find  $\alpha_I$ ,  $\alpha_2$ ,..., $\alpha_L$  such that  $L_D$  is maximized along with  $\sum_{j=1}^{L} \alpha_j Y_j$  is equal to zero and  $0 \le \alpha_j \le C$  for  $\forall \alpha_j$ .

For non-zero  $\alpha_j^*$ ,  $j = 1, 2, \dots, L_s$ ,  $w^*$  is obtained from (6) and  $b^*$  is calculated as follows:

$$b^{*} = Y_{j} \left( 1 - \zeta_{j} \right) - \sum_{j=1}^{L_{i}} \alpha_{j}^{*} Y_{j} X_{j}^{T} X_{j}$$
(9)

### B. Non-Linear SVM

Non-linear SVM classifier is used to solve non-linear classification problems through a kernel function. Kernel function uses transformation operator  $\phi(.)$  to map two classes of training data points in an input space  $R^d$  onto a higher dimensional feature space H so that the two classes of training data points can be separated by a hyperplane [25].

$$\phi: R^d \to H \tag{10} \tag{1}$$

Mainly, kernel function is used to convert non-linear classification problems into linear classification problems.

Relation between kernel function  $K(X_j, X_i)$  and mapping operator  $\phi(.)$  [26] is shown as

$$K(X_{j}, X_{i}) = \phi(X_{j})^{T} \phi(X_{i}) \qquad \forall X_{j}, X_{i} \in \mathbb{R}^{n}$$
(11)

Thus, dual formulation of problem is as follows: Find  $\alpha_1, \alpha_2, \dots, \alpha_L$  such that

$$L_{D} = \sum_{j=1}^{L} \alpha_{j} - \frac{1}{2} \sum_{j=1}^{L} \sum_{i=1}^{L} \alpha_{j} \alpha_{i} Y_{j} Y_{i} K (X_{j}, X_{i}) \text{ is maximized and}$$
  
(a)  $\sum_{j=1}^{L} \alpha_{-j} Y_{j} = 0$   
(b)  $0 \le \alpha_{-j} \le C$  for  $\forall \alpha_{-j}$ 

For non-zero  $\alpha_{j}^{*}$ ,  $j = 1, 2, \dots, L_{s}$ ,  $w^{*}$  is obtained from (6) and  $b^{*}$  is calculated as follows:

$$b^{*} = Y_{j} - \sum_{j=1}^{L_{s}} \alpha_{j}^{*} Y_{j} K \left( X_{j}, X_{j} \right)$$
(12)

Thus, classification of a test example Z is done as

$$class(Z) = sign\left(\sum_{j=1}^{L_s} \alpha_j^* Y_j K(X_j, Z) + b^*\right)$$
(13)

Most commonly used kernel functions in SVM [27], [28] are defined as follows:

i. Linear kernel function

$$K(x, y) = x^T y$$
(14)

ii. Quadratic kernel function

$$K(x, y) = (1 + x^{T} y)^{2}$$
 (15)

iii. Gaussian RBF kernel function

$$K(x, y) = \exp \left(-\frac{||x - y||^2}{2\sigma^2}\right)$$
 (16)

where  $\sigma$  is the kernel width

C. Least-Squares SVM

In LS-SVM, QP problem of the standard soft-margin SVM is transformed into linear problem. This transform is performed [29] as

Slack variables  $\zeta_j$  of the inequality constraints  $Y_j (w^T X_j + b) \ge 1 - \zeta_j$  for  $\forall j \text{ and } \zeta_j \ge 0$ are replaced with error variables  $e_j$ ; (ii) the term  $C \sum_{j=1}^{L} \zeta_{j}$  in the objective function  $\frac{1}{2} w^{T} w + C \sum_{j=1}^{L} \zeta_{j}$  is replaced by  $\gamma \frac{1}{2} \sum_{j=1}^{L} e_{j}^{2}$ ,

where  $\gamma$  is a tuning parameter. Thus, the formulation of the classification problem for LS-SVM is as follows:

Objective function: Minimize  $\frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{j=1}^{L} e_j^2$ Subject to the constraints:

Subject to the constraints:

$$Y_{j}\left(w^{T}X_{j}+b\right)\geq 1-e_{j} \quad for \quad \forall j$$

Lagrangian formulation of the above said problem is expressed by

$$L_{LS}(w,b,e,\alpha) = \frac{1}{2}w^{T}w + \gamma \frac{1}{2}\sum_{j=1}^{L}e_{j}^{2} - \sum_{j=1}^{L}\alpha_{j}\left\{Y_{j}(w^{T}X_{j}+b) - 1 + e_{j}\right\}$$
(17)

According to Karush-Kuhn-Tucker condition [30], the following conditions for optimality [31] are obtained:

$$\frac{\partial L_{LS}}{\partial w} = 0 \qquad \Rightarrow \qquad w = \sum_{j=1}^{L} \alpha_{j} Y_{j} X_{j}$$
(18)

$$\frac{\partial L_{LS}}{\partial b} = 0 \qquad \Rightarrow \qquad \sum_{j=1}^{L} \alpha_j Y_j = 0 \tag{19}$$

$$\frac{\partial L_{LS}}{\partial e_j} = 0 \quad \Rightarrow \quad \alpha_j = \gamma e_j \quad for \quad \forall j$$
(20)

$$\frac{\partial L_{LS}}{\partial \alpha_j} = 0 \quad \Rightarrow \quad Y_j(w^T X_j + b) - 1 + e_j = 0 \quad for \quad \forall j \quad (21)$$

The above set of linear equations is used to find the solution of the problem.

# III. CLASSIFIER PERFORMANCE MEASURES

For evaluating the performance of classifier to classify MCCs as benign and malignant, mainly confusion matrix [32] and ROC analysis [33] are used. A confusion matrix is a table that contains information about actual and predicted classifications done by a classifier. Table I shows confusion matrix.

TABLE I Confusion Matrix							
			Actual				
Predicted		Positive	Negative				
	Positive	TPs	FPs	Positive Predictive Value			
	Negative	FNs	TNs	Negative Predictive Value			
		Sensitivity	Specificity	Accuracy			

In confusion matrix, *Sensitivity*, *Specificity*, *Positive Predictive Value*, *Negative Predictive Value* and *Accuracy* are defined as

$$Sensitivity = \frac{TPs}{TPs + FNs}$$
(22)

$$Specificity = \frac{TNs}{TNs + FPs}$$
(23)

$$Positive \ Predictive \ Value = \frac{TPs}{TPs + FPs}$$
(24)

Negative Predictive Value = 
$$\frac{TNs}{TNs + FNs}$$
 (25)

$$Accuracy = \frac{TPs + TNs}{TPs + FPs + TNs + FNs}$$
(26)

where, *TPs*, *TNs*, *FNs* and *FPs* are number of true positive decisions, number of true negative decisions, number of false negative decisions and number of false positive decisions taken by a classifier respectively.

ROC analysis is based on statistical decision theory that has been widely used in medical decision making. In ROC analysis, ROC curve is a popular tool to measure classifier performance in CAD system. ROC curve is a plot of classifier's Sensitivity versus its 1- Specificity at all possible threshold values. To draw ROC curve, x-axis is 1-Specificity and y-axis is Sensitivity. The terms Sensitivity, Specificity and 1- Specificity are synonymous with True Positive Rate, True Negative Rate and False Positive Rate respectively. ROC curve depicts the tradeoffs between True Positive Rate and False Positive Rate to describe the inherent discrimination capacity of CAD system. Area under the ROC curve  $(A_Z)$  is an important criterion for evaluating diagnostic performance [34]. The ROC curve is in the range between 0.0 and 1.0. So,  $A_Z$  lies between 0.0 and 1.0. The value of  $A_Z$  is equal to 1.0 when CAD system has perfect performance i.e. True Positive Rate is 100% and False Positive Rate is 0%. The value of  $A_Z$  can be computed by Trapezoidal rule or Simpson's rule.

Hosmer and Lemeshow [35] gave the following general rule to measure the discrimination power of a classifier based on ROC curve:

- If 0.5 < Az < 0.6 : This means no discrimination i.e. fail classifier
- If 0.6≤*Az*<0.7 : This means poor discrimination i.e. poor classifier
- If 0.7≤Az<0.8 : This means fair discrimination i.e. fair classifier</li>
- If 0.8 < Az < 0.9 : This means good discrimination i.e. good classifier
- If 0.9 \u2224 z \u2224 1.0 : This means excellent discrimination i.e. excellent classifier

# IV. EXPERIMENTAL RESULTS AND DISCUSSION

In order to establish the credibility of LS-SVM classifier for classifying MCCs as benign or malignant, a comparative evaluation of the relative performance of LS-SVM classifier for different kernel functions is made. For this comparative evaluation, experiments are performed on data extracted from mammogram images of DDSM database [36]. All experiments are conducted on MATLAB 7.7 software. Confusion matrix and ROC analysis are used to measure the performance of classifier. In this study, a total of 380 suspicious areas are collected, which contain 235 malignant and 145 benign samples, from mammogram images of DDSM database. It is a standard benchmark database for mammographic image analysis research community that is maintained at the University of South Florida. 50 features are extracted for each suspicious region of mammograms. Such features are shown in Appendix. After this, an optimal subset of 23 features is selected by Particle Swarm Optimization (PSO) method [37]. In this study, linear, quadratic and Gaussian radial basis kernel functions are considered. 191 samples are randomly selected from 380 samples for training purpose and the remaining samples are used for testing. The training samples are not used during the testing stage.

First, linear kernel function is chosen and 10 experiments are run to measure the performance of LS-SVM with it for classifying MCCs. Tabular results of 10 random experimental runs of LS-SVM with linear kernel function are shown in Table II. Due to page constraint, confusion matrices and ROC curves of only 1<sup>st</sup> and last experimental runs are shown in Figs. 1 and 2, respectively. The average accuracy from confusion matrices is 0.8884 while average accuracy from ROC curves is 0.8867 with a sensitivity of 0.9274 and a

specificity of 0.8250. A common ROC curve of 10 random experimental trials is plotted by logarithmic function. Such curve is shown in Fig. 3. Area under this ROC curve is 0.9398. Thus, the overall accuracy of LS-SVM with linear kernel function is 0.9050 that is shown in Table V.

Random Experimental Trial No.	Confusior	Matrix	Accuracy from Confusion Matrix	Accuracy from $A_Z$	Sensitivity	Specificity
1	105	10	0 8836	0.0754	0.8974	0.8611
1	12	62	0.8850	0.8/34		
2	110	15	0.8826	0.8853	0.0402	0.7917
2	7	57	0.8850		0.9402	
3	110	9	0.0153	0.9122	0.9402	0.8750
2	7	63	0.9155			
4	109	17	0.8677	0.8690	0.9316	0.7639
7	8	55	0.0077	0.0070		
5	110	17	0.8730	0.8766	0.9402	0.7639
5	7	55				
6	111	15	0.8889	0.8929	0.9487	0.7917
0	6	57				
7	110	12	0.8995	0.8986	0.9402	0.8333
,	7	60	0.0775			
8	108	10	0.8995	0 8942	0.9231	0.8611
C C	9	62	0.0770	0.0712	0.7201	0.0011
9	102	8	0.8783	0.8687	0.8718	0.8889
2	15	64				
10	110	13	0 8942	0 8941	0 9402	0 8194
	7	59	0.0712	0.0711	5.5 102	0.0171
Mean			0.8884	0.8867	0.9274	0.8250
S. D.			0.0142	0.0142	0.0243	0.0459

TABLE II

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Fig. 1 Confusion matrices for 1<sup>st</sup> and last experimental trials of LS-SVM with Linear Kernel function to differentiate benign and malignant MCCs



Fig. 2 ROC curves for 1<sup>st</sup> and last experimental trials illustrate the performance of LS-SVM with Linear Kernel function to differentiate benign and malignant MCCs



Fig. 3 Common ROC curve for 10 random experimental trials illustrates the performance of LS-SVM with Linear Kernel function to differentiate benign and malignant MCCs

After the performance analysis of linear kernel function LS-SVM, quadratic kernel function is considered. Tabular results of 10 random experimental runs of this classifier are shown in Table III. Confusion matrices and ROC curves of 1<sup>st</sup> and last experimental runs are shown in Figs. 4 and 5, respectively. The average accuracy from confusion matrices is 0.8371 while average accuracy from ROC curves is 0.8270 with a sensitivity of 0.8521 and a specificity of 0.8125. A common ROC curve obtained from 10 random experimental trials is shown in Fig. 6. Area under this ROC curve is 0.8769. Thus, the overall accuracy of LS-SVM with quadratic kernel function is 0.8470 that is shown in Table V.

TABLE III

TABULAR RESULTS OF 10 RANDOM EXPERIMENTAL TRIALS OF LS-SVM WITH QUADRATIC KERNEL FUNCTION FOR CLASSIFYING MCCs AS BENIGN OR MALIGNANT

Random Experimental Trial No.	Confusio	n Matrix	Accuracy from Confusion Matrix	Accuracy from Az	Sensitivity	Specificity
1	100	14	0.8360	0.8253	0.8547	0.8056
	17	58				
2	98	11	0.8413	0.8308	0.8376	0.8472
	19	61				
3	102	15	0.8413	0.8317	0.8718	0.7917
	15	57				
4	101	16	0.8307	0.8205	0.8632	0.7778
	16	56				
5	100	14	0.8360	0.8253	0.8547	0.8056
	17	58				
6	99	14	0.8307	0.8196	0.8462	0.8056
	18	58				
7	97	11	0.8360	0.8256	0.8291	0.8472
	20	61				
8	95	10	0.8307	0.8214	0.8120	0.8611
	22	62				
9	104	16	0.8466	0.8391	0.8889	0.7778
	13	56				
10	101	14	0.8413	0.8310	0.8632	0.8056
	16	58				
Mean			0.8371	0.8270	0.8521	0.8125
S. D.			0.0055	0.0061	0.0221	0.0294

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Fig. 4 Confusion matrices for 1<sup>st</sup> and last experimental trials of SVM with Quadratic Kernel function and LS method to differentiate benign and malignant MCCs



Fig. 5 ROC curves for 1<sup>st</sup> and last experimental trials illustrate the performance of LS-SVM with Quadratic Kernel function to differentiate benign and malignant MCCs



Fig. 6 Common ROC curve for 10 random experimental trials illustrates the performance of LS-SVM with Quadratic Kernel function to differentiate benign and malignant MCCs

At the end, Gaussian radial basis kernel function is considered. In Gaussian radial basis kernel function, the value of sigma ( $\sigma$ ) is set to 2. Tabular results of 10 random experimental runs of this classifier are shown in Table IV. Confusion matrices and ROC curves of 1<sup>st</sup> and last experimental runs are shown in Figs. 7 and 8, respectively. The average accuracy from confusion matrices is 0.8656 while average accuracy from ROC curves is 0.8676 with a sensitivity of 0.9282 and a specificity of 0.7639. A common ROC curve obtained from 10 random experimental trials is shown in Fig. 9. Area under this ROC curve is 0.8717. Thus, the overall accuracy of SVM with Gaussian radial basis kernel function is 0.8683 that is shown in Table V.

TABLE IV TABULAR RESULTS OF 10 RANDOM EXPERIMENTAL TRIALS OF LS-SVM WITH GAUSSIAN RADIAL BASIS KERNEL FUNCTION FOR CLASSIFYING MCCS AS BENIGN OR MALICMANT

Random Experimental Trial No.	Confusio	n Matrix	Accuracy from Confusion Matrix	Accuracy from $A_Z$	Sensitivity	Specificity
1	108	15	0.8730	0.8708	0.9231	0.7917
	9	57				
2	108	19	0.8519	0.8526	0.9231	0.7361
_	9	53				
3	111	20	0 8624	0.8719	0 9487	0 7222
5	6	-0 52	0.0021	0.0715	0.9 107	0.7222
4	108	15	0.8730	0.8708	0.9231	0 7917
	9	57	0.0750	0.0700	0.9251	0.7917
5	110	17	0.8730	0.8766	0 9402	0 7639
5	7	55	0.0750	0.0700	0.9402	0.7057
6	107	16	0.8624	0.8592	0.9145	0 7778
0	107	56	0.0024	0.0372	0.9145	0.7778
7	113	21	0.8677	0.8853	0.9658	0 7083
/	115	51	0.8077	0.8855	0.9058	0.7085
0	4	10	0.9677	0.9761	0.0497	0 7261
8	111	52	0.8677	0.8/01	0.9487	0.7301
0	0	55	0.9624	0.9522	0.0002	0.0222
9	103	12	0.8624	0.8532	0.8803	0.8333
	14	60				
10	107	16	0.8624	0.8592	0.9145	0.7778
	10	56				
Mean			0.8656	0.8676	0.9282	0.7639
S. D.			0.0067	0.0109	0.0239	0.0382

Fea



Fig. 7 Confusion matrices for 1st and last experimental trials of LS-SVM with Gaussian Radial Basis Kernel function to differentiate benign and malignant MCCs



Fig. 8 ROC curves for 1st and last experimental trials illustrate the performance of LS-SVM with Gaussian Radial Basis Kernel function to differentiate benign and malignant MCCs



Fig. 9 Common ROC curve for 10 random experimental trials illustrates the performance of LS-SVM with Gaussian Radial Basis Kernel function to differentiate benign and malignant MCCs

TABLE V
PERFORMANCE OF LS-SVM WITH DIFFERENT KERNEL FUNCTIONS FOR
DIFFERENTIATING BENIGN AND MALIGNANT MCCS

Kernel	Average	Average	Accuracy	Overall
Function	Accuracy from	Accuracy	from	Accuracy
	Confusion	from ROC	Common	
	Matrices	Curves	ROC Curve	
Linear	0.8884	0.8867	0.9398	0.9050
Quadratic	0.8371	0.8270	0.8769	0.8470
Gaussian	0.8656	0.8676	0.8717	0.8683
Radial Basis				

# V.CONCLUSION AND FUTURE SCOPE

In this paper, an attempt is made to establish the credibility of LS-SVM classifier with different kernel functions for classifying MCCs as benign or malignant. For this purpose, three kernel functions: linear, quadratic and Gaussian radial basis are used. For this study, experiments are conducted on MATLAB 7.7 software. Experiments are performed on 380 suspicious areas collected from mammogram images of DDSM database. A set of 23 most suitable features selected by PSO is used. The performance of the classifier is measured from confusion matrix and ROC analysis. From the experimental results, it is observed that the overall correct classification rate of LS-SVM with linear, quadratic and Gaussian radial basis kernel functions is 90.50%, 84.70% and 86.83%, respectively. From these experimental results, it is observed that LS-SVM with linear kernel function belongs to excellent classifiers category according to Hosmer and Lemeshow's rule, while LS-SVM with quadratic and Gaussian radial basis kernel functions belongs to good classifiers category. Results of this study are quite promising. The proposed work can be a part of developing a CAD system for early detection of breast cancer. Thus, this research work could, in a way, significantly contribute towards eventually detecting DCIS type breast cancer which is the main challenge for radiologists.

Although the achieved performance is satisfactory for mammogram images of DDSM databases, further testing can also be performed on the mammogram images of other standard databases.

	APPENDIX
	TABLE VI
	EXTRACTED FEATURES FROM MAMMOGRAM
ture No.	Feature
1	Mean from Gray Level Histogram Moments Method
2	Standard Deviation from Gray Level Histogram Moments Method
3	Relative Smoothness from Gray Level Histogram Moments Method
4	3rd Moment from Gray Level Histogram Moments Method
5	4th Moment from Gray Level Histogram Moments Method
6	Uniformity from Gray Level Histogram Moments Method
7	Havrda and Charvat Entropy from Gray Level Histogram Moments Method
8	Maximum Probability from Gray Level Co-occurrence Matrix (GLCM)
9	Contrast from GLCM
10	Energy from GLCM
11	Homogeneity from GLCM
12	Correlation from GLCM
13	Sum Average from GLCM
14	Sum of Squares: Variance from GLCM
15	Sum Variance from GLCM
16	Difference Variance from GLCM
17	Information Measure of Correlation 1st from GLCM
18	Information Measure of Correlation 2nd from GLCM
19	Havrda and Charvat Entropy for GLCM from GLCM
20	Havrda and Charvat Sum Entropy from GLCM

22       Average from Window based Statistical Texture Feature Extraction Method         23       Stand Deviation from Window based Statistical Texture Feature Extraction Method         24       Relative Smoothness from Window based Statistical Texture Feature Extraction Method         25       Skewness from Window based Statistical Texture Feature Extraction Method         26       Kurtosis from Window based Statistical Texture Feature Extraction Method         27       Bussyness from Window based Statistical Texture Feature Extraction Method         28       Potential of a point from Window based Statistical Texture Feature Feature Extraction Method         29       Point Mask from Window based Statistical Texture Feature Feature Extraction Method         30       Average Energy from Window based Statistical Texture Feature Feature Extraction Method         31       Energy Variance from Window based Statistical Texture Feature Feature Extraction Method         32       Volatility from Window based Statistical Texture Feature Extraction Method         33       Mean from Window based Statistical Texture Feature Extraction Method         34       Standard Deviation from Wavelet Domain         35       Spectral Entropy from Wavelet Domain         36       Mean from Fourier Domain         37       Standard Deviation from Fourier Domain         38       Spectral Entropy from Fourier Domain         39<	21	Havrda and Charvat Difference Entropy from GLCM
Extraction Method23Stand Deviation from Window based Statistical Texture Feature Extraction Method24Relative Smoothness from Window based Statistical Texture Feature Extraction Method25Skewness from Window based Statistical Texture Feature Extraction Method26Kurtosis from Window based Statistical Texture Feature Extraction Method27Bussyness from Window based Statistical Texture Feature Extraction Method28Potential of a point from Window based Statistical Texture Feature Extraction Method29Point Mask from Window based Statistical Texture Feature Extraction Method30Average Energy from Window based Statistical Texture Feature Extraction Method31Energy Variance from Window based Statistical Texture Feature Extraction Method32Volatility from Window based Statistical Texture Feature Extraction Method33Mean from Window based Statistical Texture Feature Extraction Method34Standard Deviation from Wavelet Domain35Spectral Entropy from Wavelet Domain36Mean from Fourier Domain37Standard Deviation of Areas40Standard Deviation of Compactness41Maximum Area42Minimum Compactness44Standard Deviation of Compactness45Maximum Compactness46Minimum Compactness47Mean of 2 <sup>nd</sup> Central Moment48Standard Deviation of 2 <sup>nd</sup> Central Moment49Maximum 2 <sup>nd</sup> Central Moment40Standard Deviation of 2 <sup>nd</sup> Central Mo	22	Average from Window based Statistical Texture Feature
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25       Stewness non-Window based Statistical Texture Feature Extraction Method         26       Kurtosis from Window based Statistical Texture Feature Extraction Method         27       Bussyness from Window based Statistical Texture Feature Extraction Method         28       Potential of a point from Window based Statistical Texture Feature Extraction Method         29       Point Mask from Window based Statistical Texture Feature Extraction Method         30       Average Energy from Window based Statistical Texture Feature Extraction Method         31       Energy Variance from Window based Statistical Texture Feature Extraction Method         32       Volatility from Window based Statistical Texture Feature Extraction Method         33       Mean from Wavelet Domain         34       Standard Deviation from Wavelet Domain         35       Spectral Entropy from Wavelet Domain         36       Mean from Fourier Domain         37       Standard Deviation from Fourier Domain         38       Spectral Entropy from Fourier Domain         39       Mean of Areas         40       Standard Deviation of Areas         41       Maximum Area         42       Minimum Area         43       Mean of Compactness         44       Standard Deviation of Compactness         45       Maximum Compactness<	25	Feature Extraction Method Skewness from Window based Statistical Texture Feature
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32Volatility from Window based Statistical Texture Feature Extraction Method33Mean from Wavelet Domain34Standard Deviation from Wavelet Domain35Spectral Entropy from Wavelet Domain36Mean from Fourier Domain37Standard Deviation from Fourier Domain38Spectral Entropy from Fourier Domain39Mean of Areas40Standard Deviation of Areas41Maximum Area42Minimum Area43Mean of Compactness44Standard Deviation of Compactness45Maximum Compactness46Minimum Compactness47Mean of 2 <sup>nd</sup> Central Moment49Maximum 2 <sup>nd</sup> Central Moment50Minimum 2 <sup>nd</sup> Central Moment	31	Energy Variance from Window based Statistical Texture Easture Extraction Method
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<ul> <li>45 Maximum Compactness</li> <li>46 Minimum Compactness</li> <li>47 Mean of 2<sup>nd</sup> Central Moment</li> <li>48 Standard Deviation of 2<sup>nd</sup> Central Moment</li> <li>49 Maximum 2<sup>nd</sup> Central Moment</li> <li>50 Minimum 2<sup>nd</sup> Central Moment</li> </ul>	44	Standard Deviation of Compactness
46Minimum Compactness47Mean of 2nd Central Moment48Standard Deviation of 2nd Central Moment49Maximum 2nd Central Moment50Minimum 2nd Central Moment	45	Maximum Compactness
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50 Minimum 2 <sup>nd</sup> Central Moment	49	Maximum 2nd Central Moment
	50	Minimum 2 <sup>nd</sup> Central Moment

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