

Computer-Aided Diagnosis of Mammography Cancer



Loai Kinani, Umar Alqasemi

Abstract: In this study, computer-aided detection (CADE) system is optimized to reduce radiologists' workload and to improve accuracy of cancer detection by providing more quantitative (objective) decisions added to the qualitative (subjective) assessment of radiologists. The images have been collected from MIAS database. 3 databases were prepared by 3 different ROIs sizes (32x32, 42x42 & 52x52 pixels). Then, prepressing is done to enhance the peripheral of ROIs. This CADE computed parametric features from ROIs using statistics, histogram, GLCM and wavelet techniques. Sequential Forward Selection (SFS) technique is used to study the significance of features and eventually to omit redundancies. Several types of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers were trained to differentiate between normal and abnormal ROIs, then tested on another non-training set. Best overall performance results obtained with ROI size of 32x32 and histogram of 32 levels (Accuracy = 97.37%, Sensitivity= 95%, Specificity = 100%, PPV = 100% and NPV = 94.74). The results also indicate some useful features are well-representing to abnormalities across different classifiers such as: Mean, STD, Square of STD, Mode, Median, Quantile (10%), Quantile (70%), Quantile (90%), Percentile (30%), throughout multiple histogram levels both in spatial and DWT spaces.

Keywords: Mammogram, Mass, Microcalcification, computer-aided detection, medical image recognition, support vector machine.

I. INTRODUCTION

Breast cancer is the most common cause of death from cancer family in women worldwide. Early stage detection, and treatment plays important rule in decreasing mortality rate. Digital imaging or mammography is commonly for breast mass and microcalcifications (MCCs) screening and diagnosis [1]. MCCs are the main findings that point out to possibility of cancer in the breast tissue at the early stage. Mass is region which has highly dense texture compared to surrounding breast tissue, and it is described by the shape, size and location.

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One the other hand, macrocalcifications are accumulations of calcium in lymphatic vessel where they usually block these vessels in the breast tissue, which causes accumulation of wastes, and chemical imbalance, opening the door for infections, elevated immune/autoimmune response, poor tissue healing that may lead eventually to birth of cancer cells.

In addition to diagnosis techniques used by radiologists, computer-aided design (CAD) systems provide a secondary check point in detecting/affirming abnormalities, and assist in making diagnostic decisions. CAD systems are computerized algorithms developed using machine-learning techniques, specifically, algorithms similar to the ones used in artificial intelligence and face/pattern/letter recognition and data mining. For such algorithms, a prior data is required to train classifiers for them to be used on future data[2]. In CAD systems, various algorithms are used to analyze medical images and give a response to aid the radiologist. In general, there are two types of responses and, consequently, two types of CAD systems. In CADE (computer-aided detection) systems, the general aim of the system is to detect abnormalities in medical images regardless of their type of abnormality. Therefore, the output of a CADE system is binary (abnormal or normal). CADE system can be used to reduce the number of suspicious regions that could potentially be overlooked by the radiologist. Also, CADE can be used to confirm radiologist decision about a specific suspicious area. The second type is computer-aided diagnosis (CADx) systems developed to be an aid for the radiologist in better identification of abnormality type (i.e. benign, malignant, etc.).

II. LITERATURE REVIEW

Many studies were done to improve CAD system accuracy of early detection and diagnose the abnormalities in women breast tissues. R. Nithya et. al. (2011), proposed a CAD system to classify abnormal vs. normal tissue of mammogram images. A total of 250 images were collected from digital mammogram database (DDSM). Gray Level co-occurrence matrix (GLCM) features were calculated for 4 different directions or angles (0°,45°,90°,145°) in 4 different distances (1,2,3,4). In the study, five features were calculated under GLCM (energy, entropy, correlation, sum of square variance and homogeneity). A neural network was used for classification, divided to three layers (input, output, and hidden layer), resulting 96% accuracy, 100% sensitivity, and 96% specificity.

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Recorded results led to better performance in CADe. Statistical features with feature selection method could have improved overall accuracy of the system [6].

Rajkumar K.K, G. Raju et. al. (2014), proposed a CADx system to Detect and Classify the abnormal mammogram images using Lazy Classifiers. Multi-stage classification method applied. The first stage is to apply a set of GLCM features applied and extracted from multiple region of interest (ROIs: 8x8, 16x16, 32x32) taken from mini-MIAS database. Then, the images classified to normal and abnormal using lazy classifiers (instance-based classifier (K*), Instance-based Learning (IBL), Locally Weighted Learning (LWL)). After that, all abnormal images resulted from the first stage classified to its illness type depending upon architectural as well as texture patterns found in the image ROI. First stage classifier best result obtained on 32x32 pixel ROI with accuracy 92.40% and 86.18% for the second stage classification. It was noticeable that better accuracy obtained in the first and second stage corresponding with increment of ROI size for the three kind of lazy classifiers [8].

Mohamed E. Elman, et. al. (2015), proposed CADx system for classify masses in mammogram images. Images have been collected from the digital database for screening mammography (DDSM) with resolution of 50 micron and grayscale level of 12-bit. Images down sampled by 0.25 by nearest- neighbor interpolation. The ROI taken manually from the image in window of 32x32 pixels. Tao Wu technique applied for ROI enhancement. Fifty-nine (59) features were used to characterize the normal and abnormal images such as first order statistical parameters, wavelet decomposition and GLCM features. Sequential floating forward selection (SFFS) and sequential forward selection (SFS) used for feature selection. Then multiple classifiers were used to classify the images. Best result obtained by KNN classifier with 95.36% Accuracy, 98% specificity, and 96% sensitivity. Recorded results proved the approached CAD was practical for application. It was noticeable that SFFS provided excellent results and showed that SFFS technique can extract the useful features better than SFS [9].

Ancy C A, et. al. (2017), proposed CADe for detection of tumor in mammograms using SVM. Images collected from University of South Florida Digital Mammography (USFDM) databases. A total of 100 pair of images were included for testing the efficiency of the method. Starting with Image denoising using curvelet transform to remove unnecessary noise from selected images. Then contrast enhancement with brightness preserving using recursive mean separate histogram equalization [RMSHE] followed by median filtering and gray level thresholding to perform the morphological segmentation. Five GLCM texture features were extracted. Then Linear SVM is used to classify whether the segmented tissue from image is tumor or not. The accuracy of the method reached 81% with 73% sensitivity and 99% specificity. Specificity rate reveals that GLCM based SVM technique can give better classification results with easy implementations [10].

R.D. Ghongade et. al. (2017), proposed CADx system for breast cancer using random forest (RF) Classifier. Mammogram images with 1024x1024 pixels were used from MIAS database. First, gaussian filter was applied to denoise

and smooth the selected images. Then histogram equalization was used to enhance the images contrast. Segmentation is done using region-based method to enhance masses from image background. Otsu's method was applied to execute clustering-based thresholding and then image normalization process done by applying a multiplication of binary mask with the original image. GLCM was used for texture features extraction. Fast Correlation Based Feature Selection (FCBF) method applied to choose the useful features. Image classification is done by Random Forest algorithm to classify the normal, benign and malignant images. The method has achieved 97.32% accuracy, 97.45% sensitivity and 98.13% specificity. The study result showed that RF classifier provides good classification accuracy by decreasing the false positives (FPs) and false negatives (FNs) depending upon the features selection optimization[11].

R. Vijayarajeswari et. al. (2019), proposed CADe to classify mammogram images using SVM classifier and Hough transform. The study focused on fatty-glandular breast cases excluding dense ones. 95 Images collected from Mini-MIAS database to include normal, benign and malignant types. All unwanted information and background noise were removed and pectoral muscle segmentation step occurred in preprocessing stage. Intensity features (entropy, variance, mean and standard deviation) after Hough transform applied on the processed images. The accuracy of classification reaches 94%, obtained by SVM classifier. The study focused on intensity features like mean, variance and entropy can improve the results. The weak point in this study that this study only focused on fatty-glandular breast images excluding dense images, while other study usually include more type of images for more applicable results [12].

This study relied on the methodologies of previous studies to develop CADe system. Where, this study focused to use effective preprocessing technique, multiple types of useful features and effective classification techniques to provide accurate results and highlight the most effective features that contributed to improve CADe system for women breast tissues.

III. METHADODOLOGY

This section will describe the methodology of the research step by step to build up proposed computer aided detection (CADe) algorithm. Building CADe system require 5 main steps as shown in figure 2.1. The software used in this study to build the proposed CADe is MATLAB R2015a

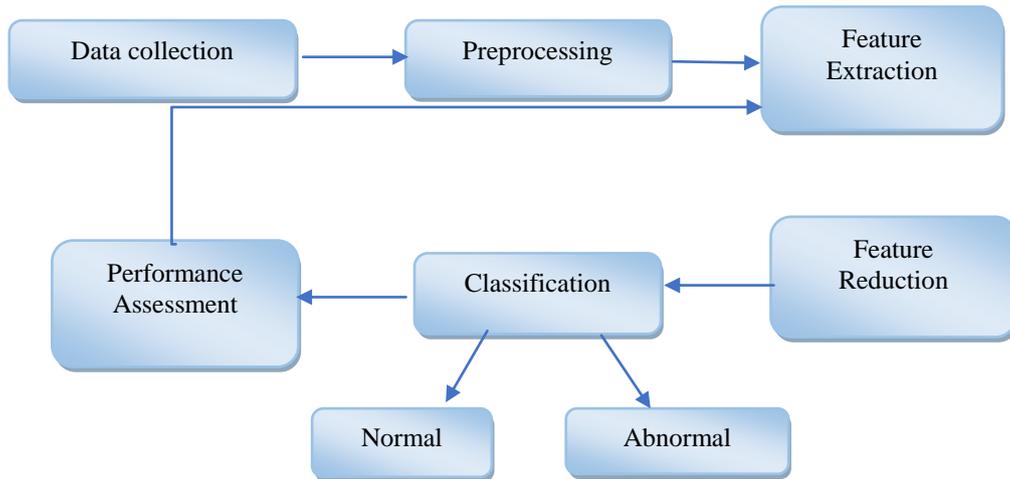


Figure 3.1. (A diagram represent the research CADe algorithm design).

3.1. Data collection:

The MIAS database were used through this study. The free database contains digitized images at 50-micron pixel edge and every image is 1024 × 1024 pixels[13]. The database contains of 322 images, divided to three different types of cases (208 normal, 51 malignant and 63 benign) mammograms. 230 out of the 322 images are used here, including 115 normal and 115 abnormal images. All 6 types of abnormalities were included in this study (Asymmetry, Architectural distortion, Well-defined masses, ill-defined masses, Speculated masses and Calcification). Images were divided into two groups: 154 images (77 normal & 77 abnormal) as learning set to train classifiers and 76 images (38 normal & abnormal) to test the performance of classifiers.

3.2. Preprocessing:

3.2.1. Region of Interest (ROI):

Three ROIs were cropped manually one by one from each full image of sizes: 32x32, 42x42 & 52x52 pixels to study each with our algorithm to find the best size in terms of performance, and to test the consistency of results.

3.2.2. Image Enhancement:

Images enhancement technique by Tao Wu et al.[14] used to denoise and enhance the contrast between different tissues which will lead to better image visibility. The concept of this technique is to estimate the normalized thickness profile (NTP) of a breast from a mammogram image and enhance the interested area. Preprocessing step was proven as mentioned in previous literature reviews that it leads to more effective result of overall CADe system. The method algorithm of Tao Wu is described as the following:

- a. Background image segmentation by Otsu thresholding
 - b. Generate blurred images
 - c. Multiply the segmented images (SI) with blurred image (BI) to make all pixel outside breast region equal to zero.
 - d. normalize thickness profile (NTP) of BI by applying multiple multi-threshold segmentation technique.
- The method uses 5 threshold values (T_n) calculated by the following equation:

$$T_n = I_{ave} F_n \tag{3.1}$$

Where I_{ave} is the average intensity of (BI) and $F_n = (1.2, 1.1, 1.0, 0.9, 0.8)$. Each threshold of T_n , the BI was rescaled to get new pixel value V reset to:

$$V = \begin{cases} \frac{V}{T_n}, & V \leq T_n \\ 1, & otherwise \end{cases} \tag{3.2}$$

NTP obtained by calculating average of the five rescaled images. In figure 2.3 represent a summary of Tao Wu image enhancement technique steps.

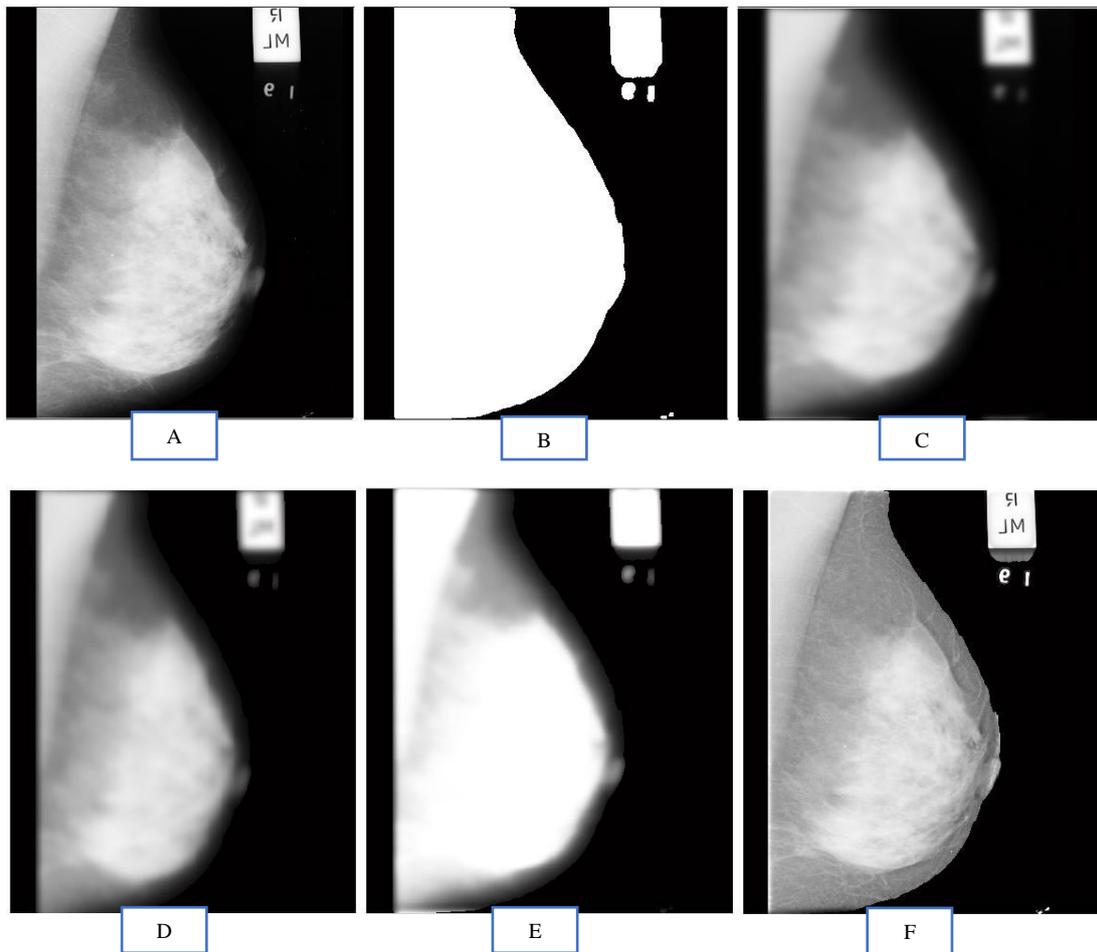


Figure 3.3. (Tao Wu image enhancement technique steps: (A) Original image, (B) Otsu thresholding SI, (C) BI, (D) BI after multiply with SI, (E) NTP image, (F) PE image).

3.3. Feature Extraction:

This step plays a main factor in CAD performance. the extracted features act as the mathematical description of characteristics for classifiers to be able to distinguish normal from abnormal lesions. The features extracted from ROI as follows:

- Statistical and shape features on ROI. Those features are: (Mean, STD, Square of STD, Mode, Median, Quantile, Percintile, Third Moment, Entropy, Skewness, kurtosis, Variance, Smoothness)
- GLCM features with level of 32 and shift or distance ($d = 1, 2$ and 3) in all direction (angles = $0^\circ, 45^\circ, 90^\circ$ and 135°). Those features are: (Contrast, Energy, Correlation, Homogeneity, Entropy, Third Moment, Skewness, kurtosis, Variance)
- Histogram features with two no. of levels (16 and 32)
- Same Statistical features and GLCM features computed from different transformed ROI domains: two types of Daubechies wavelet decomposition domain (db1, db4).

The statistical features were calculated after Daubechies wavelet decomposition transform for details coefficients matrices HH, LH and HL (vertical, and diagonal, respectively) from the matrix using the wavelet Daubechies

(db1 and db4) and HL (db1) coefficient matrix used for GLCM features.

3.4 Feature Selection:

The total number of features extracted with histogram of level 16 was 462 features, and with level 32 was 574. After that, Sequential Forward Selection (SFS) method were used to reduce the number of features and to find the best useful feature set that result best outcome for each classifier. SFS technique is one of the simplest and probably fastest feature selection algorithms, where features are added incrementally while watching classifier performance to decide whether each feature is contributing to improve overall accuracy or not.

3.5 Classification:

This process contains two main phases, learning and testing phases. The features that were selected from the previous stage will be used in the classification stage. In the learning phase, known data represent clearly the nature of the lesion whether it is a normal or abnormal, to teach and train the classifier. In the testing phase, classification was done using trained structure of classifier. In this study SFS were used with five classifiers (level 3 and 5 K-voting Nearest Neighbor (KNN) classifiers, and three SVM classifiers of different kernel (Linear, Polynomial and MLP).

IV. RESULTS & DISSCUSSION

Results were obtained by using a test ROI set of 76 images (38 normal & 38 abnormal). Then, 5 parameters (PPV, NPV, Sensitivity, Specificity and Accuracy) used to evaluate the performance of each classifier. Following tables and figure show the study best results by presenting the performance of each classifier with highlight on useful features by using SFS as feature reduction technique.

Table 4.1 Present overall CADe performance evaluation Results of 32x32 ROIs with Histogram level=32 (in %).

	KNN		SVM		
	K=3	K=5	Linear	Polynomial	Mlp
ERROR RATE	15.7 9	14.4 7	02.63	06.58	22.37
Accuracy	84.2 1	85.5 3	97.37	93.42	77.63
Sensitivity	82.5 0	81.4 0	95.00	97.14	73.33
Specificity	86.1 1	90.9 1	100	90.24	83.87
PPV	86.8 4	92.1 1	100	89.47	86.84
NPV	81.5 8	78.9 5	94.74	97.37	68.42
AUC	84.2 1	85.5 3	97.37	93.42	77.63
No. of Features	5	8	7	5	3

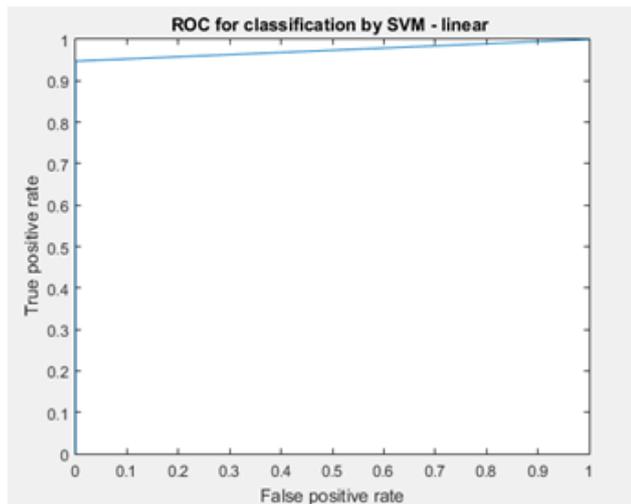


Figure 4.1 Present the ROC of Linear SVM classifier of 32x32 ROIs with Histogram level=32.

Table 4.2 Present overall CADe performance evaluation Results of 42x42 ROIs with Histogram level=16 (in %).

	KNN		SVM		
	K=3	K=5	Linear	Polynomial	Mlp
ERROR RATE	19.7 4	17.1 1	06.58	75.00	14.4 7
Accuracy	80.2 6	82.8 9	93.42	25.00	85.5 3
Sensitivity	81.0 8	79.0 7	97.14	17.24	80.0 0
Specificity	79.4 9	87.8 8	90.24	29.79	93.5 5
PPV	78.9 5	89.4 7	89.47	13.16	94.7 4
NPV	81.5 8	76.3 2	97.37	36.84	76.3 2
AUC	80.2 6	82.8 9	93.42	25.00	85.5 3
No. of Features	6	7	4	4	3

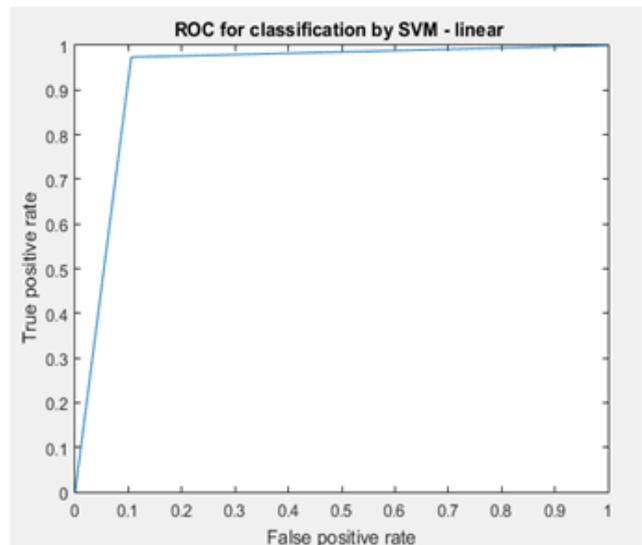


Figure 4.2 Present the ROC of Linear SVM classifier of 42x42 ROIs with Histogram level=16.

Table 4.3: Present overall CADe performance evaluation Results of 52x52 ROIs with Histogram level =32 (in %)

	KNN		SVM		
	K=3	K=5	Linear	Polynomial	Mlp
ERROR RATE	22.3 7	23.6 8	05.26	19.74	14.4 7
Accuracy	77.6 3	76.3 2	94.74	80.26	85.5 3
Sensitivity	76.9 2	73.8 1	97.22	79.49	88.5 7
Specificity	78.3 8	79.4 1	92.50	81.08	82.9 3
PPV	78.9 5	81.5 8	92.11	81.58	81.5 8
NPV	76.3 2	71.0 5	97.37	78.95	89.4 7
AUC	77.6 3	76.3 2	94.74	80.26	85.5 3
No. of Features	2	7	6	3	5

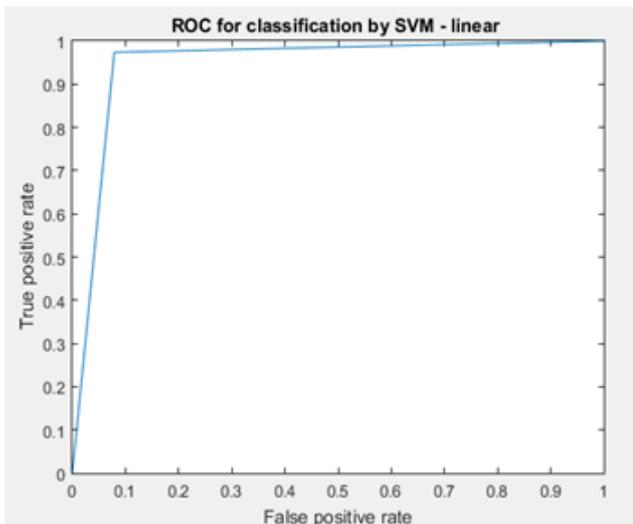


Figure 4.3 Present the ROC of Linear SVM classifier of 52x52 ROIs with Histogram level=32.

Previous results with different image sizes showed promising performance. Comparing between classifiers performances, it was noticeable that SVM linear had the highest performance. SVM linear has the best performance reached with ROI size 32x32 pixels while using histogram level =32. Recorded results were: accuracy = 97.37%, Sensitivity = 95%, Specify = 100%, PPV = 100%, NPV=94.74%. This result reached using 7 features only after SFS. It was noticeable that better results achieved in general while using histogram with level =32 in all ROI sizes. Also, good stability in results were remarkable with different image sizes which can tell that the used methodology in this study is reproducible. The results also indicate some useful features are well-representing to abnormalities across different classifiers such as: Mean, STD, Square of STD, Mode, Median, Quantile (10%), Quantile (70%), Quantile (90%),

Percentile (30%), throughout multiple histogram levels under spatial and DWT spaces.

V. CONCLUSION

The study introduces a developed CADe system to support radiologists in better detection of abnormalities in mammogram images including microcalcification to support early detection of cancer. MIAS database were used to propose CADe system. 3 different sizes of ROIs were prepared to compare and test the stability of proposed CADe system. Good performance stability of the system observed with Linear SVM classifier with different ROIs. Best result was obtained with ROI of 32x32 pixel. Accuracy of system reached 97.37% with 100% Specificity and 95% Sensitivity. The result was better from many previous studies and competitive to many other. Using a huge number of different features support the CADe system to be picky enough to separate normal from abnormal images of 6 different types of abnormalities. Many useful features well-fitting to data across different classifiers such as: Mean, STD, Square of STD, Mode, Median, Quantile (10%), Quantile (70%), Quantile (90%), Percentile (30%), throughout multiple histogram levels under spatial and DWT spaces.

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