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Detection and Classification of Abnormal Mammogram Images Using Lazy Classifiers

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***Abstract*— Feature extraction and selection is the primary part of any mammogram classification algorithms. Statistical texture features of mammogram images provide excellent classification results in tumor identification. In this paper we propose a Computer Aided Diagnosis (CAD) system which uses the second order statistical texture features called Gray Level Co-occurrence Matrices (GLCM) along with the lazy classifiers named K*,IB1 and LWL for the detection and classification of different types of abnormalities in mammogram Images. GLCM feature measures the relationship between individual pixels with respect to its neighboring pixels compared to the normal first order statistical features named the histogram and intensity features. The classification performance achieved by the GLCM features using different machine learning algorithms are better than that obtained with first order statistical features. Different types of features in the GLCM extracted in different direction of the Region of Interest (ROI) of mammogram images are put together as the feature vector for the classification. This method is applied on three different sizes of ROIs extracted from mammogram images in the Mini-Mias database. The results obtained on these three sets of ROIs are excellent and promising.**

Index Terms— GLCM, IBL, Kstar, Lazy classifier, LWL

I. INTRODUCTION

Breast cancer is the one of the most threatening disease found among women in all over the world. It stands second in position for the cause of deaths in women, especially in the developed and under developed countries [1]. Breast cancer is common among men also. It accounts 1% of total breast cancer found in the world [2] [3]. In India itself, breast cancer accounts 23% of all female cancers followed by cervical cancer which is only 17.5% [4]. There is no effective diagnosis methods suggested so far for this disease. The only way to decrease the mortality rate of the breast cancer is the early detection [5]. The commonly used diagnostic methods for breast cancer include biopsy, mammography, thermograph and ultrasound image [6]. The mammography, which is a non-invasive method, is considered as the best approach among all other diagnostic methods suggested so far [7] [8] [9]. In spite of the development in technology in modern digital world, early detection and recognition of doubtful abnormalities in digital mammogram is a very difficult task [5] [10]. The primary reason is that the mammography provides relatively low contrast images especially in the case of dense or heavy breasts.

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The symptoms of abnormal tissue also may remain quite subtle [11]. The detection of tumors and classification of the mammogram images are the standard clinical practice for the diagnosis of breast cancer. Soft computing methods such as neural networks and fuzzy logics are now available for the early detection of cancer cells in a human body, even before physical symptoms appear [12]. The biopsy is an approach normally used by the radiologist for identifying cancer cells manually through a microscope. Biopsy, most of the time, do not identify exact tumor locations of the specimen. Therefore radiologist performs unnecessary biopsy which is time consuming and cause inconvenience to the patient. As a measure to improve the diagnosis, Researchers are focusing on the development of computer aided detection system for identifying tumors or abnormalities from digital mammogram. Once an abnormality is detected on the mammogram image using the CAD system, then the radiologist can recommend for biopsy which in turn reduce the need for unnecessary biopsies. In addition, the CAD system can also be considered as a second opinion for the radiologists to diagnosis the disease [13] [14] [15]. In this paper we focus on classification of digital mammogram into normal or cancerous, which may lead to the design of efficient CAD Systems

Different techniques have already been proposed to improve the accuracy of breast tumor classification. New developments must meet or exceed the high standards of performance set by the existing algorithms. The common CAD systems include image acquisition, enhancement of the acquired image, segmentation or extraction of the regions of interest followed by extracting features from the region of interest and finally the classification for identifying abnormalities. Segmentation is an essential step of any CAD system since it extract regions those have high probability of lesions. It also reduces the amount of data to process so that performance of the CAD system can be improved. Classification is the final step of the CAD system, which identifies the normal or abnormal mammogram images in the dataset [18][19].

Mammography lesions such as microcalcifications and masses are usually small and low in contrast compared to contiguous breast tissue. Therefore they are very hard to detect. Image enhancement can improve the accuracy of the diagnosis by the radiologists. [18]. Various image enhancement techniques like thresholding, low and high pass filters, contrast stretching, histogram modeling, Gradient operators etc. are used for reducing the noise, suppressing the background details and edge sharpening [20]. The usual task of mammogram enhancement is to increase the contrast as well as sharpen the edges or borders of the mammogram. Once an enhanced mammogram image is obtained, the most doubtful area where abnormality occurs can be extracted for further examination. This extracted portion is called Region of Interest (ROI) of the image. This process is called segmentation which usually corresponds to the extraction of objects from the background. The segmentation can be done in order to locate suspicious area of the mammogram. The wavelet based segmentation, fractal models, fuzzy based approaches, contour detection are the some of the advanced segmentation technique used in mammogram image analysis. It is possible that multiple ROIs of the same mammogram be extracted for the analysis and classification. Texture information plays an important role in the analysis and detection of breast tumors in mammograms. Once a mammogram ROI is obtained, the suspicious area where abnormality occurs can be identified by extracting important texture features in the image. These features characterize tumors or abnormality in the images [16]. Extracted features are then analyzed using different classifiers likes Artificial Neural Networks, Hybrid Neural network classifiers, K-Nearest Neighbors, Support Vector Machines etc. Fuzzy based approaches are also used for classifying the mammogram images based on the feature set extracted [23].

Computer aided diagnosis of breast tumor is one of the challenging task in the field of medical image processing. There are good numbers of works already published in this area and most of them reported good results. It is a known fact that we cannot rely 100% on any of these systems. Hence there is scope for further works in this area. The performance of a classification system can be evaluated using parameters such as sensitivity and specificity [2]. An ROI may be classified as either cancerous (positive) or normal (negative). The final decisions belong to any four possible categories: true positive (TP), true negative (TN), false positive (FP) and false negative (FN). FN and FP represents two kinds of errors. An FN error implies that true abnormality was not detected and a FP error occurs when a normal region was falsely identified as abnormal image. A TP decision is correct judgment of an existing abnormality and a TN decision means that a normal region was correctly labeled [2] [17]. Therefore the accuracy and performance of any CAD system is evaluated based on the Sensitivity, Specificity and Accuracy. They are defined as follows:

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \qquad (1)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \qquad (2)$$

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} \qquad (3)$$

In this paper we propose a new multilevel classification scheme for classifying mammogram images. The feature vector is formed from the Gray Level Co-occurrence Matrix (GLCM) value extracted from four different orientations of ROIs. A set of lazy classifiers are then used for classification. Initially the systems classify the mammogram images into normal or abnormal. Then all the abnormal images classified in the first level are further classified into appropriate categories depending upon architectural as well as texture patters found in the image or ROI.

The rest of the paper is organized as follows: Section II discusses about the related study conducted in this area. In section III we explain about the creation of GLCM matrix and the features extracted from them. Different machine learning algorithms used for the classification are discussed in section IV. The proposed method for feature extraction and the classification is discussed in Section V. Dataset used for the experiment and results are explained in Section VI and finally the conclusion is given in VI.

II. RELATED WORK

Feature extraction is the primary part of any mammogram classification algorithms. Commonly three types of features namely texture feature, positional features and shape features are used for the classification purpose. Texture features are the alteration and variation of surface of the image that can be characterized as the space distribution of gray levels in a neighborhood. Positional features describes the location wise gray level distribution of the image and shape feature extract the shape of an object in the images based on the variation of intensity distribution of the gray level.

There are two types of texture measures: first order and the second order. The first order texture measures are based on the statistical measures calculated from the pixel value of the image whereas the second order texture measures statistical features of the pixel value with respect to its neighboring pixels. The histogram features and intensity features are examples of first order texture features. Intensity features and histogram features are the simplest features based on the pixel intensities useful for the identification of hidden patterns in a mammogram. The GLCM, a second order texture feature is extracted based on a group of pixels in an ROI. Compared to the standard statistical features, the GLCM features have much more relevance due to the repeating pattern.

Different classification techniques are being used for the classification of masses in the mammogram images. Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), Binary Decision Tree (BDT), Support Vector Machines (SVM) and Bayesian Network (BN) are some of the prominent classification methods. The performance of the above systems mainly depends on the features selection rather than the training and classification of the system. A review of some of the prominent works in this area is given below.

A comparative study made by the R. Nithya and B Santhi [21] on the above feature extraction methods shows excellent result with GLCM features compared to other methods. The study used a sample of 50 mammogram images from the DDSM database. The same authors[22] proposed another method for classification of normal and abnormal patterns in Digital mammograms for the breast cancer diagnosis using GLCM features and ANN. The work reported sensitivity and specificity more than 90% for a sample set of 50 digital mammogram images from the DDSM dataset.

A.Mohd Khuzi et.al [17] proposed a method for the detection and classification of masses and non-masses in a mammogram images using GLCM features. They extracted the features from the ROIs which segmented using different segmentation algorithms namely Otsu, Thresholding and K-means. The accuracy of the classification is measured with sample set consisting of 20 abnormal and 20 normal images from the Mini-Mias. The work reported more that 80% for both Otsu's and the thresholding techniques and 70% for K-Mean.

A hybrid feature reduction method namely Linear forward selection and genetic algorithm for reducing the GLCM feature sets was proposed by Vasantha and Bharathi [25] [26]. In this work 60 images from DDSM database and 118 images from Mini-Mias database were used with decision tree classifier. They could achieve 86% accuracy with DDSM and 95% with Mini-Mias Database.

Using ANN and GLCM feature, Abdulla and Zaki [27] proposed a method for detection of masses in digital mammogram and achieved 91 % sensitivity and 84 % specificity for classifying 90 mammogram images randomly selected from the Mini-Mias database. Islam et al. [28] also proposed a classification method using ANN and GLCM features to classify benign-malignant classes of mammogram images which achieved 90 % sensitivity and 84% specificity.

III. GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM)

Feature extraction and selection of the suitable features from the extracted set is a very important step in the development of any CAD system for the detection and classification of mammogram images. The feature can be classified broadly into statistical and semantic types. Both categories of features have its own advantages and disadvantages for the classification task. Feature extraction based on texture patterns are the most prominent one for the identification of mass/tumors in an image. There are two types of statistical texture features that can be extracted for the classification purpose. They are first order statistical features and second order statistical features. The GLCM is a second order statistical feature extracted from an image based on the neighboring pixels. The intensity values of neighboring pixels form a group which represents certain repeating nature of texture pattern in an image. This repeating pattern is local to any image portion so that it can be better analyzed. The GLCM is a two dimensional array which takes into account of the specific position of a pixel relative to other pixels [17]. The GLCM matrix shows the tabulation of how often different combination of pixel brightness values occur in an image. Each entry P (i, j) of a GLCM corresponds to the number of occurrences of the pair of gray levels i and j which are at a distance **d** apart in original image [29]. A single direction might not give enough and reliable texture information. Therefore the GLCM matrices are constructed in different orientation Ө, such as 0^0,45^0,90^0 and 135^0 at a distance of **d**. The fundamental texture descriptors derived from GLCMs namely contrast, energy, homogeneity and correlation of the gray levels used as the features for the classification. The contrast measures the amount of local variations present in an image, while energy is the sum of squared elements in GLCM. Energy may also be referred as uniformity of the angular second moment. The homogeneity refers to the closeness of the distribution of elements in GLCM to the GLCM diagonal. Finally correlation shows how correlated a pixel is to its neighbor over the whole image [17]. These measures are mathematically defined as follows.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \tag{4}$$

$$\text{Energy} = \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ij}^2 \tag{5}$$

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{6}$$

$$\text{Correlation} = \frac{\sum_{i}\sum_{j} P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{7}$$

IV. LAZY CLASSIFIERS

A classification problem occurs when an object needs to be assigned to a predefined group or class based on a number of observed attributes related to that object [32]. Different types of classification algorithms are available today for the classification in which eager learning and instance based learning algorithms are most prominent. Lazy learning classifiers are instance based or memory based classification algorithm proposed against the common eager learning algorithms. They are the important category of classifiers that can be implemented and tested easily with minimum cost. This learning algorithm utilizes a kind of distance measure between test instances and training instances for the classification. Entropy and distance measures are the two common methods adopted by the Lazy classifiers.

The common eager learning methods eagerly compile the training data into some concept descriptors such as rule sets, decision trees, artificial neural network and graphical models. After constructing such type of models, common eager learning methods attempt to seek a particular general hypothesis, which covers the entire instance space. But the lazy learning models do not conduct any processing of developing a model for classification before they encounter the unseen instance to be classified. The lazy classifier constructs model only when they are directed to classify the unseen instance and discard all the customized models and all the intermediate results after the learning process for the unseen instance completes. Therefore lazy learning algorithms need much less training costs but more storage and computational resources than the eager algorithms. Lazy learning algorithms can make use of the characteristics of the unseen instance to explore a richer hypothesis space during the classification. Due to this richer hypothesis space, lazy learning methods outperform significantly some of the common eager learning methods.

Lazy learning exhibits many advantages in learning scenarios. Common eager learning methods need to learn a new global classifier every time the training data is updated. When the training data is large and complex, it is not economical for the service provider to conduct eager learning frequently. Lazy learning methods have no such problems. Generally, the updating of training data is the only operation required by lazy learning methods. Another learning scenario for which lazy learning is competitive is that the learning target class is not fixed and the attribute set is large. Lazy learning handles each classification as an independent learning process, and hence it can be customized to the unseen instance and focuses only on the local data patterns [33]. In this paper we use three different instance based classifiers K*, IBL and LWL algorithms.

A. K* classifier

K * is an instance based classifier that classifies the test instance based on the classes of those training instances similar to the test instance determined by some similarity functions. The similarity function is determined by using entropy as a distance measure. The result obtained by this method is comparatively better than the several other machine learning algorithms.

The similarity function computes the similarity between a test instances against the instances in the concept descriptor computed using the training instances in the samples. Let x_i, y_i denotes test instance and concept descriptor respectively, then the similarity function between these two instances are computed by using the following equation

$$Similarity(x_i, y_i) = -\sqrt{\sum_{i=1}^{n} f(x_i, y_i)} \qquad (8)$$

Where the instances are described by n attributes. We define $f(x_i, y_i) = (x_i - y_i)^2$ for numeric valued attributes and $f(x_i, y_i) = (x_i \# y_i)$ for Boolean and symbolic-valued attributes. Missing attributes values are assumed to be maximally different from the value present. If the both instances are missing, then $f(x_i, y_i)$ yields 1. The function $f(x, y)$ is the entropy computed using the concept descriptors of the training samples using the equation

$$E(S) = \sum_i p_i \log p_i \qquad (9)$$

Where $p_i = \frac{s_i}{|s|}$, S_i denotes the number of training instances with class C_i, and $|S| = \sum_i S_i$ be the total number of training instances.

B. IBL Classifier

Storing and using specific instances improves the performance of several supervised learning algorithms. Instance-based Learning algorithm generates classification prediction using only specific instances. It does not maintain a set of abstractions derived from specific instances. This approach extends the nearest neighbor algorithm which requires large storage requirements similarity function is used for categorizing the matches between testing samples against specific instances. Using these specific instances, Instance based learning algorithm reduces the cost incurred for updating concept descriptors and increases the learning rates. Instance based learning algorithm is derived from the nearest neighbor pattern classifier, which uses only selected instances to generate classification prediction. Therefore instance-based learning algorithm reduces storage requirements and at the same time there is small degradation in classification accuracy [34]

Each instance in IBL classifier is represented by a set of attribute-value pairs. This set of attributes defines an n-dimensional *instance space*. Exactly one of these attributes corresponds to the *category attribute;* the other attributes are *predictor attributes. A category* is the set of all instances in an instance space that have the same value for their category attribute. However, IBL algorithms can learn multiple overlapping concept descriptions simultaneously. The concept description is a function that maps instances to categories that yields the classification. An instance-based concept description includes a set of stored instances and possibly some information concerning their past performance during the classification. This set of instances can change after each training instance is processed. However, IBL algorithms do not construct extensional concept descriptions. Instead, concept descriptions are determined by how the IBL algorithms selected similarity and the classification functions uses the current set of saved instances. The classification function determines how the set of saved instances in the concept descriptions are effectively used to predict the values for the category attribute.

The IBL classification function used for defining concept description have the following components:

1. *Similarity Function:* This computes the *similarity* between a testing instances *i* and the instances in the concept description. .

2. *Classification Function:* This receives the similarity function's results and the classification performance records of the instances in the concept description. It yields a classification for the instance *i*.

3. *Concept Description Updater:* This maintains records on classification performance and decides which instances to include in the concept description. Inputs include *i*, the similarity results, the classification results, and a current concept description. It yields the modified concept description.

The similarity and classification functions determine how the set of saved instances in the concept description are used to predict values for the category attribute. Therefore, IBL concept descriptions not only contain a set of instances, but also include these two functions.

IBL algorithms differ from most other supervised learning methods: they do not construct explicit abstractions such as decision trees or rules. Most learning algorithms derive generalizations from instances when they are presented and used for simple matching procedures to classify subsequently presented instances. This incorporates the purpose of the generalizations at the presentation time. IBL algorithms perform comparatively little work at the presentation time since they do not store explicit generalizations. However its work load is higher when presented with subsequent instances for classification, at which time they compute the similarities of their saved instances with the newly presented instance. This obviates the need for IBL algorithms to store rigid generalizations in concept descriptions, which can require large updating costs to account for prediction errors. [35]

C. LWL classifier

Lazy learning methods defer processing of training data until a query needs to be answered. This usually involves storing the training data in memory, and finding relevant data in the database to answer a particular query. Relevance is often measured using a distance function, with nearby points having high relevance. One form of lazy learning finds a set of nearest neighbors and selects or votes on the predictions made by each of the stored points.[33]
Locally Weighted Learning (LWL) is lazy classifier that uses statistical learning techniques for training and classifying complex tasks. It provides an approach to learning models of complex phenomena, dealing with large amounts of data, training quickly, and avoiding interference between multiple tasks during control of complex systems. LWL methods can even deal successfully with high dimensional input data that have redundant and irrelevant inputs while keeping the computational complexity of the algorithms linear in the number of inputs.[33][34] LWL methods come in two different strategies. Memory-based LWL is a "lazy learning" method that simply stores all training data in memory and uses efficient lookup and interpolation techniques when a prediction for a new input has to be generated [33] [34]. This kind of LWL is useful when data needs to be interpreted in flexible ways, for instance, as forward *or* inverse transformation. Memory-based LWL is therefore a "least commitment" approach and very data efficient. Non-memory-based LWL has essentially the same statistical properties as memory based LWL, but it avoids storing data in memory by using recursive system identification techniques [37]. In this way, non-memory-based LWL caches the information about training data in compact representations, at the cost that a flexible re-evaluation of data becomes impossible, but lookup times for new data become significantly faster.

V. PROPOSED METHOD

The proposed method presents a novel approach for computer aided diagnosis (CAD) system for the detection of the abnormalities in breast tumors. It consists of two levels of classification; first, a method is devised for identifying and classifying the risk level of the breast mammograms. i.e normal, benign and malignant. In the second level, all the abnormal images in the dataset are used for further level of classification based on the types of abnormalities or distortion such as calcification, asymmetric distortion, architectural distortion, circumference masses, speculated and ill defined masses. The architecture of the proposed system is given in Fig 1.

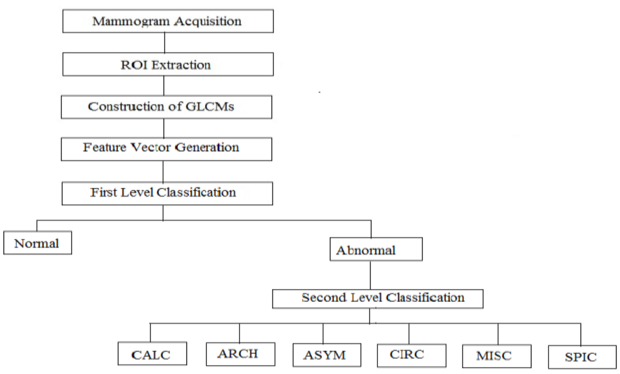

Fig 1: Architecture of the proposed system

For classification GLCM features discussed in section III are extracted from the ROIs of the dataset. The GLCM matrices are generated in four different orientations for three different sizes of ROIs (8 x 8, 16 x 16 and 32 x 32 pixel sizes). The GLCM s are constructed by taking pair of image cells at ***d =1*** distance apart and incrementing the matrix position corresponding to the gray level of both cells. Thus the system generated four different GLCMs in four different orientations such as 0^0,45^0,$90^0$and 135^0 . Then the system extracts features such as contrast (C), Energy (E), Homogeneity (G) and Correlation (R) of the gray level values in the GLCM matrix of the ROIs. All the four features extracted from the different orientations of the GLCM matrix are combined together to form a feature vector, which comprises a set of 16 features. This feature vector acts as the basis for the classification.

The classifier is trained using the feature vector so extracted for the different sets of ROIs of size 8x8, 16x16 and 32x32 from the images in Mini-Mias database. The most common lazy learning algorithms such as K*, IB1 and LWL are used for training and testing of the ROIs. The training and testing datasets of the ROIs are prepared by dividing the entire dataset of the feature vector into ten different folds of equal sizes. Then nine different folders of the dataset are used for training and the remaining one folder of feature dataset is used for testing. The processes of training and testing are repeated for each set of folders and the performance is evaluated by taking the average of test result obtained in each folder.

Algorithm for Mammogram Classification using Lazy classifier

1: Extracted Mammogram ROIs of different sizes like 32 x 32 pixels, 16 x 16 pixels and 8 x 8 pixel sizes based on the abnormality center from the original mammogram images of size 1024 x 1024 pixels from the Mini-Mias database.
2: From the ROIs extracted of different pixel size like 32 x 32, 16 x, 16 and 8 x 8, the Gray level co-occurrence matrices in four different orientations (0^0, 45^0, 90^0 and 135^0) are constructed at unit distance.
3: The features like contrast, Energy, Homogeneity and Correlations are computed for each GLCM constructed in step 2.
4: Formed a feature vector of 16 features which comprising the features computed at step 3 in all four different GLCMs constructed in a mammogram image.
5:The feature vector computed in step 4 is grouped as training and testing set for classification.
6: Using Weka lazy classifier K*, IBL and LWL, the training set is used for training.
7: The performance of the lazy classifier is evaluated on testing dataset.

VI. DATA SETS AND RESULTS.

A. Dataset

Mammogram images are the low intensity gray scale images which show the details of the patient breast in terms of pixel values or intensity distribution inside of it. The details could be normal tissues, vessels, muscles, different types of masses and noise. Each type of masses has different properties of shape, size and brightness that are described in terms of its intensity distribution of the image. Generally these properties are measured as different features of the mammogram images of the dataset. The radiologist makes use of these features for the effective diagnosis of the breast tumor if it is identified.

In this study we used a set of mammogram images provided by Mammographic Image Analysis Society (Mini-MIAS) [24]. The database contains left and right breast investigated and labeled by an expert radiologist. From these dataset regions of interest (ROIs) of different sizes (8 x 8, 16 x 16 and 32 x 32 pixels) are extracted for our investigation. The ROIs are extracted from the original mammogram images are based on the abnormality center of the cancerous images that are already marked by the radiologist. But the non-cancerous images are extracted with respect to the center of the original mammogram image. For practical evaluation of the proposed system, the entire dataset which comprises 322 ROIs of different types of lesions as shown in Table I are used. While extracting ROIs of cancerous images, multiple abnormal regions are extracted and they are treated as a separate ROIs of the same image and it is also included the dataset for the classification.

VII. RESULTS

The dataset used for the experiment comprises of 330 ROIs extracted from 322 mammogram images from the Mini-Mias database. The set consists of 207 normal, 54 malignant and 69 benign images. The different sizes of ROIs (8 x 8, 16 x16 and 32 x 32 size of pixels) of each mammogram image in the dataset are extracted based on the abnormality center of the image. Then we formed three different sets of GLCM feature vector for each size of ROIs and classified using three different lazy classifiers namely K*, IBL and LWL available in Weka software. The classification is done in two levels. In the first level of the classification the proposed algorithm identified the risk level of the images in the dataset such as Normal, Benign and Malignant. The confusion matrix generated by the different classifier for the first level classification is shown in Table II(see appendix).

Based on the confusion matrix generated by the classifier, the performance of the different classifiers with varying ROI sizes are evaluated. The evaluation result is shown in Table III. Now we could arrive at the following conclusions regarding our algorithm. The classification accuracy obtained for K* is the best followed by IB1 and LWL. The accuracy of the classification algorithm shows significant increase on increasing the size of ROIs irrespective of the classifiers. Irrespective of the ROIs size, the performance of the LWL classifier is poor compared to other two classifiers. The performances of our algorithm using three lazy classifiers are also shown in Fig 2.

Table 1: Lesion distribution of MIAS database

LESION	RISK	#
Normal		207
Architectural distortion[ARCH]	Benign	09
	Malignant	10
Asymmetry[ASYM]	Benign	06
	Malignant	06
Microcalcification[CALC]	Benign	12
	Malignant	13
Circumscribed masses[CIRC]	Benign	19
	Malignant	04
Ill-defined masses[MISC]	Benign	06
	Malignant	08
Spiculated lesions[SPIC]	Benign	11
	Malignant	08
Total		322

Table III: Classification accuracy (in %) of mammogram images using different Lazy classifiers.

ROI Size	K*	IB1	LWL
8 x 8	73.33	72.73	63.94
16 x 16	83.33	83.03	63.64
32x32	92.40	92.10	63.83

Fig 2: Performance evaluation of the different lazy classifiers in the first (primary risk) level classification.

In the second level of the classification, classifiers are trained to classify all the abnormal images in the dataset into different classes such as calcification, Architectural distortion, Asymmetric distortion, circular distortion, ill defined and speculation. The confusion matrix generated by the three lazy classifiers in the second stage of the classification is shown in Table IV (see appendix). Based on the confusion matrix; the classification accuracy obtained by three lazy classifiers is shown in Table V. The table reveals that the performance of the algorithm is good for K* and IB1 of ROI size 32x32 pixel. As stated in the first level classification, the performance of the sub classification also improves significantly on increasing size of ROIs. Finally, the performance of the LWL classifier is very poor irrespective of the ROIs size compared to other two classifiers. Graphical representations of the performance of the classification algorithms are shown in figure V.

Table V: Classification accuracy (in %) of mammogram images using different Lazy Classifiers

ROI Size	K*	IB1	LWL
8 x 8	50.41	50.41	33.33
16 x 16	67.48	65.04	38.21
32x32	86.18	86.18	37.40

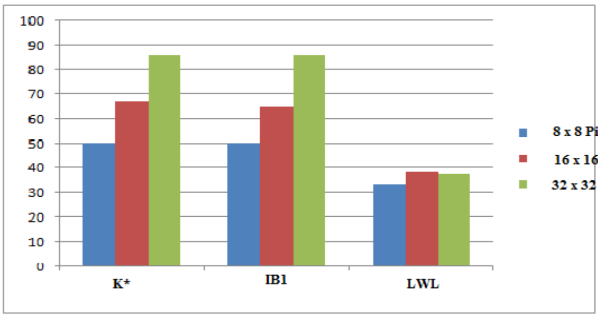

Fig 3: Performance evaluation of the different Lazy classifiers in sublevel risk.

VIII. CONCLUSION

The second order statistical texture features play a significant role in the classification of any CAD system. In this paper we proposed an automatic classification system for classifying mammogram images in two different stages. In the first stage, the system classifies the images in the dataset into normal, malignant and benign types. In the second stage of the classification all the abnormal images in the dataset are further classified into different sub categories of abnormalities. The feature vectors used for the classification are generated based on the GLCM matrix constructed in different orientations of the ROIs of the mammogram images. Finally, classification is done using different lazy classifiers - K*, IB1 and LWL. The performance of the system is measured using the accuracy obtained by the different classification algorithms. It is observed that the performance of the proposed system with second order statistical feature is excellent.

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Table II: Confusion matrix generated by different lazy classifiers on Mini-Mias Database

		8 x 8			16 x 16			32 x 32		
K *		N	M	B	N	M	B	N	M	B
	N	206	0	1	206	1	0	206	0	1
	M	33	21	0	16	38	0	10	42	1
	B	54	0	15	37	1	31	13	0	56
	T	**293**	**21**	**16**	**259**	**40**	**31**	**229**	**42**	**58**
IB1		N	M	B	N	M	B	N	M	B
	N	207	0	0	207	0	0	206	0	1
	M	33	21	0	18	36	0	10	42	1
	B	57	0	12	37	1	31	13	0	56
	T	**297**	**21**	**12**	**262**	**37**	**31**	**229**	**42**	**58**
LW L		N	M	B	N	M	B	N	M	B
	N	207	0	0	205	0	2	207	0	0
	M	50	4	0	52	2	0	51	2	0
	B	69	0	0	65	1	3	67	1	1
	T	**32 6**	**4**	**0**	**32 2**	**3**	**5**	**325**	**3**	**1**

N: Normal M: Malignant B: Benign

Table IV: Confusion matrix generated by different lazy classifiers on Mini-Mias Database

		8 x 8 Pixel Size						16 x 16 Pixel Size						32 x 32 Pixel Size					
K *		1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
	1	30	0	0	0	0	0	17	0	0	12	1	0	30	0	0	0	0	0
	2	11	7	0	1	0	0	0	8	0	10	1	0	6	13	0	0	0	0
	3	9	0	5	0	0	1	0	0	10	5	0	0	2	0	13	0	0	0
	4	18	0	0	7	0	0	0	0	0	25	0	0	4	0	0	21	0	0
	5	8	0	0	0	6	1	0	0	0	3	12	0	3	0	0	0	12	0
	6	12	0	0	0	0	7	0	0	0	8	0	11	2	0	0	0	0	17
	T	88	7	5	8	6	9	17	8	10	63	14	11	47	13	13	21	12	17
IB1		1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
	1	30	0	0	0	0	0	30	0	0	0	0	0	30	0	0	0	0	0
	2	11	8	0	0	0	0	11	8	0	0	0	0	6	13	0	0	0	0
	3	9	0	6	0	0	0	5	0	10	0	0	0	2	0	13	0	0	0
	4	18	2	0	5	0	0	15	0	0	10	0	0	4	0	0	21	0	0
	5	8	0	1	0	6	0	4	0	0	0	11	0	3	0	0	0	12	0
	6	12	0	1	0	0	6	8	0	0	0	0	11	2	0	0	0	0	17
	T	88	10	8	5	6	6	73	8	10	10	11	11	47	13	13	21	12	17
LWL		1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
	1	30	0	0	0	0	0	14	0	0	14	2	0	28	0	0	0	2	0
	2	15	0	0	0	4	0	5	3	1	10	2	0	17	0	0	1	1	0
	3	11	0	1	0	3	0	5	0	2	6	2	0	7	0	0	2	6	0
	4	20	0	0	1	4	0	3	0	0	22	0	0	15	0	0	10	0	0
	5	8	0	0	0	7	0	5	0	0	4	6	0	4	0	0	4	7	0
	6	13	0	1	0	3	2	10	0	0	9	0	0	14	0	0	3	1	1
	T	97	0	2	1	21	2	42	3	3	65	12	0	85	0	0	20	17	1

1: CALC 2: CIRC 3: ARCH 4: ASYM 5: MISC 6: SPIC