An Automated Mass Classification System in Digital Mammograms using Contourlet Transform and Support Vector Machine

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ABSTRACT
In this paper, an efficient automated mass classification system for breast cancer in digitized mammograms using NonSubsampled Contourlet Transform (NSCT) and Support Vector Machine (SVM) is presented. The classification of masses is achieved by extracting the mass features from the contourlet coefficients of the image and the outcomes are used as an input to the SVM classifier for classification. The system classifies the mammogram images as normal or abnormal, and the abnormal severity as benign or malignant. The evaluation of the system is carried on using mammography image analysis society (MIAS) database. The experimental result shows that the proposed method provides improved classification rate.

General Terms
Image classification, Artificial Intelligence, Data Mining.

Keywords
Mammogram, Mass classification, Benign, Malignant, NSCT, SVM

1. INTRODUCTION
Breast cancer has become the most hazardous types of cancer among women in the world. The world health organization's International Agency for Research on cancer (IARC) estimates that more than 400,000 women expire each year [1]. The occurrence of breast cancer is increasing globally and disease remains a major public health problem. According to American college of Radiology (ACR) statistics one out of nine women will develop breast cancer during their life span.

Early detection of breast cancer is essential in reducing life losses [2]. Mammography is a best radiological screening techniques in detecting breast cancer which makes it possible to detect lesions in the breast using low doses of radiation. The use of mammography results in a 30 % to 40 % decreased death rate in screened women. Although radiographic breast screening has allowed for accurate diagnosis of breast disease at earlier stages of development, 10 – 30 % of malignant cases are not detected for a range of reasons such as abnormalities that are not observable, abnormalities that are misinterpreted and technical problem in the imaging process [3]. Also retrospective studies have shown that in current breast cancer screening between 10 % and 25 % of the tumors are missed by the radiologist [4]. Digital mammograms are among the most complicated medical images to be read due to their low contrast and the differences in the types of tissues. Thus, the task of the radiologist is tedious in the case where a significant number of mammograms require fast and accurate interpretation.

A computer aided detection (CAD) system could be very useful to draw the awareness of the radiologist to a tumor he might otherwise have unnoticed. The CAD methods provide a valuable "second opinion" to the radiologist. Strategy has been proposed and when combined with film evaluation improves overall performance for detection and classification of breast cancer and may reduce the observer disparity. This would diminish the number of unnecessary biopsies in patient's physical and mental sufferings.

In this paper automatic mass classification into benign and malignant is presented based on features extracted from the contourlet coefficients using Nonsubsampled Contourlet Transform (NSCT), the mammogram images are classified by using a classifier based on Support Vector Machine (SVM). This paper is organized as follows: Section 2 briefly reviews some existing techniques for mass classification. Section 3 provides the theoretical background of Contourlet transform and SVM classifier. Section 4 presents the proposed method. Section 5 demonstrates the simulation results and their performance evaluation. Section 6 draws conclusion of this paper.

2. LITERATURE REVIEW
Literature survey shows several techniques that have been proposed to classify the masses as benign or malignant using various methodologies. Computerized schemes to classify masses by optimizing certain criteria to classify cases into one of mutually exclusive classes are developed in [5]-[7] and the elevated performance for linear separable problems but poor performance for nonlinear separable data were shown. This classification is based on linear discriminant analysis. The features required to distinguish the benign from malignant masses are abnormality dependent.

Linear discriminant analysis (LDA) in mixture with stepwise feature selection in [8] was trained and tested on morphological features extracted using the machine segmentation and radiologist segmentation and A_z area under the receiver operating characteristics (ROC) 0.89 was obtained whereas for speculation features it was 0.88.

Lisboa [9] developed the scheme to classify the masses using Artificial Neural Network (ANN). ANNs are very useful tools in various medical diagnostic systems. The key attributes like distributed representations, local operations, and non-linear processing make ANN appropriate for taking few complex decisions from massive amount of data. Thus when expert knowledge is unavailable in full-fledged sense as for example in case of masses, ANN provides alternative and better solutions.

J.L.Viton et. Al. [10] developed a two level hierarchical method is used to classify the masses where Bayesian classifier exists in each level. In first level the speculated masses are discriminated from non-speculated masses. In the second level masses with fuzzy edges are separated from well defined edges among the non-speculated edges. Bayesian network uses a probabilistic approach to determine the class conditional probability density functions for background and tumor in breast cancer detection application.

Alginahi et. al. [11]-[12] developed ANN-based technique for thresholding composite digitized documents with non-uniform and complex background. To classify masses this method uses 8 statistical and textural features of an image. A common database and the same genetic algorithm were used to optimize both the Bayesian belief network and neural network in [5] and [13]-[14] and the results show that the performance of the two classifiers converged to the same level. Therefore, it is obvious that the performance of CAD systems mostly depends on feature selection and training database than the classifiers.

Furthermore, various classification methodologies have been reported for the characterization of ROI such as, rule-based systems [14] and [15], fuzzy logic systems [16], statistical methods based on Markov random fields [17] and support vector machines [18]. In addition some work reported in the literature employs neural network for cluster characterization and data mining technique for detection and classification of digital mammograms [19]-[21].

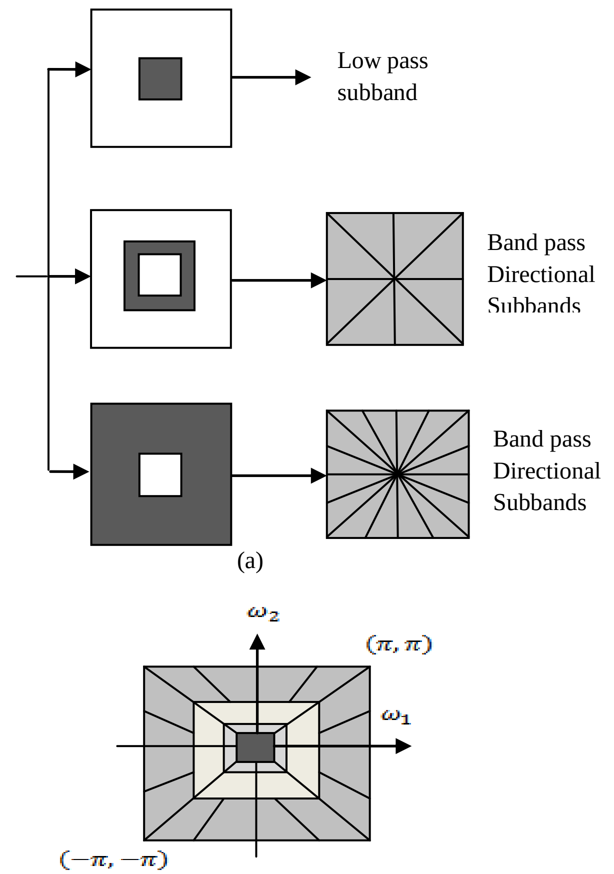
The main goal of this paper is to develop a better CAD technique for classification of mass in digital mammograms using Contourlet transform and Support vector Machine. First, the features are extracted from the contourlet coefficients using Nonsubsampled Contourlet Transform (NSCT). Second, the mammogram images are classified by using a classifier based on Support Vector Machine (SVM). The purpose of the system is to determine the abnormal severity of masses in digital mammograms as benign or malignant.

3. METHODOLOGY

The proposed system is built based on Contourlet transform of the image and by applying SVM for building the classifiers. In this section the theoretical background of both the approaches are introduced.

3.1 Contourlet Transform

The Contourlet transform is an extension of the wavelet transform which uses multi scale and directional filter banks. Here images are oriented at various directions in multiple scales, with flexible aspect ratios. The Contourlet transform effectively captures smooth contours images which are the dominant feature in natural images. The main difference between Contourlet and other multi scale directional systems is that the Contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, the Contourlet transform uses iterated filter banks, which makes it computationally efficient. The Contourlet transform [22] is a multidirectional and multi scale transform that is constructed by combining the Laplacian pyramid [23], [24] with the directional filter bank (DFB) proposed in [25]. Due to down samplers and up samplers present in both the Laplacian pyramid and the DFB, the Contourlet transform is not shift-invariant.



(b)

Fig.1. The Nonsubsampled Contourlet transform. (a) Nonsubsampled filter bank structure that implements the NSCT (b) Idealized frequency partitioning.

Fig. 1(a) displays an overview of the NSCT [22]. The structure consists in a bank of filters that splits the 2-D frequency plane in the sub bands illustrated in Fig. 1(b).This transform can thus be divided into two shift-invariant parts: 1) a non sub sampled pyramid structure that ensures the multi scale property and 2) a non sub sampled DFB structure that gives directionality.

The multi scale property of the NSCT is obtained from a shift-invariant filtering structure that achieves sub band decomposition similar to that of the Laplacian pyramid. This is achieved by using two-channel non sub sampled 2-D filter banks. Fig. 2a & 2b illustrates the Nonsubsampled pyramid (NSP) decomposition with J =3 stages. The ideal pass band support of the low-pass filter at the jth stage is the region $[((-\pi)/2j),(\pi/2j)]^2$. Accordingly, the ideal support of the equivalent high-pass filter is the complement of the low-pass, i.e., the region$[((-\pi)/(2j-1)),(\pi/(2j-1))]^2$ / $[((-\pi)/2j),(\pi/2j)]^2$. The filters for subsequent stages are obtained by up sampling the filters of the first stage. This gives the multi scale property without the need for additional filter design. This structure is thus different from the separable nonsubsampled wavelet transform (NSWT).

In particular, one band pass image is produced at each stage resulting in J+1 redundancy. By contrast, the NSWT produces three directional images at each stage, resulting in 3J+1 redundancy.

Non sub sampled Directional Filter Bank (NSDFB): The directional filter bank of Bamberger and Smith [25] is constructed by combining critically-sampled two-channel fan filter banks and re sampling operations. The result is a tree-structured filter bank that splits the 2-D frequency plane into directional wedges. A shift-invariant directional expansion is obtained with a non sub sampled DFB (NSDFB). The NSDFB is constructed by eliminating the down samplers and up samplers in the DFB .This is done by switching off the down samplers/ up samplers in each two-channel filter bank in the DFB tree structure and up sampling the filters accordingly. This results in a tree composed of two-channel NSFBs as shown in Fig. 3a and Fig 3b illustrates the four channel decomposition. The synthesis filter bank is obtained similarly. The NSCT is flexible in that it allows any number of directions in each scale. In particular, it can satisfy the anisotropic scaling law. This property is ensured by doubling the number of directions in the NSDFB expansion at every other scale. The NSCT [10] is constructed by combining the NSP and the NSDFB as shown in Fig. 1(a). Eight sub bands have been produced and some of the Nonsubsampled Contourlet coefficients.

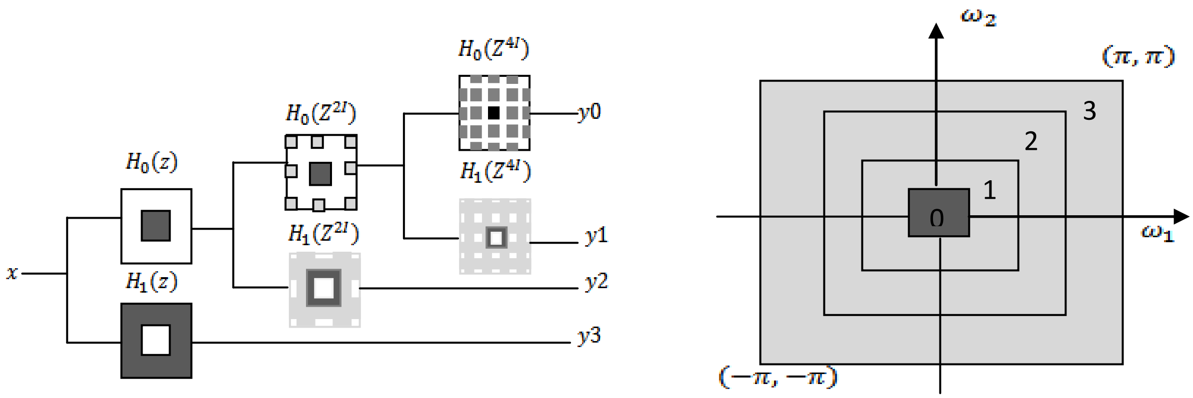


Fig.2.Nonsubsampled pyramid (a) Three-stage pyramid decomposition. (b) Sub bands on the 2-D frequency plane

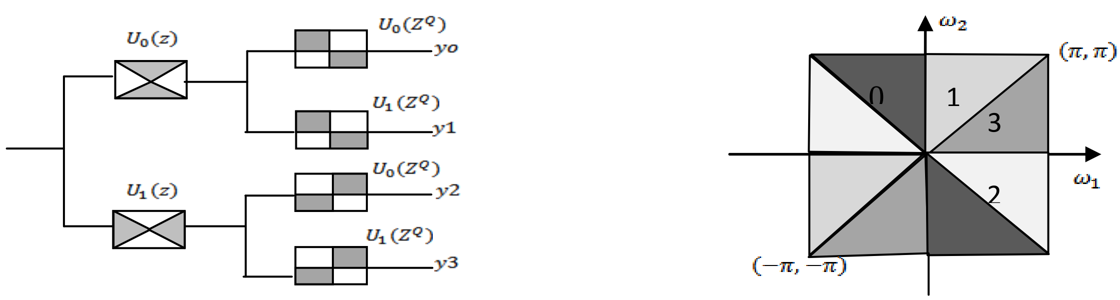


Fig.3. Four-channel Nonsubsampled directional filter bank constructed with two-channel fan filter banks. (a) Filtering structure (b) Corresponding frequency decomposition

3.2 Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member of. Since an SVM is a classifier, then given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, an SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. The SVM are based on the concept of decision planes that define decision. A boundaries decision plane is one that separates between assets of objects having different class memberships. SVM is a useful technique for data classification. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one “target value” (class labels) and several “attributes” (features) [26].

SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basis functions are automatically obtained during training. The performance of SVM largely depends on the kernel [27]. The optimal one is the one that separates the data with the maximal margin. SVMs identify the datapoints near the optimal separating hyperplane which are called support vectors. The distance between the separating hyperplane and the nearest of the positive and negative datapoints is called the margin of the SVM classifier. The separating hyperplane is defined as

$$D(x) = (w, x) + b \quad (1)$$

Where x is a vector of the dataset mapped to a high dimensional space, and w and b are parameters of the hyperplane that the SVM will estimate. The nearest datapoints to the maximum margin hyperplane lie on the planes.

$$(w.x) + b = +1 \; for \; y = +1 \quad (2)$$

$$(w.x) + b = -1 \; for \; y = -1 \quad (3)$$

Where y=+1 for class ω_1 and y=-1 for class ω_2. The width of the margin is given by $m = 2/\|w\|$. Computing w and x is then the problem of finding the minimum of a function with the following constraints:

- Minimize $m(w) = \frac{1}{2}(w.w)$
- Subject to constraints $y_i[w.x_i + b] \geq 1$

4. PROPOSED SYSTEM

The proposed system mainly consists of two different stages which include the feature extraction and classification stage. All the stages are explained in detail in the following sub sections.

4.1 Feature Extraction Stage

Feature extraction is an essential pre-processing step for pattern recognition and machine learning problems. It is often decomposed into feature construction and feature selection. In our approach, Contourlet coefficients are used as features to classify the mammogram images .The following section gives the overview of feature extraction of the digital mammogram. The Feature Extraction stage is shown in Figure 4.

In the Image pre-processing stage, the undesired distortion is suppressed and enhancement of image features and are carried out to improve the image data. The digital mammograms in the MIAS database [28], 50% of the mammograms comprised of the background with a lot of noise. To eliminate the background information and the noise, ROI image of size 800 X 800 is selected from the center of the input image. Global gray levelthresholding is applied to the ROI Image. The upper threshold and lower threshold are set to 260 and 140 respectively. Then the adaptive histogram equalization is used to improve the contrast in the mammograms before feature extraction. Figure 5 shows the steps involved in the preprocessing mammograms.

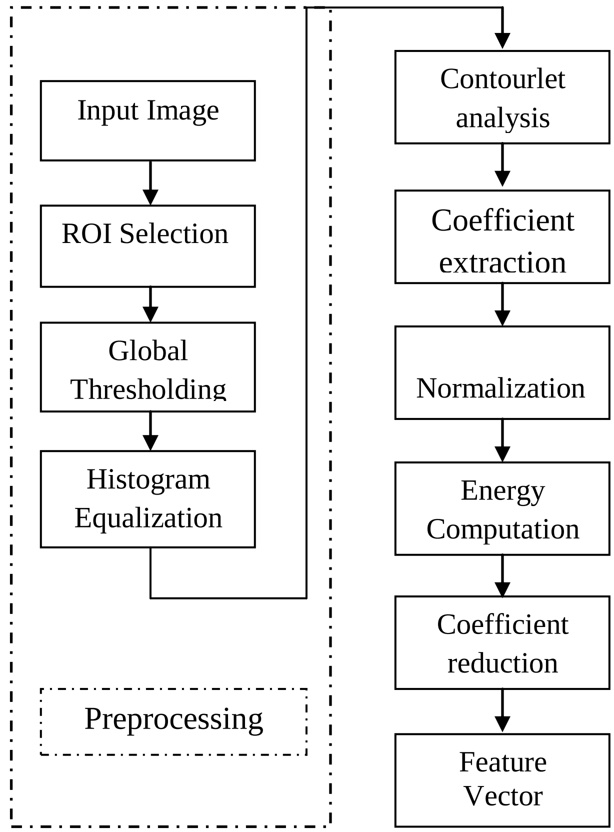
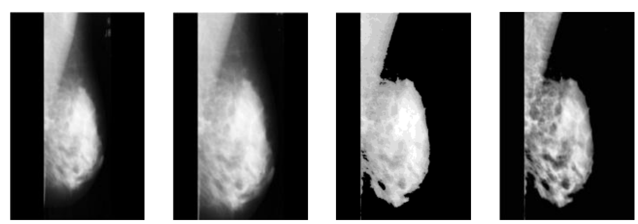


Fig.4. Feature Extraction Stage



(a) (b) (c) (d)

Fig.5. (a) Input image (b) ROI image (800 X 800) (c) Global thresholding (d) Enhanced image

4.1.1 Feature Vector Creation

The enhanced image is decomposed by using the NSCT at three different scales from 2 to 4. For an R level NSCT, we have 2R directional sub bands. The Contourlet coefficients of all the sub bands are used as feature vectors individually. All the directional sub band coefficients are normalized in order to simplify the coefficient value. This is achieved by dividing each feature vector by its maximum value. Then the energy is calculated for each vector by squaring every element in the vector. The produced values are considered as features for the classification process.

As the size of ROI image is 800 x 800 and it produces high number of coefficients that are stored in a two dimensional (2D) array. To reduce the number of features by summing a predefined number of energy values together, the coefficients in 2D array is converted into 1D Array. In the proposed technique, summation of 100 and 1000 energy values per features is used. The proposed features are extracted from the training set images and stored in an array called feature vector which will be sued for training the classifier.

4.3 Classification Stage

The SVM classifier was built with two phases. In the first stage, the classifier is applied to classify mammograms into normal or abnormal categories. The mammogram is considered to be abnormal if it contains tumor (mass). If abnormal the image enters the second stage where the abnormal mammogram is further classified into malignant or benign. The Classification Stage is shown in Figure 6

5. EXPERIMENTAL RESULTS

To assess the performance of the proposed system, many computer simulations and experiments with mammogram images were performed. The numbers of training and testing sets are shown in Table 1. The simulations are performed by summing 100 and 1000 Contourlet coefficients per feature and trained with the two stage SVM classifier. The results from the classifier are listed out in Table 2 to Table 5. From the tables, it clearly found that the combined scale feature set gives the better classification rate than the single scale features for first stage classification. Among the combined scale features, 3-4 combination gives 98.61% average classification rate for first stage classification and for the second stage classification, the 3 level feature gives the better average classification rate.

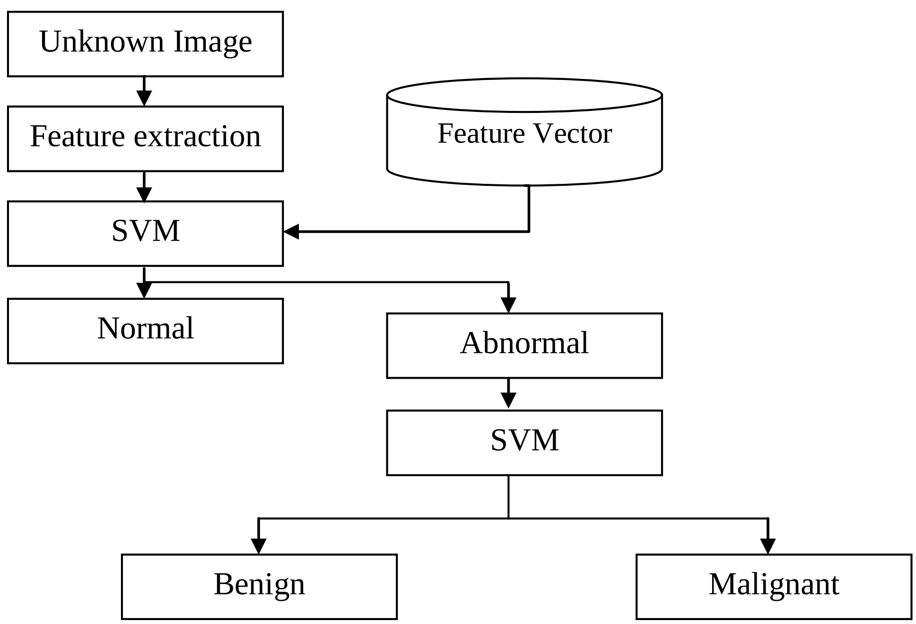


Fig.6. Classification Stage

Table 1 Number of training set and testing set

Category	No. of Training Set	No. of testing Set
Normal	60	100
Abnormal	34	56
Mass (Benign)	15	37
Mass(Malignant)	10	19

Table 2 Classification rates of Normal and Abnormal image for 100 and 1000 features

Scale	Classification rate (100 features)			Classification rate (1000features)		
	Normal (%)	Abnormal (%)	Average (%)	Normal (%)	Abnormal (%)	Average (%)
2	97	94.64	95.82	99	96.43	97.71
3	96	92.86	94.43	99	96.43	97.71
4	95	91.07	93.03	98	92.86	95.43

Table 3 Classification rates of Benign and Malignant for 100 and 1000 features

Scale	Mass (100 features)			Mass (1000 features)		
	Benign (%)	Malignant (%)	Average (%)	Benign (%)	Malignant (%)	Average (%)
2	89.19	78.95	84.1	89.19	73.68	81.44
3	94.59	78.95	86.77	91.89	84.21	88.05
4	89.19	78.95	84.1	94.59	78.95	86.77

Table 4 Different Scale Combination of Classification rate by 100 and 1000 features in Normal and Abnormal images

Scale	Classification rate (100 features)			Classification rate(1000 features)		
	Normal (%)	Abnormal (%)	Average (%)	Normal (%)	Abnormal (%)	Average (%)
2-3	96	92.86	94.43	97	96.42	96.71
3-4	95	91.07	93.03	99	98.21	98.61
2-4	96	94.64	95.32	98	94.64	96.32

Table 5 Different Scale Combination of Classification rate by 100 and 1000 features in Benign and Malignant images

Scale	Mass (100 features)			Mass (1000 features)		
	Benign (%)	Malignant (%)	Average (%)	Benign (%)	Malignant (%)	Average (%)
2-3	91.89	78.95	85.42	89.19	78.95	84.1
3-4	89.19	78.95	84.1	94.59	78.95	86.77
2-4	89.19	78.95	84.1	94.59	78.95	86.77

6. CONCLUSION

In this paper, an effective method for building a computer-aided diagnosing system for classification of masses in digital mammograms is proposed. We have developed and analyzed Contourlet transform for features extraction, and support vector machine for classification process. Our classification system produces very promising results with more than 81% for all the cases. Experimental results show that the combined scale feature set and single level feature set give the better classification rate for classifying the mammograms into normal or abnormal and the abnormal severity as benign or malignant respectively. This work can be extended to evaluate on other benchmark databases for consistency.

7.ACKNOWLEDGMENT

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