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Linear Discriminant Analysis Algorithm Using To Detect Mammogram Image Classification with Feature Selection Process

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ABSTRACT

This Breast cancer is one of the most prevalent lumps in women increased day by day around in worldwide. The scheme for the detection of breast cancer is the Mammographic technique that is used at the very earlier stage. In this paper kinds of classification Linear Discriminant Analysis (LDA) is used to analyze the mammographic images. The classification method is using the image pre-processing in wavelet decomposition and image enhancement. The results are verified with 322 mammogram images which are size for 1024×1024 with PGM format. The results show that the proposed algorithm can able to classify the images with a good performance rate of 97.84%. It can be concluded that supervised learning algorithm gives fast and accurate classification and it works as an efficient tool for classification of breast cancer cells.

Key words: Breast cancer, Mammographic technique, Linear Discriminant Analysis, 2 Dimensional Discrete Wavelet Transform.

1. INTRODUCTION

Mammography Cancer causes 1 in 8 deaths worldwide and is rapidly becoming a global pandemic. According to the International Agency for Research on Cancer, there were 12.7 million new cancer cases up to 2008. If the rates don't change, the global cancer burden is expected to be nearly doubled (i.e.,) 21.4 million cases and 13.5 million deaths by 2030.

According to the World Health Organization (WHO), the toll of cancer and other chronic diseases is greater in low and middle income countries where publics develop chronic diseases at younger ages who suffer longer – often with preventable complications – and die sooner than those in high-income countries. The economic toll is equally alarming in 2008, cancer accounts for nearly $1 trillion due to economic losses causes premature death and disability.

Early Breast cancer is one of the frequent and leading causes of mortality among woman, especial in developed countries. Age is one of the risk factor for breast cancer. Women within the age of 40-69 have more risk of breast cancer. In western countries about 53% - 92% of the population has this type of disease. In a Phillipine study [2] a mammogram screening were done to 151,198 women. Out of which 3479 women had this disease and were referred for diagnosis. Though breast cancer leads to death, early detection can increase the survival rate. The current diagnostic method for early detection of breast cancer is mammography. Mammography is of low dose X-ray projections of the breast, and one of the best methods for detecting cancer at the early stage.

Mammography at present is the best available technique for early detection of breast cancer[3]. In mammographic images early signs of breast cancer, such as bilateral asymmetry, can be revealed. Bilateral asymmetry is asymmetry of the breast parenchyma between corresponding regions in left and right breast. The most common breast abnormalities that may indicate breast cancer are masses and calcifications. Early detection and treatment are considered as the most promising approaches to reduce breast cancer mortality. Mammogram image is considered as the most reliable, low cost, and highly sensitive technique for detecting small lesions[4].

One of the main points that should be taken under serious consideration when implementing a robust classifier for recognizing breast tissue is the selection of the appropriate features that describes and highlights the differences between the abnormal and the normal tissue in an ample way. Feature extraction is an important factor that directly affects the classification result in mammogram classification. Most systems extract features to detect and classify the abnormality as benign or malignant from the textures[5-6]. A particular image type is given by mammographic images that are typically X-ray captures of breast region displaying points with high intensities that are suspected of being potential tumours. Early diagnostic and screening is crucial for appearing in the mammogram images that could indicate a potential presence of a benign or malignant tumour.Breast cancer is the most common type of cancer in women, while the mortality rate of breast cancer in females over 40 years is extremely high. If detected early, it can be treated early, and the mortality rate of breast cancer can be reduced [7]. One example of this is filtering impulse noise. If pre-processing aims to correct some degradation in the image, the nature of a priori information is important [8-9].

Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements [10].Here, in this experiment the SVM is trained with the images from training dataset whose classes are known. In total 322 training images are taken from dataset. The basic idea of an SVM classifier is illustrated in Fig.1. This Fig.1 shows the simplest case in which the data vectors (marked by ‘X’s and ‘O’s) can be separated by a hyper plane. In such a case there may exist many separating hyper planes. Among them, the SVM classifier seeks the separating hyper plane that produces the largest separation margin. Such a scheme is known to be associated with structural risk minimization [11-13].

Matsubara et al. [14] developed an adaptive thresholding technique for the detection of masses. They used histogram analysis techniques to divide mammograms into three categories ranging from fatty to dense tissue. Potential masses were detected using multiple threshold values based on the category of the mammogram. A number of features such as circularity, area, and standard deviation were used to reduce the number of false positives. Li et al. [15] developed a method for lesion site selection using morphologic enhancement and stochastic model–based segmentation technique. A finite generalized Gaussian mixture distribution was used to model histograms of mammograms. The expectation maximization algorithm [16] was used to determine the parameters of the model. The segmentation was achieved by classifying pixels using a new Bayesian relaxation labeling technique. An underlying motivation for this technique was that it could incorporate neighborhood information into the classification process and that this would help improve the process. They argued that for the purpose of lesion site selection, sensitivity should be the sole criterion for evaluation and thus did not incorporate a false-positive detection step.

Kobatake et al. [17] modeled masses as rounded convex regions and based on this idea, developed an ‘‘iris filter’’ to enhance and detect masses. The iris filter was practical to a gradient image that has generated by Perwitt-type operators (see Chapter 4.13). The output of the filter was computed by measuring the average convergence of the gradient over the region of hold up of the filter. The peaks of the output of the filter were selected as centers of tumor candidates. The filter was then reapplied locally to sense the borders of candidate masses. Finally, texture features were computed from the candidates and were used to decrease FPs. The authors showed that one of the compensation of using this filter was that the output of the filter would be constant in spite of of the contrast between a rounded convex region and the background.

Petrick et al. [18] developed a two-stage algorithm for the enhancement of suspicious objects. In the first stage, they future an adaptive density-weighted contrast-enhancement (DWCE) filter to enhance objects and suppress background structures. The middle idea of this filtering method was that it used the density value of each pixel to weight its local 1200 Handbook of Image and Video Processing contrast. In the first stage, the DWCE filter and a simple edge detector (Laplacian of Gaussian) were used to extract ROIs containing possible masses. In the second stage, the DWCE was reapplied to the ROI. Finally, to reduce the number of FPs, they used a set of texture features for classifying detected objects as masses or normal. They further enhanced the detection algorithm by adding an object-based region growing algorithm [19].

Polakowski et al. [20] used a single difference of Gaussian (DoG) filter to detect masses. The DoG filter was intended to equal masses that were approximately 1 cm in diameter. ROIs were chosen from the filtered image. They used nine features based on size, contrast, circularity and Laws texture features to reduce the number of false positives and to then categorize ROIs as malignant or normal. The DoG filter, which is a band-pass filter, has been used by several researchers for the preliminary task of detection of potential masses in an image. The DoG filter would be matched to the size of the mass. Since,the size of masses varies from a few millimeters to several centimeters [23], a number of DoG filters would be necessary, which would increase the computational complexity. Since the size of a potential mass is not known a priori, several researchers have used multiscale region-based methods for the detection of masses. Brzakovic et al. [21] use a two-stage multiresolution approach for detection of masses. First they identified suspicious ROIs using Gaussian pyramids (Chapter 4.2) and a pyramid linking technique based on the intensity of edge links. Edges were linked across various levels of declaration. This was followed by a classification stage, where the ROIs were classified as malignant, benign, or normal on the basis of features like shape descriptors, edge descriptors, and area.

Qian et al. [22] developed a multi-resolution and multi-orientation wavelet transform for the detection of masses and spiculation analysis. They observed that customary wavelet transforms cannot extract directional information, which is crucial for a spiculation detection task and thus, they introduced a directional wavelet transform. It shows the partitioning of the frequency domain with the directional wavelet transform. They note that in comparison, a conventional wavelet transform would produce a rectangular partitioning of the frequency domain. An input image was decomposed into two output images using the directional wavelet transform. One was a smoothed version of the original image and was used to segment the boundary of the mass. The second contained the high-frequency information and was used for directional feature extraction. The key ideas of the method were that at coarser resolutions, features such as the central mass region can be easily detected, whereas at finer resolutions, detailed directional features such as spicules can be localized.

Therefore, the image processing technology has been adapted automatically to the breast images which select the suspicious regions, and provide alerts to assist doctor's diagnosis, reduce misdiagnosis rates due to fatigue of doctors, and improve diagnostic accuracy. In order to assist physicians in clinical diagnosis, a set of breast cancer detection algorithm was designed in this paper through the linear discriminant analysis (LDA). Now we are going to the best available technique for support vector machine or linear discriminant analysis using 2 dimensional discrete wavelet transform method.

2. PROPOSED METHOD

2.1 Images Preprocessing

The testing is done by the record images occupied from Mammographic Image Analysis Society (MIAS), which has 322 samples be in the right place to three different categories such as normal, benign and malign. The database involves 199 normal images, 69 benign and 54 malign cases, which measured abnormal are 123. These database images are of 1024 x 1024 pixel sizes and taking the related information like breast contour, therefore the pre-processing of these images is required.

2.2 Linear Discriminant Analysis

Selective Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier or, more commonly, for dimensionality reduction before later classification.

There are many possible techniques for classification of data. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two commonly used techniques for data classification and dimensionality reduction. Linear Discriminant Analysis easily handles the case where the within-class frequencies are unequal and their performances have been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability.

The use of Linear Discriminant Analysis for data classification is applied to classification problem in speech recognition. We decided to implement an algorithm for LDA in hopes of providing better classification compared to Principal Components Analysis. The prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. In PCA, the shape and location of the original data sets changes when transformed to a different space whereas LDA doesn't change the location but only tries to provide more class separability and draw a decision region between the given classes. This method also helps to better understand the distribution of the feature data. Fig.1 will be used as an example to explain and illustrate the theory of LDA.

LDA produces at most rank feature projections, if the classification error estimates establish that more features are needed, some other method must be employed to provide those additional features LDA is a parametric method which assumes unimodal Gaussian Likelihoods, If the distributions are significantly non Gaussian, the LDA projections may not preserve complex structure in the data needed for classification

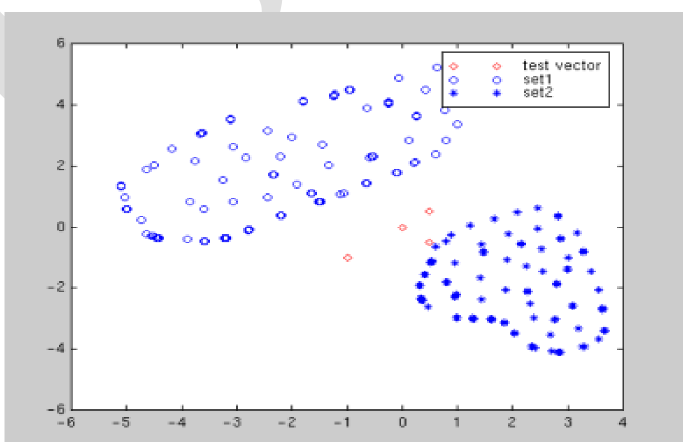

Fig.1. Linear Discriminant Analysis for the test vector

2.3 Dimensional Discrete Wavelet Transform

Two-dimensional wavelets are a natural extension from the single dimension case. As a concept they can be applied to many two-dimensional situations, such as 2D functional spaces. However they really come into their own when images are considered. In a world where digital images are processed by computers ever second, methods for condensing the information carried in an image are needed. Also with so many different images in circulation via the internet methods are needed for computational analysis of the content of these images. Two-dimensional wavelets provide ways to tackle both of these problems.

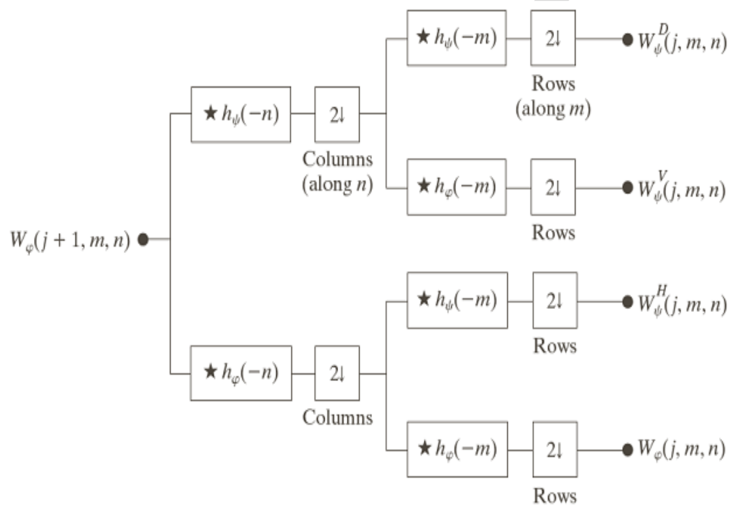

Fig.2. Implementation of 2 Dimensional Discrete Wavelet Transform

3. RESULTS AND DISCUSSION

In total 322 samples have been taken from dataset. Figure 3 shows the feature selection process of 23 statistical. Figure 3 shows the LDA output for non- linear system which is the major drawback in the system. In figure (4 & 5), plot for linear system (feature set 1& 2) where the red dot represents the low and green represents the high value. Fig 4 &5 shows the LDA training plot for two features set 1 & 2.

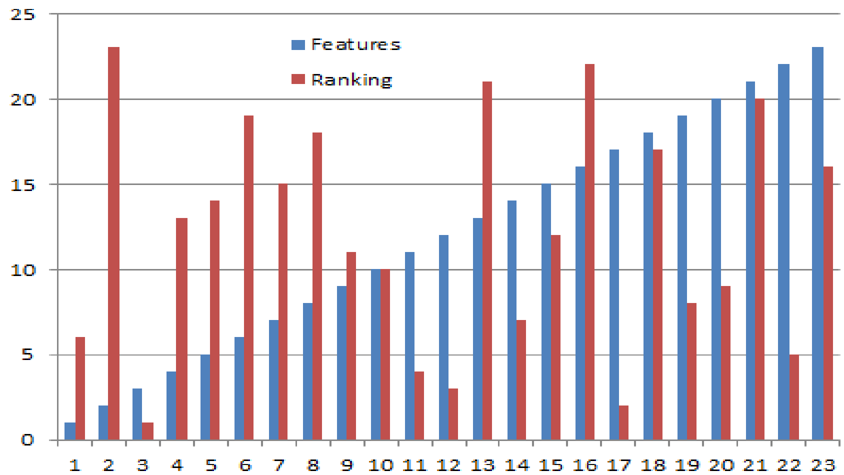

Fig.3. Feature selection process of 23 statistical

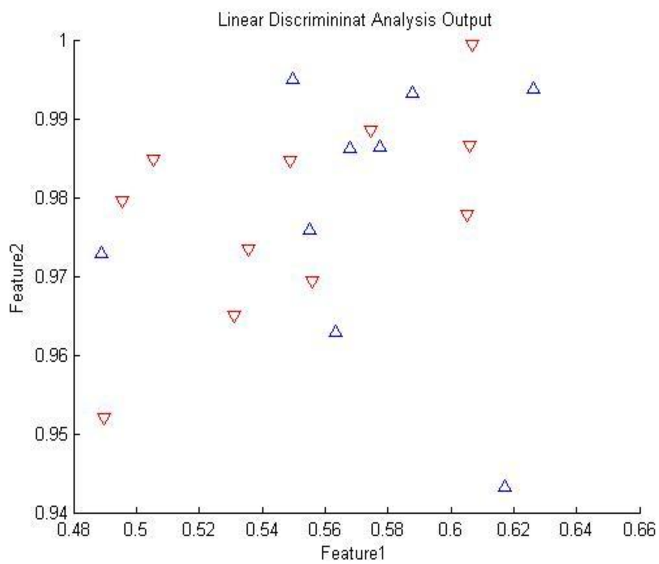

Fig.4. LDA validation plot for two feature set1

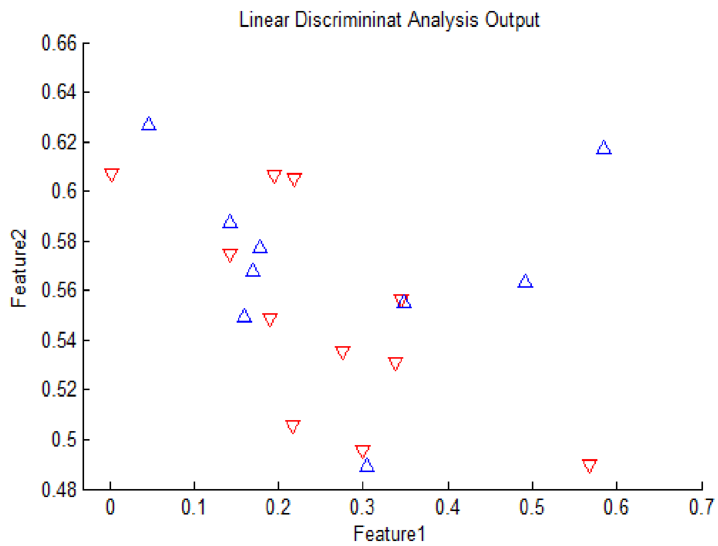

Fig.5. LDA validation plot for two feature set2

The Fig.8 Shows the LDA training plot for two features set 1 & 2. LDA tries to find out the dimensionality. It is used find the linear combination of features which separates two or more classes of objects.

TABLE I. System time complexity analysis (Time in seconds)

Images	LDA System
Image01	0.973
Image02	0.875
Image03	1.458
Image04	0.058
Image05	0.958
Image06	2.007
Image07	1.025
Image08	0.932
Image09	2.27
Image10	0.932
Image11	0.945
Image12	1.843

The above Table I shows the LDA system by examining the 12 different images.

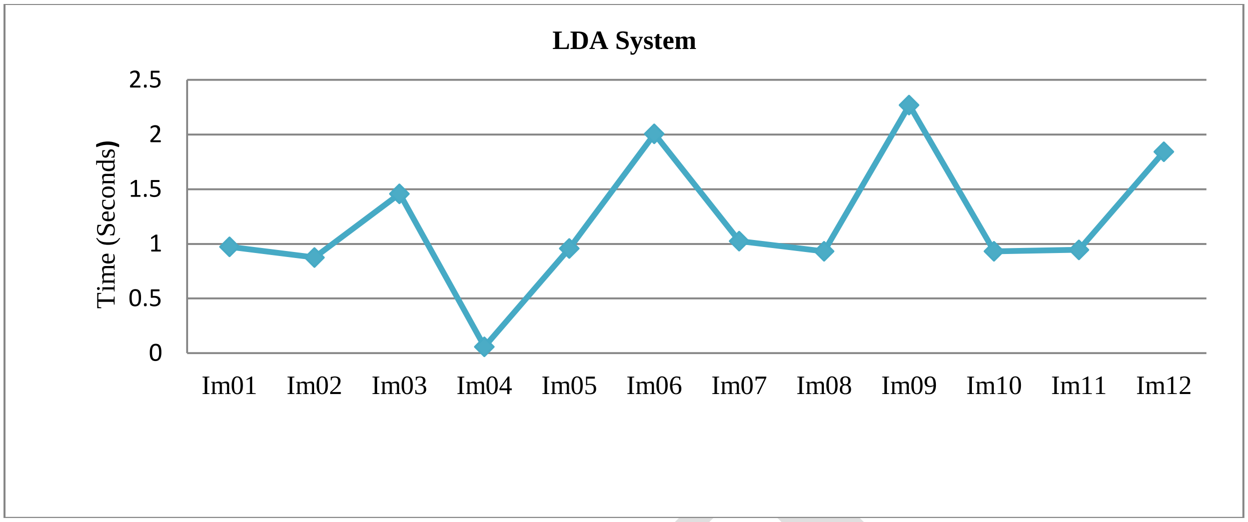

Fig.6. Chart of System time complexity analysis

Fig.6.chart of system time complexity analysis has mentioned 12 different kinds of images in MIAS database and executed each the images to produce dissimilar time. Finally it has shown Table II and fig.7.the overall average time complexity.

TABLE II. Overall average time complexity

Images	LDA System
Overall average	1.189667

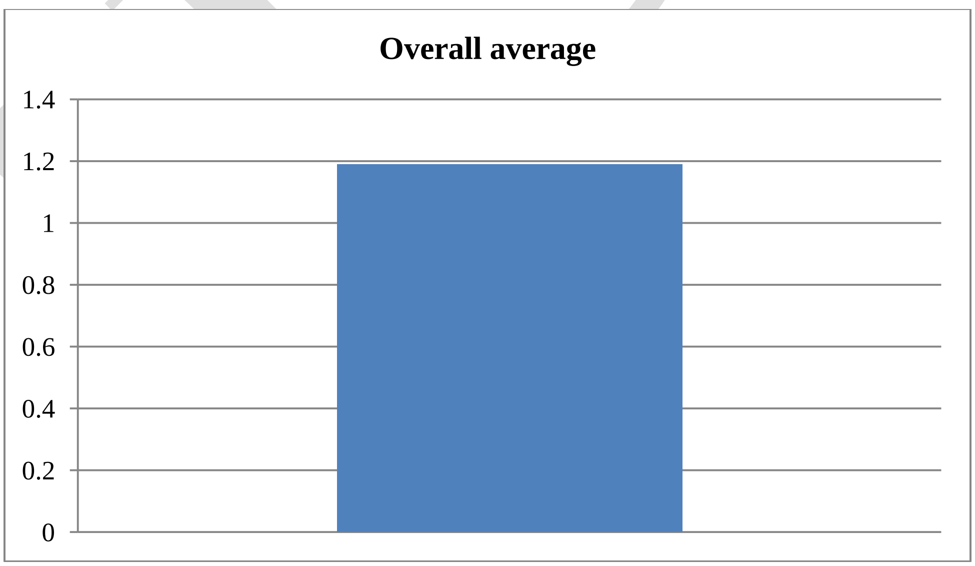

Fig.7. Chart of Overall average time complexity

TABLE III LDA of Results

System	Image set-1	Image set-2	Classification accuracy in %
LDA	40N,48AB	643N,50AB	97.84%

The Table III shows System outputs Result comparison with ground truth (N*-Normal, AB*-abnormal).The above table shows the LDA system for different image sets. Finally, the classification accuracy is observed which shows normal and abnormal images.

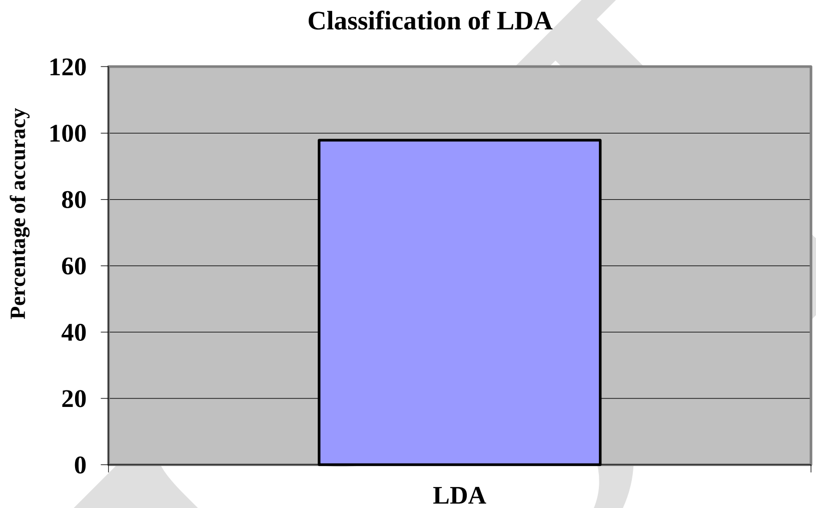

Fig.8.Classification accuracy of LDA

4. CONCLUSION

This paper proposes a comparison of the system performance on the classification of breast cancer. Linear discriminant analysis is taken into account for this process. Here we have used the textural features and discrete wavelet's energy features then the Genetic algorithm for selection of best features. Using the selected set of features values, the linear discriminant analysis get trained. Finally Linear Discriminant Analysis is a best classifier to classify the mammogram images. This technique might be improved by using a more advanced model and needs to be evaluated using a larger image database.

5. FUTURE WORK

While comparing the results of LDA the system seems to be better, but in the case of medical field the accuracy is more important than any other parameters of the system. In another side from the literature survey shows that the neuro fuzzy system is better in classification accuracy. In future, it will design a knowledge based inference system for the detection of breast cancer from Mammogram images.

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