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Analysis Of Micro calcification Severity In Mammograms Using Non-Sub Sampled Transform

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Abstract:

This project proposes a new approach for detecting Microcalcification in digital mammograms employing the combination of non sub sampled Contourlet transform (NSCT) and SVM (SUPPORT VECTOR MACHINE) and NN (NEURAL NETWORKS) for building the classifiers. The detection of Microcalcification is achieved by extracting the Microcalcification features from the Contourlet coefficients of the image and these results are used as an input of SVM and NN system. The system classifies the mammogram images as normal or abnormal, and abnormal severity as benign or malignant. The experiments demonstrate that our approach can provide better performance in terms of Sensitivity, Specificity, Positive predictive value, Negative predictive value, Accuracy, Classification rate, Classification Latency, Precision and Recall. The evaluation of the system is carried on Mammography Image Analysis society (MIAS) database.

I.Introduction

For years, cancer has been one of the biggest threats to human life; it is expected to become the leading cause of death over the next few decades [14]. Based on statistics from the World Health Organization (WHO) [15], cancer accounted for 13% of all deaths in the world in 2004; deaths caused by cancer are expected to increase in the future, with an estimated 12 million people dying from cancer in 2030 [16].

Of all the known cancers, breast cancer is a major concern among women. It is the second-most common and leading cause of cancer deaths among women [15]. According to published statistics, breast cancer has become a major health problem in both developed and developing countries over the past 50 years, and its incidence has increased in recent years. In the United States, in 2007, there were an estimated 178,480 new cases of breast cancer diagnosed and 40,460 deaths from this disease among women [14]. At present, there are no effective ways to prevent breast cancer, because its cause remains unknown. However, efficient diagnosis of breast cancer in its early stages can give a woman a better chance of full recovery.

Therefore, early detection of breast cancer can play an important role in reducing the associated morbidity and mortality rates. Computer-aided detection or diagnosis (CAD) systems, which use computer technologies to detect abnormalities in mammograms such as calcifications, masses, and architectural distortion, and the use of these results by radiologists for diagnosis [4], can play a key role in the early detection of breast cancer and help to reduce the death rate among women with breast cancer. Thus, in the past several years, CAD systems and related techniques have attracted the attention of both research scientists and radiologists. For research scientists, there are several interesting research topics in cancer detection and diagnosis systems, such as high-efficiency, high-accuracy lesion detection algorithms, including the detection of masses, detection of architectural distortion, and the detection of bilateral asymmetry.

Radiologists, on the other hand, are attracted by the effectiveness of clinical applications of CAD systems. The aim of this paper is to provide an overview of CAD systems and related techniques developed in recent years. It is also intended to draw the attention of more research scientists to the research field of CAD for breast cancer, and advance research on the detection and diagnosis of breast cancer and related techniques, such as image processing, computer technology, and radiological imaging.

In the context of a screening program, a "detection mammogram" refers to a mammogram on which cancer is detected, and the term "prior mammogram" refers to a mammogram acquired at the last scheduled visit to the screening program prior to the detection of cancer [10]. When breast cancer is detected in a screening program in a particular individual, the case is referred to as "screen-detected cancer." The term "interval cancer" indicates a case where breast cancer is detected outside the screening program in the interval between scheduled screening sessions. Studies on prior mammograms of interval-cancer cases with the particular goal of detection of architectural distortion [11]–[13] could help in developing strategies for the detection and treatment of breast diseases at their early stages.

II. Literature Survey

There are several imaging techniques for examination of the breast, including magnetic resonance imaging, ultrasound imaging, and X-ray imaging. Mammography is a specific type of imaging that uses a low-dose X-ray system to examine the breast, and is currently the most effective method for detection of breast cancer before it becomes clinically palpable [5]. Mammography offers high-quality images at a low radiation dose, and is currently the only widely accepted imaging method used for routine breast cancer screening. Current guidelines of the American Cancer Society (ACS) recommend that women aged 40–49 years have a routine mammogram every one to two years, with the first beginning at age 40.

A good amount of research on diagnosis of breast cancer with WBCD is found in literature. Many of them show good classification accuracy. Albrecht, Lappas, Vinterbo, Wong, and Ohno-Machado [1], applied a learning algorithm that combined logarithmic simulated annealing with the Perceptron algorithm and the reported accuracy was 98.8%. Pena-Reyes and Sipper [2], used the classification technique of fuzzy-GA method, reaching a classification accuracy of 97.36%. Setiono [3], employed the classification based on a feed forward neural network rule extraction algorithm. The reported accuracy was 98.10%. Quinlan [4] achieved 94.74% classification accuracy using 10-fold cross validation with C4.5 decision tree method. Hamiton, Shan, & Cercone, [5] obtained 94.99% accuracy with RIAC method, while Ster & Dobnikar, [6] obtained 96.8% with linear discreet analysis method. The accuracy obtained by Nauck and Kruse [7] was 95.06% with neuron- fuzzy techniques. In Goodman, Boggess, and Watkins [8], used three different methods, optimized learning vector quantization (LVQ), big LVQ, and artificial immune recognition system (AIRS), and the obtained accuracies were 96.7%, 96.8%, and 97.2%, respectively. In the method proposed by Abonyi and Szeifert [9], an accuracy of 95.57% was obtained with the application of supervised fuzzy clustering technique. In Polat and Gunes [10], least square SVM was used and an accuracy of 98.53% was obtained. Mehmet Fatih Akay, increased the accuracy to 99.51%, by combining SVM with feature selection [11].

MICROCALCIFICATION MODEL

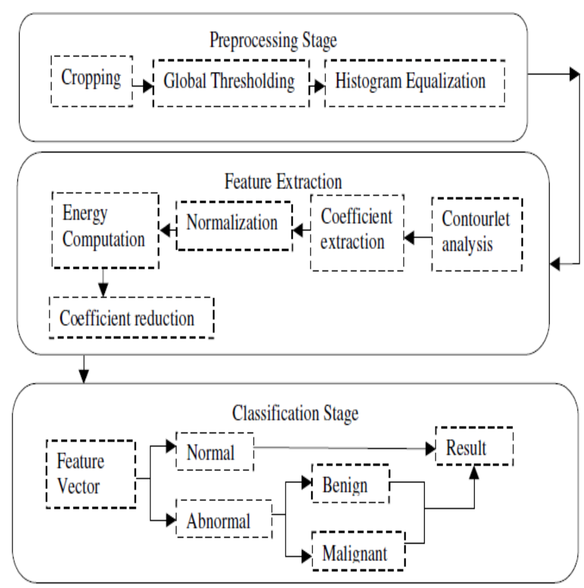

Fig.1. Block Diagram Of The Proposed Microcalcification Model

PROPOSED MODEL:

Region Of Intersection:

Most of the mammogram images are very large (has size 1024 X1024) and almost 50% of the whole image comprised of the background with a lot of

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noise. To eliminate the background information and most of the noise, ROI is selected from the center of the image and the size of the ROI images is 800 x 800.

Global Gray Level Thresholding:

It is used to segment the mammogram region only.The pixels between a pre-selected upper-threshold (255)and lower-thresholding (140) of the gray level histogram is retained and all others are set zero. To apply this technique upper and lower thresholds are determined to make sure that the region of interest pixels values are between these thresholds.

Histogram Equalization:

Adaptive histogram equalization is a technique used to improve contrast in images.It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image.

Histogram Equalization is applied on the entire image. Adaptive Histogram Equalization is applied on the 3*3 over lapped block on the whole image.

III. Feature Extraction

Feature extraction is an essential pre-processing step to pattern recognition and machine learning problems. It is often decomposed into feature construction and feature selection.In our approach, Contourlet coefficients are used as a feature to classify the mammogram images.

Contourlet Coefficients Extraction:

The original image is decomposed by using the NSCT at two different scales.

For an R level NSCT, we have 2^R directional sub bands. The Contourlet coefficients of four sub bands (W1, W2, W3, and W4) are used as feature vectors individually. These feature vectors are given to the neural networks as input.

Normalization:

Normalization is the process that changes the range of pixel intensities to a new range and is used to simplify the coefficient value.

This is achieved by dividing each feature vector by its maximum value.The results of this operation is that all vectors values become less than or equal one.Normalized sub bands will have the values between 0 to 1.

Energy computation:

We compute the energy for each vector by squaring every element in the vector. The produced values are considered as features for the classification process.

Energy=sum(square(each sub band value)).

Feature reduction:

The size of ROI image is 800 x 800 and it produces high number of coefficients. The Contourlet coefficients 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.

Neural network:

The back propagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards.

The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

Classification Stage:

We build a neural network classifier with two phases. In the first one, the classifier is applied to classify mammograms into normal and abnormal cases. The mammogram is considered abnormal if it contains tumor (microcalcification). Finally, the abnormal mammogram is classified into malignant or benign in the second stage.

NN in training mode:

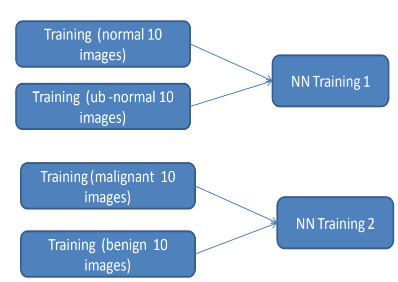

Fig: 2 NN Training mode

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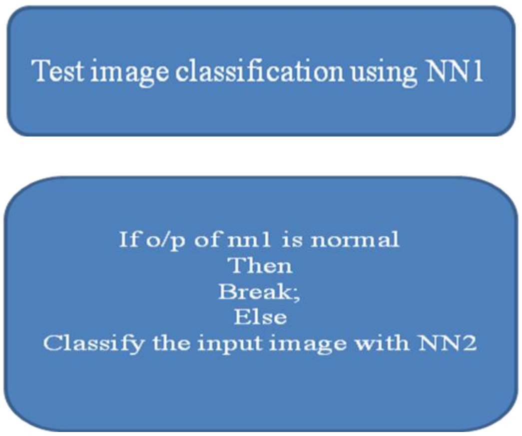

Fig:3 Flow of using NN classifier

IV.Simulation Results

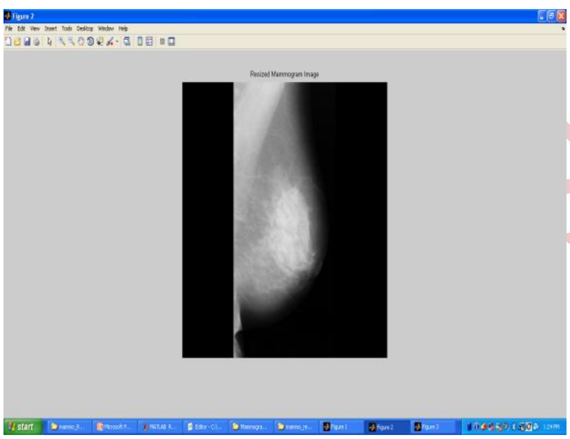

Fig: 4 Resized image

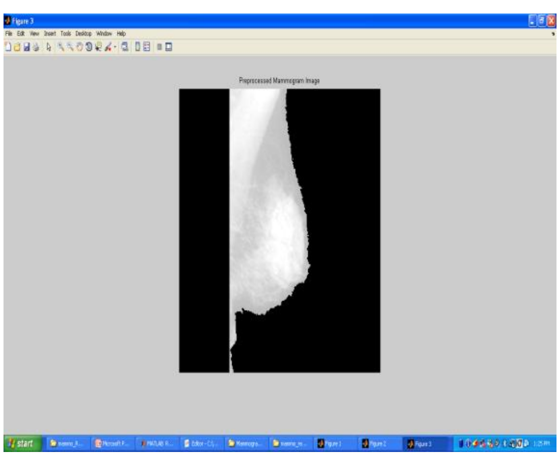

Fig. 5 adaptive histogram equalization

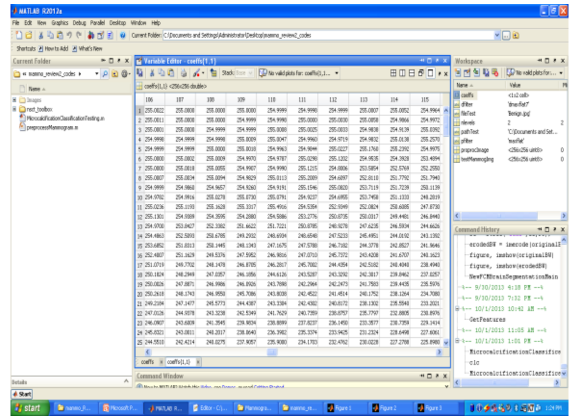

Fig.6 NSCT Coefficients

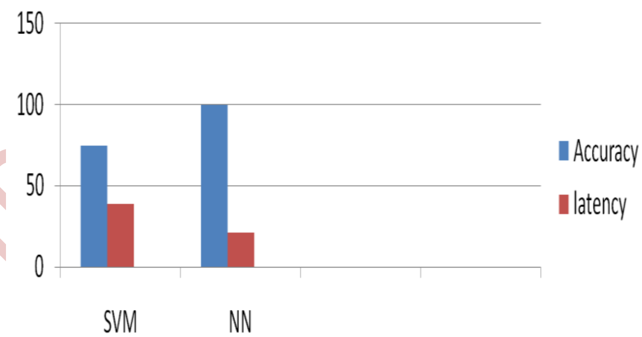

Fig 7 Performance Evaluation Graph

Category	SVM	Neural Networks
Classification Accuracy(%)	75	100
Elapsed Time(Sec)	3.93sec	2.1sec

Table 1: Performance analysis

	Sensitivity	Specificity	Positive predictive value	Negative Predictive value
NN	0.836837	0.990682	0.935229	0.968280
SVM	0.762173	0.995936	0.966597	0.955417

Table 2: Evaluation parameters values

V. Conclusion

In this project ,the detection of Microcalcification is achieved by extracting the Microcalcification features from the Contourlet coefficients of the image and these results are used as an input of NN and SVM system. The system classifies the mammogram images as normal or abnormal, and abnormal severity as benign or malignant. The experiments demonstrate that our approach can provide better performance Classification Latency & Accuracy. The experiments demonstrate that our approach can provide better performance in terms of Sensitivity, Specificity, Positive predictive value, Negative predictive value, Accuracy, Classification rate, Classification Latency, Precision and Recall. The evaluation of the system is carried on Mammography Image Analysis society (MIAS) database.

VI.References

[1]. A. A.Albrecht, G. Lappas, S. A. Vinterbo, C. K Wong, and L. Ohno- Machado "Two applications of the LSA machine". Proceedings of the 9th international conference on neural information processing pp. 184–189, 2002.

[2]. C. A.Pena-Reyes, and M. Sipper, "A fuzzy-genetic approach to breast cancer diagnosis." Artificial Intelligence in Medicine vol.17, pp.131–155, 1999.

[3] R.Setiono, "Generating concise and accurate classification rules for breast cancer diagnosis. Artificial Intelligence in Medicine" vol.18 (3), pp.205–217, 2000.

[4]. E.Osuna, R.Freund, and F. Girosi, "Training support vector machines: Application to face detection". Proceedings of computer vision and pattern recognition, Puerto Rico pp. 130–136. 1997.

[5.] H. J .Hamiton,N. Shan, and N. Cercone "RIAC: A rule induction algorithm based on approximate classification." Technical Report CS. University of Regina, pp.96-06,1996.

[6.] B.Ster, and A.Dobnikar, "Neural networks in medical diagnosis: Comparison with other methods." Proceedings of the international conference on engineering applications of neural networks pp. 427–430. 1996.

[7.] T.Joachims, Transductive inference for text classification using support vector machines. Proceedings of international conference machine learning. Slovenia. 1999.

[8]. D.E.Goodman, L. Boggess, and A.Watkins, "Artificial immune system classification of multiple-class problems". Proceedings of the artificial neural networks in engineering pp. 179–183. 2002.

[9]. J.Abonyi, and F. Szeifert, "Supervised fuzzy clustering for the identification of fuzzy classifiers." Pattern Recognition Letters, vol.14(24), 2195–2207,2003.

[10]. K.Polat, and S.Gunes, "Breast cancer diagnosis using least square support vector machine." Digital Signal Processing, vol.17(4), 694–701. 2007.

[11]. Mehmet Fatih Akay "Support vector machines combined with feature selection for breast cancer diagnosis" Expert Systems with Applications, Elsivier. Vol.36, pp. 3240–324,2009.

[12] A. Jemal, L. X. Clegg, E.Ward, L. A. G. Ries, X.Wu, P.M. Jamison, P. A. Wingo, H. L. Howe, R. N. Anderson, and B. K. Edwards, "Annual report to the nation on the status of cancer, 1975–2001, with a special feature regarding survival," *Cancer*, vol. 101, no. 1, pp. 3–27, 2004.

[13] R. G. Blanks, M. G. Wallis, and S. M. Moss, "A comparison of cancer detection rates achieved by breast cancer screening programmes by number of readers, for one and two view mammography: Results from the UK national health service breast screening programme," *J. Med. Screen.*, vol. 5, no. 4, pp. 195–201, 1998.

[14] K. Doi, "Computer-aided diagnosis in medical imaging: Historical review, current status and future potential," *Computerized Med. Imag. Graphics*, vol. 31, no. 4–5, pp. 198–211, 2007.

[15]. R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. New York: Wiley-Interscience, 2001.

[16].S. Haykin, *Neural Networks: A Comprehensive Foundation*, 2nd ed. Upper Saddle River, NJ: Prentice Hall, 1999.

[17].Kurt Rossmann Laboratories for Radiologic Image Research. ROC Software ROCKIT, 2010 [Online]. Available: http://wwwradiology.uchicago.edu/krl/roc_soft6.htm