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cision making process such as pattern classification [11]. A Statistical intensity based features are extracted from the mammograms for classification. Feature extraction step is important step to get high classification rate. A set of features are extracted in order to allow a classifier to distinguish between normal & abnormal pattern. The abnormality can be identified on the basis of textural appearance. Extracted features are used in Support vector machine classifier to train it for the recognition of particular class either normal or abnormal. The ability of the classifier to assign the unknown object to the correct class is dependent on the extracted features [12].

Let, L be the number of possible intensities in an image $M \times N$ pixels, z_i , i = 0;,1, 2,…L – 1 their intensity values, and n_i the absolute frequence that z_i occurs in the image. P is the probability of Zi occurs in the image.

1. Mean:

It is the average value of intensity of the Image.It is defined as,

(1) $$\mu = \sum_{i=0}^{L-1} z_i P(z_i)$$

2. Standard Deviation:

It is the square root of the variance.The standard deviation is the estimate of the mean μ square deviation of gray pixel value P (Zi) from its mean value.The Standard deviation is defined as,

(2) $$\mathrm{SD} = \sqrt{\sigma^2} = \sqrt{\sum_{i=0}^{L-1} (Zi - \mu^2) P(Zi)}$$

3. Entropy:

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.It is defined as,

(3) $$\mathrm{E} = -\sum_{i=0}^{L-1} P(Zi) \log_2 [P(Z\,i)]$$

4. Skewness:

Skewness, S characterizes the degree of asymmetry of a pixel distribution in the specified window around its mean. It is of a distribution is defined as,

(4) $$s = \frac{E(Z-\mu)^3}{\sigma^3}$$

5. Kurtosis:

Kurtosis, K measures the Peakness or flatness of a distribution relative to a normal distribution.It is defined as,

(5) $$\mathrm{k} = \sum_{i=0}^{L-1} (Zi - \mu^4) P(Z\,i)$$

6. Variance:

The average of squared differences from the mean. Variance is the square root of standard deviation. It is defined as,

(6) $$\sigma^2 = \sum_{i=0}^{L-1} (Z\,i - \mu^2) P(Z\,i)$$

7. Energy:

Energy is a measure of the uniformity.
It is defined as sum of square of pixel values of element.
It is defined as:

(7) $$E = \sum_{i=0}^{L-1} [P(Z\,i)]^2$$

8. Correlation:

The operation called correlation is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighboring pixels.
It is is defined as:

(8) $$C = \frac{\sum_i \sum_j P(\mathrm{i,j}) - \mu_x \mu_y)}{\sigma_x \sigma_y}$$

9. Smoothness:

Relative smoothness, R is a measure of grey level contrast that can be used to establish descriptors of relative smoothness. The smoothness is defined as:

(9) $$S = R = 1 - \frac{1}{1+\sigma^2}$$

Where, σ is standard deviation.

10. RMS: Root Mean Square:

The RMS (Root Mean Square) computes the RMS value of each row or column of the input, along vectors of a specified dimension of the input, or of the entire input. The RMS value of the jth column of an M-by-N input matrix u is given by below equation:

(10) $$y = \sqrt{\frac{\sum_{i=1}^{M} |u_{ij}|^2}{M}}$$

2.5 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 takes a set of input data, and predicts, for each given input, which of two possible classes the input is a member of, which makes the SVM a non-probabilistic binary linear classifier [13]. 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. More formally, a support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

The basic idea of SVM is that it projects data points from a given two-class training set in a higher dimensional space and finds an optimal hyperplane. The optimal one is the one that separates the data with the maximal margin. SVMs identify the data points near the optimal separating hyperplane which are called support vectors. The distance between the separating hyperplane and the nearest of the positive and negative data points is called the margin of the SVM classifier.

The separating hyperplane is defined as

(11) D(x)=(w.x)+b

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 data points to the maximum margin hyperplane lie on the planes

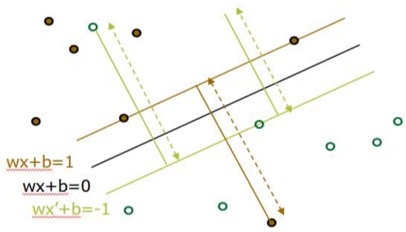


Figure 2.6: Representation of Hyper planes

Where y=+1 for class w_1 and y=-1 for class W_2.

The width of the margin is given by $m = \frac{2}{\|w\|}$.

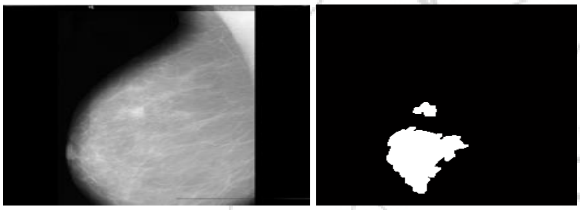
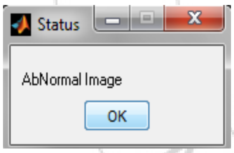


Figure 2.7: a) Original Image b) Segmented Image c) Status of Mdb265



3. Database

Total numbers of 322 samples are obtained from mammograms containing microcalcifications from Mammographic Image Analysis Society (MIAS). These were divided into training and testing set. The training set contains 285 samples, of which, 255 normal, benign and malignant cases. Remaining 30 samples are used for testing SVM classifier. Testing set contains 15 cases of normal and 15 cases of abnormal respectively.

3 Receiver Operator Characteristic

The Receiver Operating Characteristics (ROC) curve of the implemented classifier can be plotted by providing several values of sensitivity and specificity based on SVM classifiecation having accuracy 83%.

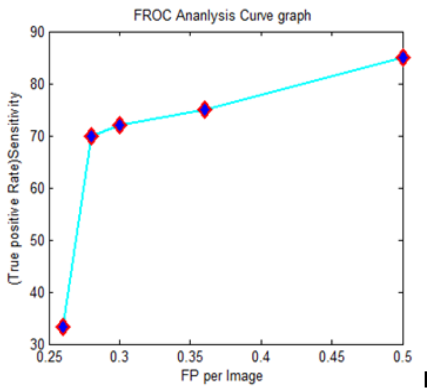


Figure 2.8: FROC Curve

4. Conclusions

Mammography is one of the best methods in breast cancer detection, but in some cases, radiologists cannot detect tumors despite their experience. Such computer-aided methods like presented in this paper could assist medical staff and improve the accuracy of detection.

In this paper, we present a classification of mammograms using SVM classifier. The proposed classification scheme has been applied on MIAS database image. Experimental results show that, high accuracy 83% of classification of MCCs obtained with the proposed SVM classifier can help radiologists in making an accurate diagnostic decision, which can reduce unnecessary biopsies. Our future work is to extend the various different features and other classification type of mammogram.

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References

[1] Jawad Nagi , Sameem Abdul Kareem , Farrukh Nagi , Syed Khaleel Ahmed "Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms", 2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010), Kuala Lumpur, Malaysia, pp87-99,2010.

[2] R. Ramani "The Pre-Processing Techniques for Breast Cancer Detection in Mammography Images**"** I.J. Image, Graphics and Signal Processing, pp 47-54, 2013.

[3] D. Sujitha Priya "Breast Cancer Detection In Mammogram Images Using Region-Growing And Contour-Based Segmentation Techniques" International Journal of Computer & Organization Trends ,Volume 3, Issue 8 Sep 2013,ISSN: 2249.

[4] Jawad Nagi,1, Sameem"Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms"2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010), Kuala Lumpur, Malaysia, 30th November - 2nd December 2010.

[5] Armen Sahakyan "Segmentation of the Breast Region in Digital Mammograms and Detection of Masses" Interna-

ISSN (Online): 2347-3878
Volume 3 Issue 2, February 2015

tional Journal of Advanced Computer Science and Applications, Vol. 3, No.2, 2012.

[6] R. Subash Chandra Boss, K. Thangavel, D. Arul Pon Daniel " Automatic Mammogram image Breast Region Extraction and Removal of Pectoral Muscle".

[7] Pragathi. J, H. T. Patil "Segmentation Method for ROI Detection in Mammographic Images using Wiener Filter and Kittler's Method" International Journal of Computer Applications (0975 – 8887) International Conference on Recent Trends in engineering & Technology , pp27-33, 2013.

[8] S. Shanthi, V. Murali Bhaskaran "Computer Aided System for Detection and Classification of Breast Cancer", International Journal of Information Technology, Control and Automation (IJITCA) Vol.2, No.4, October 2012.

[9] Jaime S. Cardoso, Ines Domingues, Amaral, "Pectoral muscle detection in mammograms based on polar coordinates and the shortest path", 32nd Annual International Conference of the IEEE EMBSBuenos Aires, Argentina, August 31 - September 4, 2010.

[10] K. Parvati, b. S. Prakasa rao, and m. Mariya das"Image Segmentation Using Gray-Scale Morphology and Marker-Controlled Watershed Transformation", hindawi publishing corporation Discrete dynamics in nature and society volume 2008, article id 384346, 8 pages-doi:10.1155/2008/384346,2008.

[11] Zaheeruddin , Z. A. Jaffery a, Laxman Singh "Detection and Shape Feature Extraction of Breast Tumor in Mammograms" Proceedings of the World Congress on Engineering 2012 Vol II ,WCE 2012, July pp4 - 6, London, U.K.,2012.

[12] R. Ramani "The Pre-Processing Techniques for Breast Cancer Detection in Mammography Images" I.J. Image, Graphics and Signal Processing, pp 47-54, 2013.

[13] Zhiqiong Wang, GeYu, YanKang, YingjieZhao, QixunQu "Breast tumor detectionin digitalmammography basedon extreme learning machine", Neurocomputing 128(2014)175–184, 2013 Elsevier