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Breast Cancer Detection using Support Vector Machine

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Abstract: Women affected by breast cancer widely all around the world. The most commonly used screening method to detect breast cancer by using Mammographic images. In this paper, watershed segmentation algorithm is used for segmentation and the support vector machine is used to detect either benign or malignant. This avoids unwanted biopsy and stress for women.
Keywords: Pre-processing, Segmentation, Support vector machine, Mammogram.

I.   INTRODUCTION

The diagnosis of disease is done by analysing or grading the image. To study the image pathologists identify the characteristics of tissue. Breast tumours are uncontrollable. It is more basically exist in women than in men. If the disease is detected then the grading process will performed, which deals with spreading of infected cells all over the tissue. In this paper it is motivated that detecting and classifying breast cancer accurately. Watershed segmentation method is used in imaging that helps the specialists to examine the picture for understanding abnormalities of cancer. Support vector machine classifies the findings of either benign or malignant.

A.   Background Work

Researchers have been trying to develop a way to utilize electromagnetic waves to image the human body in order to detect cancer. Some years back microwave system was the possible solution. X-rays were also be used to detect breast cancer. But they caused side effects to the breast tissues of the patients. The currently used methods is x-ray mammography, the presence of tumour is being detected by comparing properties of cancerous and normal breast tissue. Different image processing techniques are applied for image texture classification, gland and nuclei segmentation, cell counting, cell type identification or classification to deriving quantitative measurements of disease features from histological images. It supports to automatically determine whether a disease is present within analysed samples or not. Also this research will help to decide the different grades or severity of disease if the disease is present in the sample. Computer aided histopathological study has been conducted for various cancer detection and grading applications, including prostate, breast, renal cell carcinoma, pediatric tumour neuro-blastoma and lung cancer grading [1]-[3],[5],[6]. Using different segmentation, feature extraction and classification techniques the researchers analysed histopathology images. The overall literature survey says that there are various methods are already used in medical images. They are beneficial as well as many challenges exist. Researchers used various organs like breast, prostate, follicular lymphoma, colon glands, meningioma tumour and oral mucosa. Methods such as hierarchical normalized cut, colour gradient active contour, colour texture cell Gaussian mixture model based segmentation and object graph approach were used for segmentation. Texture classification using fractal textures, classification using nonlinear quantization and support vector machine were used for classification approach [4], [7]-[11].Texture has been studied as a breast cancer risk factor independent of average breast density [12]-[17], but the results have not been adequately adjusted for breast density and other risk factors. For example, a negative significant correlation between regional skewness, fractal dimension, results cancer risk [13]. However, the regional skewness and fractal dimensions had no association with breast cancer after adjusting for other risk factors and overall breast density. One feature, lacunarity, remained significant [12].

II.   PREPROCESSING

A.   Localization

Localization is a process of locating the required part of an image. In this paper, for localization Hough transform is used to improve the diagnosis of image analysis. It supports to find the edges of a suspected part in an image. The Hough transform is a technique which can be used to isolate features of a particular shape within an image. Because it requires that the desired features be specified in some parametric form. Hough transform is used for the detection of regular curves such as lines, circles, ellipses.

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B. Segmentation

In pre-processing, image segmentation separates objects of interest from back ground through various methods in image processing i.e., removal of unwanted particles from the image by their intensity values. It enhances the image quality to get good results. In this work Watershed algorithm is used to process segmentation. A binary image is produced by the Watershed Transform, 1(black) is assigned or watersheds, and 0 (white) assigned to regions surrounded by dams. In image processing, watershed is a transformation used to define grey scale images. It represents the brightness of each point in the image and finds the edges.

III.   FEATURE EXTRACTION

Feature extraction involves reducing amount of resources required to describe large set of data. In this process if the input data of an algorithm is too large to be performed then it can be transformed into a reduced set of features. Features are extracted either at the cellular or at the tissue-level. Morphological characteristics of image are measured to find abnormality or to classify the image for different grades of disease. The cellular-level features focuses on quantifying the properties of individual cells without considering spatial dependency between them. For a single cell, the morphological, textural, fractal, and or intensity-based features can be extracted. In this work textural features are considered for further processing. Grey level histogram is used in this work to extract the features such as skewness and kurtosis. Skewness is a measure of the symmetry in a distribution. A symmetrical dataset will have a skewness equal to 0. So, a normal distribution will have a skewness of 0. Skewness essentially measures the relative size of the two tails. Kurtosis is a measure of the combined sizes of the two tails. It measures the amount of probability in the tails. The value is often compared to the kurtosis of the normal distribution, which is equal to 3. If the kurtosis is greater than 3, then the dataset has heavier tails than a normal distribution. If the kurtosis is less than 3, then the dataset has lighter tails than a normal distribution.

IV.   CLASSIFICATION

In order to classify a set of data into different classes or categories, the relationship between the data and the classes into which they are classified must be well understood. It is the process of assigning pixels in the image to categorize them. Support vector machine with quadratic kernel algorithm is applied to classify the results. Support vector machine is a supervised learning methods with associated learning algorithms that analyse data used for classification [18]-[20]. This maximizes the margin between two classes. Nonlinear classifiers are implemented by applying kernel trick to maximum-margin hyper plane [9]. The resultant algorithm is similar with the exception that each dot product is substituted by a nonlinear kernel function. This permits the algorithm to adjust the maximum-margin hyper plane in an altered feature space [12].

V.   EXPERIMENTAL RESULTS

A. Performance Evaluation

The dataset used in this work was obtained from trusted online database Mammogram Image for Analysis Society (MIAS). A database image of 150 counts was called for training and testing the detection as well as classification processes. The sample of each dataset is divided into 75 percentage of training and 100 percentage of testing categories. The support vector machine classifier is trained with the training data set. During testing each testing image is compared with the trained images and classified. To evaluate the performance of the proposed approach using evaluation metrics such as sensitivity, specificity and accuracy are computed using the following equations 1, 2 and 3.

$$\text{Sensitivity \%} = \frac{TP}{TP+FN} \times 100 \tag{1}$$

$$\text{Specificity \%} = \frac{TN}{TN+FP} \times 100 \tag{2}$$

$$\text{Accuracy \%} = \frac{TP+TN}{N} \times 100 \tag{3}$$

Where, TP True Positive, TN True Negative, FP False Positive , FN False Negative, N Number of inputs. The textural features such as gray level, contrast, homogeneity, correlation and energy are also calculated from the grey level histogram. The features such as skewness and kurtosis are obtained by using the equation 4 and 5.

$$\text{Skewness} = \left\{ \frac{n}{(n-1)(n-2)} \sum \frac{(x_i - \bar{x})^3}{s^3} = \frac{n}{s^3(n-1)(n-2)} \right. \tag{4}$$

$$\text{Kurtosis} = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \frac{(x_i - \bar{x})^4}{s^4} \right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{5}$$

Where, n is the sample size, x_i is the ith x value, x is the average and s is the sample standard deviation.

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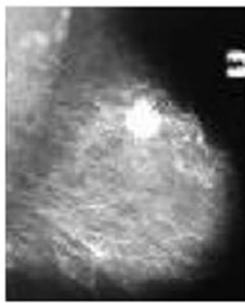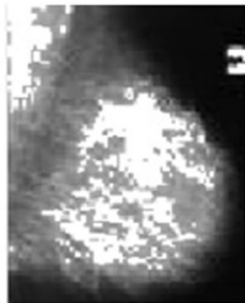

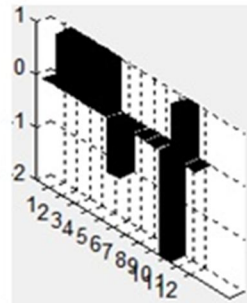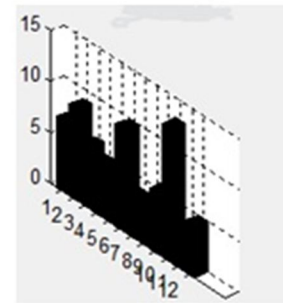Fig. 1.a. Original Image   Fig. 1.b. Processed Image   Fig 1.c. Skewness   Fig 1.d. Kurtosis

The Fig. 1.a. represents the original mammography image and the processed image is shown in Fig. 1.b. The skewness value and kurtosis value are represented in image Fig 1.c. and Fig 1.d. respectively. The resultant values are passed as input for two class support vector machine. The quadratic kernel function of support vector machine is given in equation 6.

$$(6)$$

$$k(x, y) = \sqrt{\|x-y\|^2 + c^2}$$

Where k is the kernel, x and y are input vectors derived from input space. The power of the polynomial used in this case is equal to two. It is very much suitable to construct non trivial function. If the feature points are nonlinear then this quadratic kernel has applied to separate the feature points. In this work, the experimental work results 87 percentage of accuracy.

VI.   CONCLUSIONS

Early detection of breast cancer is most important, since localized cancer can only be cured. Mammogram Image for Analysis Society dataset is used for this work. To detect the breast cancer earlier, pre-processing is presented with Hough transform and Watershed segmentation algorithm. The classification of support vector machine with quadratic kernel algorithm results better performance of 87 percentage of accuracy.

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