CLASSIFICATION OF MAMMOGRAM IMAGES

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ABSTRACT

Breast cancer is the most dangerous and incurable disease for women. Detecting breast cancer in early stages may increase the women life span. But it is not easy to identify the microcalcification in mammogram images because of its tiny size. In this paper, an author attempted to classify the mammogram images into cancer and non-cancer images by extracting low-level features. The extracted features are classified by a neural network and the SVM classifier. The neural network and the SVM classifier are trained by 150 images and tested by 50 images. The neural network accuracy is based on the mean square error and the regression analysis of the network. If the mean square error and the regression of the neural network attain low-value means, the accuracy of the network is high. Similarly, precision and recall are responsible for the SVM classifier. The database used here is the MIAS database.

KEYWORDS: Breast Cancer, Mammogram Images, Neural Networking Tool, Wavelet Transform.

INTRODUCTION

Breast cancer is caused due to lack of exercise, usage of alcohol, hormone surgery during menstruation cycle, having children at late, family genes, etc. About 5 to 10% of women are affected by breast cancer due to family gene inheritance. The survey shows that about 80% of breast cancer is found out by the lump in the breast region, which varies from the rest breast tissues. Other than the lumps, the symptoms for breast cancer include thickening of the breast tissues, swelling, itching, change in the position of the nipple, etc. In the early stages, a mammogram is used to diagnose breast cancer. Nowadays, many treatments are introduced to diagnose breast cancer includes radiation therapy, surgery, and hormone therapy. The report shows that in 2015, 533600 women were died due to breast cancer [1]. To increase the life span of women, detecting breast cancer in the early stage is necessary.

Here, an author attempted to identify the mammogram images into cancer and non-cancer images.

DATABASE

The database used in this project is downloaded from Mammography Image Analysis Society (MIAS). MIAS [2] dataset contains 322 images taken from 161 patients, including left and right breast. For classification, 200 images are used.

METHODOLOGY

The method to classify the mammogram images includes the following steps: pre-processing,
histogram equalization, binarization, wavelet transform, wave decomposition, wave reconstruction, feature extraction, and, classification.

**PRE-PROCESSING**

Before start to analyze or process the images, the images should be pre-processed [3]. Pre-processing is needed to remove the unwanted noises present in the image. To remove the noise such as artifacts, low-intensity label, and high-intensity label in mammogram images, the median filter is used.

**MEDIAN FILTER**

Median filter [4] is a nonlinear filter which is used to Remove the background noise and the noise present in the input image. Media filter takes place in every pixel of the image. For every pixel \((P_i)\) in an m*n image, 3*3 neighborhood pixels are selected. Then the 9-pixel values in the 3*3 neighborhood are sorted from smallest to largest values and select the median pixel value \((P_{mi})\). Replace the pixel \(P_i\) by \(P_{mi}\). Repeat this for all the pixels in the image. Then, the median filter output is given as an input for histogram equalization.

**HISTOGRAM EQUALIZATION**

Histogram [5] of the image defines several occurrences of gray level in the image against the gray level image. The histogram of the dark image is fully clustered towards the low gray level, and the bright image is clustered in a high gray level. The low and high gray level of an image is spread equally by applying histogram equalization. Histogram equalization is a process that attempts to spread out the gray level of the image so that they are evenly distributed across the range. The output of the median filtered gray level image is spread out equally by histogram equalization [6] and given as an input for binarization.

**BINARIZATION**

The threshold value for binarization is calculated by OTSU method. Binarization [7] is done by comparing every pixel value in an image with a threshold value. In binarization, the image can be represented by using only two different pixel values, namely 0 (black) and 1 (white). If the pixel value in an image is greater than the threshold value obtained by OTSU, it is assigned as 1 (white) if it is lesser than the threshold value, it is assigned as 0 (black). After image binarization, the image is in the form of 0’s and 1’s. Then, the binarization image is multiplied with the original mammogram image.

The threshold value for the abnormal image obtained by OTSU method is 0.7824. To obtain binarization, every pixel in an image is compared with the threshold value 0.7824. So, the pixel values which are all greater than the threshold value 0.7824 is considered as 1 (white), and the pixel values which are all lesser than the threshold value 0.7824 is considered as 0 (black).

**WAVELET TRANSFORM**

The microcalcification occurs in the image are high-frequency components [8], and hence, before applying wavelet transform to the image, the image has converted into a negative image. An image negative means the light areas in the image are appear dark, and dark areas appear light. The negative image has less contrast. If we take negative of negative of an image, we get the original image, that is Neg (neg (x)) =x.

Wavelets are powerful tools [9] that can be used in signal processing, image processing, and data compression. Wavelet transforms are an excellent alternative to Fourier transforms in many situations. In Fourier analysis, a signal is decomposed into periodic components; in wavelet analysis, a signal is decomposed into components localized in both time and frequency domains. Thus, wavelet transforms are ideal
when signals are not periodic. The orthogonal wavelet transform is used here.

**WAVE DECOMPOSITION**

The images are decomposed into different frequency bands by applying multilevel 2-D wavelet decomposition [10] using specific orthogonal wavelet decomposition filters. Daubechies wavelet with 3 level transforms are used here, and approximation coefficients for an image are taken for further analysis. For every row in the image, a one-dimensional wavelet transform is applied. The two-dimensional wavelet transform is applied to every column of the image by using the one-dimensional splitting algorithm, i.e. horizontal and vertical lines separately.

Approximation coefficient is obtained by applying the horizontal low-pass filter in rows and the vertical low-pass filter in the column of the image. Horizontal coefficients are obtained by using the horizontal low-pass filter followed by the vertical high-pass filter for the rows and columns, respectively. Vertical coefficients are obtained by applying the horizontal high-pass filter in rows followed by the vertical low pass filter in columns. Finally, the diagonal coefficients are obtained by applying the horizontal and vertical high-pass filters successively for rows and columns, respectively. Where $j+1 cA$ is the approximation coefficients of an image, $hj D+1$ is the horizontal coefficients of an image, $vc D+1$ is the vertical coefficients of an image, and $dc D+1$ is the diagonal coefficients of an image. Fig 1 shows an example of wave decomposition.

$$E_r = 100 \sum \frac{v^2}{c^2}$$

$$E_d = 100 \sum \frac{h^2}{c^2}$$

$$E_p = 100 \sum \frac{d^2}{c^2}$$

Where $H$ is a horizontal coefficient, $V$ is a vertical coefficient, $D$ is a diagonal coefficient, and $A$ is an approximation coefficient.

Approximation coefficients give the information’s about every pixel in the image; horizontal factors provide the information about the horizontal pixel in the image, similarly vertical and diagonal coefficients gives the information about vertical and diagonal pixels present in an image. Hence approximation coefficients images are taken to extract features. Figs. 2-5 shows an approximation, diagonal, horizontal, and vertical coefficients of abnormal images.
Figure 2. Approximation coefficients for abnormal image

Figure 3. Horizontal coefficients for abnormal image

Figure 4. Diagonal coefficients for abnormal image

Figure 5. Vertical coefficients for abnormal image
FEATURE EXTRACTION

The features extracted for classification are low-level features such as mean, variance, standard deviation, entropy, the difference between the maximum and minimum pixel value (difference_1), and the difference between the maximum and mean pixel (difference_2). These features are extracted from the wave decomposition image. The difference between the maximum and minimum pixel value (difference_1) and the difference between the maximum and mean pixel (difference_2) are calculated by using the morphological top-hat filter. By using Top-hat, morphological filter operations [7] are computed. The six statistical features are extracted by using the following equations (4-9),

\[
\text{Mean} = \frac{1}{N}\sum_{m,n} u(m,n) \quad \text{Mean} = \frac{1}{N}\sum_{m,n} u(m,n)
\]

\[
\text{Variance} = \frac{1}{N}\sum_{m,n} (u(m,n) - \text{mean})^2
\]

\[
\text{Variance} = \frac{1}{N}\sum_{m,n} (u(m,n) - \text{mean})^2
\]

\[
\text{SD} = \sqrt{\text{Variance}} \quad \text{SD} = \sqrt{\text{Variance}}
\]

\[
\text{Entropy} = e(-\log pu) \quad \text{Entropy} = e(-\log pu)
\]

\[
\text{Diff}_1 = \max(u(m,n)) - \min(u(m,n)) \quad \text{Diff}_1 = \max(u(m,n)) - \min(u(m,n))
\]

\[
\text{Diff}_2 = \max(u(m,n)) - \text{mean} \quad \text{Diff}_2 = \max(u(m,n)) - \text{mean}
\]

\[
\text{Diff}_3 = \max(u(m,n)) - \text{mean} \quad \text{Diff}_3 = \max(u(m,n)) - \text{mean}
\]

Where, u(m,n) is the pixel value in an image of m\textsuperscript{th} row and n\textsuperscript{th} column, N is the total number of pixels present in the image and pu is the probability of occurrence of pixel values in an image.

The shape features are extracted by morphology operation. Opening and closing are two important operators in morphology operation. Opening and closing are nothing but erosion and dilation. The basic effect on opening is somewhat like erosion; it removes some of the bright pixels from the edge of regions of foreground pixels. The opening is dual of closing. Opening the foreground pixels with a particular structural element is equivalent to closing the background pixels with the same elements.

DILATION

The output image from the wavelet transform and a structuring element is given as an input to the dilation operation. The structuring element is either in matrix format (m\times m) or small binary image format. Here, a 3 \times 3 structuring element is repeatedly used in an image to remove the bright pixels in an edge of the image.

EROSION

Erosion operation takes a set of coordinates points known as structuring element and an image which is to be eroded as an input.

Then by using this morphological erosion operation, two differences are calculated, such as difference 1 and difference 2. Difference 1 is a difference between the maximum pixel value in the image to a minimum pixel value in the image, and the difference 2 is a difference between the maximum pixel values in the image to mean pixel value in the image.

RESULTS AND DISCUSSIONS

NEURAL NETWORK

A Neural Network is a system of programs and data structures [11] that approximates the operation of the human brain. Neural network tool has three layers. The first layer has an input neuron; it sends the data to the third layer of output neurons via the second layer of the network. Neural network tool is too complex systems if it has more layers of neurons, either input neurons or output neurons. “weights” is the parameter, that manipulates the data in the calculations.
The six low-level features such as mean, standard deviation, variance, entropy, the difference between the maximum and minimum pixel value (difference_1), and the difference between the maximum and mean pixel (difference_2) are trained by the neural network tool. The neural network takes the above said six features as input and classifies the image into cancer affected image and non-cancer image. A Levenberg Marquardt algorithm is used to identify the microcalcification in a mammogram.

The low-level features are loaded as the input data into nftool and fix the target. The loaded features for all the 200 images are randomly divided for training and testing. Then the number of hidden neurons are given to create the network. The Neural Network Fitting Tool (nftool) trains a network by the six features, and the performance of the network is evaluated by mean square error and regression analysis. If the mean square error and regression analysis are obtained as high, the network has to train again by increasing the hidden neurons of the network.

![Analysis of abnormal images](image)

**SVM CLASSIFIER**

The SVM classifier is a supervised learning algorithm, which separates two classes of images on either side of the hyperplane. The classifier's accuracy is based on the 4 tuning parameters, namely kernel, gamma, margin, and regularization. Regularization optimizes the classifier to reduce the number of misclassifications. The number of misclassification of images is increased by choosing the low regularization value, i.e. the accuracy of the classifier can get the increase by improving the regularization.

Low gamma value considers the images which are far away from the hyperplane and high gamma value consider only the images which are closest to the hyperplane.

Right margin of the hyperplane can increase the classifier accuracy. The good margin doesn't allow the respective classes images to cross the hyperplane for misclassification. The final and main parameter to tune the classifier is "kernel," which plays an important role in SVM classifier. Here linear kernel is used to classify the images into normal and abnormal. For nonlinear classifier, we can use 'rbf,' 'poly' and others. Choosing these four parameters is important to improve the classifier accuracy.

The performance of the neural network is compared with SVM classifier. SVM classifier classifies the images into normal and abnormal images by using the same features which are used for the neural network. Table 1 shows the results of the classification.

**PERFORMANCE MEASURE**

An author attempted to found out a key feature...
to classify the mammogram images. The neural network tool and SVM classifier are first trained by four statistical features such as mean, standard deviation, variance, entropy, and obtained 61.3% and 62.48% accuracy, respectively. Then, the nftool and SVM classifier are trained by six features (mean, variance, standard deviation, entropy, the difference between the maximum and minimum pixel value (difference_1), and the difference between the maximum and mean pixel (difference_2)), and attains 71.32% and 79.95% accuracy, respectively.

The result shows that SVM classifier attains high accuracy than the neural network tool. Precision and recall for the nftool and SVM classifier are calculated by using True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). The formula used to calculate precision and recall are,

\[
\text{Precision} = \frac{TP}{TP+FP} \quad (10)
\]
\[
\text{Recall} = \frac{TP}{TP+FN} \quad (11)
\]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Features</th>
<th>Precision</th>
<th>Recall</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM classifier</td>
<td>Mean, Variance, Standard Deviation, Entropy, Diff_1, Diff_2</td>
<td>78</td>
<td>82</td>
<td>79.95</td>
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<td>62</td>
<td>62.48</td>
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<tr>
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<td>58</td>
<td>61.3</td>
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<tr>
<td>Neural Network</td>
<td>Mean, Variance, Standard Deviation, Entropy, Diff_1, Diff_2</td>
<td>68</td>
<td>75</td>
<td>71.32</td>
</tr>
</tbody>
</table>

The number of misclassification images in SVM classifier with six features (mean, variance, standard deviation, entropy, the difference between the maximum and minimum pixel value (difference_1), and the difference between the maximum and mean pixel (difference_2)) are lower than the SVM classifier with four features (mean, variance, standard deviation, entropy). But the nftool with six features attains 71.32% than the SVM classifier with four features (mean, variance, standard deviation, entropy). From Fig. 7, it is shown that the classifier trained by six feature attains high accuracy than the classifier trained by four features.

![Figure 7. Performance analysis of the classifier](image-url)
CONCLUSIONS

The first stage (Preprocessing stage) attains 95% accuracy for removing the noises. The low-level statistical features are extracted from the wavelet transformed image and given as the input to the neural network and the SVM classifier. The neural network toolbox is trained by 150 images and tested by 50 images. It classifies the normal and abnormal images with 71.32% accuracy in NN tool and 79.95 % of accuracy in SVM classifier. The accuracy of the classifier can improve by increasing a large number of datasets to train the classifier and also by extracting a high-level feature. In the future, the accuracy of the classifier can enhance by extracting high-level features.

REFERENCES