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Mammogram classification scheme using 2D-discrete wavelet and local binary pattern for detection of breast cancer

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Mammogram classification scheme using 2D-discrete wavelet and local binary pattern for detection of breast cancer

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Abstract. In this paper, we propose a new mammogram classification scheme to classify the breast tissues as normal or abnormal. Feature matrix is generated using Local Binary Pattern to all the detailed coefficients from 2D-DWT of the region of interest (ROI) of a mammogram. Feature selection is done by selecting the relevant features that affect the classification. Feature selection is used to reduce the dimensionality of data and features that are not relevant, in this paper the F-test and Ttest will be performed to the results of the feature extraction dataset to reduce and select the relevant feature. The best features are used in a Neural Network classifier for classification. In this research we use MIAS and DDSM database. In addition to the suggested scheme, the competent schemes are also simulated for comparative analysis. It is observed that the proposed scheme has a better say with respect to accuracy, specificity and sensitivity. Based on experiments, the performance of the proposed scheme can produce high accuracy that is 92.71%, while the lowest accuracy obtained is 77.08%.

1. Introduction

One of the most effective methods to detect and identify breast cancer is through mammography examination using X-ray, images generated from the X-ray called a mammogram. An analysis of the mammography images that were previously done manually by the radiologist can be replaced with renewable technologies by utilizing digital image processing, so that the results obtained is not subjective and to overcome the radiologist's feel that not confident with the results of the analysis [1]. The main purpose of image processing is to gather information, screening or invertigation, diagnose, therapy and control, as well as monitoring and evaluation[2]. There are several studies that have been done by utilizing digital image processing, Dhawan et al in [3] using wavelet decomposition on a gray-level image to classify the mammograms and obtained the accuracy values is 81%. Liu et al in [4] using a wavelet-based statistical feature and the binary tree as a classifier obtain classification accuracy of 84.2% on a mammogram. Rashed et al in [5] use some type of daubechies wavelets on the classification mamm-ogram, obtained a classification accuracy of 87.06%. Buciu et al in [6] using a filter gabor based on wavelet for feature extraction, PCA for feature selection (dimension reduction) and support vector machine as classifier to classify images of mammograms as a normal-abnormal (performance classification 79%) and benign-malignant (performance classification 78 %).

The literature survey reveals about the existing classification schemes for digital mammogram images. However, most of them are not able to provide a high accuracy. It has been seen that the dimension of extracted feature space is so high due to large varieties of normal and abnormal tissues present in the breast. The use of high dimensional feature space may degrade the performance of the classification scheme. From a large feature space, only some of the features are effective and significant for the mammogram classification. Therefore, in addition to feature extraction, feature

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selection is also the key step in mammogram classification, which selects only the significant features from available feature space. So there is a need to develop some new feature extraction and selection algorithms to increase the accuracy of classification rate. In this paper, we have proposed an effective feature extraction algorithm using two dimensional discrete wavelet transform (2D-DWT) based multiresolution analysis along with gray-level co-occurrence matrix (GLCM) to compute texture features for mammographic images. A feature selection algorithm has been applied using two statistical feature selection methods such as two-sample t and F-test to select significant features from extracted features. Utilizing these significant features, a back propagation neural network (BPNN) has been used as classifier to predict the mammogram, whether it is a normal or abnormal.

2. Methods

In this chapter elaborated on the research methodology used in this study as well as the contribution of the proposed. Illustration groove research methodology can be seen in Figure 1.

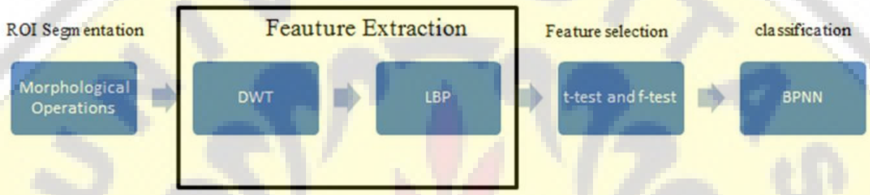

Figure 1. Research Methodology.

On a mammogram, a region that represents cancer is a region that containing a mass, so that before the classification is done then the mammogram image will be preprocessing to detect the location of the mass. Areas that are important in an image or referred to as the region of interest (ROI)[7,8]. Examples of ROI on the mammogram image is shown in Figure 2. There are several stages in the detection and segmentation ROI on a mammogram image. The purpose of this phase is to get the point of cancer on a mammogram image (mass) which may indicates the someone has breast cancer or not. Stages of detection and segmentation of the mass can be seen in Figure 3.

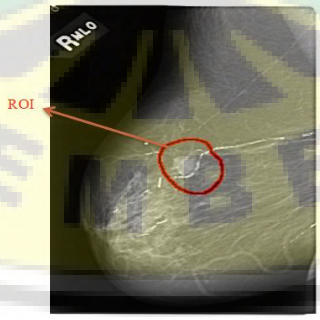

Figure 2. ROI in mammogram.

Figure 3. Stage detection and cropping ROI.

2.1 Discrete Wavelet Transform

Extraction of the image features a mammogram done with the method of combining 2D-DWT and LBP. DWT can be used for image transformation, wavelet transformation process is done in a pretty simple concept. Transformed the original image is divided (decomposed) into four sub-new image to replace him. Each sub-image of ¼ times the size of the original image. Sub-image at the top right, bottom left and bottom right will seem like a crude version of the original image because it

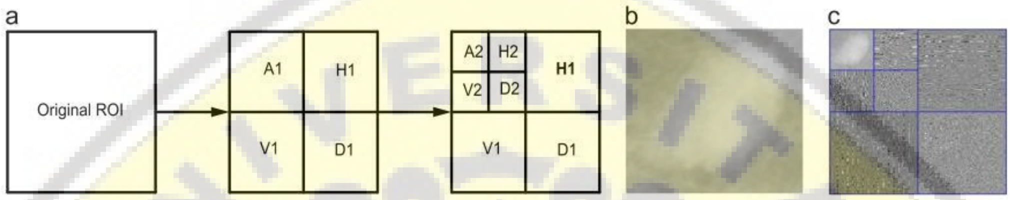

Figure 4. a) decomposition process b) Original ROI c) Result.

contains high frequency components of the original image. As for the first sub-image on the left looks like the original image and looks smoother (smooth) because it contains low frequency components of the original image. Discrete wavelete transform performed in this study is a level 2 which will produce 7 new sub-image. Stages of DWT in this study can be seen in Figure 4.

2.2 Local Binary Pattern

The original LBP operator labels the pixels of an image with decimal numbers, called Local Binary Patterns or LBP codes, which encode the local structure around each pixel[9, 10]. It proceeds thus, as illustrated in Fig.1: Each pixel is compared with its eight neighbors in a 3x3 neighborhood by subtracting the center pixel value; The resulting strictly negative values are encoded with 0 and the others with 1; A binary number is obtained by concatenating all these binary codes in a clockwise direction starting from the top-left one and its corresponding decimal value is used for labeling. The derived binary numbers are referred to as Local Binary Patterns or LBP codes.

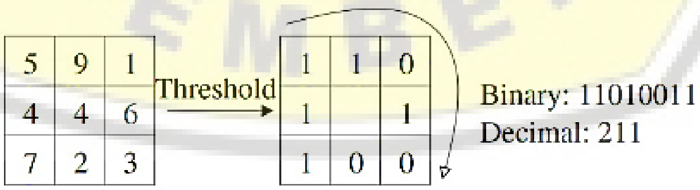

Figure 5. An example of the basic LBP operator

2.3 Feature Selection

Selection feature is one of the stages before the classification process. Feature selection is done by selecting the relevant features that affect the classification. Selection feature is used to reduce the dimensionality of data and features that are not relevant. Selection feature is also used to enhance the effectiveness and efficiency of the performance of classification algorithms. In this research feature selection using statistical methods that is two sample T-test and F-test. T-test known as partial test, which is to examine how the influence of each independent variable individually against the dependent

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variable. This test can be done with compare T arithmetic with T-table or view column on the significance of each T. F-test known as simultaneous test or tests Model / Anova test, a test to see how the influence of all independent variables together against the dependent variable. T-test or F-test functions to generate hypotheses whether a feature that a significant class of the same features in other classes. If the model is significant then the model can not be used for classification, otherwise if non / not significant then the regression model can be used for the classification process. For algorithm T-

```
R: Total number of selected features
Functions ttest() and vartest() compute the null hypothesis
values of two vectors at different values of significance
level, by two-sample t and F-test respectively
Create two empty vectors v1 and v2
Initialize α, 0 < α < 1
for i ← 1 to M do
  Clear contents of vector v1 and vector v2
  for j ← 1 to N do
    if target_class[j] = 1 then
      Append feature_matrix[i, j] to v1
    else
      Append feature_matrix[i, j] to v2
    end if
  end for
  h1[i] ← ttest(v1, v2, α)
  h2[i] ← vartest(v1, v2, α)
  for l ← 1 to 2 do
    if hk[i] = 1 then
      Append feature_matrix[i, 1 : N] to selected_featurek
    end if
  end for
end for
```

Figure 6. F-test and T-test Algorithm

test and F-test can be seen in Figure 6.

3. Result and Discussion

The data used in this study are the images obtained from the database mammographic Image Analysis Society (MIAS) and DDSM. Data obtained through the website http://peipa.essex.ac.uk-/pix/mias, and DDSM from http://marathon.csee.usf.edu/. With the amount of data mammogram image is 317, with 208 images is normal and 109 is abnormal.

3.1 Selection Featuren Experiment

Selection feature is used to reduce the dimensionality of data and features that are not relevant. Selection feature is also used to enhance the effectiveness and efficiency of the performance of classification algorithms. Feature selection method used is F-test and T-test and parameters that affect the two methods are the significant level. The trial also performed on stage feature selection in a way to alter the parameter values significant level, it is intended to determine the relationship level with a significant variable selection results of existing features. Values that becoming significant level test parameters are 0.1, 0.3, 0.5, 0.7, 0.9.

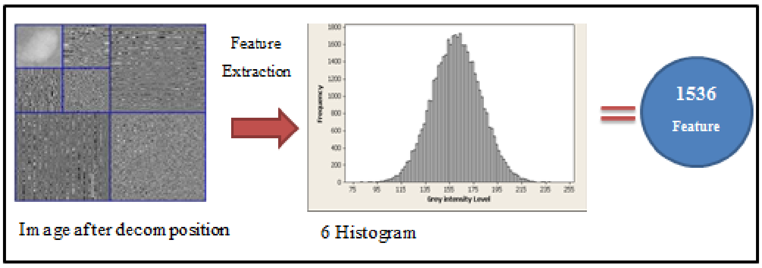

Figure 7. Simulation of feature extraction and selection.

The F-test and T-test will be performed to the results of the feature extraction dataset. Every single mammogram image will produce 7 sub image after decomposed using discrete wavelet transform, but in this research, image that to be used for the extraction feature process are only 6 sub image, that is sub image of a horizontal decomposition level 1 and 2, vertical decomposition level 1 and 2, and the diagonal decomposition level 1 and 2. One sub image of mammogram will produce one histogram after feature extraction process using LBP, while the one histogram is composed of 256 features so 6 sub image mammogram will generate 1536 feature. Simulation of feature extractiom and selection mammogram image untill be a dataset features can be seen in Figure 7 and the results of feature selection can be seen in Table 1.

Table 1. Feature Selection Result.

Significant level	Number of Feature LBP (R)	
	T-test	F-test
0.1	758	453
0.3	1010	775
0.5	1173	1021
0.7	1330	1226
0.9	1478	1443

Can be seen in Table 1, the largest number of feature is 1478 that produced when using T-Test as selection features method, LBP as feature extraction method and the value of significant level is 0.9. Based on the results obtained in Table 1 also can be concluded that higher the value of significant level make the feature will be less to reducted so the number of selection feature result will be same with the initial feature before the feature selection phase, and vice versa the lower the value of significant level make the feature will be more to reducted and produce less independent features. The cause of significant level is inversely proportional to the results of feature selection is due to the significant level used as a benchmark to determine a feature considered independent or not, so if the value of the significant level higher then the chances of a feature considered to be independent will be smaller.

3.2 Classification Experiment

Testing is done by comparing the traditional LBP method using discrete wavelet transform and without discrete wavelet transform. The performance of the method can be seen in Table 2 and Table 3.

Can be seen in Table 2 the performance of a combination of discrete wavelet transform and local binary pattern generating high accuracy that is 92.70% of feature selection F-test with a significant level value of 0.9 and 0.7. At trial using feature selection T-test combinations of discrete wavelet transform and a full neighbor local binary pattern get the highest accuracy is 85.42% on the value of the significant level is 0.1. For the sensitivity and specificity of this combination produces the highest value on a test using the F-test with a significant level of 0.9 and 0.7. Lowest accuracy value for a combination of discrete wavelet transform and a full neighbor local binary pattern obtained at feature selection methods are used T-test with a significant level value of 0.5 which is 77.08% while for feature selection methods F-test lows accuracy obtained at significant level of 0.5. From Table 2 also obtained the fact that the specificity and sensitivity is directly proportional to the accuracy.

Table 2. Performance of DWT+lbp.

Method	Significant Level	R	TP	TN	FP	FN	Sensitivity	Specifisity	Accuration (%)
T-test	0.9	213	21	57	12	6	0.78	0.83	81.25
	0.7	206	22	56	11	7	0.76	**0.84**	81.25
	0.5	197	16	62	17	1	0.94	0.78	81.25
	0.3	188	17	60	16	3	0.85	0.79	80.20
	0.1	175	22	51	11	12	0.64	0.83	76.04
F-test	0.9	216	21	57	12	6	0.78	0.83	81.25
	0.7	211	19	59	14	4	0.83	0.81	81.25
	0.5	207	22	58	11	5	0.81	**0.84**	**83.33**
	0.3	192	22	57	11	6	0.79	**0.84**	82.29
	0.1	174	1	63	32	0	**1.00**	0.67	66.67

Table 3. Performance of LBP.

Method	Significant Level	R	TP	TN	FP	FN	Sensitivity	Specifisity	Accuration (%)
T-test	0.9	213	26	55	7	8	0.76	0.89	84.37
	0.7	206	25	56	8	7	0.78	0.88	84.37
	0.5	197	20	54	13	9	0.69	0.81	77.08
	0.3	188	24	54	9	9	0.73	0.86	81.25
	0.1	175	26	56	7	7	0.79	0.89	85.42
F-test	0.9	216	29	60	4	3	**0.91**	**0.94**	**92.71**
	0.7	211	29	60	4	3	**0.91**	**0.94**	**92.71**
	0.5	207	26	50	7	13	0.67	0.88	79.17
	0.3	192	25	57	8	6	0.81	0.88	85.42
	0.1	174	26	54	7	9	0.74	0.89	83.33

For the traditional local binary pattern the performance can be seen in Table 3 to produce the highest accuracy is 83.33% on feature selection F-test with a significant level value of 0.5. At trial using feature selection using the T-test traditional local binary pattern methods the highest value only on the value of significant levels of 0.9, 0.7, and 0.5 that the accuracy is 81.25%. The sensitivity of this combination produces a perfect score when use feature selection F-test with a value of significant levels of 0.1, while for specificity highest value obtained when accuracy also got the highest score that is the feature selection F-test with a value of significant levels of 0.5 and 0.3 with a value specificity is 0.84, and feature selection T-test with a significant level of 07. The lowest accuracy on local binary pattern obtained when feature selection F-test used with a significant level value of 0.7 which is 66.67%. From Table 4 and Table 5 obtained the fact that the proposed method keeps getting higher accuracy than traditional local binary pattern although without performing discrete wavelet transform decomposition on mammogram image.

4. Conclusions

Based on the method of application has been made and the results obtained from a series of trials that have been conducted on the proposed scheme 2D-discrete wavelet transform and local binary pattern (LBP) traditional, it can be concluded on this study that the proposed scheme is better in an average accuracy than other scheme. Based on experiments, the performance of the proposed scheme can produce high accuracy that is 92.71%, while the lowest accuracy obtained is 77.08%. In the histogram result when using LBP the trend of high bit value histogram is 0 and 255, it indicates that proposed method (dwt+lbp) is sensitive against noise. Higher The value of significant level make the feature will be less to reducted so the number of selection feature result will be same with the initial feature before the feature selection phase, and the lower value of significant level make the feature will be more to reducted and produce less independent features.

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