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Mammograms Classification using Gray-level Co-occurrence Matrix and Radial Basis Function Neural Network

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Abstract

Computer Aided Diagnosis (CAD) is used to assist radiologist in classifying various type of breast cancers. It already proved its success not only in reducing human error in reading the mammograms but also shows better and reliable classification into benign and malignant abnormalities. This paper will report and attempt on using Radial Basis Function Neural Network (RBFNN) for mammograms classification based on Gray-level Co-occurrence Matrix (GLCM) texture based features. In this study, normal and abnormal breast image used as the standard input are taken from Mammographic Image Analysis Society (MIAS) digital mammogram database. The computational experiments show that RBFNN is better than Back-propagation Neural Network (BPNN) in performing breast cancer classification. For normal and abnormal classification, the result shows that RBFNN’s accuracy is 93.98%, which is 14% higher than BPNN, while the accuracy of benign and malignant classification is 94.29% which is 2% higher than BPNN.

1. Introduction

In terms of cancer, breast cancer is the second killer after lung cancer. It mostly found in woman [1]. This dangerous illness is caused by lesion that can be classified into two categories, which are benign and malignant. Benign is harmless lesion which can be removed and unlikely to recur, while malignant is cancerous cell which highly potential to grow up and spread to other parts of the body [2]. Most of breast cancer patient do not notice
about its presence and died before they get proper medication. Thus, breast cancer detection on the early stage is necessary in order to reduce the number of death [1].

One valuable detection tools to identify breast cancer at early stage is through visual inspection on radiographic (X-ray) images (known as mammograms) [3]. However, by using this technique, the classification of normal, benign, and malignant become a complex job due to variations of tissue characteristics, such as shape, grey level, size, intensities, and location [4]. Besides, the specificity of visual inspection is low with high sensitivity [5]. In order to reduce the number of false-negative, diagnosis greater than 2% change of being malignant will be recommended to biopsy [6]. Thus, an improvement in interpreting mammograms becomes an important issue.

Some previous studies show that Computer Aided Diagnosis (CAD) can simplify the process of interpreting mammograms and giving more accurate result [7]. The output of CAD is used to help radiologist in the detection of breast cancer [8]. In the last two decades, researchers proposed various types of classifier in order to create an effective and optimal CAD for mammograms. Artificial neural network always have a good performance in pattern recognition rather than the other without implementing ANN [9].

In 1996, Berkman Sahiner et al. [10] used a Convolution Neural Network (CNN) classifier to classify normal and abnormal breast tissue from mammograms. The experiment was done by using gray level difference statistics (GLDS) and spatial gray level dependence (SGLD) features which were computed from different sub-regions. Then, the features were used as an input for CNN classifier.

Sung-Nien Yu and Yu-Kun Huang [11] proposed a wavelet filter method to detect cancer region by calculating the mean pixel value. In order to extract the features of mammograms, Markov random field (MRF), fractal models, and statistical textural feature were used. Then, for the classification process, all extracted features were inputted into Back-propagation neural network (BPNN) with three layers.

In 2010, Islam M. et al. [12] introduced an effective method for benign – malignant classification of digital mammograms. The authors used seven texture features (extracted for each ROI) as the input for Multi-layer Perceptron (MLP) classifier with 7 units in input layer, 5 units in hidden layer and 1 unit in the output layer. The result was claimed to give promising result with 90.91% sensitivity and 83.87% specificity.

The combination of Gray-level Co-occurrence Matrix (GLCM) and Artificial Neural Network (ANN) model had been done by Man To Wong et al. [13]. GLCM is used to produce twelve texture feature of mammograms. The four significant output of GLCM was used as the input for ANN model to classify either mass or non-mass region. The accuracy rate of this research is about 86%.

The research on Mammogram Mass Classification using GLCM and RBFNN by Abdul Jaleel shows the classification accuracy for benign-malignant is 93.7% [14]. The other research performed by Dheeba and Wiselin shows that Detection of Microcalcification Clusters in Mammograms using Back-propagation Neural Network (BPNN) give 84.3% accuracy [15].

All methods describe in the previous paragraphs are some implementation of neural network model. Another neural network model which is considered as a good classifier is Radial Basis Function Neural Network (RBFNN) [16]. There are many applications that implemented using RBFNN, such as electroencephalogram (EEGs) classification [17] and weather forecast [18]. In electroencephalogram (EEGs) classification when diagnosing epilepsy produce 93.3% accuracy. Besides, RBFNN can be used to improve the weather forecast accuracy.

Based on those previous researches, this paper intends to use GLCM texture-based for feature extraction and use them as the input for benign and malignant classification using RBFNN. The main goal of this study is to devise the best neural network model classifier for benign and malignant lesion of mammograms.

2. Materials and Methods

2.1. Materials

Data set used in this study is digital mammograms taken from the published MIAS database (http://peipa.essex.ac.uk/ipa/pix/mias/). In this database, the original MIAS database are digitized at 50 micron pixel edge and has been reduced to 200 micron pixel edge and clipped or padded so that every image is 1024 X 1024 pixels. All images are held as 8-bit gray level scale images with 256 different gray levels (0-255) and physically in portable gray map (pgm) format. In total, MIAS database consists of 330 images which divided into 208 normal images, 68 benign images, and 54 malignant images. So, there are 64% of normal data, 20% of benign data, and 16% of malignant data.

In general, data set is separated into training and testing set with the composition of 70:30, except for BPNN,
the data set is divided into training, validation, and testing set with the composition of 70:15:15.

2.2. Methods

This study is divided into three main processes, which are pre-processing, feature extraction, and classifier. Two classifiers are used in this study; they are Back-Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN). Before the data set get into classifier, it will be pre-processed first. Then, the features of each mammogram will be extracted using Gray-level-Co-occurrence Matrix (GLCM) to get the features vector containing the texture information of the mammogram. For the development and evaluation of the proposed system, the two different classifiers (BPNN, RBFNN) will be trained multiple times in order to achieve best accuracy. The classification process is divided into two major steps, which are:

1. Phase I (Normal – Abnormal Classification)
   Phase I would be a preliminary round for detecting any abnormalities. During this process, the classifier will be trained by a training set containing normal and abnormal mammograms. The predicted abnormal results from this phase will be taken as inputs for the second classification phase.

2. Phase II (Benign – Malignant Classification)
   The purpose of the second phase is to predict the abnormalities type of cancer. Output for this structure is divided into two classes, which is benign or malignant.

The study design flowchart is presented on Figure 2.

![Figure 1. Classification Methodology](image)

2.2.1. Pre-processing

The purpose of data pre-processing is to enhance the quality of data set by reducing irrelevant data that potentially interfere the training process. In this study, three irrelevant data are discarded from training set since the centroid of mass is not specified. They are 059.pgm, 212.pgm, and 214.pgm whose type is benign. Therefore, total
data used in this study is 327 digital mammograms. Some process also performed in the processing step, which are cropping on the Region of Interest (ROI) and resizing an image of a mammogram to be 128 x 128 pixels.

![Image before (left) and after (right) pre-processing using sample mdb028.pgm](image)

**2.2.2. Feature Extraction**

Feature extraction is important in the process of getting the meaningful characteristic or information used in classification [19,20,21]. Gray-level co-occurrence matrix (GLCM) is the technique to evaluate textures by considering the spatial relationship of the pixels. This method calculates the occurrence of pairs of pixels with specific values and in a specified spatial relationship in an image. The spatial relationship is means the pixel of interest and the pixel to its immediate right (horizontally adjacent). After that, it will produce the statistical method from the calculation matrix. The GLCM used in this experiment calculate the occurrence of gray-level value \( i \) in specific spatial relationship to a pixel of \( j \) and then sum the number of \( i \) appears in the specific spatial relationship to pixel with value of \( j \) in the image.

In this experiment, feature extraction is useful to isolate either normal – abnormal or benign – malignant lesion classification. Several prior studies show that the GLCM is an effective method for image texture analysis. The GLCM has been applied in several researches regarding image texture analysis and still become the significant aspect for the research. For this reason, GLCM method will be used for digital mammogram texture extraction in this study.

The matrices are constructed at a distance of \( d = 1 \) and for direction of \( \theta \) given as \( 0^\circ, 45^\circ, 90^\circ \) and \( 135^\circ \). Then, four directions are used to extract the texture information for each masses and non-masses tiles area. The texture descriptors derived from GLCM are contrast, energy, homogeneity and correlation of gray level values. Haralick shows that there are 14 textural features [22]. But, according to Chia-Hung Wei et al. [23], the 4 dominant features of GLCM based on t-test are ASM, Correlation, Sum Entropy, and Sum Variance. Thus, this experiment will use only those 4 features.

- **ASM**
  ASM shows the homogeneity properties of an image size or the size of the proximity of each element of the occurrence matrix.
  \[
  ASM = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}
  \]  

- **Correlation**
  Correlation indicates the size of the linear relationship of the neighborhood pixel gray level.
  \[
  Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j}
  \]  

- **Sum Entropy**
  Entropy shows the size of the irregular shape of an image.
  \[
  SumEntro = \sum_{i=2}^{2N} p_{x+y}(i)\log(p_{x+y}(i))
  \]  

- **Sum Variance**
  Sum variance shows the high frequency of occurrence that equally concentrated in the lowest and highest cells of the co-occurrence matrix.
  \[
  Sum_var = \sum_{i=2}^{2N} (i - SumEntro)^2p_{x+y}
  \]

**2.2.3. Validity**

The accuracy rate of each classifier is evaluated using confusion matrix. For comparing the performance of
cancer detection of each classifier, specificity and sensitivity is used. Sensitivity and specificity are statistics used to measure the significance of a test related to the presence or absence of the disease. Equations (5) and (6) are used to calculate these two parameters, respectively.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{5}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \tag{6}
\]

where TP is true positive, FN is false negative, TN is true negative, and FP is false positive. Based on the above Equation (5) and (6), it can be concluded that sensitivity indicates the number of disease that is correctly predicted by the positive test while specificity indicates the number of patients without disease who test negative. Thus, it is a measure of test performance whose purpose is to distinguish between patients who do and do not suffer from the disease.

2.2.4. Back-propagation Neural Network (BPNN)

Artificial Neural Network (ANN) is claimed to be one of the powerful classifier that is suited for complex input – output relationship [12]. It adapts the ability of human brain neuron in perceptual acts [24]. ANN trains the artificial neurons using defined input then calculates the best weight of each neuron so that the minimum error can be met. The error rate is usually represented using mean square error (MSE) which can be obtained from the calculation:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{7}
\]

One of popular ANN algorithm is Back-propagation Neural Network (BPNN) that can adjust the weight of each neuron during training process in order to minimize the MSE. Several researches proofs that BPNN is more robust. By this reason, this study uses the BPNN as one of the classifier used for mammograms. The construction of BPNN chosen in this study consists of input layer, hidden layer, and output layer. The study evaluates the performance of BPNN using the degree of 0, 45°, 90°, 135° with the combination of 10, 15, 20, 25, and 30 nodes in order to get best structures of BPNN.

2.2.5. Radial Basis Function Neural Network (RBFNN)

RBFNN used in this study consists of input vector, one layers of RBF neuron, and an output layer with one node for each category or class of data as shown in Figure 3.

![Figure 3. The construction of RBFNN algorithm](image)

Here are the descriptions of the proposed method: The input vector is consists of 4 dimensional vectors that will be classified. The 4 dimensional vectors are ASM, Correlation, Sum Entropy, and Sum variance. The Hidden layer has a variable number of neurons. The number of hidden neurons in RBF net is equal to the total epoch in
training, where the maximum epoch may not exceed the number of training set. The number of hidden neurons used in this experiment is 84 since the number of training set is 85. The output layer consists of a set of nodes to be classified. The value of the output layer is rounded and then thresholded using two rules, which are:

\[
IF \ x > k \ THEN \ x = k
\]

\[
IF \ x < j \ THEN \ x = j
\]

where \( x \) is the output value, \( k \) is upper threshold value, and \( j \) is lower threshold value.

Typically, a classification decision is made by assigning the input to the category with the highest score. Euclidean distance is computed from the point being evaluated to the center of each neuron, and a radial basis function (RBF) (also called a kernel function) is applied to the distance to compute the weight (influence) of each neuron. The kernel function that is frequently used by the most researchers is Gaussian function as can be seen in eq. 10:

\[
\phi_j = \exp\left(\frac{-(x-c_j)^2}{2\sigma_j^2}\right)
\]

here \( \phi_j \) is the \( j^{th} \) radial basis function, \( x = (x_1, x_2, ..., x_d)^T \) is the input vector, \( c_j = (c_{1j}, c_{2j}, ..., c_{dj})^T \) are the center vector, and \( \sigma_j^2 \) is the spread. The output of RBF network \( y \) which is the linear sum of radial basis function is given as follows:

\[
y = \sum_{j=1}^{p} w_j \phi_j
\]

where \( Y \) is the output of the RBF network, \( p \) is the number of the hidden layer neuron, and \( w_j \) is the weight from \( j^{th} \) neuron to the output layer [25]. In this work, we use two RBFNN, where the first RBFNN is used to classify whether the data is classified as normal or abnormal, and the second RBFNN is used to classify whether the data is classified as benign or malignant.

3. Result and Discussion

3.1. Result

3.1.1. Back-propagation Neural Network (BPNN)

The accuracy result of BPNN for normal – abnormal and benign – malignant classification is shown on the Table 1. Figure 4 and Figure 5 show respectively the confusion matrices of normal – abnormal and benign – malignant classification using BPNN.

Table 1. Accuracy result of normal – abnormal and benign – malignant classification using BPNN

| Degree | Node | Accuracy Phase I | Accuracy Phase II |
|--------|------|------------------|-------------------|
| 0°     | 10   | 79.5             | 74.6              |
|        | 15   | 79.2             | 69.8              |
|        | 20   | 80.1             | 66.7              |
|        | 25   | 78.6             | 68.3              |
|        | 30   | 77.4             | 77.8              |
| 45°    | 10   | 72.4             | 92.1              |
|        | 15   | 70.9             | 71.4              |
|        | 20   | 75.2             | 65.1              |
|        | 25   | 72.7             | 77.8              |
|        | 30   | 76.1             | 73                |
| 90°    | 10   | 74.3             | 71.4              |
|        | 15   | 73.1             | 76.2              |
|        | 20   | 74.9             | 84.1              |
|        | 25   | 74.3             | 61.9              |
|        | 30   | 75.2             | 73                |
The accuracy result of normal – abnormal and benign – malignant classification is presented on Table 1. Based on the confusion matrix, the sensitivity of the best combination is 81.6% and the specificity is 76.9%.

| Degree | Node | Phase I | Phase II | Overall |
|--------|------|---------|----------|---------|
| 0°     | 84   | 92.77%  | 83.33%   | 90.36%  |
| 45°    | 84   | 93.98%  | 97.22%   | 91.57%  |
| 90°    | 84   | 92.77%  | 88.89%   | 89.16%  |
| 135°   | 84   | 93.98%  | 94.44%   | 91.57%  |

### Table 2. Accuracy, Sensitivity, and Specificity of classification using RBFNN

3.1.2. Radial Basis Function Neural Network (RBFNN)

Table 2 shows the accuracy, sensitivity, and specificity of normal – abnormal classification (Phase I), benign – malignant classification (Phase II), and overall accuracy using RBFNN.

3.2. Discussion

This work was conducted to get the highest accuracy using one input layer, one hidden layers and one output layer. Based on the BPNN result shown in Table 1, the best accuracy of normal and abnormal classification using BPNN is obtained on the combination of 20 nodes with ROI of 0°. Then, the combination of 10 hidden nodes and 45° produce the best accuracy with 92.1% when classifying benign and malignant cancer type. On the other hand, Table 2 shows that RBFNN can produce 93.98% accuracy rate in the degree of 45° and 135° for the first phase. It also shows that in benign and malignant classification, RBFNN achieve 94.29% accuracy for 45°.

According to the confusion matrices presented in Figure 4 and 5, the sensitivity of the best combination in normal and abnormal classification is 88.9% while the specificity is 94.4%. For benign and malignant classification, BPNN can achieve 81.6% sensitivity and 76.9% specificity. Meanwhile, the sensitivity of RBFNN on normal and abnormal classification is 94.44% and the specificity is 93.62%. In classifying benign and malignant, RBFNN produce 100% sensitivity and 89.47% specificity.

Compared to the previous research in mammogram classification [14,15], the accuracy is also improved by dividing the classification step into two major phase, they are normal – abnormal classification and benign – malignant classification.
4. Conclusion

Based on the experiment conducted, it can be concluded that RBFNN is more accurate in classifying digital mammogram image with sensitivity of 97.22% and specificity of 91.49% for normal and abnormal classification, while in classifying benign and malignant lesion, RBFNN’s sensitivity is 100% and specificity is 89.47%. Overall RBFNN performance accuracy in classifying both normal – abnormal and benign – malignant is 91.57%. Since GLCM and BPNN obtain promising result, we know that those methods can be applied in a medical decision support system.

For future work, another texture based features extraction, such as wavelet or curvelet, may be used in breast cancer classification in the purpose of improving the accuracy.

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