

Medical Image Classification using Neural Networks Techniques

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Abstract- Detection of tumors at an early stage is one important step in diagnosing abnormalities in a mammogram. In many cases, preprocessing process of raw images will involve image enhancement, filtering and determination of its textural feature. Similarly, this study also use the same affirmed preprocesses towards its images. One of the Gabor wavelet based algorithm namely Gabor filter was used to extract the feature of mammogram images. The output of this filter was then being used for classification purpose, so as to determine the characteristics of the normal tissue and abnormal tissue. Since Radial Basis Function (RBF) network is the best classifier for classifying problems particularly in term of its high accuracy rate, this classifier was used in this research. The performances of these classifiers were compared with Back Propagation (BP) network. 10-fold cross validation techniques was applied in order to measure the percentage of accuracy of RBF classifier. The work conducted proves that Radial Basis Function (RBF) network has outperformed BP network in classifying the normal and abnormal tissue of cell with 92.27% and 88.28% accuracy respectively.

Keywords- Mammogram; RBF; BP; Gabor filter

I. INTRODUCTION

One of the main factors contributing to the increased mortality rate among women in the world today is breast cancer. Although there are many treatment procedures offered but ones that are really effective and highly promising remains an issue until now. Most medical images such MR, CT contain large area of background noise which are useless in medical diagnoses and the background noise outside the diagnostic region should be removed before encoding [13]. Thus, the preprocessing of that image should be performed first in order to overcome this problem [16][17]. One of the tools that have been used for imaging organs and soft tissues in the human body is diagnostic ultrasound. The process of tumors detection can be performed using gray-scale type images that have been taken from the human bodies. By using this tool, liver focal diseases concentrated in a small area of the liver tissue, the rest being normal [9]. Based on this approach, the consequence of the error in detection and classification are costly. Process of classification is difficult and complex to be undergone especially involve the large sample of data set. Moreover,

complex structures in appearance and signs of early disease are often small or subtle [5]. Biopsy is one of the approaches that have been used in the process classification of the tumors. According to this approach, it is very difficult to diagnose the existence, type and level of diseases the risk of post hemorrhage is very high [9]. However, to differentiation and for early detection of these diseases is clearly desirable. Therefore the primary purpose of this study to suggest a better solution, that is by classifying human tissue in medical imaging, whether they fall into either normal or abnormal category. This study focused on a number of mammogram samples and concentrated only in a small area of the mammogram while the remaining area are normal.

II. DIGITAL SCREENING MAMMOGRAM

Mammography is a special type of imaging technique that produces an x-ray image of a breast that serves to detect tumors and cysts [5] and also to differentiate between cancerous and noncancerous tissues. Although better and right treatments can be given to patients that cancer successfully detected at early stage, most medical tests are not perfect. According to American Cancer Society articles, mammography method can detect up to an average of 80% - 90% of breast cancers without any symptoms. Diagnostic mammogram is different from screening mammogram because it requires more x-ray samples so as to obtain more view of the breast from several angles and hence take a longer time to process. There are indicators and specific factors to determine the category of a normal mammogram, malignant and benign [8]. Suspicious areas that are determined from detailed pictures will be used by radiologists for further analysis.

III. PREPROCESSING OF MEDICAL IMAGE

Medical images that are used to detect tumors and cysts can also help to distinguish between non-cancerous and cancerous disease [8]. In essence, these images are different from ordinary photographic images because it reveals the internal anatomy of the image rather than just the visual facade of the photographic image [10]. Image preprocessing refers to the initial processing of raw images in order to obtain correct geometric distortions [18], as well as to calibrate the data

radiometrically and to eliminate noises and clouds that are presented in the data.

A. Gaussian Filter

Noise in images is always perceived as something undesirable and it may come in the form of unwanted variation in brightness and color. Medical images such as mammogram, magnetic resonance (MR) and computer tomography (CT); contain a large area of background noise, which is considered useless in medical diagnosis [13]. There are several image filtering methods that can be applied on an image such as rough set theory [12], median filter [11], Weiner filtering etc. The one that is used in this study is Gaussian filter and it is essentially a group of low-pass filter. This type of filter will allow low-frequency components to pass through it while blocking the high-frequency components.

B. Gabor Filter

Gabor filters is a linear filter whose impulse response is defined by the harmonic function multiply with Gaussian function. The Gabor is defined as:

$$\lambda, \theta, \phi, \sigma, \gamma(x, y) = \exp\left(\frac{-x^2 + \gamma^2 y^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \phi\right) \quad (1)$$

$$x' = x \cos \theta + y \sin \theta$$

$$y' = -x \sin \theta + y \cos \theta$$

where arguments x and y specify the position of light impulse in the visual fields. The Gabor function specifies the value of parameters; wavelength, orientation, phase offset, aspect ratio. Bandwidth of the wave will be calculated and displayed as an intensity map image in the output window.

IV. NEURAL NETWORK CLASSIFICATION

Previous studies conducted by other researchers gave the idea that further study on this subject may be carried out by using the Radial Basis Function (RBF)-based methods. This method was chosen particularly due to its simplicity, robustness and its optimum approximation [2].

A. Radial Basis Function Classifier

Various classification tasks are more amenable to RBF network as compared to the Back Propagation (BP) network and normally RBF network consists of at least three different layers [4]. The way in which network is used for data modeling is different for approximation time-series and in pattern classification. The topology of the RBF network is embedded from the multilayer feed forward. The network consists of three different types of layer which are the input layer, hidden layer and output layer. Nonlinear transformation is applied from the input layer to the hidden layer. The accuracy of the approximation will depend on the how high is the dimension of the hidden layer space and whether the number of hidden nodes is equal or not with the number of training data. The first layer calculates the distance of weighted input neurons with net input using radial basis

function neurons. Meanwhile the second layer calculates the weighted from input neurons using linear function. The output layers implement the weighted sum of hidden unit outputs which is shown as:

$$\psi_k(X) = \sum_{j=1}^L \lambda_{jk} \phi_j(X) \quad (2)$$

For $k = 1, \dots, M$ where λ_{jk} are the output weight, each corresponding to the connection between hidden and output unit

M represent the number of output units

λ_{jk} Show the contribution of hidden unit to the respective output unit.

The output of the RBF network is confined within the interval of (-1, 1) in most pattern classification application. In this study, the radial basis transfer function was used to calculate a layer output from the net input. Basically the radial basis layer has no neurons and this step is repeated until network mean square error is achieved or maximum numbers of iteration are reached.

B. Back propagation Classifier

BP neural network was used as the classifier in this study because it has the potential of learning and actually converging when being presented with large amounts of data [8]. The function of this algorithm is to train the input data in order to get the desired output and this network implementation was based on the concept of feed-forward neural network. Feed-forward network has a layered structure in which each layer is made up of a number of nodes that receives their input from the layer directly below it and send their output to the layer directly above it. The activation function used by each neuron is the sigmoid activation function [7]. This function is defined by:

$$O_j = \frac{1}{1 + \exp(-\sum_i w_{ji} O_i + v_j)} \quad (3)$$

Where O_j is the j th element of actual output pattern produced by input pattern

w_{ji} is the weight from i th to j th neurons

v_j is the threshold of the j th neurons

V. EXPERIMENTAL RESULT

In this case, the pixel size of the cropped image is 30 x 30 resolutions. The area of interest in mammograms consists of high-density regions, represented by light shades of gray and white.

A. 2D Gabor Filter

The Gabor function for the specified values of the parameters wavelength, orientation, phase offset, aspect ratio and bandwidth will be calculated and displayed as an intensity

map image in the output window. The output of filtered images was calculated based on the filter output value that have been produced. The experiment result of the output filtered image was applied with 2D Gabor filter and the description of the parameters is shown in the Figure 1 and Table I below:



Figure 1. Effect of 2D Gabor filter with different input parameter

TABLE I. DESCRIPTION OF PARAMETER THAT HAS BEEN USED

Parameter	γ	λ	b	θ	ϕ	s
Image						
Left	0.1	8	1	0	0.7	1
Middle	0.1	15	1	0	1	1
Right	0.1	6	1	0	0.5	1

B. Classification using RBF Network

There were a total of 120 instances used in this experiment in which 60 instances for normal cell and 60 instances for abnormal cell. These instances were separated into two parts, one for training part and the other for testing part. The first 70% of the instances which equal to 84 instances from different pattern were used for input training process. Parameters such as the performance goal of error MSE, spread constant (sigma value of transfer function), maximum number of neuron and the number of neuron between displays were determined. It was observed that the larger the spread constant the smoother the function approximation will be. Radial basis was used as the transfer function and Gaussian function was used as the activation function. Analysis shows that the most suitable parameter values of spread constant was found to be 10 and the overall performance of different parameter used are as shown in the Table II below.

TABLE II. OVERALL PERFORMANCE OF RBF NETWORK WITH DIFFERENT SPREAD CONSTANT

Spread Constant	5	10	20	30	40	50
Criteria (%)						
Train Err	0.00	0.00	0.08	0.04	0.15	0.16
Test Err	23.92	7.73	8.23	10.07	10.42	10.99
Avg Err	23.92	7.73	8.41	10.16	10.77	11.37
Classification	76.08	92.27	91.59	89.84	89.23	88.63
Num of Epoch	76	76	76	74	76	74

C. Classification using BP Network

A total of 120 instances had been split into 70% instances for training and the remaining 30% instances for testing in the same way as the RBF network. 5 layers were used; 6 neurons (tansig function) on input layer, 10 neurons (tansig function) on layer 2, 5 neurons (tansig function) on layer 3, 4 neurons (tansig function) on layer 4 and 1 neurons (purelin function) on output layer. Hyperbolic tangent sigmoid activation function was used because the net was best suited for the learning rate and error that had been chosen. The performance of BP network was tested with different parameter of learning rate and momentum constant. The best value of learning rate and momentum constant found from this experiment was 0.2 and 0.9. Table III below shows the average performance of BP network for three numbers of training and testing.

TABLE III. AVERAGE PERFORMANCE OF BP NETWORK WITH DIFFERENT PARAMETER (THREE TIMES RUNNING)

Learning Rate	0.1	0.2	0.3	0.5	0.5	0.2
Momentum Constant	0.7	0.7	0.7	0.7	0.9	0.9
Error (%)	13.69	13.69	13.86	14.21	15.67	11.72
Classification (%)	86.31	86.31	86.14	85.79	84.33	88.28

The overall analysis shows that the RBF network performs better as compared to BP network particularly in term of the percentage of correct classification, error occurrences and also processing time.

TABLE IV. OVERALL PERFORMANCE OF RBF AND BP CLASSIFIERS

Criteria	RBF	BP
Processing Time (s)	24.75 s	382 s
Train Error (%)	0.00 %	1.30%
Test Error (%)	7.73 %	8.68 %
Total Classification Error (%)	7.73 %	11.72 %
Classification Accuracy (%)	92.27 %	88.28 %

10-fold cross validation was applied in order to evaluate the classification experiment. Dataset was randomly partitioned into ten disjoint subsets of equal size. The cross-validation process was then repeated 10 times (the *folds*), with each of the 10 subsamples used exactly once as the validation data. Datasets were tested using 10-fold partition and the average rate obtained for all folds were 81.64%. The work conducted proves that Radial Basis Function (RBF) network has outperformed BP network in classifying the normal and abnormal tissue of cell with 92.27% and 88.28% accuracy respectively. Gabor filter was effective for texture classification because it achieved higher classification rate [1],[9]. One advantage of using Gabor filter is that the image after being applied with feature extraction helps to reduce the dimensionality of the data during the training process [3]. The analysis shows that the classification result of BP network also

gave higher accuracy rate but it will consume more processing time [6] for both training and testing process. Comparing to BP network, the total processing time for RBF network, both for training and testing process was found to be shorter and the memory required for processing was lesser.

VI. DISCUSSION AND CONCLUSIONS

This study concludes that the performance of RBF network was determined to be higher than BP network in term of classification accuracy rate. RBF network consumed lesser time and memory space as compared to BP network since it requires less processing time for both training and testing. As for the future works this study could be extended by performing classification experiment using more number of classes of tissue images, and it shall not be limited into just normal or abnormal tissue only. Feature selection techniques may also be applied in order to optimize the accuracy rate. Other than that, the combination of hybridization approaches together with classifier may also be a worthy effort of continuing this study.

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