Artificial Neural Networks in Medical Images for Diagnosis Heart Valve Diseases

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Abstract

Neural networks are currently a hot research area in medicine. Medical image recognition algorithms have been widely applied to help with the diagnosis of various diseases more accurately. This paper presents an image processing-based artificial neural network for the diagnosis of heart valve diseases. The goal of the paper is to implement image processing techniques by extracting texture features from medical echocardiography images, combining intensity histogram features and Gray Level Co-occurrence Matrix (GLCM) features, then developing an artificial neural network for automatic classification based on back-propagation algorithm to classify heart valve diseases more accurately. The proposed method performance was evaluated in terms of precision, recall and accuracy. The experimental results confirm the efficiency of the proposed method that provides good classification efficiency.

Keywords: *Computer-Aided Diagnosis (CAD), Neural networks, Texture Features, Intensity Histogram Features, GLCM Features, Back-Propagation Classifier, Heart Valve Diseases.*

1. Introduction

Medical and healthcare sector are a big industry directly related to every citizen's quality of life. Image based medical diagnosis is one of the important service areas in this sector [1].

In recent years, considerable efforts have been made in CAD using medical images to improve a clinician's confidence in the analysis of medical images. Evaluation of medical images by a clinician is qualitative in nature and may vary from person to person. A lot of research efforts have been directed to the field of medical image analysis with the aim to assist in diagnosis and clinical studies [2].

The number of medical images has grown significantly in the recent years. These images are very important for clinical diagnosis, localization of pathology, study of anatomical structure, treatment planning, evolution of therapy, computer integrated surgery, surgical planning, post-surgical assessment and abnormality detection [3].

Researches showed that the most human deaths in the world are due to heart diseases. Heart valve disorders are of importance among the heart diseases. For this reason, early detection of heart valve disorders is one of the most important medical research areas [4].

Nowadays, cardiologists have access to diverse techniques such as electrocardiograms, chest X-rays, ultrasound imaging, doppler techniques, angiography and transesophageal echocardiograph to better inspect and scrutinize the functionality of heart [5].

Echocardiography is a common clinical procedure for diagnosing heart diseases, especially valve ones. When digital echocardiographies are available, computer-aided diagnosis may help physicians in having a more accurate decision [6].

Various artificial intelligence techniques such as artificial neural network and fuzzy logic are used for classification problems in the area of medical diagnosis [7].

Most of these computer-based systems are designed by using artificial neural network techniques [8].

Artificial Neural Networks (ANNs) are one of the popular methods for classification problems compared to most traditional classification approaches. ANNs are nonlinear, nonparametric, and adaptive. They can theoretically approximate any fundamental relationship with arbitrary accuracy [9].

There are four reasons to use ANN as a classifier: (i) weights representing the solution are found by iterative training, (ii) it has a simple structure for physical implementation, (iii) it can easily map complex class distributions, and (iv) generalization property of the ANN produces appropriate results for the input vectors that are not present in the training set [10].

ANNs have been of increasing interest in medical image processing [1, 2].

In summary, the applications of ANNs in medical image processing have to be analyzed individually, although many successful models have been reported in the literature. ANN has been applied to medical images to deal with the issues that cannot be addressed by traditional image processing algorithms or by other classification techniques. By introducing artificial neural networks, algorithms developed for medical image processing and analysis often become more intelligent than conventional techniques [11].

The structure of this paper is as follows: section 2 presents the framework of the proposed method, the algorithm used in this system is commonly divided into three stages: preprocessing, feature extraction and Back-Propagation Classifier. Section 3 describes the process of designing the ANN. Section 4 is the experimental results, followed by conclusions at section 5.

2. **Proposed method**

The proposed method comprises three stages: preprocessing, feature extraction and back-propagation as classifier. Figure 1 shows the block diagram of the proposed Back-Propagation Artificial Neural Network (B-PANN) method.

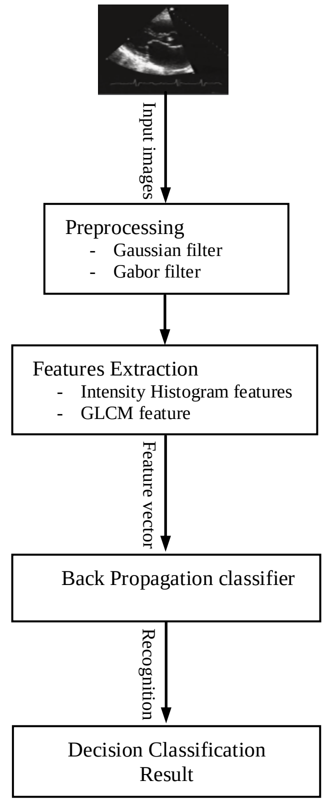

Fig.1. Block diagram of the proposed B-PANN

The proposed method is detailed in Figure 2

Input: a set of medical echocardiography images

Output: classification of the echocardiography images for each disease

Begin

Step1: preprocessing phase (image processing)

- convert images to gray scale
- resize the images
- reducing noise by applying Gaussian filter
- images enhancement with the application of Gabor filter

Step 2: feature extractions

- compute the intensity histogram features: Mean, Standard deviation, Skewness, Kurtosis, Energy, Entropy.
- compute GLCM features: Contrast, Correlation, Entropy, Homogeneity.

Step 3: Determine the structure of B-PANN

- Number of input neurons
- Number of output neurons

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- learning rate
- Number of hidden neurons
- Number of epochs
- Activation function

Step 4: classification phase(training and testing with Back-Propagation classifier)

Input:

A set of input features of echocardiography images to be classified

Processing (Back-Propagation Algorithm)

Output:

The final classification output

End

Fig .2 the proposed algorithm

2.1. Preprocessing

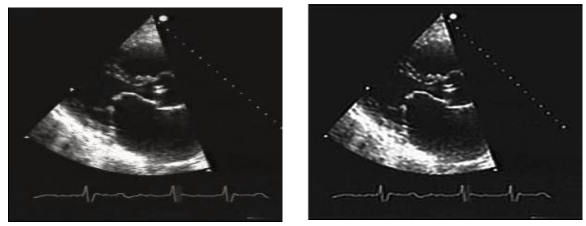
Image preprocessing refers to the initial processing of raw image to correct geometric distortions, calibrate data radio metrically and eliminate the noise and clouds in the data [12]. A preprocessing phase of the images is necessary to improve the quality of the images and make the feature extraction phase more reliable. Preprocessing is always a necessity whenever the data to be mined are noisy, inconsistent or incomplete. Preprocessing significantly improves the effectiveness of the pattern recognition techniques [13].

One of the most important stages in medical images detection and analysis is the use of image enhancement techniques which improve the quality (clarity) of images for human viewing. Removing blurring and noise, increasing contrast and revealing details are examples of enhancement operations [14].

This section introduces the preprocessing techniques on the images before the features extraction phase. The following two methods (Gaussian and Gabor filters) are used for making the image better and enhance it from noising corruption to interference.

2.1.1 Gaussian Filter

The medical images contain a large area of background noise, which is useless in medical diagnosis. Gaussian filter is group of low-pass filters which passes over low-frequency components and reduces high-frequency components [12]. Gaussian filter is a filter whose impulse response is Gaussian function. Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay [15]. The proposed method reduces the noise by applying the Gaussian filter in the preprocessing stage. Figure 3 describes (a) the original image and (b) reducing noise by Gaussian filter.



y

(a) Original image (b) Gaussian filter

Fig.3. the result of applying Gaussian filter

2.1.2 Gabor Filter

Gabor function has been recognized as a very useful tool in computer vision and image processing, especially for texture analysis, due to its optimal localization properties in both spatial and frequency domains [14].

Gabor filter has been successfully applied to the fields of image processing and image analysis, including edge detection, texture image segmentation/discrimination, texture classification/recognition and image enhancement [16, 17].

Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by the Gaussian function [18]. Because of the multiplication-convolution property, the Fourier transform of the Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function [12, 19].

Gabor filter has been extended to 2D operation. A 2D Gabor filter is an oriented complex sinusoidal grating modulated by a 2D Gaussian function [16, 17, 20]

$$h(x,y) = g(x,y)\exp[2\pi j(Ux+Vy)] = h_R(x,y) + jh_1(x,y) \qquad (1)$$

Where (U,V) is a single spatial frequency, $g(x,y)$ is the Gaussian function with scale parameter σ, and $h_R(x,y)$ and $h_I(x,y)$ are the real and imaginary parts of $h(x,y)$, respectively

$$g(x,y) = \frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \qquad (2)$$

Gabor filter is a band pass filter centered on frequency (U,V), with a bandwidth determined by σ. The parameters of the Gabor filter are represented by the spatial frequency U, V and the scale σ. Usually, a radial frequency

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$f = \sqrt{U^2 + V^2}$, with orientation θ = $\tan^{-1}$(V/U), are used in polar coordinates to specify the filter (f, θ, σ). Gabor filtered output of an image *i(x,y)* is obtained by the convolution of the image with the specified Gabor function. The local energy measure at a point *(x,y)* is defined as [16].

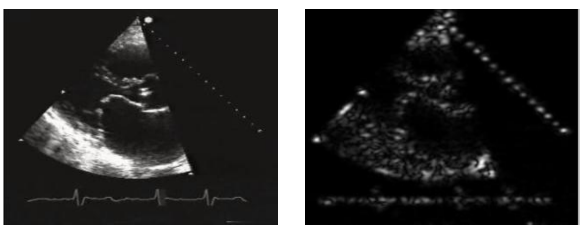
$$E(x, y| f ,\theta,\sigma) = C_R^2(x, y| f ,\theta,\sigma) + C_1^2(x, y| f ,\theta,\sigma) \qquad (3)$$

where

$$C_R(x, y| f ,\theta,\sigma) = \sum_{I=-w}^{w} \sum_{m=-w}^{w} i(X + l, y + m) h_R(l, m)$$

$$and\ C_1(x, y| f ,\theta,\sigma) = \sum_{I=-w}^{w} \sum_{m=-w}^{w} i(X + l, y + m) h_1(l, m) \quad (4)$$

represent the discrete convolution of the real and imaginary components of *h(x,y)* with the image over a given neighborhood with a fixed window size of M = 2w +1. The resulting feature image, *E(x,y),* contains a distribution of local energy measures, which depend strongly on the choice of the design parameters (f, θ, σ) of the single Gabor filter [16]. Figure 4 describes (a) the original image and (b) the enhanced image using Gabor Filter.



(a) Original image (b) Enhanced by Gabor

Fig.4 the results of applying Gabor enhancement technique

2.2. Features Extraction

During the process of developing the CAD systems, feature extraction is one of the most important steps for recognizing abnormal regions from the medical image [21]. Image feature extraction is an important step in medical images classification. These features are extracted using image processing techniques [7]. The texture feature was used in various areas including face detection, face recognition, medical research and satellite image analysis [22]. Texture features have been utilized for many medical image applications [23].

Texture feature is one of most important feature analysis methods in CAD systems for disease diagnosis [19]. Texture features such as intensity histogram, GLCM, Gray Level Difference Method (GLDM), Gray Level Run-Length Method (GLRLM) and the Spatial Gray Level Dependent Method (SGLDM) have been widely used to represent medical image characteristics that are inaccessible to human observers [21, 24]. Intensity histogram features and GLCM features are extracted in our paper.

2.2.1. Intensity Histogram Features

In general, any image processing and analysis application would require particular features for classification /segmentation. Mainly texture features and statistical features are of more significant in pattern recognition. A frequently used approach for texture analysis is based on statistical properties of intensity histogram. One such measure is based on statistical moments [25, 10]. One of the simplest ways to extract statistical features in an image is to use the first-order probability distribution of the amplitude of the quantized image. They are generally easy to compute and largely heuristic [26, 23]. The first order histogram estimate of P(b) is simply

$$P(b) = \frac{N(b)}{M} \qquad (5)$$

where b is a gray level in an image, M represents the total number of pixels in a neighborhood window of specified size centered around the pixel, and N(b) is the number of pixels of gray value b in the window where 0 ≤ b ≤ L -1 [26]. The following table shows texture features extracted based on the intensity histogram features in this work.

Table 1. Some texture features extracted based on the intensity histogram features [26].

Features	***Equation***
Mean	$S_M = \bar{b} = \sum_{b=0}^{L-1} bP \quad (6)$
Standard deviation	$S_D = \sigma_b = \left[\sum_{b=0}^{L-1} (b-\bar{b})^2 p(b)\right]^{1/2} \quad (7)$
Skewness	$S_S = \frac{1}{\sigma_b^3} \sum_{b=0}^{L-1} (b-\bar{b})^3 P(b) \quad (8)$
Kurtosis	$S_K = \frac{1}{\sigma_b^4} \sum_{b=0}^{L-1} (b-\bar{b})^4 P(b) - 3 \quad (9)$
Energy	$S_N = \sum_{b=0}^{L-1} [P(b)]^2 \quad (10)$
Entropy	$S_E = \sum_{b=0}^{L-1} P(b)\log_2\{P(b)\} \quad (11)$

2.2.2. GLCM Features

GLCM is a second-order method for measuring gray level textures in an image [27].

GLCM is frequently used method for medical image analysis, facial analysis and classification. This method provides information regarding the relative position of two pixels with respect to each other [22, 28]. The following table shows texture feature extracted from GLCM in this work.

Table 2. some texture features extracted from gray level co-occurrence matrices [29].

Features	**Equation**
Homogeneity	$H=\sum_{i=0}^{G-1}\sum_{i=0}^{G-1}\{P(i,j)\}^2$ (12)
Contrast	$C=\sum_{n=0}^{G-1}\left\{n^2\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)\right\}, \lvert i-j\rvert=n$ (13)
Entropy	$E=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)\log\{P(i,j)\}$ (14)
Correlation	$O=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{ijP(i,j)-(m_i m_j)}{\sigma_i\sigma_j}$ (15)

Where i and j: row and column numbers in the GLCM matrix, m_i and σ_i are the mean and standard deviation of P(i,j) rows, and m_j and σ_j the mean and standard deviation of P(i, j) columns, respectively.

2.3 The Back-Propagation Classifier

One of the most common ANN used for classifications is the feed-forward network. In a feed-forward network, the neurons in each layer are only connected with the neurons in the next layer. Feed-forward networks commonly use the back-propagation (B-P) supervised learning algorithm to dynamically alter the weight and bias values for each neuron in the network [11]. A back-propagation neural network was created to classify the images is presented in [30].

2.3.1. The architecture of B-P ANN

In this paper, a neural network to perform image classification is constructed as follows; it has three layers; input, hidden and output layer. The number of neurons in the input layer is determined by the number of features selected. The number of neurons in the output layer is determined by the number of classes represented in the network. The number of hidden neurons is determined based on experiments, starting with a single node and increasing the number of nodes until the highest performance was found [31, 32, 33].

The architecture of the neural network is illustrated in the following Figure.

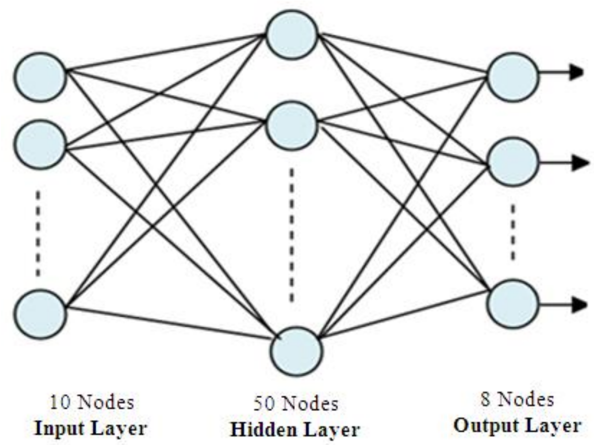


Fig.5. the architecture of B-P ANN

The following table shows the architecture and parameters of the designed B-P ANN.

Table.3 The architecture and parameters of the designed B-P ANN

ANN architecture:	
Number of input neurons	10
Number of hidden neurons in hidden layer	50
Number of output neurons	8
Activation function	Log-sigmoid
ANN training parameters	
Learning rule	Back-propagation
Learning rate	0.1
Number of epochs	3000
Error rate measure	MSE(Mean squared error)

3. Training and Testing

A training stage consists of five major steps:

1. Load an image from a database.
2. Pre-process and extract the features of the image by the selected features discussed earlier.
3. Applying features (feature vector) an input to B-P Algorithm.
4. Training the back- propagation neural network.
5. Save as .mat file.

A Testing stage consists of five major steps:

1. Loading of an image to be tested from a database.

2. Pre-process and extracting the features of the image by the feature extraction techniques discussed earlier.
3. Application of extracted features as input to a trained neural network.
4. B-P algorithm makes decision according to value of features.
5. Checking output generated from a neural network.

Figure 6 shows the training and testing stages of B-PANN.

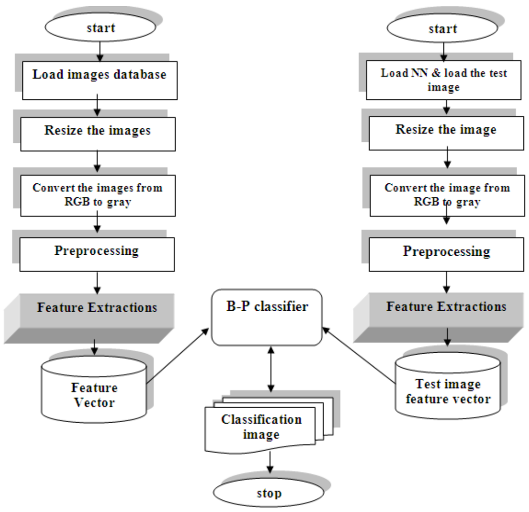


Fig. 6 Training & Testing stages of B-P ANN

4. Experimental Results

The proposed method has been implemented using MATLAB. The image database in the experiment is provided by Mansoura University Hospitals, several radiological center and CDs by the web. Our database contains 120 medical echocardiography images. These images are organized in 8 classes of 15 images: Aortic Regurge (AR), Aortic Stenosis (AS), Mitral Regurge (MR), Mitral Stenosis (MS), Pulmonary Regurge (PR), Pulmonary Stenosis (PS), Tricusped Regurge (TR) and Tricuspid Stenosis (TS). In order to evaluate the performance of this work, precision, recall and Accuracy were used. These measures are defined as: [34, 35]

$$\text{Accuracy} = \frac{\text{Number of Comrctly Classified Testing Samples}}{\text{Total Number of Testing Samples}} \times 100 \qquad (16)$$

$$Precision(P) = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} \quad 0 \le P \le 1 \qquad (17)$$

$$\text{Re}\,call\,(R) \frac{\text{True positives}}{\text{True positives} + \text{False negatives}} \quad 0 \le R \le 1 \qquad (18)$$

where True positives: correctly identified.

False positives: incorrectly identified

False negative: incorrectly denied

Recall measures the proportion of the positive examples that are correctly identified while precision measures the proportion of the nominated positive examples that are correct [35]. Precision is the fraction of the number of true positive predictions divided by the total number of true positives and false positives in the set. Recall is the fraction of the number of true positive predictions divided by the total number of true positives and false negatives in the set.

In the experiment, 80 echocardiography images of heart valve diseases were used as test images. The proposed method was used to distinguish eight different heart valve diseases through automatic recognition. The results were then compared with the results of manual interpretation by medical professionals to determine the accuracy rate of the proposed scheme.

Performance of B-P classifier

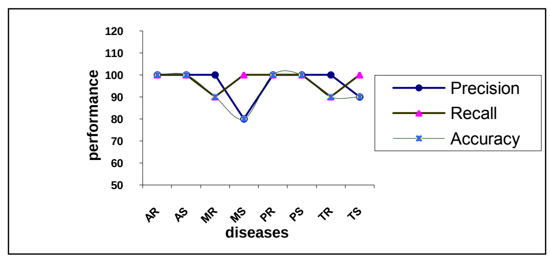


Fig.7. the relation between precision, recall and accuracy.

The experimental results shown in Figure 7 prove that the proposed scheme is capable of automatically recognizing different heart valve diseases in echocardiography images by using the B-P classifier, as the accuracy rate was a perfect 1.00 for AR, AS, PR, PS. As for MR, TR, TS the accuracy rate was 0.90, and the MS, the accuracy rate was 0.80. Altogether, the total accuracy rate was 93.75%, The experimental results confirm the efficiency of the proposed method in recognizing valve heart diseases.

In another method to evaluate the performance of this work, precision and recall were used [36].

Precision: is the fraction of the relevant images which has been retrieved (from all retrieved):

Precision=A/B

Where, A is "Relevant retrieved" and
B is "All Retrieved images"

Recall: is the fraction of the relevant images which has been retrieved (from all relevant):

Recall=A/D

Where, A is "Relevant retrieved" and
B is "All Retrieved images in Database"

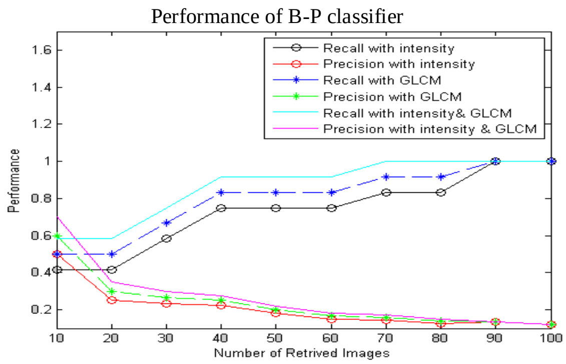


Fig.8 the relation between precision /recall v_s number of retrieved images

A retrieved image is considered as a correct match if it is the same category as the query image. The results for the query image are compared with database images. We then count how many of these belong to the correct category and define the retrieval rate. The higher value of both precision and recall shows better performance of the method.

In this work, we compare the performance of individual classifier with different features: intensity histogram features, GLCM features, and combined features (intensity histogram and GLCM).

The average retrieval precision / recall vs. number of retrieved images curves for intensity histogram features, GLCM features and combined intensity histogram and GLCM features are plotted in Figure 8. It can be seen from Figure 8 that the combined method (features) achieves higher performance in terms of the retrieval precision and recall than with applying intensity histogram features and GLCM features.

5. Conclusions

In this paper, approach based on image processing and neural network technology using feed forward neural network trained by the error back-propagation algorithm that allowed its use to classify heart valve diseases is proposed. The preprocessing techniques applied to the images are the Gaussian filter and the Gabor filter, the proposed method of feature extraction is the combination of intensity histogram features and GLCM features. All these features were fed as input to the B-P ANN which used to identify the various heart valve diseases.

The performances of the classification algorithm are evaluated using precision-recall and accuracy rate. The results demonstrate the effectiveness of the proposed algorithm.

With the help of the proposed method, beginner physicians and other professionals who work in the field of heart diseases will be able to classify heart valve diseases and give diagnosis of heart valve diseases with high accuracy and efficiency. For hospitals and other medical centers, this means a great relief on the demand of human resources.

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