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Breast Cancer Diagnosis Using Fuzzy Feature and Optimized Neural Network via the Gbest-Guided Artificial Bee Colony Algorithm

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Abstract

The correct diagnosis of the breast cancer is one of the major problems in the medical field. This paper presents an improved classifier for automated diagnostic systems of breast cancer tumors. The proposed diagnostic system consists of a combined fuzzy clustering optimized neural network (FCONN) algorithm for the classification of the breast cancer tumors using fuzzy c-means clustering (FCM) algorithm and optimized neural network. FCM is used for extracting the efficient features and ONN is used for intelligent classification. In neural networks training, the hyper-parameters have very important roles for their recognition accuracy. Therefore, Gbest-guided artificial bee colony (GABC) algorithm is proposed for selecting the appropriate parameters of the classifier. The proposed system is tested on Wisconsin Breast Cancer (WBC) database and simulation results show that the recommended system has a high accuracy.

1. Introduction

Breast cancer is the first current cancer and the second element of death amongst women. In 2014, there were reported approximately 207090 newly diagnosed cases and 30840 deaths in the United States [1]. Since the reason of breast cancer is unknown, the methods for preventing this disease are not specified, thus, really recognizing the existence of tumor and the type of cancerous tumor would have a very important role on getting decision of doctors for applying the methods of true treatment and therefore reclaiming people’s life (more than 40%) [2]. In recent years, the mammography method has been used widely for early recognizing of cancerous tumor [3].

Usually mammography is away for detecting the presence of cancerous tumors. However, determining the type of the tumor is much more challenging. Some of the characteristics of malignant tumors are clustered calcification, isolated ducts poorly defined mass and etc. Experts (doctors) physically look at mammograms to detect deformation that may be taken as an indicator

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of cancerous changes [4]. It is clear that these methods of recognition are not reliable ones due to the human mistakes and errors of medical devices. Many investigators believe that automation of the mammogram screening analysis increases the rate of early detection.

With this aim, several approaches have been proposed for breast cancer recognition. Marcano et al. [5] used artificial metaplasticity neural network to classify WBC. Neuro-fuzzy approach was used to diagnosis breast cancer [6-11]. The associated rules and neural networks were used to classify the WBC [12]. NN and multivariate adaptive regression splines approach was used to classify the BC pattern [13]. In Ref. [14], hybrid hidden Markov model (HMM)-fuzzy was used for breast cancer identification. Also, support vector machine (SVM) was used for breast cancer detection [15, 16].

In designing the computer-aided diagnostic (CAD) system, the most important point is the integration of suitable feature extraction and pattern classifier such that they could operate in coordination to make effective and efficient CAD system. This paper proposes the usage of fuzzy c-mean (FCM) clustering algorithm for making a neural network system more effective. The structure of the proposed system is composed of two sub-networks: fuzzy classifier and neural network (NN). The fuzzy self-organizing layer performs the pre-classification task and the following neural network works as final classifier. The fuzzy stage is responsible for the analysis of the data distribution and grouping them into clusters with different membership values. Based on these membership values, the NN classifies the applied input vector [17]. By this act, a number of segments in training set are reduced using FCM clustering in self-organizing layer before inputs are presented to NN. The details of proposed method are presented in next sections. The remaining of paper is organized as follow. Section two presents the proposed method. Section three introduces the needed concepts. The section four presents simulation results and finally section five concludes the paper.

2. General Structure of the Proposed Method

Different solutions for breast cancer recognition are presented in the literature, such as the multi layer perceptron (MLP) approach, neuro-fuzzy systems, SVM, self-organizing map and the Learning vector quantization (LVQ). We will present the combination of the fuzzy self-organizing layer and the ONN connected in cascade, named the FCONN. Figure 1 shows the general scheme of this method.

The self-organizing layer is responsible for clustering of the input data. However, it is fuzzy clustering, in which the input vector x is pre-classified to all sets with the different membership values. The penetration of the data space is better and the localization of the input vector x in the data space is more precise. The outputs of self-organizing sub-network (membership values or fuzzy features) form the input vector to the ONN. ONN sub-network is responsible for the final classification of the breast cancer tumor.

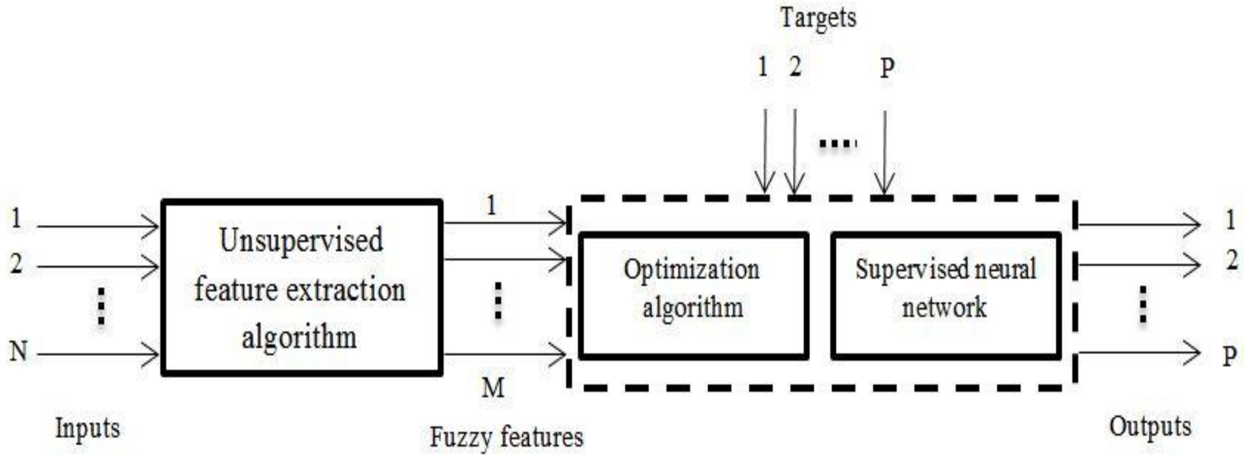

Figure 1. General scheme of the proposed method (FCONN)

In ONN sub-network the most important parameters of the neural networks e.g. learning rate, the number of basis function and their respective centers and widths are subjected to evolution using GABC algorithm [18]. Next sections present the main parts of the proposed method.

3. Optimization

3.1. GABC-MLPNN

In this approach, the most important parameters of a MLP neural network (BP with momentum), i.e., the number of hidden neurons, learning rate parameter (ε) and momentum parameter (μ) are subject to evolution using GABC. Each bee in the algorithm represents ε and μ values [19].

The MLP network is initialized with a single neuron in the hidden layer, and the network is built incrementally. The number of hidden neurons is increased orderly and in every increase, the optimum value of learning rate parameter (ε) and momentum parameter (μ) are calculated. The mean square error (MSE) is used as network performance scale. The maximum number of hidden neurons will be equal with the number of training samples. After finishing algorithm the number of hidden neurons, learning rate parameter (ε) and momentum parameter (μ) are related with best performance equal of optimum quantity of suggested system. It is clear from the above explanation that there are five control parameters used in the GABC algorithm: the number of food sources which are equal to the number of employed bees (S), the value of ‘‘*limit*’’, the maximum cycle numbers (MCN) and the parameter *C*. The pseudo code for GABC-MLPNN is listed in Figure 2.

1.WBC database
2. Fuzzy clustering
3. Create MLPNN with a neuron in hidden layer
4. Initialization
Repeat
Employed bee stage: Perform an update process for each solution in the solution population.
Onlooker stage: Randomly select solutions depending on their fitness values, then perform the same update process for each selected solution.
Scout stage: Select one of the most inactive solutions, then replace it by a new randomly generated solution
Until (conditions are satisfied)
5. Add a neuron to hidden layer. If the number of hidden neurons is equal with the training samples, stop the algorithm, otherwise create a MLPNN and go to step 4.
6. Output the best solution

Figure 2. Pseudo code of GABC-MLPNN

3.2. GABC-RBFNN

In this method, the most important parameters of RBFNN i.e. the number of radial basis functions, centers and widths of radial basis functions by using of bees algorithm will be estimated. Each bee in the algorithm represents the center and spread values. The widths of the basis function are initialized randomly in the range [0, 10] and the centers are selected randomly between the inputs in the training set. All networks are initialized with a single basis function in the hidden layer, and the network is built incrementally. The number of radial basis functions is increased orderly and in every increase, the centers and optimum widths of these functions are calculated. The mean square error (MSE) is used as network performance scale. The maximum number of radial basis function will be equal to the number of training samples. After finishing algorithm the number of radial basis functions, centers and widths are related with best performance equal of optimum quantity of suggested system.

3.3. GABC-PNN

In this approach, the most important parameter of a PNN, i.e., the widths, is subjected to evolution using GABC. Each bee in the algorithm represents the width value.

4. Simulation Results

In this section we evaluate the performance of the proposed recognizer. This study has used WBC database. In order to compare the performance of classifiers, the *k*-fold cross validation technique is used. The *k*-fold cross validation technique proposed by Salzberg [20] was employed in the experiments, with *k*=4. The data set was thus split into 4 portions, with each part of the data sharing the same proportion of each data class. 3 data portion were used in the training process, while the remaining part was used in the testing process. The ANN-training methods were run 4 times to allow each slice of the data to take turn as a testing data. The classification accuracy rate is calculated by summing the individual accuracy rate for each run of testing, and then dividing the total by 4.

4.1. Performance Evaluation of Fuzzy Clustering Neural Network (FCNN)

First we have evaluated the performance of the recognizer without optimization. Table 1 shows the RA of classifiers. Results imply that the proposed features have effective properties in breast cancer diagnosis. For example, MLPNN with WBC database has 95.31% recognition accuracy, while its performance increases with using fuzzy features value up to 96.92%.

Table 1. Comparison among the FCNNs

Classifier	Input	Recognition accuracy (%)
MLP	WBC	95.31
MLP	FF	96.92
RBF	WBC	92.31
RBF	FF	**97.01**
PNN	WBC	90.15
PNN	FF	93.67

4.2. Performance Evaluation of Fuzzy Clustering Optimized Neural Network (FCONN)

In next step, we apply GABC algorithm to find the optimum parameters of the NNs. Table 2 shows the obtained results. From this table it can be found that recognition accuracy is increased to 99.16% and the optimization significantly improves the performance of recognizer.

Table 2. Comparison among the FCONN

Classifier	Input	C	Recognition accuracy (%)
MLP	WBC	1.5	97.88
MLP	FF	1.5	99.02
RBF	WBC	1	97.91
RBF	FF	1.5	99.16
PNN	WBC	1.5	94.21
PNN	FF	2	97.19

4.3. Effects of the Parameters C of the GABC Algorithm on the Performance of the FCONN

The parameter C of GABC algorithm plays an important role in controlling the exploration and exploitation of the new candidate solution search. Roughly speaking, when the parameter C increases from zero to a certain value, the exploitation of GABC algorithm enhances, while the exploration decreases relatively. In this subsectionو we have investigated the sensitivity of the recognition system with respect to the C which results shown in Table 3. GABC-RBFNN with fuzzy features is considered as classifier. From Table 3 it can be observed that with the increase of parameter value C , the mean beast recognition accuracy of the optimized network firstly increases (which means the recognition gets better), and then begins to decrease (which means the recognition gets worse) at a certain point. It can be also observed that the performances of GABC algorithm with C = 0.5, 1.0, 1.5, 2 are all superior to ABC algorithm. And, GABC algorithm with C = 1.5 has the best performance among the tested algorithms.

Table 3. Recognition accuracy of the recognizer for different values of C (GABC-RBFNN with fuzzy features).

Classifier	C	Recognition accuracy (%)
ABC	-	98.56
GABC	0.5	98.77
GABC	1	99.07
GABC	1.5	99.16
GABC	2	98.88
GABC	2.5	98.48
GABC	3	98.31
GABC	3.5	98.22
GABC	4	98.05

In order to compare the performance of GABC with another optimizer, we have used a genetic algorithm (GA) to evolve the RBF neural network. Table 4 shows the obtained results. It can be seen that the success rates of GABC-RBFNN is higher than the performance of other systems.

Table 4. Comparison between the performance of GABC-RBFNN and GA-RBFNN

Recognition system	Recognition accuracy
GA-RBFNN	98.44
GABC-RBFNN	99.16

5. Conclusions

Accurate recognition of breast cancer tumor is very important for sufficient treatment. This study has investigated the design of an automatic and accurate system for detection of the breast cancer tumor. Based on the experimented results, this paper recommends the use of hybrid system for diagnoses of the breast cancer. The complexity of the recognition system is very low in comparison with other works. The highest level of accuracy ever obtained various methods using WBC database was 95.31%. The proposed method improves the accuracy up to 97.01% by using fuzzy feature as the neural network’s inputs. Furthermore, optimizing the structure of the neural networks and using fuzzy feature as the input of optimized classifier significantly, improves the accuracy of the proposed system up to 99.16%.

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