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Abnormal Breast Detection Via Combination of Particle Swarm Optimization and Biogeography-Based Optimization

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Abstract. The breast cancer is the most common cancer among women. To detect it in an accurate way, we designed a new abnormal breast detection system based on the hybridization of particle swarm optimization and biogeography-based optimization. The simulation results showed the sensitivity achieved 87.90±0.88%, the specificity achieved 87.20 ±2.74%, and the accuracy achieved 87.55 ±1.34%. Our method is better than two state-of-the-art methods.

1. Background

The breast cancer is the most common cancer among women in China, USA, and other countries. There are a massive of types of abnormal breast in the early stage of breast cancer. The famous mini-MIAS database [1] have collected in total six types: (1) Circumscribed Mass; (2) Asymmetry; (3) Architectural distortion; (4) Calcification; (5) Ill-defined masses; (6) Spiculated masses.

Traditionally, the manual check suffers from inter-expert and intra-expert variance. Besides, the emotion will influence the identification accuracy. Hence, scholars tend to use computer-vision techniques. For example: Liu (2016) [2] proposed a weighted-type fractional Fourier transform. Wu (2016) [3] proposed a chaotic adaptive real-coded biogeography-based optimization. Chen (2016) [4] proposed a two-stage algorithm. In the first stage, they employed wavelet energy entropy (WEE) as the feature. In the second stage, they used the linear regression classifier (LRC) as the classification tool. Abdel-Zaher (2016) [5] used deep belief networks. Magna (2016) [6] employed an ensemble of artificial immune system models.

We analyzed above methods, and found their identification accuracy is low and can not be applied in practical situation. The main reason is their classifier is not trained well. Hence, our team proposes a novel hybrid algorithm, which is a hybridization of particle swarm optimization (PSO) [7] and biogeography-based optimization (BBO) [8].

2. Materials and Methods

200 images from the mini-MIAS database [1] were selected. 100 are of abnormal breast image, and the rest 100 are of normal breast image. All the six abnormal types were regarded as one “Abnormal” class. The preprocessing step was used according to reference [3]. It includes the additive and multiplicative noise reduction, image enhancement, background, and pectoral muscle removal.

Two-level wavelet entropy (WE) was used as the features of brain images. The WE is based on a wavelet transform followed by the entropy calculation over the wavelet subbands [9-13]. Haar wavelet was chosen, as it is the most common wavelet used in various fields.

We used the single-hidden-layer back propagation neural network (BPNN) [14-16] as the classifier. The training of BPNN is not robust, since the initialization will be updated at random for each training. To solve it, scholars have proposed numerous bioinspired algorithms [17, 18]. In this study, we proposed a Hybridization of Particle swarm optimization and Biogeography-based optimization (abbreviated as HPB). The former one mimics the bird swarm [19], while the latter one mimics the migration behavior over islands [20-22]. The core idea is to divide the population into two halves: One performs PSO and the other performs BBO. In each iteration, both PSO and BBO perform searching individually. Nevertheless, in the update, the best of the whole population are selected from the whole population. Our method is different from the HBP algorithm proposed in literature [23].

3. Experiments and Results

The 10x10-fold cross validation was used. The sensitivity results are shown in Table 1. The specificity results are shown in Table 2. The accuracy results are shown in Table 3.

Table 1. Sensitivity Result

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	90	70	100	90	90	90	80	90	90	90	88
R2	100	100	100	70	90	100	90	70	80	80	88
R3	80	90	90	100	90	90	100	60	80	100	88
R4	90	80	100	90	90	80	100	90	80	90	89
R5	100	90	80	100	80	80	90	100	80	80	88
R6	80	80	100	100	60	90	80	90	90	100	87
R7	80	100	80	80	80	80	100	100	80	100	88
R8	100	90	90	90	90	80	80	80	100	90	89
R9	90	80	80	90	80	70	90	100	100	100	88
R10	100	90	80	70	100	80	100	70	80	90	86
Average											87.90±0.88

Table 2. Specificity Result

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	70	90	80	100	80	90	90	80	90	90	86
R2	80	100	100	90	90	90	100	90	90	90	92
R3	90	80	90	90	100	90	100	80	80	80	88
R4	90	90	80	70	90	90	100	90	90	80	87
R5	80	90	100	90	90	100	100	70	90	80	89
R6	80	90	90	70	80	80	80	90	90	100	85
R7	80	90	100	90	100	90	100	90	80	70	89
R8	90	90	90	80	90	90	80	60	70	100	84
R9	90	70	100	60	90	70	90	80	90	90	83
R10	100	100	90	90	90	60	100	80	80	100	89
Average											87.20±2.74

Table 3. Accuracy Result

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	80	80	90	95	85	90	85	85	90	90	87.0
R2	90	100	100	80	90	95	95	80	85	85	90.0
R3	85	85	90	95	95	90	100	70	80	90	88.0
R4	90	85	90	80	90	85	100	90	85	85	88.0
R5	90	90	90	95	85	90	95	85	85	80	88.5
R6	80	85	95	85	70	85	80	90	90	100	86.0
R7	80	95	90	85	90	85	100	95	80	85	88.5
R8	95	90	90	85	90	85	80	70	85	95	86.5
R9	90	75	90	75	85	70	90	90	95	95	85.5
R10	100	95	85	80	95	70	100	75	80	95	87.5
Average											87.55±1.34

The sensitivity, specificity, and accuracy over 10x10-fold cross validation are 87.90±0.88%, 87.20±2.74%, and 87.55±1.34%, respectively. In terms of accuracy, our result is better than MIP-TPS method [24] and GLCM + SVM [25] as shown in Table 4.

Table 4. Comparison

Method	Accuracy
MIP-TPS [24]	84.8±3.1
GLCM + SVM [25]	62.0
Our Method	87.55±1.34

In the future, we shall discuss other optimization algorithms, which may serve as training algorithms, such as genetic algorithm [26, 27], artificial bee colony [28-30], bacterial chemotaxis optimization [31, 32], and firefly algorithm [33]. Besides, some variants of SVM shall be tested, including fuzzy SVM [34, 35] and twin SVM [36, 37].

4. Conclusion and Discussions

Our team proposed a novel hybridization of PSO and BBO. The experiment result shows its effectiveness. We shall enroll more data in our future studies.

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