An Improvement of MRI Brain Images Classification Using Dragonfly Algorithm as Trainer of Artificial Neural Network

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Abstract

Computer software is frequently used for medical decision support systems in different areas. Magnetic Resonance Images (MRI) are widely used images for brain classification issue. This paper presents an improved method for brain classification of MRI images. The proposed method contains three phases, which are, feature extraction, dimensionality reduction, and an improved classification technique. In the first phase, the features of MRI images are obtained by discrete wavelet transform (DWT). In the second phase, the features of MRI images have been reduced, using principal component analysis (PCA). In the last (third) stage, an improved classifier is developed. In the proposed classifier, Dragonfly algorithm is used instead of backpropagation as training algorithm for artificial neural network (ANN). Some other recent training-based Neural Networks, SVM, and KNN classifiers are used for comparison with the proposed classifier. The classifiers are utilized to classify image as normal or abnormal MRI human brain image. The results show that the proposed classifier is outperformed the other competing classifiers.

Keywords: MRI Brain Images, Artificial Neural Network, Dragonfly Algorithm, Backpropagation Training Algorithm, Principal Component Analysis.

Introduction

Magnetic resonance imaging (MRI) is used to classify brain tissues. Computer-based medical decision support systems are now widely used in medical area, such as cancer research, heart diseases, brain tumors, and many other medical applications [1-3].

Manual analysis (interpretation) of MRI images are tedious and costly (in time and money) due to the large amount of image data. This imposes to develop computer-aided diagnosis software. In other words, automatic human brain classification is motivated nowadays. Automatic classification as normal/diseased for Human Brain (HB) using MRI images becomes very important in clinical studies. Classification of HB using MRI images can be achieved by either supervised learning such as ANN, k-nearest neighbors (k-NN), Artificial Neural Network (ANN) and support vector machine (SVM), or unsupervised learning such as self-organization map (SOM) [4, 5]. In this research, supervised machine learning algorithms (ANN) is used for HB classification using MRI images under two categories (normal or abnormal). This is because; supervised learning classifiers perform better than unsupervised classifiers in terms of accuracy of classification process [6].

Traditional artificial neural network (ANN) uses multilayer feed forward neural network algorithm and back propagation algorithm (BP) to modify the weight. ANN used gradient descent (GD) strategy for weight optimization. Meta-heuristic has been effectively applied on ANN to speed the training process by replacing the GD strategy by iterative evolutionary strategy or swarm intelligence strategy [7-10].

Meta-heuristic algorithms are used to find good (near-) optimal solutions at a reasonable cost (in terms of computationally or time) but without guaranteeing feasibility or optimality [11]. Meta-heuristic algorithms use different strategies for example genetic algorithm (GA) and particle swarm optimization (PSO). These algorithms search iteratively to find the global (or near-global) optimum but in some time trapped in local optimum.

Dragonfly algorithm (DA) is one of modern meta-heuristic bio-inspired algorithm developed by [3] .DA is used in this research to train ANN to speed up training as well as to avoid local minimum problem of ANN.

Wavelet transform is used in MRI brain images classification, because it contains different levels of resolution. The problem of this method requires large storage as well as it is expensive computationally. Therefore, dimension reduction technique, the principal component analysis (PCA), is used. PCA is attractive where it efficiently reduces dimensions of the data, thus it reduces the computational cost of data processing. Hence, the contribution of this paper is using Dragonfly Algorithm (DA) to train ANN instead of BP algorithm to overcome the local minimum problem.

Organization of this paper is as follows: Section 2 summarizes the related works of this research. The proposed methodology is presented in Section 3. Experiments settings, which include evaluation metrics, evaluation dataset, and competing classifiers are described in Section 4. Results and discussion are displayed in Section 5. Finally, conclusion is presented in Section 6.

Related Works

Authors in [7] show that the PSO is better than BP in weight modification of ANN. Authors in [12] use an improved GA for tuning of parameters of ANN. Hybrid of GA and PSO is used in [9] for ANN parameter optimization where this hybrid method surpasses the separated PSO and GA in fuzzy Neural Network. Authors in [10] used optimized particle swarm optimization (OPSO) for acceleration the training of ANN.Therefore, structure of proposed learning model is similar to traditional neural network; but with little modifications for better ability of learning.

Therefore, in this research, ***Dragonfly algorithm*** is used as trainer for ANN instead of GD strategy in BP algorithm.

Proposed Methodology

In proposed brain MR images analysis, advanced median filter is utilized as pre-processing method for image preparation to next step (segmentation). Fuzzy C-mean clustering is the segmentation method that is used to segment the MRI brain image depending on the grey levels of images, as detailed in [13]. Fig. 1 displays the block diagram to methodology of the proposed model. Details of feature extraction and reduction methods is similar to the research in [14].

Artificial Neural Network Based Classifier

ANN is a mathematical model contains number of connected nodes (processing elements) structured by layers, it simulates the human brain, as depicted in Fig. 2. The ANN is considered as parallel distributed processor that stores empirical knowledge and making it ready for taking a decision [17].

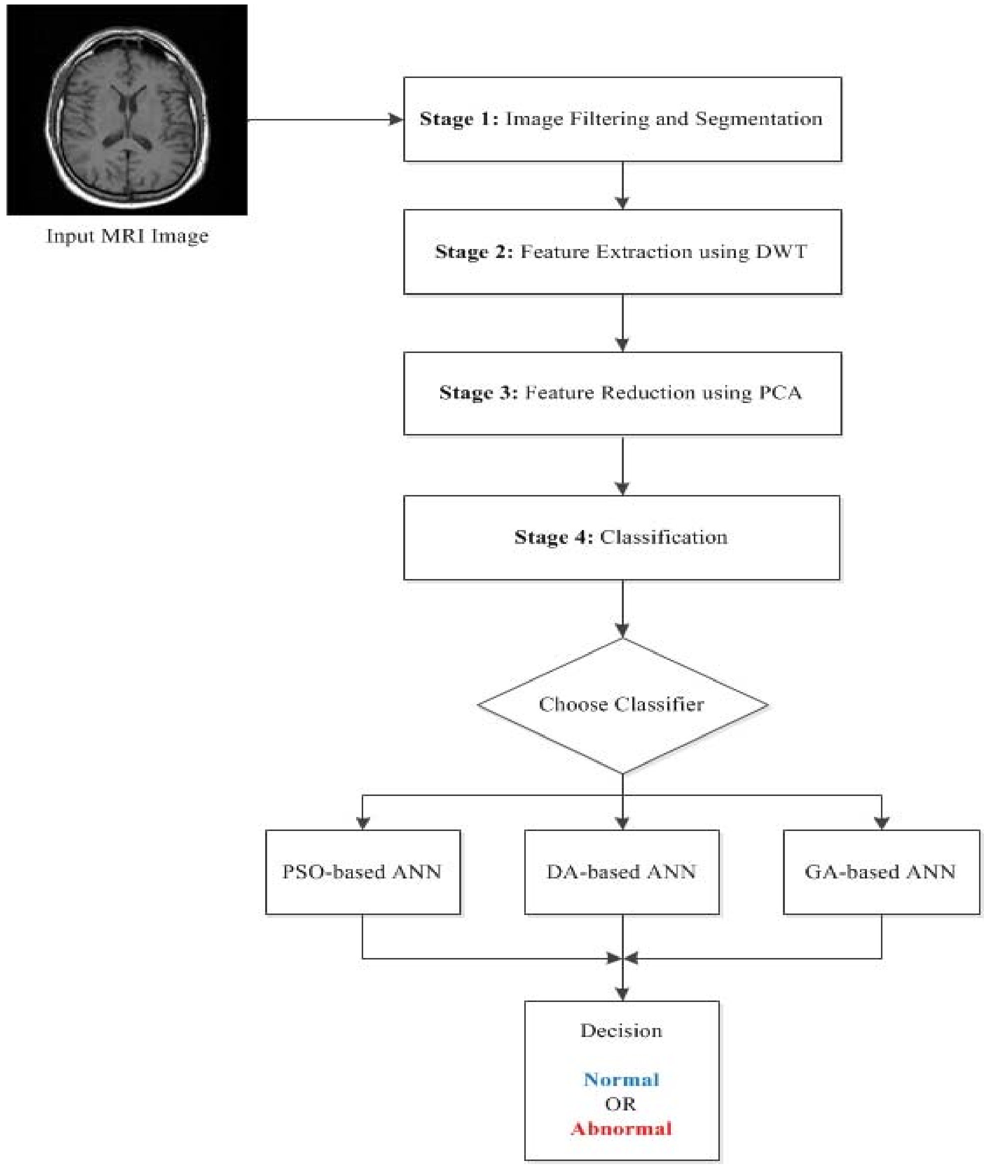


Figure (1): Block Diagram of the Proposed Methodology

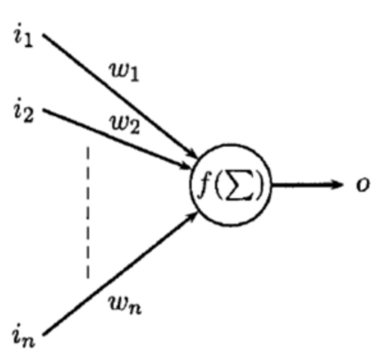


Figure (2): Structure of ANN (adopted from [15]

ANN is employed as a classifier where it required three layers. The first layer contains 7 inputs that represent the 7 feature vectors selected from PCA (from wavelet coefficients) whereas hidden layer contains four neurons. The output layer contains one neuron to represent normal and abnormal human brain.

The most commonly utilized training algorithm of ANN is the back-propagation algorithm, as detailed in [15]. ANN will be trained to modify weights and biases of the nodes' connection; this is to ensure the desired mapping. In training phase, the feature vectors will be as input to ANN, then ANN will try to modify and adjust its variable parameters (weights and biases) to find the relationship between the input and outputs [15].

However, finding optimal parameters of ANN is a difficult task. This is because the search process is trapped in local minima. There are many algorithms are used to train Neural Network, such as genetic algorithm (GA) and particle swarm optimization (PSO). However, these algorithms require high computational costs, as well as they easily trapped the local minima problem, hence they would not find the optimal weights of the Neural Network. Therefore, Accuracy of ANN classification is degraded due to the above problem of inaccurate parameters of neural network.

Dragonfly Algorithm

Genetic Algorithms and swarm intelligent algorithms such as PSO and Ant colony optimization (ACO) are designed to speed up search process in the huge search space. They still have some limitations to deal with optimization problems, local minima problem. Some of enhancements of these algorithms are achieved. Firefly algorithm is one of these enhancements; it is based on the flashing characteristics of tropical fireflies [16] and Bat Algorithm [17] that depend on the echolocation characteristics of real bats. In this research, Dragonfly algorithm is proposed to overcome limitations of the previously mentioned algorithms. The researchers in [3] demonstrate that Dragonfly algorithm (DA) behaves more stable than GA and PSO when solving some test problems due to the stochastic nature of these algorithms where results of DA have a statistical significant improvement over GA and PSO. Steps of Dragonfly algorithm are depicted in figure (3) [3].

Experiments Settings

The following subsections identify experiments settings that are used to measure the effectiveness of the proposed methodology which includes: i) metrics that will be used to evaluate the performance of the proposed methodology. These metrics are sensitivity, specificity and classification accuracy. ii) MRI brain images database that are utilized to evaluate proposed method, as detailed in Section 4.2. iii) The competing methods that are identified in Section 4.3.

Evaluation Metrics

Results of competing methods are evaluated by using the following performance metrics, which are defined as follows:

1. **Sensitivity**: it is the possibility of recognizing patient cases (positive cases) correctly. It is also called Recall (or) True positive rate. It can be computed as in Eq. (1).

$$Sensitivity = \frac{TP}{(TP + FN)} * 100 \quad \dots\dots\dots\dots\dots (1)$$

2. **Specificity:** it is the possibility of recognizing the healthy cases (negative cases) correctly.It can be computed as in Eq. (2).

$$Specifity = \frac{TN}{(TN + FP)} * 100 \quad \ldots\ldots\ldots\ldots\ldots..\ldots\ldots (2)$$

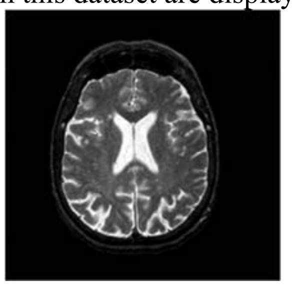
3. **Accuracy:** It is the possibility of recognizing the patient and healthy cases together correctly. It can be computed as in Eq. (3).

$$Accuracy = \frac{TP + TN}{(TN + TN + FP + FN)} * 100 \quad \ldots\ldots\ldots\ldots\ldots (3)$$

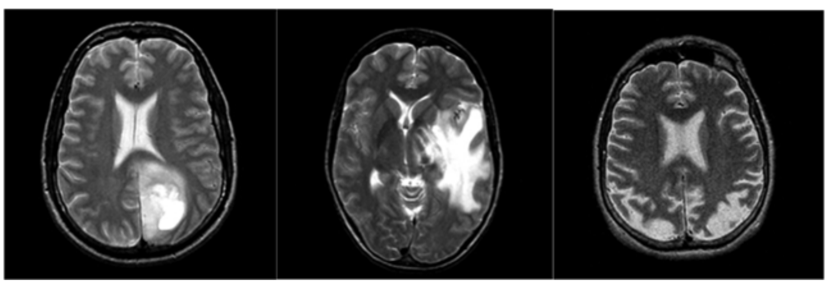
Where TP, TN, FP, and FN are well known values of confusion matrix that resulted from classification process.

Data Set

In this section, the proposed methodology is applied on a real human brain MRI dataset. Total images in this dataset are 270 where 160 images are abnormal and 110 are normal. These MR images were at size 256 × 256 pixels. These images were obtained from[18, 19], therefore, this dataset will be called HMS-DB in this research. It contains images of different diseases' categories as follows: i) normal, ii) Glioma, iii) Metastatic bronchogenic carcinoma, iv) different tumors types in brains, and v) Alzheimer's disease. In figure (3), some normal and abnormal MRI images samples from this dataset are displayed.



(A: Normal brain)



(B: Abnormal brains)

Figure (3): Samples MR Images from HMS-DB Dataset[18]

Competing Methods

The proposed method "dragonfly algorithm-based ANN" (DA-based ANN) classifier will be the first competing methods. The other competing methods are Genetic Algorithm-based ANN (GA-based ANN) [9], PSO-based ANN [8], and the original Backpropagation-based ANN (BP-based ANN) [15]. Additionally, SVM and KNN classifiers are also used for comparison to demonstrate the effectiveness of the proposed classification method.

Results and Discussion

In these experiments, ANN based on four different training methods are used for classifying MRI human brain images as normal or abnormal.

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Table (1): Classification rates of proposed algorithm with different training types of ANN using HMS-DB Dataset

Method (Classifier)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Original BP-based ANN	77	68	75
GA-based ANN	82	70	80
PSO-based ANN	83	72	80.5
Proposed DA-based ANN	**89**	**83**	**85**

In this experiment, MRI dataset that have healthy and diseased brain are classified by the competing classifiers. The experimental results of the proposed DA-based ANN classifier is compared with other competing classifiers as shown in table (1), which shows the percentage classification in terms of three evaluation metrics.

The analysis of the experimental results shows that classification accuracy (85%) is achieved using DA-based ANN classifier and it has higher rate compared with other classifiers. In other metrics, sensitivity and specificity, the DA-based ANN is also outperformed other competing classifiers, figure (4) shows visual comparison among competing classifiers in terms of the three evaluation metrics. This figure illustrates superiority of DA-based ANN on other classifiers.

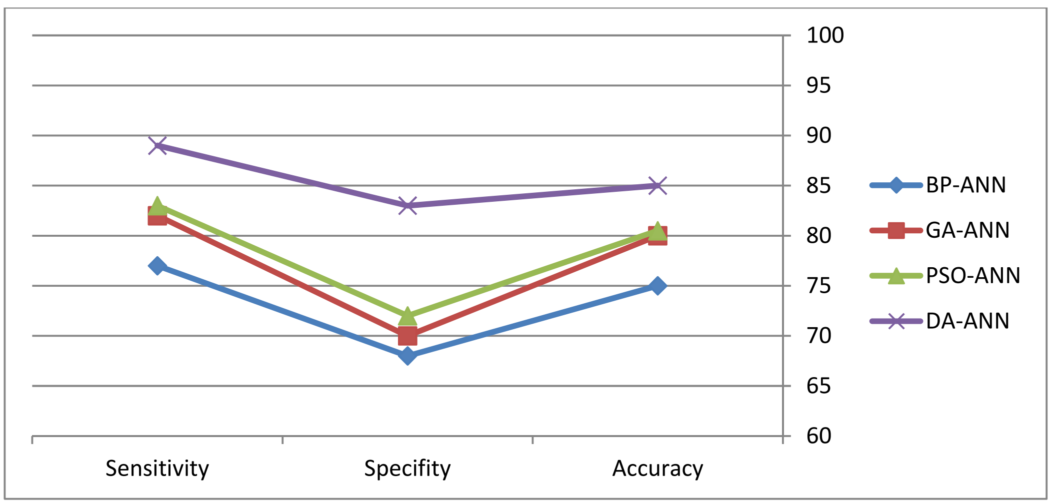

Figure (4): Classification Rates for Competitive Classifiers

To evaluate the effectiveness of the proposed method, another comparison is achieved with other well-known classifiers. Proposed DA-ANN is compared with SVM and KNN, on the same MRI datasets as depicted in table (2). This comparison shows that the proposed method has the highest classification accuracy than other classifiers.

Table (2): Classification rates of proposed algorithm with SVM and KNN classifiers on HMS-DB dataset

Method (Classifier)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Original BP-based ANN	77	68	75
SVM	85	75	83
KNN	80.3	71	79
Proposed DA-based ANN	**89**	**83**	**85**

Conclusion

Medical software represents one of the important issues in making diagnostic decisions for patients. In this research, an improvement of MRI brain image classification model is proposed. The proposed model contains wavelet transform as feature extraction, PCA as dimension reduction for features, and ANN for classification. The contribution of this model is using dragonfly algorithm as trainer of ANN (DA-based ANN) instead of backpropagation algorithm. DA-based ANN outperforms other state of the art classifiers (different training algorithm of ANN, SVM, and KNN classifiers) in terms of accuracy, sensitivity, and specificity evaluation metrics.

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