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A COMPARATIVE STUDY ON THE APPLICATION OF BINARY PARTICLE SWARM OPTIMIZATION AND BINARY GRAVITATIONAL SEARCH ALGORITHM IN FEATURE SELECTION FOR AUTOMATIC CLASSIFICATION OF BRAIN TUMOR MRI

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ABSTRACT

Researches on automatic classification for brain tumor had been done extensively, yet there is still room for improvement. Many approaches have been focused on image segmentation and classifier algorithm, yet little number of researches done on feature selection. This paper presents a study on the applications of two popular Swarm Intelligence algorithms: Binary Particle Swarm Optimization and Binary Gravitational Search Algorithm for optimizing feature selection of Gray-Level Co-occurrence Matrix. The classifier that is used in this paper is k-Nearest Neighbor. Benchmarking is done by comparing both swarm intelligence algorithms mentioned. The result indicates Binary Particle Swarm Optimization performs better compared to Binary Gravitational Search Algorithm.

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Keywords: brain tumor; gray level co-occurrence matrix; nearest neighbor; binary particle swarm optimization; binary gravitational search algorithm.

1. INTRODUCTION

Brain tumor occurred when there is collection of one or more of abnormal growth leads mass of cells that in the brain [1]. Brain tumor like many other oncology diseases can caused severe corresponding effects to a human life. The conventional way of detecting the tumor is by obtaining data in term of magnetic resonance images (MRI) and based on the data the expert will inspect the MRIs manually to see whether the patient had tumor. As the researches in the medical imaging areas progress, there is a great interest to automate classification of diseases of a patient based on data obtained from the patient with less supervision by the experts. In the area of brain tumor detection, detection can be done by performing several post processing procedures on the MRIs.

Based on Fig. 1 obtained from [2], a normal brain has an image as in Fig. 1(a) while someone with brain tumor has an image as in Fig. 1(b)-(c). Fig. 1(b) is a patient that have benign tumor which is not harmful to the patient. Fig. 1(c) is an MRI of a patient with malignant tumor which is harmful to the patient health.

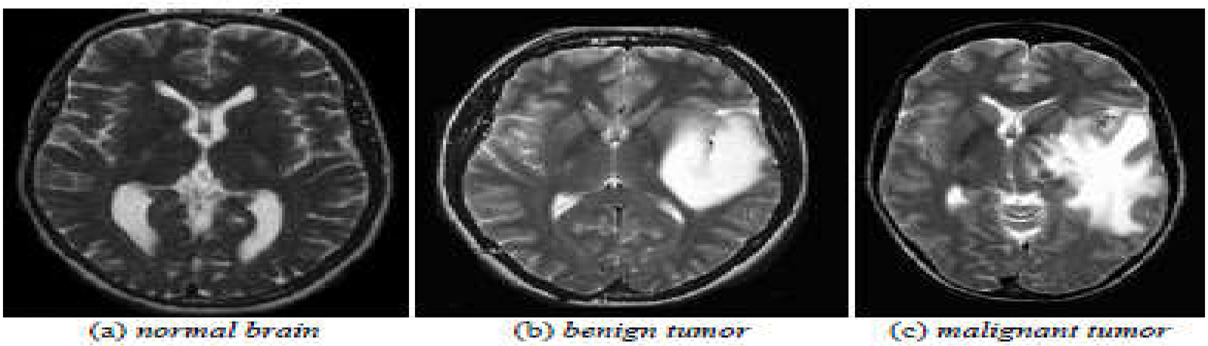

Fig.1. The T2 weighted images of brain MRIs [2]

Many literatures had proposed numerous approaches in classifying a patient with brain tumor using MRIs with different classifiers such as knowledge based technique [3], neural network (NN) [4, 29-32], support vector machine (SVM) [5]. In [6] proposed MRI image segmentation using Water Flow Algorithm and Fuzzy Entropy as pre-processing method to reduce the noise, in [7] proposed the application of K-means clustering with texture pattern matrix for MRI segmentation. In [8] proposed the application of Convolutional Neural Network for brain tumor segmentation (BTS) in MRI images, in [9] studied the implementation of Self Organizing Map and Discrete Wavelet Transform in BTS. S. In [10] proposed the application of a fast multilevel thresholding for BTS.

Application of Swarm Intelligence (SI) also in classification of Brain MRI images had been seen increasing. In [11] automated the segmentation by using a modified Fuzzy C Means with Ant Colony System. In [12] proposed classification of brain images using Firefly Algorithm as optimizer and Support Vector Machine (SVM) as the classifier. There also several literatures on the application of SI as feature selector: in [13] proposed the application of Bacteria Foraging Optimization, in [14] proposed the Hybrid Tolerance Rough Set-Firefly. In [16] proposed the implementation of improved Artificial Bee Colony Algorithm. In [17] proposed the application of Fish Swarm Metheuristic [33-35].

Based on [13-17], optimized features as input for classifier bring two significant benefits: reduces the time taken for classification and increase the performance of the classifier. The time taken for classification will be reduced because only optimized features are selected as input for the classifier, therefore classifier requires less computation time compare to when all features are selected. The performance of the classifier also will increase as the features that contributed to the best performance of classifier are selected while the non-performing features are left out.

This study implements the same framework as the proposed approach by [2]. It proposed a hybrid approach consists of three main components: feature extraction using wavelet and spatial gray-level dependence method, feature selection using Genetic Algorithm and classification using Support Vector Machine classifier. While this paper uses gray-level co-occurrence matrix (GLCM) as feature extraction, Binary Particle Swarm Optimization (BPSO) [23-28] and Binary Gravitational Search Algorithm (BGSA) as feature selectors and k-Nearest Neighbour (k-NN) as classifier.

Next section will explain in details of the proposed approaches: BPSO and BGSA. Result obtained by both approaches will be analyzed in section three. Section four will concluded the finding.

2. METHODOLOGY

Fig. 2(a)-(b) shows our proposed approaches using BPSO and BGSA. Both approaches start by having extracting features from the MRI images. Note that in this research, the MRI images are taken from [2, 17]. GLCM is used as feature extraction used for both approaches. BPSO is used as optimization algorithm to select optimal feature for BPSO-based approaches as shown in Fig. 2(a), while BGSA is used to perform the same task for BGSA-based approaches (shown in Fig. 2(b)). Both approaches used k-NN as classifier, where the classifier classified then check the accuracy of the classification. The result of accuracy of the classification is then send to the optimization algorithms as feedback for the algorithms to improve the feature selection. The process is repeated until stopping condition met and the best result is taken as the final result.

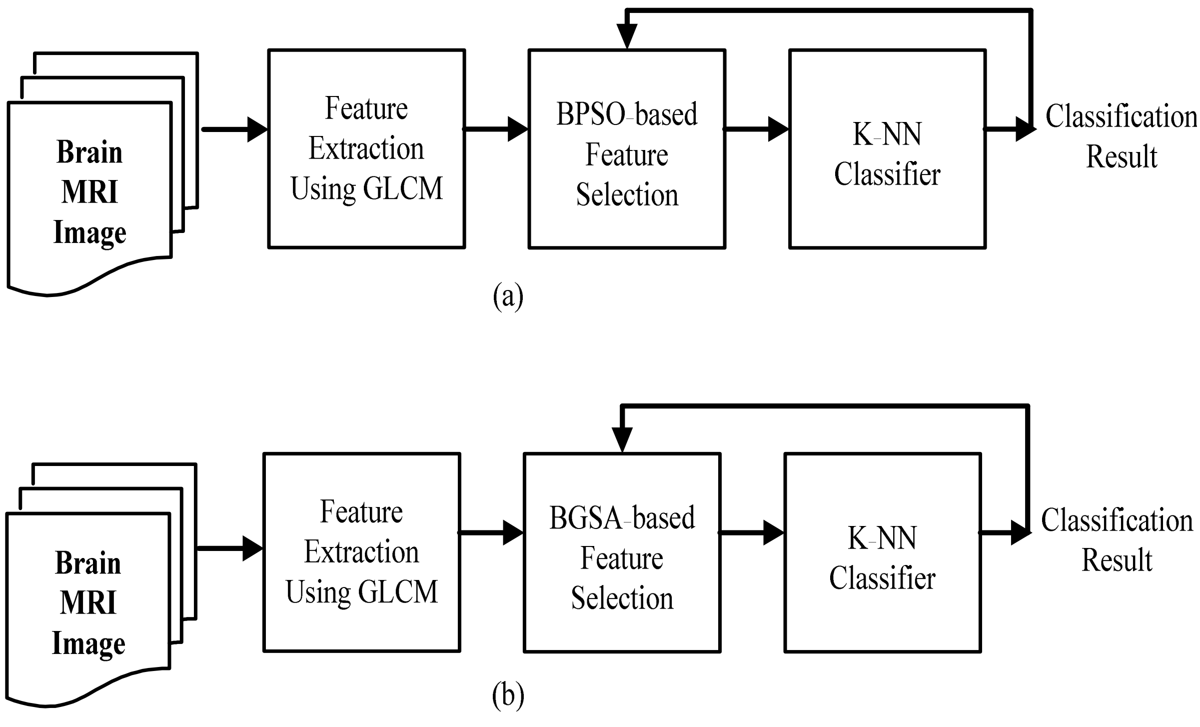

Fig.2. (a) BPSO-based proposed approach (b) BGSA-based proposed approach

The wavelet is not used for image enhancement. For the proposed approaches, only 11 features of the mean of GLCM from [18] are computed. These features are in Table 1.

Table 1. Extracted texture features

Feature Number	Feature (Mean)
1	Angular second moment
2	Contrast
3	Correlation
4	Variance
5	Inverse difference moment
6	Sum average
7	Sum variance
8	Sum entropy
9	Entropy
10	Difference variance
11	Difference entropy

These features than is feed into BPSO and GSA accordingly as input. PSO was introduced by [19]. The algorithm had been widely used for solving continuous-based optimization problems. It proposed a discrete or binary based of PSO for discrete problems in [20]. The adapted BPSO used for the proposed approach as listed in Algorithm 1, where the mathematical equation is based in [21].

Algorithm 1: BPSO Algorithm for feature selection for Brain MRI classification

Initialize all particles with a random position and velocity in the search space based on model in (1)

while stopping condition not met

    for each particle **do**

        Calculate the fitness of the particles

        if particle fitness better than previous $pbest$ **then**

            Set particle fitness value as new $pbest$

        end if

        if particle fitness value better than the current $gbest$ **then**

Set fitness value as the new $gbest$

end if

end for

for each particle **do**

Update particle velocity

Update the particle position

Perform correction if the updated particle position does not meet the constraint requirement

end for

end while

Present $gbest$ solution

GSA was introduced by [22]. It claimed the algorithm performed better for benchmark mathematical optimization problems compared to PSO. A year later, it proposed the binary version of GSA, BGSA in [23]. The adapted BGSA used for the proposed approach as listed in Algorithm 2, where the mathematical equation is based in [23].

Algorithm 2: BGSA Algorithm for feature selection for Brain MRI classification

Initialize values of G and v

Generate initial population by having agent randomly assigned at the search space based on model in (1)

while stopping condition not met

for each particle **do**

Calculate the fitness of the agent using (2)

if agent fitness value better than the current $global\ best$ **then**

Set fitness value as the new $global\ best$

end if

end for

Update the G, $best$ and $worst$ of the population

```
    for each agent do
        Calculate M and α
        Update agent velocity and position
    end for
end while
Present global best solution
```

A population consists of a number of particles are randomly initialize in a search space of p-dimension as Equation (1).

$$x_n = [b_1, b_2, \dots, b_p]^T \tag{1}$$

where x_n is the n-th particle and b_p is the p-th dimension of the search space. Each dimension represents a feature with a binary value of either 0 or 1. 0 means the feature is not selected and 1 means the feature is selected. Number of search space required is equal to number of features implemented, in this case, $p = 11$. For example, $x_7 = [1,0,1,1,1,0,0,0,1,1,0]^T$ means the candidate solution for the 7th particle proposed the selection of six features: angular second moment (feature no: 1), correlation (feature no: 3), variance (feature no: 4), inverse difference moment (feature no: 5), entropy (feature no: 9), difference variance (feature no: 10).

The fitness value of the particle is calculated based on Equation (2).

$$Fitness = (11 - N_b) \times Accuracy \tag{2}$$

where N_b is the number of features used. The fitness of the proposed approaches is dependent on accuracy of the classifier and the number of features used. The best condition occurred when accuracy obtained is high, while the number of features used is low.

The classifier chosen for the proposed approach is k-NN. The main idea of k-NN is that the prediction of a test data is based on the output of the majority of its k-neighbour. A simple example as illustrated in Fig. 3, where the test data (blue) will be classify as green if $k = 5$ and red for $k = 7$. In the proposed approach, k is set to 3, $k = 3$.

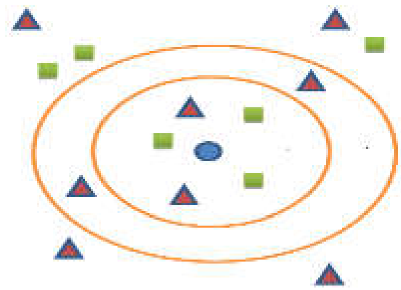

Fig.3. Classification using k-NN

Next section will discuss the result obtained from both methods.

3. RESULTS AND DISCUSSION

Thirty MRIs taken for training and testing are taken from [2, 17]. Parameters chosen for BGSA and BPSO are listed in Table 2. The optimal features obtained by [2] are mean of contrast, mean of homogeneity, mean of sum average, mean of sum variance and range of autocorrelation.

Table 2. Parameters values in BPSO and BGSA

	BPSO	**BGSA**
Common Optimization Parameters		
Number of agents	15	15
Number of iterations	100	100
Number of dimensions	11	11
BPSO Parameters		
Inertia weight	0.9	Not applicable
Social coefficient	1.42	Not applicable
Cognitive coefficient	1.42	Not applicable
BGSA Parameters		
ε	Not applicable	1
β	Not applicable	0.7
G	Not applicable	1

In this research, the cross validation of three folders was implemented. The k-NN parameter, k is set to three, $k = 3$. The accuracy of the proposed approaches is calculated using Equation (3).

$$Accuracy = \frac{Correct\ prediction}{Total\ prediction} \times 100\% \quad (3)$$

The result obtained by the proposed approaches as shown in Table 3. The accuracy of BPSO is at 83.3% which are really good while all the image misclassify is false negative (FN) which means there is no patient with cancer is classify as healthy. The accuracy of BGSA is only at 76.7%. The authors would like to highlight that the result obtained is a preliminary finding as the database of 30 images is too small to claim the proposed approaches effectives. On the other hand, the result obtained is a good indicator that BPSO performs better than BGSA.

Table 3. Result obtained

	BPSO	**BGSA**
Total number of images	30	30
Training	10	10
Testing	20	20
Image misclassified	5	7
Classification accuracy	83.3%	76.7%
Feature selected	Mean correlation, mean variance and mean entropy	Mean correlation and mean variance

4. CONCLUSION

This paper performs a comparative study of the applications of BPSO and BGSA in selecting features for brain MRI classification. The result obtained indicates BPSO performs better than BGSA for this application.

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