

Firefly algorithm for training the radial basis function network in ultrasonic supraspinatus image classification

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Abstract

The physicians observed the echo-texture and the shape changes of supraspinatus to decide the severity of rotator cuff disease in the clinical standard ultrasound examination. It is not reliable because the accuracy of visual observation depends on the experience of physicians. This article proposes a new algorithm called **Firefly RBF** network to training the radial basis function neural network by applying the firefly algorithm for classifying the different supraspinatus disease groups that are normal, tendon inflammation, calcific tendonitis and tendon tears of the ultrasound supraspinatus images based on the texture analysis technology. The texture features are generated from four methods those are the grey-level co-occurrence matrix, the texture spectrum, the fractal dimension and the texture feature coding method to analyse the tissue characteristic of supraspinatus. The F-score measurement are used to select powerful features those are generated from the four texture analysis methods for comparison in the training stage, meanwhile, the proposed Firefly RBF network is used to discriminate test images into one of the four disease groups in the classification stage. Experimental results showed that the percentage of correct classification was more than 93.7% that is superior to other methods in the classification of ultrasonic supraspinatus images.

Keywords: Radial basis function network, Firefly algorithm, Ultrasonic supraspinatus image, Texture analysis

1 Introduction

The injuries of the supraspinatus of the rotator cuff muscles, such as tendon inflammation, calcific tendonitis and tendon tears always cause in the human shoulder pained. For this reason, clinical physicians routinely observe the disease symptoms of supraspinatus using the ultrasound imaging examination. Recently, the Neer's classification system [1] has become a popular method that separates different diseases of supraspinatus into three stages in clinical diagnosis. The inflammation manifestations, such as edema or hemorrhage, usually exhibit in supraspinatus of Stage 1. The supraspinatus of Stage 2 is more serious and considered irreversible. Fibrosis and calcification always appear. Stage 3 generally involves a tendon rupture or tear. If the tendon rupture arises in the supraspinatus, it may require further repair. In clinical, ultrasonic examination has proved to be useful diagnostic tool in patients with shoulder pain and/or limited range of motion. Iagnocco et al. [2] explained how to use the ultrasonography to the careful qualitative assessment of a wide range of changes of different anatomic structures of rotator cuff tendons such as tendonitis, tendon tears and calcific deposits. Arsian et al. [3] used the 7.5-MHz linear-array transducer to grab images of patients with physical examination suggestive rotator cuff injury under longitudinal view. This study demonstrated that the bursa fluid and biceps effusion were high correlated with symptoms of rotator cuff injury. Chiou et al. [4] proposed the diagnosis criteria for

classification of full/partial supraspinatus tears of patients with shoulder pain. The sensitivity and specificity of experiments in applying the diagnosis criterion are 0.98 and 0.87. Marcello et al. [5] used criterion that are (a) one or more cuff tendon(s) was not visible, (b) focal non visibility of one the tendons, and (c) defect of well defined discontinuity of the tendons to diagnose of the rotator cuff tear. AI-Shawi et al. [6] proposed a study on the detection of full thickness rotator cuff tears using the ultrasound. The accuracy of the detection of large and massive tears, moderate tears and small tears are 96.5%, 88.8% and 91.6%. Up to now, most studies still used a subjective evaluation in terms of a visual inspection of the images or measurements of the muscle disorders, however, the accuracy of diagnosis by subjective evaluation always depends on the experiences of clinical physician, and therefore the quantitative evaluation is required.

The quantitative evaluation of tissue characteristics of supraspinatus is an important issue in clinical diagnosis that measured the distribution of the grey scales of the pixel in the areas of supraspinatus in the ultrasonic image to describe tissue characteristics. Nielsen et al. [7] proposed a method, a so-called "blob analysis", related to the higher order grey-level statistics of the image for quantitative ultrasound tissue characterization to measure the discrepancy of supraspinatus muscle and the right vastus lateralis muscle. They found that the first order histogram features are effective in classification the shoulder and thigh muscles. It is deficient to discuss the

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classification of other impingement syndromes such as inflammation and tendon calcification of the rotator cuff. In our past studies, we proposed a comparative article of using the various multi-class support vector machines to classify ultrasonic supraspinatus images into the four disease groups [8]. The results reveal that the fuzzy support vector machine is the most powerful for classifying the ultrasonic supraspinatus images. The classification rate by using the fuzzy support vector machine can achieve 90%. Furthermore, the comparisons of the maximum likelihood, error-correcting output code, fuzzy SVM and the multi-class radial basis function network methods had discussed in classification of supraspinatus images [9]. It concluded the radial basis function network has better performance than the fuzzy SVM method, however, its correct classification rate is only 92.6% that is not able to satisfy in the requirement of clinical diagnosis.

The firefly algorithm is a new swarm-based approach for optimization, in which the search algorithm is inspired by social behaviour of fireflies and the phenomenon of bioluminescent communication. There are two important issues in the firefly algorithm that are the variation of light intensity and formulation of attractiveness. Yang [10] that simplifies the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function. The attractiveness is proportional to their brightness. Furthermore, every member x_i of the firefly swarm is characterized by its bright I_i , which can be directly expressed as an inverse of a cost function for a minimization problem. Lukasik & Zak [11] applied the firefly algorithm for continuous constrained optimization. Yang [12] compared the firefly algorithm with the other meta-heuristic algorithms such as genetic and particle swarm optimization algorithms in the multimodal optimization. These works had the same conclusions that the algorithm applied the proposed firefly algorithm is superior to the other existing meta-heuristic algorithms. In this paper, we developed a new RBF neural network classifier called the **Firefly RBF** (i.e., the **Firefly** algorithm to training the **radial basis function**) neural network that is used to classify the four disease groups of the ultrasonic supraspinatus images. In experiments, the results of Firefly RBF network are compared with the above-mentioned other four methods. Experimental results revealed that the proposed Firefly RBF neural network is superior to those of the methods. Its correct classification rate can reach 93.75% that is very close to the diagnostic reports of clinical physicians with the rich experiences. The remaining of this paper is organized as follows. The feature extraction and selection are summarized in Section 2. Section 3 describes how to apply the firefly algorithm for training the radial basis function network in the classification of the ultrasound supraspinatus images. Some experimental results of classifying supraspinatus images are discussed in Section 4, and finally, the conclusions are presented in the Section 5.

2 Feature extraction and selection

The texture-based measurement had been applied to ultrasound images for diagnosing diseases over a decade. Horng et al. [9] compared texture descriptors that include the grey-level co-occurrence matrix (GLCM), the fractal dimension (FD), the texture spectrum (TS), the statistical feature matrix, and the texture feature coding method (TFCM) in the classification of the chronic liver diseases. In this work, it found that features generated from the grey-level co-occurrence matrix and texture feature coding method were effective for classifying the three liver states that are normal liver, hepatitis and cirrhosis. Another work [6] used the grey-level co-occurrence matrix (GLCM), the fractal dimension (FD), the texture spectrum (TS), and the texture feature coding method (TFCM) to extract features for classifying the ultrasonic supraspinatus images based on the characteristics of echo-texture. In summary, each region R of the supraspinatus image can extract 80 features that are generated from the above-mentioned four texture analysis methods. In these features, 56 features were generated from GLCM, eight features from TS, two from FD and the others from TFCM.

Feature selection has become the focus of much research in the area of application for which datasets with tens or hundreds of thousands of features are available. The universal algorithms of feature selection are often divided into two groups that are wrapper and filter approaches [13]. The wrapper model consists of two phase that are feature subset selection phase, and learning and testing phase. The feature subset selection selects the best subset using a classifier's accuracy as a criterion. The learning and testing phase provides a classifier that is learned from the training data with the best feature subset and is tested on test data. Filter approach is built on the intrinsic properties of the data, not on a basis of particular classifier. A filter model of feature selection also consists of two phases, that are one is feature selection that uses some measures such as F-score measurement or mutual information as search criteria, another phase is that the classifier is learned on the training data with the selected features. The F-score measures had been reliable than the mutual information method [9], so in this paper F-score measure is adopted as the search criteria to search powerful features form the those extracted from above-mentioned four texture analysis methods.

The feature ranking approaches use a principal or auxiliary mechanism to select the best feature set for classification. Because of their simplicity and scalability, the approaches have been widely applied. F-score ranking method is one of the feature ranking approaches. The larger the F-score measure of feature is, the more likely this feature is more discriminative. Given training features x_k , $k=1, 2, \dots, n$ if the number of positive and negative instances are n_+ and n_- , respectively, then the F-score of the i^{th} feature is defined as follows:

$$F_score(i) = \frac{(\bar{x}_i^{(+)} - \bar{x}_i)^2 + (\bar{x}_i^{(-)} - \bar{x}_i)^2}{\frac{1}{n_+ - 1} \sum_{k=1}^{n_+} (x_{k,i}^{(+)} - \bar{x}_i^{(+)})^2 + \frac{1}{n_- - 1} \sum_{k=1}^{n_-} (x_{k,i}^{(-)} - \bar{x}_i^{(-)})^2}. \quad (1)$$

In Eq. (1), the \bar{x}_i , $\bar{x}_i^{(+)}$ and $\bar{x}_i^{(-)}$ are the average of the i^{th} feature of the whole, positive and negative data sets, respectively; $\bar{x}_i^{(+)}$ is the i^{th} feature of the k^{th} positive instance, and $x_{k,i}^{(-)}$ is the i^{th} feature of the k^{th} negative instance. In experiments, we calculate the average of F-score measure that is obtained by computing between two different groups in order to analyse the discrimination of each texture feature.

3 Training RBF network by using the firefly algorithm

3.1 RADIAL BASIS FUNCTION NETWORK

The radial basis function network is a popular type of network that is very useful for pattern classification. A radial basis function (RBF) network is considered a special three-layered network shown in Fig 1.

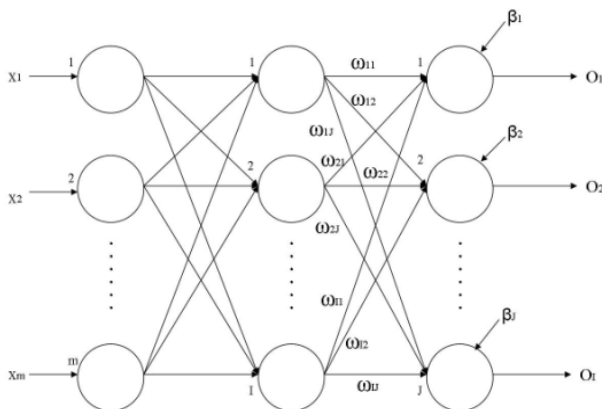


FIGURE 1 The structure of radial basis function network

The input nodes pass the input values $x=(x_1, x_2, \dots, x_m)$ to the internal nodes that construct the hidden layer. Each unit of hidden layer implements a specific activation function called radial basis function. The nonlinear responses of hidden nodes are weighted in order to calculate the final outputs of network in the output layer. The input layer of this network has m units for m dimensional input vectors. The input units are fully connected to I hidden layer units, which are in turn fully connected to the J output layer units, where J is the number of output layer. Each neuron of the hidden layer has a parameter mean vector called centre. Figure 1 shows the detailed structure of an RBF network. Each input data x with m dimensions, $x=(x_1, x_2, \dots, x_m)$, are located in the input layer, which broadcast to hidden layer. The hidden layer has I neurons and each neuron compute the distance between the centres and the inputs. Each activation function of the neuron in hidden layer is

chosen to be Gaussians and is characterized by their mean vectors c_i and its spread parameter α_i ($i=1,2, \dots, I$). That is, the activation function $\phi(x)$ of the i^{th} hidden unit for an input vector x is given by:

$$\phi_i(x) = \exp[-\alpha_i \cdot \|x - c_i\|^2]. \quad (2)$$

The ϕ_i affects the smoothness of the mapping, thus, the output value of the neuron j of output layer \bar{y}_j for training sample x , are given by $o(x)$ in Eq. (3).

$$o(x_i) = (\bar{o}_1, \bar{o}_2, \dots, \bar{o}_j) \quad (3)$$

$$\bar{o}_j = \sum_{h=1}^I w_{hj} \phi_h(x_i) + \beta_j$$

The weights, w_{ij} ($i=1,2, \dots, I, j=1,2, \dots, J$), is the i^{th} node of output of hidden layer that transmitted to j^{th} node of the output layer, and β_j is the bias parameter of the j^{th} node of output layer determined by the RBF network training procedure. In practice, the training procedure of RBF is to find the adequate parameters w_{ij} , α_i , β_i and c_i such that the error metrics such as the mean square error (MSE) is minimum.

$$MSE(w, \alpha, \beta, c) = \frac{1}{N} \sum_{k=1}^N \|d(x_k) - o(x_k)\|^2, \quad (4)$$

where the $d(x_i)$ and $o(x_i)$ are the desired output vector and actual output vector for training sample x_i . In (4), the N is the number of the training samples. The traditional implementation of RBF network uses the gradient descent algorithm to construct the structure of RBF network. In this paper, the gradient descent algorithm is called the Gradient-RBF neural network.

3.2 FIREFLY ALGORITHM

Firefly algorithm (FA) was developed by Xin-She Yang at Cambridge University in 2008. In the firefly algorithm, there are three idealized rules: (1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex; (2) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly. As firefly attractiveness one should select any monotonically decreasing function of the distance $r_{i,j} = d(x_j, x_i)$ to the chosen j^{th} firefly, e.g. the exponential function.

$$r_{i,j} = \|x_i - x_j\|, \quad (5)$$

$$\beta \leftarrow \beta_0 e^{-\gamma r_{i,j}}, \quad (6)$$

where the β_0 is the attractiveness at $r_{i,j} = 0$ and γ is the light absorption coefficient at the source. The movement

of a firefly i is attracted to another more attractive firefly j is determined by

$$x_{i,k} \leftarrow (1 - \beta)x_{i,k} + \beta x_{j,k} + u_{i,k}, \tag{7}$$

$$u_{i,k} = \sigma(\text{rand1} - \frac{1}{2}). \tag{8}$$

The particular firefly x_i with maximum fitness will move randomly according to the following equation.

$$x_{i^{\max},k} \leftarrow x_{i^{\max},k} + u_{i^{\max},k}, \text{ for } k=1,2,\dots,c, \tag{9}$$

$$u_{i^{\max},k} = \sigma(\text{rand2} - \frac{1}{2}). \tag{10}$$

When rand1 , rand2 are random vector whose each element obtained from the uniform distribution range from 0 to 1; (3). The brightness of a firefly is affected or determined by the landscape of the fitness function. For maximization problem, the brightness I of a firefly at a particular location x can be chosen as $I(x)$ that is proportional to the value of the fitness function.

3.3 FIREFLY RBF NEURAL NETWORK

In the proposed algorithm each individual of the fireflies is composed of the parameters of weights (w), spread parameters (α), centre vector (c) and the bias parameters (β) of network structure of Fig. 1. The mean vector c_i of the i -th neuron of hidden layers is defined by $c_i = (c_{i1}, c_{i2}, \dots, c_{im})$, therefore, the parametric vector of position y_{f_i} of each glow-worm f_i with $IJ + I + mI + J$ parameters is expressed as:

$$y_{f_i} = (w_{11}^i, w_{12}^i, \dots, w_{IJ}^i, \alpha_1^i, \alpha_2^i, \dots, \alpha_I^i, c_{11}^i, c_{12}^i, \dots, c_{1m}^i, \dots, c_{I1}^i, c_{I2}^i, \dots, c_{Im}^i, \beta_1^i, \beta_2^i, \dots, \beta_m^i, \dots, \beta_J^i)$$

In fact, each of fireflies can represent into a parameter vector that can construct a specific RBF network for classification. In our proposed Firefly RBF neural network, the applied fitness function is given in Eq. (11), that is to say, the algorithm of Firefly RBF network is to select the optimal vectors f_{best} of firefly of specific trained Firefly RBF network can maximize the fitness function defined in the Eq. (11).

$$J(y_{f_i}) = \frac{1}{1 + \text{MSE}} = \frac{1}{1 + \frac{1}{N} \sum_{k=1}^N \|d(x_k) - o(x_k)\|^2}, \tag{11}$$

where $d(x_k)$ and $o(x_k)$ are denoted to the desired output vector and actual output vector for training sample x_k of RBF network designed by parametric vector y_{f_i} . The N is the number of the training samples.

The steps of the proposed algorithm are described as following in detail.

Step 1. (Generate the initial solutions and given parameters)

In this step, the initial population of m solutions are generating with dimension $IJ + I + mI + J$, denoted by the matrix D .

$$D = [f_1, f_2, \dots, f_m], \tag{12}$$

$$y_{f_i} = (w_{11}^i, w_{12}^i, \dots, w_{IJ}^i, \alpha_1^i, \alpha_2^i, \dots, \alpha_I^i, c_{11}^i, c_{12}^i, \dots, c_{1m}^i, \dots, c_{I1}^i, c_{I2}^i, \dots, c_{Im}^i, \beta_1^i, \beta_2^i, \dots, \beta_m^i, \dots, \beta_J^i) \tag{13}$$

where the values of weights (w) and centres (c) are assigned between -1 and 1, and the values of the spread and bias parameters α and β range from 0 to 1. Furthermore, the step will assign the parameters of firefly algorithm, that are σ , β_0 , the maximum cycle number (MCL) and γ . Let number of cycle l to be 0.

Step 2. Firefly movement

In step 2, each solution (firefly) f_i computes its fitness value $J(y_{f_i})$ as the corresponding the brightness of firefly. For each solution f_i , this step randomly selects another one solution f_j with the more bright and then moves toward to f_j based on the following equations.

$$r_{i,j} = \|y_{f_i} - y_{f_j}\| = \sqrt{\sum_{k=1}^{IJ+I+mI+J} (y_{f_{i,k}} - y_{f_{j,k}})^2}, \tag{14}$$

where the k is an index of the component of the parametric vector form 1 to

$$\beta = \beta_0 e^{-\gamma r_{i,j}}, \tag{15}$$

$$y_{f_{i,k}} = (1 - \beta)y_{f_{i,k}} + \beta y_{f_{j,k}} + u_{j,k}, \tag{16}$$

$$k = 1, 2, \dots, IJ + I + mI + J$$

where $u_{j,k} \sim U(0,1)$ is a randomly number ranged form 0 to 1 and the $y_{f_{i,k}}$ is the k^{th} element of the solution y_{f_i} .

Step 3. (Select the current best solution)

The step 3 selects the best one from the all solutions and defines as $y_{f_{\text{best}}}$, that is,

$$i^{\max} = \arg \max_i y_{f_i}; \tag{17}$$

$$y_{f_{\text{best}}} = y_{f_{i^{\max}}};$$

Step 4. (Check the termination criterion)

If the cycle number l is equal to the MCL then the algorithm is finished and output the best solution $y_{f_{\text{best}}}$. Otherwise, l increases by one and randomly walks the best solution $y_{f_{\text{best}}}$ then go to Step 2. The best solution $y_{f_{\text{best}}}$ will randomly walk its position based the following equation.

$$y_{f_{\text{best}}} = y_{f_{\text{best}}} + u_{i^{\max},k}, \quad k = 1, 2, \dots, IJ + I + mI + J, \tag{18}$$

where $u_{i^{\max},k} \sim U(0,1)$ is a random number.

4 Experimental results and discussion

4.1 IMAGE ACQUISITION AND SYSTEM EQUIPMENT

All the ultrasonic images used were recorded from 2004 to 2007, and the ages of patients ranged from 30 to 65 years. In all, 120 shoulders in 120 patients with shoulder pain who had undergone preoperative and subsequent arthroscopy were identified. The arthroscopy diagnosis was a thickness tear in 30, a tendon inflammation in 30, a calcific tendon in 30 and the normal in 30. A longitudinal view of an ultrasound image of each shoulder was acquired using an HDI Ultramark 5000 Ultrasound system (ATL Ultrasound, CA, USA) fitted with a 5.0 MHz dynamic focusing transducer (C5-40 5.0 MHz Curved Linear Array, ATL Ultrasound, CA) from National Cheng Kung University Hospital in Taiwan based on current the clinical setting for ultrasound examination. The captured images were digitized into 256×256 pixels with 256 grey levels via a frame grabber and the stored on a disk. Figure 2 (a)-(d) provides sample images of normal, tendon inflammation, calcific tendonitis and rotator cuff tears, respectively. Among the 120 acquired images, 40 supraspinatus images equally divided into the four classes were selected as the training data to search for powerful features and then to establish the Firefly RBF neural network with 4 hidden nodes for classification. The remaining 80 supraspinatus images were used as the test images for subsequent classifications.

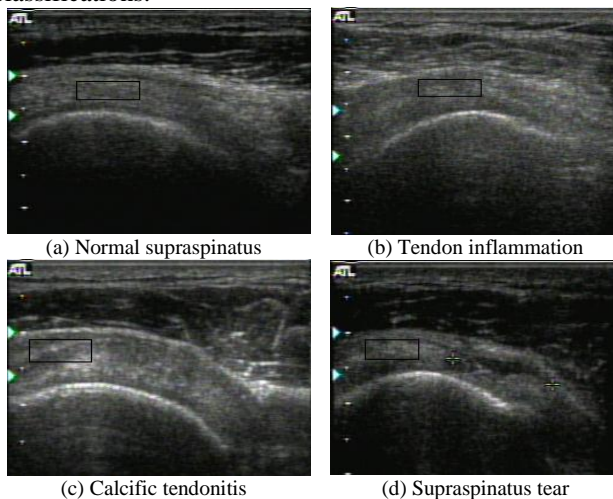


FIGURE 2 Samples of the ultrasonic images of supraspinatus. The image (a) is a normal case, image (b) is a sample of the tendon inflammation. The images (c) and (d) are calcific tendonitis and tear, respectively

The ultrasonic system settings were standardized for all of the participants and kept constant during the image acquisition. We used a depth setting of 3.0 cm. The depth-gain compensation was built into the ultrasound machine. The acoustic signal received by the ultrasonic transducer was digitized by 8 bit intensity values making the ultrasonic image. Each image consisted of pixels that were $0.1172\text{mm} \times 0.1172\text{mm} = 0.0137\text{mm}^2$. For each

image, a region of interest (ROI) with 30×60 pixels at a depth of approximately 1.5 to 2.5 cm from the body surface was manually selected by an ultrasound musculoskeletal radiologist with five years of experience in shoulder examination to extract texture features for subsequent classification. In general, radiologist avoided including the areas of ruptured tendons in the ROI selection process. All programs were implemented in Visual C++ associated with Neural Toolbox of Matlab software under on a personal computer with a 2.4GHz CPU and 1G RAM using the Window XP operating system. The parameters of the proposed Firefly RBF neural network are listed in Table 1.

TABLE 1 The used parameters of Firefly RBF neural network

Parameters	Value
Attractiveness β_0	1.0
Light absorption coefficient γ	1.0
The size of initial firefly	50
Iteration number	100
σ	0.1
Attractiveness β_0	1.0

In the experiment, each training image can be extracted to a total of 80 features that are generated from the above-mentioned four texture analysis methods. All extracted features are first required to be normalized to zero mean and unit standard deviation, which ensure the larger value input features so as not to overwhelm smaller value inputs and to reduce errors before the feature selection and classification. Table 2 lists the selected features by independent usage of the F-score criterion, that are Sum Variance (GLCM), Sum Average (GLCM), Mean Convergence (TFCM), Code Variance (TFCM) and Contrast (GLCM). The results of the texture feature selection were that all of the selected features were generated from the GLCM and TFCM. The average execution time is 0.2919 seconds for classifying an ultrasonic supraspinatus image by using Firefly RBF neural network. These results may reveal that the discriminative capability of the selected features generated from the GLCM and TFCM methods are superior to those of other methods.

TABLE 2 Texture feature selection by using the four texture analysis methods

Methods	Feature selected (d: displacement)
Four texture methods + F-scoring ranking method	Sum variance (GLCM, $d = 2$),
	Sum average (GLCM, $d = 2$),
	Mean convergence (TFCM, $d = 2$),
	Code variance (TFCM, $d = 2$),
	Contrast (GLCM, $d = 3$)

4.2 PERFORMANCE EVALUATION

In order to compare the classification results of the proposed glowworm swarm optimization trained radial

basis function network with the results of the diagnosis of clinical musculoskeletal radiologist, the supraspinatus images were evaluated and further classified with an clinical radiologist with 5 years of experiences in shoulder ultrasound examination. The correct classification rate of the 120 ultrasonic supraspinatus images by this clinical radiologist is about 95.8%. Table 3 shows the classification results by using the proposed Firefly RBF neural network. Its correct classification rate is 93.75%. In order to further investigate the performance of classification using the Firefly RBF neural network classifiers, the performance indices, such as the sensitivity, the specificity and accuracy rate are computed to compare with the results of the ML classifier, the error correcting output code (ECOC), the fuzzy SVM and the gradient descent RBF (Gradient-RBF) network algorithms. The three indices are defined in the four-class supraspinatus image classification as follows.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP}, \tag{19}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN}, \tag{20}$$

$$\text{Specificity} = \frac{TN}{TN+FP}. \tag{21}$$

TABLE 3 The classification results based on the features of Table 1 using Firefly RBF network classifier

Predicted Results	Actual Results			
	Normal	Inflammation	Calcific	Tear
Normal	20	1	0	0
Inflammation	0	18	1	0
Calcific	0	1	17	0
Tear	0	0	2	20

The definition of TP, TN, FP and FN are specified as follows.

TP (true-positive): the number of correctly diagnosed diseased cases (including tendon inflammation, calcific tendonitis and tear).

TN (true-negative): the number of correctly diagnosed normal cases.

FP (false-positive): the number of misclassifications where patients are considered as being acute disease than the actual diagnosis.

FN (false-negative): the number of misclassifications where patients are classified with less severe diseases than actual diagnosis.

In addition, an effective classification method should decrease the possibility of misclassification, especially for the false-negative rate. A high false-negative rate represents the danger to underestimate the disease severity in a patient while the clinical doctor uses the classification system; therefore, the false-negative rate may be considered as an index for evaluating the performances of the RBF networks of the two different selected feature sets. Table 4 shows the four performance

indices by using different classification algorithms. Form this table, we find that the results of Firefly RBF network is superior to other methods. The accuracy of Firefly RBF network grows 1.5% with comparison to the original gradient-descent RBF network. Furthermore, the false-negative rate by using the Firefly-RBF neural network is only 0.0375. It reveals that Firefly RBF network is promising to develop into a powerful diagnosis tool in the clinical diagnosis application of the ultrasonic supraspinatus images.

TABLE 4 The four performance indices, which are accuracy, sensitivity, specificity and false-negative rate by using the five different algorithms

Performance measures	Classification methods				
	ML	FSVM	ECOC	Gradient RBF	Firefly RBF
Accuracy	84.2%	89.1%	90.8%	92.5%	93.75%
Sensitivity	0.840	0.900	0.922	0.932	0.948
Specificity	0.833	0.860	0.900	0.904	0.909
False negative rate	0.116	0.075	0.058	0.05	0.0375

4.3 RECEIVER OPERATING CHARACTERISTIC ANALYSIS

The receiver operating characteristics (ROC) analysis is based on statistical decision theory and has been applied extensively to the evaluation of classification methods [14, 15]. The ROC curve can manifest the relationship between the true-positive fraction (TPF) and false-positive fraction (FPF) with the variations in decision threshold. In general, the area under the ROC curve (AUC), A_z , is a powerful index for assessing the classification performance of the classifier. In general, a large value of AUC is desirable as AUC values greater than 0.9 suggest that the corresponding diagnosis system is very effective. The area under curve (AUC), A_z , of ROC curves of the five different algorithms are listed in Table 5. Obviously, the proposed Firefly RBF neural network is 0.951 that is superior to other four classification algorithms.

TABLE 5 The A_z of ROC curve of the five different classification algorithms

Method	Classification methods				
	ML	FSVM	ECOC	Gradient RBF	Firefly RBF
A_z value	0.876	0.923	0.927	0.941	0.951

5 Conclusion

Traditionally, the widespread method used by radiologists to diagnose the rotator cuff injury is to examine the micro/macro changes of the supraspinatus in the ultrasonic images; however, manual observations emerge several problems such as inter-observer and intra-observer variability. In this paper, the radial basis function neural network trained by the firefly algorithm was developed as the classifier for the classification of

ultrasound supraspinatus images. Based on the results of the present experiments of the classification of ultrasonic supraspinatus images, the followings can be emphasized:

1. The correct classification rate by using the Firefly RBF neural network [16] is superior to other four classification algorithms, particularly the accuracy by using Firefly RBF network improves near 1.25% compared to gradient-descend RBF network. It reveals that the firefly algorithm is effective in the training the radial basis function neural network. The results drive a probable study to develop new training algorithm for other neural networks.
2. The lower false-negative rate and the high sensitivity and specificity using the Firefly RBF network in the classification of ultrasound supraspinatus images appear that the proposed

algorithm of this paper is a reliable algorithm, and further it has potential to develop into a practical tool for clinical diagnosis. In the future study we will examine the other texture analysis method to obtain other powerful texture features for classifications.

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References

- [1] Neer C S 1972 Anterior acromioplasty for the chronic impingement syndrome in the shoulder: A preliminary report *J. Bone Joint Surg.* **54** 41-50
- [2] Iagnocco A, Coari G, Leone A, Valesini G 2003 Sonographic study of painful shoulder *Clinical Experimental Rheumatology* **21** 355-8
- [3] Arslan G, Apaydin A, Kabaalioglu A, Sindel T, Luleci E 1999 Sonographically detected subacromial/subdelroid bursal effusion and biceps tendon sheath fluid: Reliable signs of the rotator cuff tear? *J. Clin. Ultrasound* **27** 335-9
- [4] Chiou H J, Chou Y H, Wu J J, Hsu C C, Tiu C M, Chang C Y Chang 1999 High-resolution ultrasonography of the musculoskeletal system: Analysis of 369 cases *J. Med. Ultrasound* **7** 212-8
- [5] Marcello H N-B, Jose B V, Jorge E J, Gerson M 2002 Diagnostic imaging of shoulder rotator cuff lesions *Acta. Ortop. Bras.* **10** 31-9
- [6] Al-Shawi A, Badge R, Bunker T 2008 The detection of full thickness rotator cuff tears using ultrasound *Journal of Bone and Joint Surgery-British* **90-B** 889-92
- [7] Nielsen P K, Jensen B R, Darvann T, Jorgensen K, Bakke M 2006 Quantitative ultrasound tissue characterization in shoulder and thigh muscles – a new approach *BMC Musculoskeletal Disorders* **7** 1-11
- [8] Horng M H 2009 Multi-class support vector machine for classification of the ultrasonic images of supraspinatus *Expert Systems with Applications* **36** 8124-33
- [9] Horng M H, Chen S M 2009 Multi-class classification of ultrasonic supraspinatus images based on radial basis functional neural network *Journal of Medical and Biological Engineering* **29**(5) 242-50
- [10] Yang X S 2008 *Nature-inspired Metaheuristic Algorithms* Frome; Luniver Press
- [11] Lukaski S, Zak S 2009 Firefly Algorithms for Continuous Constrained Optimization Tasks, Computational Collective Intelligence. Semantic Web, Social Networks and Multiagent Systems *Lecture Notes in Computer Science* **5796** 97-106
- [12] Yang X S 2010 Firefly Algorithm, Stochastic Test Functions and Design Optimization *Int. J. Bio-inspired Computation* **2**(2) 78-84
- [13] Liu H, Motoda H 1998 *Feature selection for knowledge discovery and data mining* Norwell, MA: Kluwer Academic
- [14] Fawcett T 2006 An introduction to ROC analysis *Pattern Recognition Letters* **27** 861-74
- [15] Gonen M 2007 *Analysing Receiver Operating Characteristic Curves Using SAS* SAS Press
- [16] Horng H M, Lee Y X, Lee M C, Liou R J 2012 Firefly Metaheuristic Algorithm for Training the Radial Basis function Network for Data Classification and disease Diagnosis, Theory and New Applications of Swarm Intelligence *InTech* 115-32

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