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Research on a New Method based on Improved ACO Algorithm and SVM Model for Data Classification

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Abstract

Because the properties of data are becoming more and more complex, the traditional data classification is difficult to realize the data classification according to the complexity characteristic of the data. Support vector machine is a machine learning method with the good generalization ability and prediction accuracy. So an improved ant colony optimization(ACO) algorithm is introduced into the support vector machine(SVM) model in order to propose a new data classification(ERURACO-SVM) method. In the ERURACO-SVM method, the pheromone evaporation rate strategy and pheromone updating rule are introduced into the ACO algorithm to improve the optimization performance of the ACO algorithm, and then the parallelism, global optimization ability, positive feedback mechanism and strong robustness of the improved ACO algorithm is used to find the optimal combination of parameters of the SVM model in order to improve the learning performance and generalization ability of the SVM model and establish the optimal data classification model. Finally, the experimental data from the UCI machine learning database are selected to validate the classification correctness of the ERURACO-SVM method. The experiment results show that the improved ACO(ERURACO) algorithm has better optimization performance for parameters selection of the SVM model and the ERURACO-SVM method has higher classification accuracy and better generalization ability.

Keywords*: Data classification, ant colony optimization algorithm, support vector machine, evaporation rate strategy, updating rule, optimization performance*

1. Introduction

Data classification is an important task in the field of data mining and machine learning [1]. It is to choose the classified training set from the data and use the classification technologies of data mining for the training set in order to set up the classification model, which is used to classify the data without classification data. The data classification methods has a wide range of applications, and can be further derived from the new algorithms. In recent years, there proposed a lot of data classification methods of data mining, such as decision tree, Bayesian, neural network, support vector machine, genetic algorithm and so on [2-6]. These data classification methods have good effect for low dimension data. However, for high dimension data, the application ability is obviously reduced. So it has actual significance for researching the data classification, which is a hot research in the field of data mining.

With the rapid development of database technology and the rapid popularization of Internet, the amount of the processing data in real application is growing exponentially, which leads to face many new problems and challenges for the traditional classifications. In order to better solve the problem of data classification, many researchers proposed a lot of new data classification methods. Wang, *et al.*, [7] combined support vector machines (SVMs) with a novel quantum ant colony optimization (QACO) algorithm to select the

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fault features. The proposed method is then tested using the benchmark Tennessee Eastman Process and shown to be effective. Lin, *et al.,* [8] proposed a particle swarm optimization (PSO) based approach for parameter determination and feature selection of the SVM, termed PSO + SVM. Several public datasets are employed to calculate the classification accuracy rate in order to evaluate the developed PSO + SVM approach. Huang and Dun [9] proposed a novel PSO-SVM model that hybridized the particle swarm optimization (PSO) and support vector machines (SVM) to improve the classification accuracy with a small and appropriate feature subset. Huang [10] proposed a novel hybrid ACO-based classifier model that combines ant colony optimization (ACO) and support vector machines (SVM) to improve classification accuracy with a small and appropriate feature subset. To simultaneously optimize the feature subset and the SVM kernel parameters, the feature importance and the pheromones are used to determine the transition probability. Zhang, *et al.,* [11] proposed ant colony optimization (ACO) algorithm to develop a novel ACO-SVM model to establish an efficient SVM so as to attain desired output with an acceptable level of accuracy. Kadri, *et al.,* [12] proposed a novel hybrid algorithm for fault diagnosis of rotary kiln based on a binary ant colony (BACO) and support vector machine (SVM). Baig and Shahzad [13] proposed a new ACO-based classification algorithm called AntMiner-C. Its main feature is a heuristic function based on the correlation among the attributes. Samadzadegan, *et al.,* [14] proposed the potential of ant colony optimization (ACO) for determining SVM parameters and selecting features. The results demonstrate a better performance of the ACO-based algorithm in regards to improving the classification accuracy and decreasing the size of selected feature subsets. Jiang and Liu [15] proposed a new method based on SSM and ACO-SVM to automatically diagnose early cirrhosis of liver in CT images. The quantitative evaluation of the proposed method shows that it can recognize liver with high accuracy whether it is normal or abnormal. Yu, *et al.,* [16] proposed an ACOS ampling that is a novel undersampling method based on the idea of ant colony optimization (ACO) to address this problem. Mostafa and Toksari [17] used ant colony optimization (ACO), radial basis function neural network (RBFNN), Kohonen's self-organizing maps (SOM), and support vector machines (SVMs) to examine the effect of various cognitive, psychographic, and attitudinal factors on organ donation. Yuan, *et al.,* [18] proposed the heuristic Ant Colony Optimization (ACO) algorithm to find the optimal parameters of Support Vector Machine (SVM) in order to obtain a multi-class SVM classifier for the failure diagnosis of an electric motor in a railway system. Turker, *et al.,* [19] proposed a novel method of training support vector machine (SVM) by using chaos particle swarm optimization (CPSO). A multi-fault classification model based on the SVM trained by CPSO is established and applied to the fault diagnosis of rotating machines. Fei[20] proposed a PSO-SVM model for diagnosis of arrhythmia cordis, in which PSO is used to determine free parameters of support vector machine. The experimental data from MIT-BIH ECG database are used to illustrate the performance of proposed PSO-SVM model. Palanisamy and Kanmani [21] proposed a novel hybrid algorithm ABCE - the combination of ABC algorithm and a classifier ensemble (CE). A classifier ensemble consisting of Support Vector Machine (SVM), Decision Tree and Naive Bayes, performs the task of classification and ABCE is used as a feature selector to select the most informative features as well as to increase the overall classification accuracy of the classifier ensemble. Li, *et al.,* [22] proposed an improved ant colony optimization (IACO) algorithm to determine the parameters of support vector machine (SVM), and then the IACO-SVM algorithm is applied on the rolling element bearing fault detection. Vieira, *et al.,* [23] proposed a modified binary particle swarm optimization (MBPSO) method for feature selection with the simultaneous optimization of SVM kernel parameter setting, applied to mortality prediction in septic patients. Wang [24] proposed a network intrusion detection method (ACO-FS -SVM) combining ant colony algorithm to select the features with a feature weighting SVM in order to improve network intrusion detection rate for feature selection problem. Mohammad, *et al.*, [25] proposed a feature decision-making ant colony optimization system based on support vector machine (SVM) for automatic recognition of different plant species through their leaf images. Turker, *et al.*, [26] proposed a nature inspired and novel FS algorithm based on standard Ant Colony Optimization (ACO), called improved ACO (IACO) to reduce the number of features by removing irrelevant and redundant data. Mahani, *et al.*, [27] proposed a method called ACOR-PSO algorithm based on computational merits of the continuous ant colony optimization (ACOR) and the particle swarm optimization (PSO) to accelerate the capability of exploitation and convergence of PSO. Panda and Abraham [28] proposed a novel method to find the best relevant feature subset using fuzzy rough set-based attribute subset selection with biologically inspired algorithm search such as ant colony and particle swarm optimization and the principles of an evolutionary process. Li et al. [29] hybridized chaotic search and gravitational search algorithm (GSA) with SVM and proposed a new chaos embedded GSA-SVM (CGSA-SVM) hybrid system in order to improve classification accuracy of SVM. Aburomman and Ibne Reaz [30] proposed a novel ensemble construction method that uses PSO generated weights to create ensemble of classifiers with better accuracy for intrusion detection. Local unimodal sampling (LUS) method is used as a meta-optimizer to find better behavioral parameters for PSO.

Although these proposed data classification methods can better realize the data classification, but the classification accuracies of them are low and slow speed. In allusion to the existing shortcomings of the SVM and improved SVM in classification, an improved ant colony optimization (ACO) algorithm is introduced into the support vector machine(SVM) model in order to propose a new data classification(ERURACO-SVM) method. The pheromone evaporation rate strategy and pheromone updating rule are use to improve the optimization performance of the ACO algorithm, which is used to find the optimal combination of parameters of the SVM model in order to improve the learning performance and generalization ability of the SVM model and establish the optimal data classification model.

The rest of this paper is organized as follows. Section 2 briefly introduces the ant colony optimization (ACO) algorithm. Section 3 briefly introduces the strategies of the pheromone evaporation rate strategy and pheromone updating rule for improved ACO algorithm. Section 4 briefly introduces support vector machine (SVM) model. Section 5 proposed parameter optimization model of SVM based on improved ACO algorithm. Section 6 gives experimental results and conclusions. Finally, the conclusions are discussed in Section 7.

2. Ant Colony Optimization (ACO) Algorithm

Ant colony algorithm (ACO) was introduced by Marco Dorigo in the early 1991 [31]. It is a metaheuristic inspired by the behavior of real ants in their search for the shortest path to food sources. The ACO algorithm consists of a number of cycles (iterations) of solution construction. During each iteration, a number of ants construct complete solutions by using heuristic information and the collected experiences of previous groups of ants. These collected experiences are represented by the pheromone trail which is deposited on the constituent elements of a solution. Small quantities are deposited during the construction phase while larger amounts are deposited at the end of each iteration in proportion to solution quality. Pheromone can be deposited on the components and/or the connections used in a solution depending on the problem. Each ant randomly starts at one city and visits the other cities according to the transition rule. After the ants complete their routes, the system evaluates the length of the routes. Then, the system uses the pheromone update rule to update the pheromone information. The learning procedure is to update the pheromone information repeatedly.

(1) Transition rule

In the route, the k^{th} ant starts from city r, the next city s is selected among the unvisited cities memorized in J_r^k according to the following formula:

$$s = \arg\max_{u \in J_r^k} [\tau_i (r,u)^{\alpha} \cdot \eta(r,u)^{\beta}] \ \ if\ q \le q_0 (Exploitation) \tag{1}$$

To visit the next city s with the probability $p_k(r,s)$,

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s)^{\alpha} \cdot \eta(r,s)^{\beta}}{\sum_{u \in J_r^k} \tau(r,u)^{\alpha} \cdot \eta(r,u)^{\beta}} & if\ s \in J_r^k \\ 0 & otherwise \end{cases} \quad if\ q > q_0 (Bias\ Exploitation) \tag{2}$$

In two formula, $p_k(r,s)$ is the transition probability, $\tau(r,u)$ is the intensity of pheromone between city r and city u in the i^{th} group, $\eta(r,u)$ is the length of the path from city r to city u, J_r^k is the set of unvisited cities of the k^{th} ant in the i^{th} group, the parameter α and β are the control parameters, q is a uniform probability [0, 1].

(2) The pheromone update rule

In order to improve the solution, the pheromone trails must be updated. Trail updating includes local updating and global updating. The local trail updating formula is given by:

$$\tau(r,u) = (1-\rho)\tau(r,s) + \sum_{k=1}^{m} \Delta\tau_k (r,s) \tag{3}$$

In the formula (3), ρ ($0 < \rho < 1$) is the pheromone trial evaporating rate. $\Delta\tau_k (r,s)$ is the amount of pheromone trail added to the edge(r,s) by ant k between time t and $t+\Delta t$ in the tour. It is given by:

$$\Delta\tau_k (r,s) = \begin{cases} \dfrac{Q}{L_k} & (\mathrm{r},s) \in \pi_k \\ 0 & otherwise \end{cases} \tag{4}$$

where Q is a constant parameter, L_k is the distance of the sequence π_k toured by ant in Δt.

3. The Strategies for Improved ACO Algorithm

3.1. The Improved Pheromone Updating Rule

In the conventional ACO algorithm, the global update rule only strengthens the pheromone concentration on the shortest path in each iteration. But the pheromone concentration of the shortest path is excessively strengthened to easily fall into local optimal solution. The optimal path in each iteration will be make full use. So the adaptive dynamic factor $\sigma \in (0,1)$ is introduced into the pheromone updating rule in order to control the updating proportion of the pheromone concentration in one iteration, which will greater strengthen the pheromone concentration on the better path. Then the pheromone concentration is used to react the path information. The pheromone concentration on the optimal path is globally updated:

$$\tau_{ij}(t+1) = \tau_{ij}(t+1) + \mu\sigma\Delta\tau_{ij} \tag{5}$$

where $\sigma = \dfrac{1}{\pi} \arctan(\dfrac{\gamma(L_{local\min} - L_{\min})}{\bar{L} - L_{\min}}) + \dfrac{1}{2}$

$\overline{L}$ is the average length of the current local optimal solution, $L_{\min}$ is the length of current global optimal solution, $L_{local\min}$ is the length of the optimal path in one iteration, γ is a parameter to control the arc tangent function. When $L_{local\min}$ is bigger and the search path is longer, the adaptive dynamic factor σ is near zero. In contrast, the adaptive dynamic factor σ is near one.

3.3. The Dynamic Evaporation Coefficient Strategy

The evaporation coefficient of pheromone ρ in the conventional ACO algorithm is a constant. The value of pheromone ρ directly relates to the global search ability and convergence speed. In the ACO algorithm, if the pheromone is too large, the selected probability of the visited path will be large, it will affect the global search ability of the algorithm. So it is the key to set the pheromone value for controlling the pheromone releasing and evaporating. The dynamic evaporation coefficient strategy is proposed. This strategy sets a large dynamic evaporation coefficient ρ at the beginning of the algorithm for enhancing the global search ability. It can not only increase the global search capability, but also accelerate the convergence.

In order to better explore the decay model of the evaporation coefficient, the curve decay model is selected according to the experiment in this paper. The curve decay model is described as follow:

$$\rho(t) = \frac{T \times (\tau_{\max} - \tau_{\min}) \times t}{T-1} + \frac{T \times (\tau_{\min} - \tau_{\max})}{T-1} \tag{6}$$

where $\tau_{\max}$ and $\tau_{\min}$ are the upper and lower of pheromone. t and T is the current iteration and the maximum iteration.

4. Support Vector Machine (SVM) Model

Support vector machine (SVM) introduced by Vapnik [32], it is one of the popular tools in a supervised machine learning method based on structural risk minimization. The basic characteristic of the SVM is to map the original nonlinear data into a higher-dimensional feature space where a hyperplane is constructed to bisect two classes of data and maximize the margin of separation between itself and those points lying nearest to the support vectors.

The given the training sample is $S = \{(x_i, y_i) \mid i = 1,2,3,\cdots,m\}$, m is the number of samples, the set $\{x_i\} \in R_n$ represents the input vector, $y \in \{-1,1\}$ indicates the corresponding desired output vector, the input data is mapped into the high dimensional feature space by using nonlinear mapping function $\phi(\bullet)$. Then the existed optimal classification hyperplane must meet the following conditions:

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = 1 \\ \omega^T x_i + b \leq -1, & y_i = -1 \end{cases} \tag{7}$$

where ω is Omega vector of superplane, b is offset quantity. Then the classification decision function is described:

$$f(x_i) = \mathrm{sgn}(\omega^T x_i + b) \tag{8}$$

The classification model of the SVM is described by the optimization function $\min\limits_{\omega,\xi,b} J(\omega, \xi_i)$:

$$\min_{\omega,\xi,b} J(\omega,\xi_i)=\frac{1}{2}\omega^T\omega+\frac{1}{2}\gamma\sum_{i=1}^{m}\xi_i^2 \quad (9)$$

$$s.t.\quad y_i[\omega^T\phi(x_i)+b]=1-\xi_i, i=1,2,3,\cdots,m \quad (10)$$

where ξ_i is slack variable, b is offset, ω is support vector, $\xi=(\xi_1,\xi_2,\cdots,\xi_m)$, γ is classification parameter to balance the fitness error and model complexity.

The optimization problem transforms into its dual space. Lagrange function is introduced to solve it. The corresponding optimization problem of the LS-SVM model with Lagrange function is shown:

$$L(\omega,b,\xi,\alpha)=\frac{1}{2}\omega^T\omega+\frac{1}{2}\gamma\sum_{i=1}^{m}\xi_i^2-\sum_{k=1}^{m}\alpha_i\{y_i[\omega^T\phi(x_k)+b]-1+\xi_i\} \quad (11)$$

where α_i is the Lagrange multiplier, and $\alpha_i \geq 0(i=1,2,3.\cdots,m)$. Then following linear equation is obtained:

$$\begin{bmatrix} 0 & L^T \\ L & \Omega+\gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ Y \end{bmatrix} \quad (12)$$

where $Y=[y_1,y_2,\cdots,y_m]^T \in R^m$, $L\in R^m$ is vector of the element m, then $Y^T=[y_1,y_2,\cdots,y_m]$, I is unit matrix, $I_m=[1,1,\cdots,1]^T$, $\alpha=[\alpha_1,\alpha_2,\cdots,\alpha_m]^T$, $\Omega=[\Omega_{ij}]_{m\times m}$, $\Omega_{ij}=y_iy_jK(x_i,x_j)$. Then the classification decision function is described as follows:

$$f(x_i)=\operatorname{sgn}(\sum_{i=1}^{m}\alpha_iy_iK(x,x_i)+b) \quad (13)$$

5. Parameter Optimization Model of SVM based on Improved ACO

The SVM is a typical pattern recognition method, before the SVM model is trained, the type and parameter σ of kernel function, and penalty factor C are determined. Therefore, the parameter σ of kernel function and penalty factor C are selected as the research object, an optimization method of parameter of SVM model is proposed under comparative experiments in the different types of kernel function. Because there has been a great deal of function test to prove that the ACO algorithm takes on the ability to jump out of local optimal solution. So the improved ACO algorithm is used to optimize the parameters (C and σ) of the SVM model. The prediction accuracy of data classification of the SVM model is selected as the objective function. The function of two variables with the parameters (C and σ) is denoted as $F(C,\sigma)$. And the C and σ is set the upper bound and lower bound, then the problem is converted into the following mathematical problems:

$$\max F(C,\sigma) \quad (14)$$

$$s.t.\begin{cases} C\in[C_{\min},C_{\max}] \\ \sigma\in[\sigma_{\min},\sigma_{\max}] \end{cases} \quad (15)$$

The C and σ are solved in one given search interval. The improved ACO algorithm is used to select the parameters of the SVM, that is to say that the improved ACO algorithm is used to solve the function optimization problem of the continuous domain in order to select the optimal C and σ for training the SVM model. The obtained optimal SVM model is used to classify the test set in order to obtain the best classification classifier with the highest classification accuracy.

The parameter optimization flow of SVM based on improved ACO algorithm is shown in Figure 1.

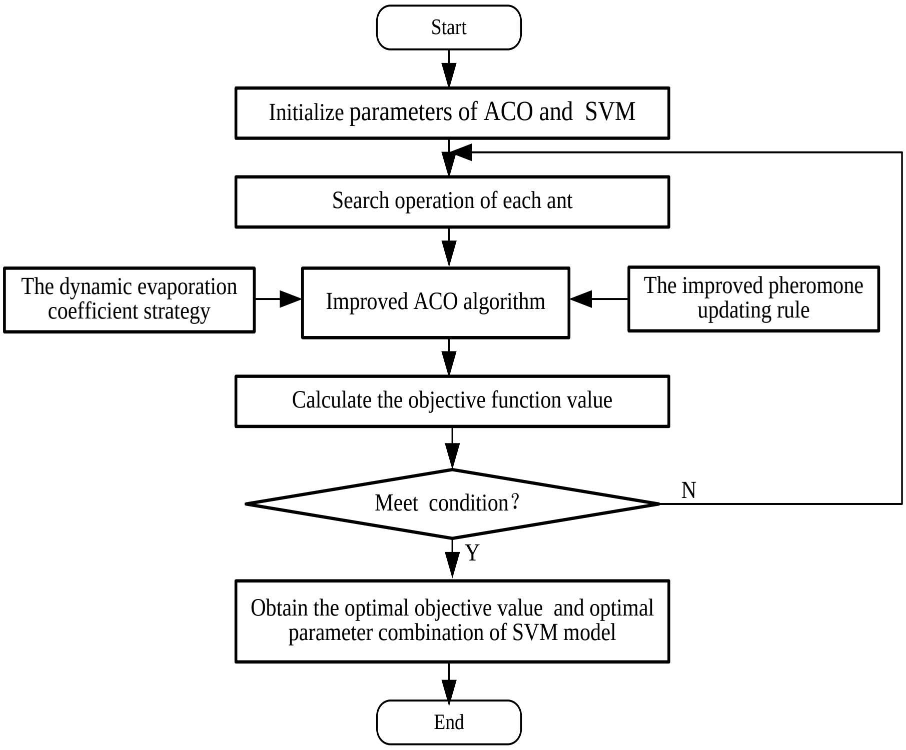

Figure 1. The Parameter Optimization Flow of SVM

6. Experimental Results and Conclusions

In order to verify the effectiveness of the proposed ERURACO-SVM method, the experiment data from UCI data set are selected in this paper. The detail describing of the experiment data is shown in Table 1. And the SVM and ACO-SVM based on ACO and SVM are selected as the contrast models in order to more accurately compare the effectiveness of the ERURACO-SVM method under the same experiment data sets. The experiment environment: Intel(R) Core i5,2.40GHz, 2G RAM, Windows XP, Matlab 2012.

Table 1. UCI Data

Data set	Samples	Train samples	Test samples	Dimension	Classification
Yeast	520	340	170	8	3
Poker hand	1088	788	300	11	54
Adult	590	350	240	14	3
Shuttle	800	500	300	20	12

The experiment selects the different initial samples, which are regarded as the training samples to train the SVM model. The initial values of parameters of

ERURACO-SVM, SVM and ACO-SVM could seriously affect the experiment results, so the most reasonable initial values of parameters of ERURACO-SVM, SVM and ACO-SVM are obtained by testing and modifying them. In this experiment, the obtained initial values of these parameters are: ants m =50, pheromone factor α =1.0, heuristic factor β =1.0, initial value of evaporation factor ρ =0.80, pheromone amount Q =100, maximum iteration times $T_{\max}$ =600. The tuning parameter C and kernel width σ is coded by binary, $C \in [0, 1000]$, $\sigma \in [0.1, 100]$, the error of optimal solution $\varepsilon = 0.005$. The RBF kernel function is selected as the kernel function of SVM model. Each data set is executed 20 times in order to fairly evaluate the accuracy of the ERURACO-SVM, SVM and ACO-SVM. Then the average value is regarded as the comparison results. The classification results are shown in Table 2 and Table 3.

Table 2. The Classification Results

Data set	Samples	SVM	ACO-SVM	ERURACO-SVM
Yeast	170	87.1%	90.6%	**95.3%**
Poker hand	300	49.0%	52.3%	65.7%
Adult	240	89.2%	91.3%	**94.6%**
Shuttle	300	62.7%	82.3%	88.3%

Table 3. The Test Result of ERURACO-SVM Method

Data set	C	σ	ERURACO-SVM
Yeast	137.6	0.1	95.3%
Poker hand	663.4	79.3	65.7%
Adult	135.1	2.8	94.6%
Shuttle	35.8	7.2	88.3%

From the experimental results of Table 2, it can be seen that the ACO-SVM method has the premature convergence, and poor local search ability. And the ERURACO-SVM method takes on the search abilities of the local optimal solution and the global optimal solution. For Yeast and Adult samples, the SVM method can only obtain the classification accuracy (87.1% and 89.2%), and the ERURACO-SVM method can obtain the classification accuracy(95.3% and 94.6%). So the classification accuracy of the ERURACO-SVM method is better than the SVM and ACO-SVM methods. The results show that the ERURACO-SVM method takes on the strong generalization ability and the higher classification accuracy.

7. Conclusion

Data classification is an important concept and technology in the data mining. It includes establishing the classification model and classifying new data. Support vector machine (SVM) is a machine learning method with the good generalization ability and prediction accuracy. The SVM model can effectively realize the classification for small sample and nonlinear problem. But the parameter of SVM model seriously affects the generalization ability and prediction accuracy on the great extent. So an improved ant colony optimization (ACO) algorithm is introduced into the support vector machine (SVM) model in order to propose a new data classification(ERURACO-SVM) method. The pheromone evaporation rate strategy and pheromone updating rule are introduced into the ACO algorithm to improve the optimization performance of the ACO algorithm. Then improved ACO algorithm is used to find the optimal combination of parameters of the SVM model. And the experimental data from the UCI machine learning database are selected to validate the classification correctness of the ERURACO-SVM method. The results show that the ERURACO-SVM method takes on the strong generalization ability and the higher classification accuracy.

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References

[1] V. Nedic, S. Cvetanovic and D. Despotovic, "Data mining with various optimization methods", Expert Systems with Applications, vol. 41, no.8, **(2014)**, pp. 3993-3999.
[2] W. Deng, R. Chen, B. He, Y. Q. Liu, L. F. Yin and J. H. Guo, "A novel two-stage hybrid swarm intelligence optimization algorithm and application", Soft Computing, vol. 16, no. 10, **(2012)**, pp. 1707-1722.
[3] W. Deng, R. Chen, J. Gao, Y. J. Song and J. J. Xu, "A novel parallel hybrid intelligence optimization algorithm for a function approximation problem", Computers and Mathematics with Applications, vol. 63, no. 1, **(2012)**, pp. 325-336.
[4] P. Kemal, "Data weighting method on the basis of binary encoded output to solve multi-class pattern classification problems. Expert Systems with Applications", vol. 40, no. 11, **(2013)**, pp. 4637-4647.
[5] J. F. Peters, Z. Suraj, S. Shan, S. Ramanna, W. Pedrycz and N. Pizzi, "Classification of meteorological volumetric radar data using rough set methods", Pattern Recognition Letters, vol. 24, no. 6, **(2013)**, pp. 911-920.
[6] W. Deng, H. M. Zhao, J. J. Liu, X. L. Yan, Y. Y. Li, L. F. Yin and C. H. Ding, "An improved CACO algorithm based on adaptive method and multi-variant strategies", Soft Computing, vol. 19, no. 3, **(2015)**, pp. 701-713.
[7] L. Wang, Q. Niu and M. R. Fei, "A novel quantum ant colony optimization algorithm and its application to fault diagnosis", Transactions of the Institute of Measurement and Control, vol. 30, no. 3-4, **(2008)**, pp. 313-329.
[8] S. W. Lin, K. C. Ying, S. C. Chen and Z. J. Lee, "Particle swarm optimization for parameter determination and feature selection of support vector machines", Expert Systems with Applications, vol. 35, no. 4, **(2008)**, pp. 1817-1824.
[9] C. L. Huang and J. F. Dun, "A distributed PSO-SVM hybrid system with feature selection and parameter optimization", Applied Soft Computing Journal, vol. 8, no. 4, **(2008)**, pp. 1381-1391.
[10] C. L. Huang, "ACO-based hybrid classification system with feature subset selection and model parameters optimization", Neurocomputing, vol. 73, no. 1-3, **(2009)**, pp. 438-448.
[11] X. L. Zhang, X.F. Chen and Z. J. He, "An ACO-based algorithm for parameter optimization of support vector machines", Expert Systems with Applications, vol. 37, no. 9, **(2010)**, pp. 6618-6628.
[12] O. Kadri, L. H. Mouss and M. D. Mouss, "Fault diagnosis of rotary kiln using SVM and binary ACO", Journal of Mechanical Science and Technology, vol. 26, no. 2, **(2012)**, pp. 601-608.
[13] A. R. Baig and W. Shahzad, "A correlation-based ant miner for classification rule discovery", Neural Computing and Applications, vol. 21, no. 2, **(2012)**, pp. 219-235.
[14] F. Samadzadegan, W. Shahzad and T. Schenk, "Simultaneous feature selection and SVM parameter determination in classification of hyperspectral imagery using Ant Colony Optimization", Canadian Journal of Remote Sensing, vol. 38, no. 2, **(2012)**, pp. 139-156.
[15] H. Y. Jiang and J. M. Liu, "Automatic liver cirrhosis diagnosis based on SSM and ACO-SVM", Journal of Information and Computational Science, vol. 9, no. 18, **(2012)**, pp. 5927-5934.

[16] H. L. Yu, J. Ni and J. Zhao, "ACOSampling: An ant colony optimization-based undersampling method for classifying imbalanced DNA microarray data", Neurocomputing, vol. 101, **(2013)**, pp. 309-318.
[17] M. M. Mostafa and M. D. Toksari, "Market segmentation of organ donors in Egypt: A bio-inspired computational intelligence approach", Neural Computing and Applications, vol. 20, no. 8, **(2011)**, pp. 1229-1247.
[18] F. Q. Yuan, K. Uday and G. Diego, "Failure diagnosis of railway assets using support vector machine and ant colony optimization method", International Journal of COMADEM, vol. 15, no. 2, **(2012)**, pp. 3-10.
[19] X. L. Tang, L. Zhuang, J. Cai and C. B. Li, "Multi-fault classification based on support vector machine trained by chaos particle swarm optimization", Knowledge-Based Systems, vol. 23, no. 5, **(2010)**, pp. 486-490.
[20] S. W. Fei, "Diagnostic study on arrhythmia cordis based on particle swarm optimization-based support vector machine", Expert Systems with Applications, vol. 37, no. 10, **(2010)**, pp. 6748-6752.
[21] S. Palanisamy and S. Kanmani, "Classifier ensemble design using artificial bee colony based feature selection", International Journal of Computer Science, vol. 9, no. 3, **(2012)**, pp. 522-529.
[22] X. Li, A. N. Zheng, X. N. Zhang, C. C. Li and L. Zhang, "Rolling element bearing fault detection using support vector machine with improved ant colony optimization", Journal of the International Measurement Confederation, vol. 46, no. 8, **(2013)**, pp. 2726-2734.
[23] S. M. Vieira, L. F. Mendonça, G. J. Farinha and J. M. C Sousa, "Modified binary PSO for feature selection using SVM applied to mortality prediction of septic patients", Applied Soft Computing Journal, vol. 13, no. 8, **(2013)**, pp. 3494-3504.
[24] X. Z. Wang, "ACO and SVM selection feature weighting of network intrusion detection method", International Journal of Security and its Applications, vol. 9, no. 4, **(2015)**, pp. 259-270.
[25] A. J. G. Mohammad, K. Shamsul, M. Faruq and J. F. Hessam, "Feature decision-making ant colony optimization system for an automated recognition of plant species", Expert Systems with Applications, vol. 42, no. 5, **(2015)**, pp. 2361-2370.
[26] T. E. Turker, T. Cumhur and C. Merve, "A wrapper-based approach for feature selection and classification of major depressive disorder-bipolar disorders", Computers in Biology and Medicine, vol. 46, **(2015)**, pp. 127-137.
[27] A. S. Mahani, S. Shojaee, E. Salajegheh and M. Khatibinia, "Hybridizing two-stage meta-heuristic optimization model with weighted least squares support vector machine for optimal shape of double-arch dams", Applied Soft Computing Journal, vol. 27, **(2015)**, pp. 205-218.
[28] M. Panda and A. Abraham, "Hybrid evolutionary algorithms for classification data mining", Neural Computing and Applications, vol. 26, no. 3, **(2015)**, pp. 507-523.
[29] C. S. Li, X. L. An and R. H. Li, "A chaos embedded GSA-SVM hybrid system for classification", Neural Computing and Applications, vol. 26, no. 3, **(2015)**, pp. 713-721.
[30] A. A. Aburomman and M. B. I. Reaz, "A novel SVM-kNN-PSO ensemble method for intrusion detection system", Applied Soft Computing Journal, vol. 38, **(2016)**, pp. 360-372.
[31] M. Dorigo and M. Gambardellal, "Ant colony system: A cooperative learning approach to the traveling salesman problem", IEEE Transactions on Evolutionary Computation, vol. 1,no. 1, **(1997)**, pp. 53-66.
[32] V. Cortesc, "Support vector networks", Machine Learning, vol. 2, no. 3, **(1995)**, pp. 273 -297.

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