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Feature Selection and SVM Parameter Synchronous Optimization Based on a Hybrid Intelligent Optimization Algorithm

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Abstract

Amid the rapid development of science and technology and the increasingly fierce market competition, low cost coupled with high performance is the key to a company's competitiveness. This requires optimizing all the links in the actual output. Hybrid intelligent algorithms can combine the advantages of different algorithms to solve a large number of optimization problems in engineering practice. Therefore, this study is focused on a hybrid swarm intelligence algorithm and its application. As a classic method of machine learning, the kernel function, which is based on the support vector machine (SVM) and the selection of the parameters in the kernel function, has an important influence on the performance of the classifier. The use of kernel function technology cannot only greatly reduce the amount of calculation in the input space, but can also effectively improve machine learning classification performance. In the field of machine learning, choosing and building the core functions is a notable difficulty. However, little research has been conducted in this area so far. In view of the above problems, this study discusses and analyzes the structure of the support frame machine core in detail, and improves the traditional parameter optimization algorithm. It also proposes a new method of fuzzy clustering algorithm automatic parameter learning combined with the basic ideas of a genetic algorithm in order to improve the parameter optimization strategy of support vector regression, so as to obtain better prediction results. Through simulation experiments, the improved hybrid core SVM and parameter optimization algorithm were applied to the ORL face database, greatly improving the recognition rate, and experiments were carried out after adding noise to the images in the face database to verify the practicability and practicality of the algorithm. The robustness and reliability of the algorithm were improved by at least 30%, thus confirming the feasibility of the proposed algorithm.

Keywords

Hybrid Intelligence, Optimization Algorithm, Feature Selection, Parameter Synchronization Optimization

1. Introduction

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With the explosive development of the internet and information technology, network information has brought us many conveniences, but negative effects in such as areas as information security have also gradually emerged. Some criminals have used information networks to illegally steal state secrets and commercial materials. Due to these threats to social stability, the importance of information security has become even more prominent. Traditional methods of identity verification mainly include ID cards, driving licenses, passwords, passwords, and so forth. Although these methods can encrypt information to a certain extent, magnetic cards, IC cards, and the like are easy to lose, and passwords are easy to forget, among many other problems, so they are gradually being abandoned by the great majority of people.

The purpose of optimization is to optimize target measurement. Efficient optimization technology is the key to saving energy, reducing costs, and improving reliability. The basic principle of traditional optimization methods is to use the idea of calculus to determine the extreme value of the objective function. However, with the increasing number of industries covered by optimization techniques, the emerging problems are becoming increasingly complicated, and traditional optimization methods seem unable to solve these problems, and are accordingly judged to be incompetent. At the present time, compared with traditional methods, some intelligent algorithms have begun to enter people's field of vision due to their own unique advantages. Intelligent algorithms are produced by imitating biological behaviors, and their principles are simple and easy to implement. Search it is highly efficient and can solve a wide range of practical engineering problems.

A study by Wen Haibiao et al. reported that when the supported carrier machine (SVM) processes large sample datasets with a large number of feature dimensions, the algorithm is very time-consuming and difficult to use in local optimal solutions. Choosing inappropriate SVM algorithm parameters will affect the classification performance of the SVM model. In order to improve the performance of the SVM, he proposed an algorithm for optimizing the synchronization of the SVM parameters, which combines particle swarm optimization (PSO), genetic algorithm (GA) perform feature selection, and parameter synchronization. Experiments using standard UCI datasets show that the polygenic scores (PGS) algorithm can effectively find the appropriate function set and parameters of the SVM algorithm, improve the convergence speed, and achieve higher classification accuracy in a smaller feature subset. However, the range of experimental error is relatively large, making it necessary to perform multiple experiments to obtain accurate results. Wang Lianhong believes that in order to eliminate unnecessary data in feature extraction and to optimize the classification performance of the SVM (support machine), some researchers have proposed to use particle algorithms to select the features and optimize the classification parameters. However, the particle algorithm is too fast and simple to calculate, so the classifier parameters often cannot be synchronized. It is applied to a discrete space, and the attribute selection and classifier parameters are not synchronized or optimized. To resolve the aforementioned problems, this study proposes a new SVM algorithm to select the features in a discrete space and to SVMs. Regarding modern parameter optimization, experimental results show that the SVM algorithm can effectively filter the feature sets, optimize the SVM parameters, reduce space complexity, and improve the face detection rate and robustness. But as the algorithm has not been practically applied, it needs to be promoted and optimized. A study by Fan reports that vector-assisted theory has been widely used in pattern classification in recent years, but the two main factors affecting classification accuracy, namely, feature selection and parameter optimization, interact with and restrict each other. He proposed a BA+SVM algorithm that uses the Bat algorithm (BA) to optimize the SVM parameters and select input data at the same time, thereby improving the classification ability of the SVM, and developed three experimental methods in 10 test datasets. The results show that, compared with the algorithm used for parameter optimization or single feature selection, the modern BA+SVM optimization algorithm has the advantages of having fewer input functions and greater accuracy. However, the algorithm runs slowly and has low practicability, and thus needs to be strengthened.

Adding the gravity of the intermediate fitness particle to the current particle to the speed update formula of the standard PSO algorithm to avoid the blind search of the particle only under the guidance of the global optimal particle and the individual optimal particle. The introduction of the intermediate fitness particle can provide the particle multiple experiences. In summary, recommendation systems are used in various fields of the Internet, which can solve the problem of "information overload" and help users to locate the range of resources they need very quickly. Therefore, studying the problem of recommender systems has become an important topic in Internet applications. The parameter synchronization optimization problem of the SVM has become the focus of research by countless experts and scholars [1]. A good optimization algorithm can produce huge application value. Collaborative filtering algorithm and particle swarm algorithm can play a role in solving the recommendation algorithm problem. When analyzing the collaborative filtering algorithm and the particle swarm algorithm, this paper mainly considers the influence of the time factor on the correctness of the collaborative filtering algorithm and the particle swarm algorithm, so as to improve the accuracy of optimization [2].

2. Related Work

At present, China's Doppler weather radar is usually used for quantitative precipitation estimation (QPE) based on the Z-R relationship. However, the estimation error of mixed precipitation is very large. In order to improve the accuracy of radar QPE, Changjiang proposed a 6-minute dynamic radar QPE algorithm based on the reflectivity data of the Doppler radar Z9002 in the Qingpu district of Shanghai and the precipitation data of automatic weather stations (AWSs) in eastern China.

Considering the time dependence and mutation of precipitation, the first 30 minutes of data were selected as training data. In order to reduce the complexity of radar QPE, the stationary wavelet transform (SWT) is used to convert the weather data into the wavelet domain, and the high and low frequency reflectivity and precipitation information are extracted. Using wavelet coefficients, a SVM was constructed on all scales to estimate the wavelet coefficients of precipitation. Finally, the estimated rainfall was obtained by inverse wavelet transform (IWT). However, the variables controlled in the experiment were not very clear [3, 4]. Cloud computing is widely accepted by individuals and enterprises in storing multimedia content. This is due to the introduction of a new architecture, which has lower service costs for computing, storage, and maintaining multimedia storage. However, cloud users must take some measures to avoid privacy problems. In order to provide multimedia security, Sukumar et al. [5] transformed the multimedia content using discrete Rajan transform (DRT) and embedded it into the selected cover image, which was generated by integer wavelet using the diamond coding scheme. The generated hidden images were stored in the cloud. When multimedia content was needed, the hidden image was downloaded from the cloud and inversely transformed by IWT. SVM provides good learning ability for the extraction process, which makes the algorithm more robust to various attacks (i.e., salt and pepper noise, Gaussian noise, clipping, compression, etc.). The experimental value of the peak signal-to-noise ratio (PSNR) was 53 and 50 for two secret images, which is better than the existing scheme. Similarly, the scheme provided better results for robustness and security evaluation. But it is not very suitable for practical applications [5]. The SVM is a powerful technology in terms of pattern classification, but its performance depends on its parameters to a great extent. Li et al. [6] proposed a new SVM, which was optimized by a new differential evolution (DE), adopted the mixed parameter setting strategy and population size adaptive method, and was simplified to FDE-PS-SVM. In the mixed parameter setting strategy, the parameter offspring of the SVM was generated by the operator with fixed evolutionary parameters, or by fuzzy logic reasoning (FLR) according to a given probability. In the population size adaptive method, the population size was gradually reduced in the search process, by trying to balance the diversity and concentration ability of the algorithm and find better SVM parameters. Some benchmark datasets were used to evaluate the proposed algorithm. The experimental results show that these two strategies can effectively search for better SVM parameters, and the performance of the FDE-PS-SVM algorithm is better than other algorithms proposed in other literatures. However, the simplification of the experimental methods needs to be improved [6].

Air pollution prediction plays an important role in helping to reduce air pollutant emissions, guiding people's daily activities and warning the public in advance. However, previous studies still have many shortcomings, such as ignoring the importance of outlier detection and correction of the original time series, and the randomness of the initial parameters of the model. To solve such problems, Wang et al. [7] proposed a hybrid model based on an outlier detection and correction algorithm and a heuristic intelligent optimization algorithm. First, the data preprocessing algorithm was used to detect and correct outliers and mine the main features of the original time series; second, a widely used heuristic intelligent optimization algorithm was used to optimize the parameters of the limit learning machine, and the prediction results of each subclass were obtained, improving prediction accuracy; and, finally, the experimental results and analysis showed that the proposed hybrid model provides accurate prediction superior to that of other comparative models, but it is not practical [7]. Over the past few decades, through research on natural organisms, a large number of intelligent algorithms based on social intelligent behavior have been widely studied and applied to various optimization fields. The learning-based intelligent optimization algorithm (LIOA) is an intelligent optimization algorithm with certain learning abilities. This is how the traditional intelligent optimization algorithm combines the learning operator or specific learning mechanism to give itself a certain learning ability, so as to achieve better optimization behavior. Li et al. [8] conducted a comprehensive survey of the LIOA. The research contents included a statistical analysis of the LIOA, classification of LIOA learning methods, application of the LIOA in complex optimization scenarios, and application of the LIOA in engineering applications. The future views and development direction of the LIOA were also discussed, but it was not applied in detail [8]. In recent years, with the widespread application of the SVM in machine learning applications, it has become very important to obtain a sparse model that is sufficiently robust to withstand the noise in the dataset. Singla et al. [9] sought to enhance the sparsity of RSVM-RHHQ (robust support vector machine-rescaled hinge loss function) using a non-smooth regularizer with non-convex and non-smooth loss functions, and used the primal dual approximation method to solve the non-smooth non-convex problem. It was soon found that this combination not only increased the sparsity of the model, but also outperformed the existing robust SVM methods in terms of robustness to label noise. In addition, the time complexity of the optimization technology was also considered. The experimental results showed that this method was superior to existing methods in terms of sparsity, accuracy, and robustness. In addition, a sensitivity analysis of the label noise regularization parameters in the dataset was conducted. However, the experimental operation was too cumbersome and too many aspects were considered, resulting in too many constraints [9]. Based on artificial intelligence technology, modern irrigation systems need to be improved all the time. In his research work, Ali et al. [10] proposed a new population-based meta-heuristic algorithm called the “control shower optimization” (CSO) algorithm for the global optimization of unconstrained problems. Modern irrigation systems are equipped with intelligent tools made and controlled by human intelligence. The proposed CSO algorithm was inspired by the function of the water allocation tool, which is used to model the search agent that performs the optimization process. CSO simulates the mechanism of the sprinkler projecting the water unit and its platform moving to the required position to plan the best search program. The proposed method has been tested with many low-dimensional and high-dimensional benchmark functions with different properties. Statistical analysis of the empirical data showed that CSO provides a solution of higher quality than several other effective algorithms, including the GA, the PSO algorithm, the DE algorithm, the artificial bee colony (ABC) algorithm, and the covariance matrix adaptive evolution strategy (CMA-ES), However, in the specific application, it is still necessary to continue investigating according to the actual situation [10]. In order to improve the marketing effects of e-commerce products, Cui et al. [11] constructed an e-commerce product marketing model based on machine learning and the SVM based on a machine learning algorithm. In addition, he also studied the classical reinforcement learning algorithm known as “Q-learning” and proposed an improved Q-learning algorithm. In addition, the mean normalization method was used to reduce the noise impact of the reward signal caused by the non-fixed time interval between decision points. Aiming at the deviation caused by the asynchronous update of time intervals in the iterative process of the Q-value function, the standardization factor was further constructed. However, the experimental data of this algorithm were not very convincing [11]. Research on intelligent algorithms has always been a hot topic in the field of human-centered computing, and continues to expand with the development of artificial intelligence. Usually, coupled data fusion algorithms usually use the information of one dataset to improve estimation accuracy and explain the relevant latent variables of other coupled datasets. Lu et al. [12] proposed several coupled image decomposition algorithms based on a coupling matrix with a tensor decomposition optimization (CMTF-OPT) algorithm and a flexible coupling algorithm, which are called the "coupled image decomposition optimization" (CIF-OPT) algorithm and the "improved flexible coupling" algorithm, respectively. Theory and experiments have shown that the effect of the CIF-OPT algorithm is robust under the influence of different noise. In particular, the CIF-OPT algorithm can accurately recover images that have lost some data elements. However, the experiment is not very representative [12]. With the continuous progress of computer and information technology, a large number of research papers are now being published online and offline all the time. With the continuous emergence of new research fields, it is difficult for users to find interesting research papers and classify them. In order to overcome these limitations, Kim and Gil [13] proposed a research paper classification system capable of clustering research papers into meaningful categories, in which papers are likely to have similar topics. The proposed system extracts representative keywords from the topics of each paper and topic through the potential Dirichlet assignment (LDA) scheme. Then, based on the word frequency inverse document frequency (TF-IDF) value of each paper, all papers are classified into research papers with similar topics by the K-means clustering algorithm. However, this experimental method did not prove to be sufficiently innovative [13].

3. Method of Feature Selection of the Hybrid Intelligent Optimization Algorithm

3.1 Basic Principles of the Particle Swarm Algorithm

At present, the most commonly used task scheduling algorithm in the cloud computing workflow management system is the particle swarm algorithm proposed by Eberhart and Shi. The origin of the particle swarm algorithm has been described in detail in the research background provided in the previous chapter. As each and every particle in the particle swarm algorithm is like a bird, the optimization process of the algorithm is like a flock of birds looking for food. The particle gradually approaches the optimal solution by adjusting its own speed and direction, just as birds flying together in a flock adjust their speed and direction of flight by cooperating with each other and sharing positional information, and then find food.

The particle swarm algorithm is the most widely used intelligent optimization algorithm because it has several characteristics that are very convenient for researchers to learn and improve, i.e., the algorithm has fewer parameters, is easy to program, and, most importantly, has a faster convergence speed. However, the particle swarm algorithm also has an obvious shortcoming in that it is very easy to fall into a local optimal solution, which makes the algorithm unable to find an accurate optimal solution after iteration [14].

3.2 Features of the Particle Swarm Algorithm

The good performance of the particle swarm algorithm mainly stems from some of its advantages, which are mainly as follows:

(1) The principles and implementation process of the particle swarm algorithm are simple and easy to understand, and relatively easy to expand. Most researchers choose the particle swarm algorithm and other intelligent optimization algorithms for fusion, and its effects are remarkable [15].

(2) The particle swarm algorithm entails the adjustment of fewer parameters and is easier to understand than other intelligent algorithms. Researchers can make appropriate improvements and optimizations to the particle swarm algorithm according to the specific optimization problems that need to be solved. Generally, it is more extensive to choose to improve the inertia weight, and the optimization effect is more obvious. The principle is shown in Fig. 1.

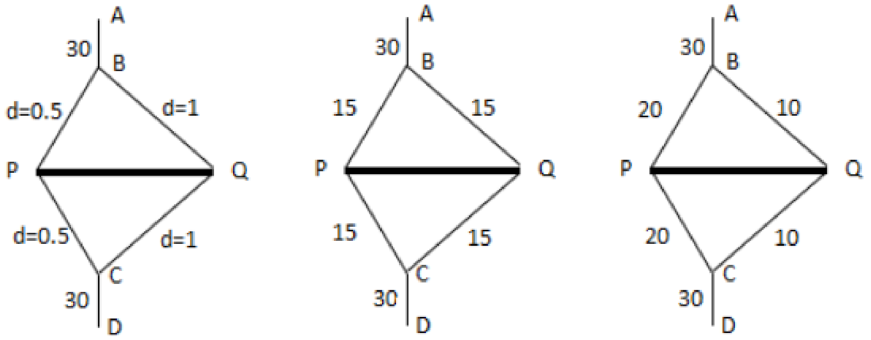


Fig. 1. Schematic diagram of the particle swarm algorithm. The picture is taken from https://image.baidu.com/.

3.3 User-based Collaborative Filtering

According to the user's behavior records, an algorithm that uses similarity statistics to identify neighboring users with similar interests or preferences is called a "user-based collaborative filtering" algorithm, and can also be called "neighbor-based." Collaborative filtering functions as follows: when a user's rating matrix R for movies or music is defined and the similarity function S between users is defined, the algorithm can estimate the items that the user may also be interested in based on the behavior information of the user's neighbors with regard to other items. Therefore, it may be reasonable to think that users give the same rating for the same product, which means that the users are "similar" to each other, and thus it is reasonable to recommend products that similar users like to target users [16, 17]. Therefore, it can be concluded that the main steps in implementing the user-based collaborative filtering algorithm are as follows:

(1) Calculate the similarity between users and find other users who are most similar to the recommended person.

(2) Calculate the items that are liked by these most similar users and are not noticed by the recommended users, and then recommend them to the latter.

3.4 Item-Based Collaborative Filtering

Since the calculation time of the user-based collaborative recommendation algorithm will increase with the increase in the number of users, Sarwar (2001) released a new recommendation algorithm, item-based collaborative filtering recommendation algorithm designed to resolve this limitation. Therefore, according to the above introduction to the user-based (item-based) algorithm, this study assumed the following in the context of e-commerce: if a product similar to a customer's favorite product is recommended to that customer, the similar product will be liked and purchased by many customers at the same time. According to this assumption, the features of the item-based collaborative filtering algorithm are as shown in Fig. 2: (1) calculate the similarity between items and (2) generate a recommendation list for target customers based on the customer's purchase history.

The MapReduce calculation process is shown in Fig. 2. Thus, where a customer purchases a large number of different commodities at one time, he or she can similarly weaken the weight of calculating the similarity between those commodities. In addition, considering the diversity of the recommendation results, when generating a recommendation list, the weight of some products that are too "hot" can also be similarly weakened., In addition, when using the user's historical purchase information, it is generally believed that the recent purchase history will be more valuable than the older purchase situation, so that some time-weight preferences and so on will also be considered.

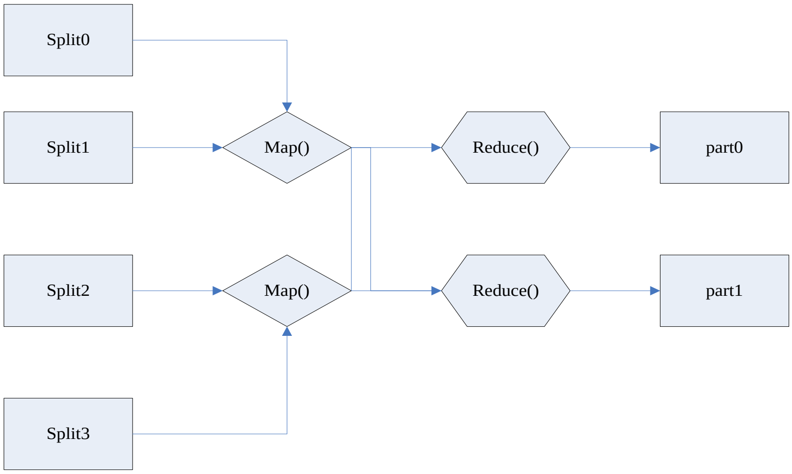


Fig. 2. MapReduce calculation process.

4. SVM Parameter Synchronization Optimization Correlation Experiment

4.1 Linear Support Vector Machine

The kernel function is the most important part of the support vector machine. The different choices of the kernel function lead to different types of SVMs. The introduction of the kernel function can transform complex nonlinear problems into easy-to-solve linear problems [18]. It has a similar function to that of the converter. This algorithm can map the original data space to a high-dimensional data space, so that the data have better linear separability in the feature space. The concept of the linear SVM is to search for an optimal classification hyperplane, which cannot only correctly separate the two types of samples, but also satisfy the interval between the classification samples to the largest extent possible and the error to the smallest extent possible. In the low-dimensional space, L is the classification line [19, 20]. If this idea is extended to the high-dimensional space, the optimal classification line becomes the corresponding optimal classification surface.

Assuming that the given sample training set $T=\{(x_1,y_1),(x_2,y_2),...,(x_n,y_n)\}$ is the category label, the expression of the classification line L in the m-space is as follows:

$$W \bullet x + b = 0 \tag{1}$$

In this formula, W is the normal vector of the classification hyperplane, "•" is the symbol for the inner product operation, and b is the offset. Converting solving the optimal classification line into a quadratic programming problem:

$$\varphi(w,b) = \frac{1}{2}||w||^2 \tag{2}$$

The linearly separable sample set satisfies:

$$y_i(w \bullet x_i) + b \geq 1, i = 1,2,\ldots,n \tag{3}$$

When Equation (3) takes the equal sign, the samples at this time are called support vectors. The Lagrange multiplier method can be used to obtain the optimal solution:

$$L(W,S,Q) = \frac{1}{n}||w||^2 - \sum_{i=1}^{n} Q\,(S(w \bullet x_i + b) - 1) \tag{4}$$

Among these, Q is the Lagrangian multiplier, and its value is greater than zero. In order to obtain the minimum value of Equation (4), one should find the derivatives of variables W and b, and then set their derivatives to 0, respectively, to obtain the following:

$$\frac{\partial L}{\partial W} = 0 \Rightarrow W = \sum_{i=1}^{n} Q x_i \tag{5}$$

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} Q\, y_i = 0 \tag{6}$$

At this time, when formulas (5) and (6) are substituted into (4), the problem is transformed into the dual problem of finding convex quadratic programming:

$$max\, w\,(Q) = \sum_{i=1}^{n} Q_i Q_j (x_i \bullet x) \tag{7}$$

4.2 Nonlinear Support Vector Machine

The previous section includes a detailed introduction to the process of solving the SVM optimal hyperplane in the linearly separable case; however, in actual problems, not all samples are linearly separable, and a large part of the samples are linearly inseparable. Linear inseparability means that the samples in the sample set cannot be completely separated by an optimal classification surface. In the case of linear inseparability, the sample input space can be transformed into a linear problem in a high-dimensional space through nonlinear transformation, and the linear optimal classification hyperplane is found in the high-dimensional space. Such a high-dimensional space is also called a “feature space” [21, 22].

Fig. 3 is a schematic diagram of the optimal classification surface of the SVM in the case of nonlinearity, and $\varphi(x)$ is a nonlinear mapping function.

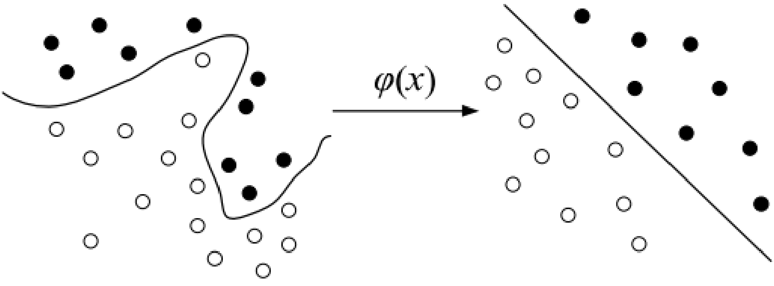


Fig. 3. Schematic diagram of the optimal classification surface of the SVM in the case of nonlinearity. The picture is taken from https://image.baidu.com/.

The SVM solves the linear inseparable situation by introducing the kernel function. The method of implementation consists is using the kernel function of the original input space to replace the inner product operation in the feature space, which can be expressed as $k(x,y)$ by mathematical expression. At this time, its classification hyperplane is expressed as:

$$w \bullet \varphi(x) + b = 0 \tag{8}$$

The classification function is:

$$f(x) = sgn(w \bullet \varphi(x) + b) \tag{9}$$

The optimal classification hyperplane is:

$$min \frac{1}{n} ||w||^n + C \sum_{i=1}^{n} w \tag{10}$$

In this formula, C is the penalty factor, and w is the slack variable, which is used to measure the actual output and the SVM. The dual problem is:

$$subject \quad to \quad 0 \leq Q_i \leq C, \sum_{i=1}^{n} yQ_i, i = 1,2,\ldots,n \tag{11}$$

Among these, let $k(x,y) = \varphi(x) * \varphi(y)$, which is called the “kernel function.” Then the classification function can be expressed as:

$$f(x) = sgn\{\sum_{i=1,j=1}^{n} Q_{i_j} K(x,y) + b\} \tag{12}$$

The corresponding sample is an SVM. The SVM replaces the inner product operation in the high-dimensional space by introducing the kernel function operation, which overcomes the "dimension disaster" problem that may be caused by multiple samples [23, 24]. When constructing the discriminant function, the traditional method consists in performing a nonlinear change first, and then inputting the result of the transformation into the feature space and performing the operation. The kernel function idea consists in first performing the inner product operation in the feature space, and then performing the linear transformation, which has the result of greatly reducing the amount of dimension and simplifying complicated problems. The output is a linear combination of M intermediate nodes, and each intermediate node corresponds to the inner product of the input sample and a support vector, so it is also called the “network structure of the support vector machine.” Since the final discriminant function actually only contains the linear combination of the inner product of the unknown vector and the support vector, the computational complexity during recognition depends on the number of support vectors [25, 26].

5. Feature Selection and SVM Parameter Synchronization Optimization Analysis

5.1 Stock Dataset Experiment and Analysis

This section gives a brief introduction to the singular spectrum transformation before discussing the experimental data. Singular spectrum analysis is mainly used to study nonlinear time series data. This method consists in constructing a trajectory matrix that can be decomposed and reconstructed from the time series it observes. With this operation, some signals representing different components of the original time series are obtained, so as to structure the time series and analyze and perform further forecasting operations [27, 28]. In this dataset, the main purpose of preprocessing using singular spectrum analysis is to reduce noise and achieve better prediction purposes.

Table 1. Grid algorithm of the stock dataset

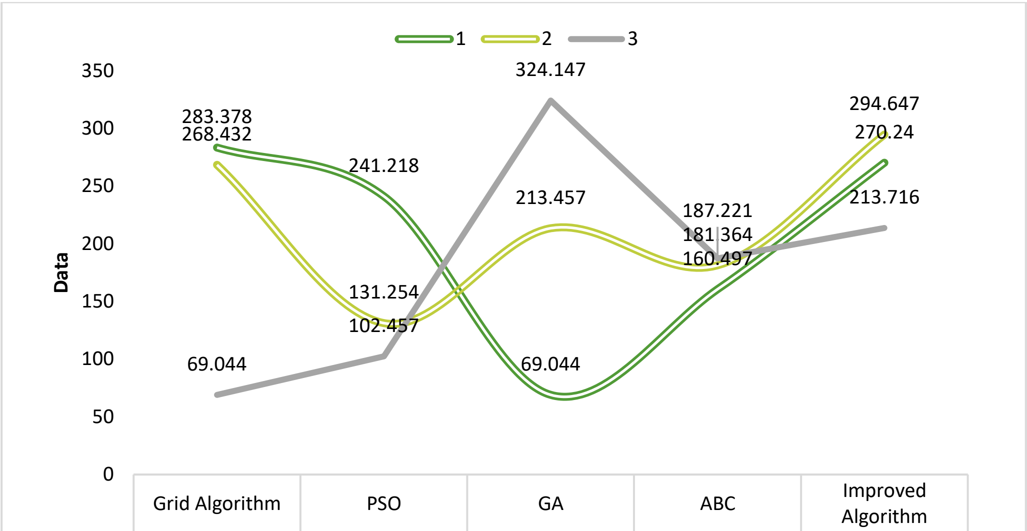
	First	Second	Third	Average value
c	2.000	2.000	2.000	2.000
σ (represented as *g* in MATLAB)	1.000	1.000	1.000	1.000
Time (s)	1755.9	1975.1	1851.2	1860.7
Mean training model (MSE)		0.00881757		

As shown in Table 1, the main steps of singular spectrum analysis are as follows: embedding, SVD decomposition, grouping, and reconstruction. Following the singular spectrum analysis, the dataset achieved the purpose of noise reduction to a certain extent, and the next step of formal data processing and prediction could be carried out. When using the grid optimization method to optimize this group of datasets, the exhaustive inefficiency of this method means the step size between grids should be 0.1 or smaller in order to achieve the same effect as other intelligent algorithms; however, in actual situations, it takes many hours to use only 0.1 step size, which is extremely inefficient. Other methods can only use the algorithm to find a better solution in just ten or tens of minutes. Therefore, in order to save time and improve efficiency, this part and subsequent datasets should adopt a 1-step step when comparing experiments using the grid optimization method.

	1	2
Grid Algorithm	0.88	0.82
PSO	0.83	0.81
GA	0.82	0.78
ABC	0.84	0.81
Improved Algorithm	0.82	0.78

Fig. 4. Stock dataset MSE comparison bar chart.

As shown in Fig. 4, the mean squared error (MSE) of the improved particle swarm optimization (improved algorithm) in this dataset will not be much lower than the MSE of the standard PSO. The main reason is that a large amount of data is used to train the value of the parameter group. But entering the "good area" is easy. In the "good area," changing *c* and *g* will not have a significant impact on MSE applications. At the same time, after simplifying the data to [-1.1], the difference between the data in the dataset is very small. Therefore, the data obtained according to the model obtained after training can easily accumulate similarity data at a certain price, because the calculation of MSE is similar. However, this does not mean that there is no need to improve this algorithm [27, 29]. In the next dataset, comparing the application of the improved algorithm with the standard PSO and the grid algorithm for MSE adaptation and calculation time, there is a more obvious improvement. In addition, when calculating the ABC algorithm and the GA, the value of parameter *c* is very high. When collecting the experimental values, many solutions were obtained in general. A part of the numerical value relatively close to this numerical value was used as the experimental value. The following records used the same processing method when dealing with the same situation.



	Grid Algorithm	PSO	GA	ABC	Improved Algorithm
1	283.378	241.218	69.044	160.497	270.24
2	268.432	131.254	213.457	181.364	294.647
3	69.044	102.457	324.147	187.221	213.716

Fig. 5. Time versus scatter curve of the Wisconsin dataset.

As shown in Fig. 5, in the experiment using this dataset, the improved algorithm of this paper is compared with the standard PSO. It plays a certain role in reducing MSE and improving the accuracy of fitting, but the improvement is limited. However, compared with the grid algorithm, ABC algorithm, and GA, the MSE solved by this algorithm is smaller. In the same time period, the parameter obtained by the grid algorithm, the MSE of the corresponding group is too high. The ABC algorithm is extremely fast in this dataset, but the MSE obtained is slightly higher [30, 31]. The GA has no great advantage in this dataset. Although the time is short, the MSE corresponding to the parameter set is not the smallest.

Similarly, as shown in Fig. 6, Keynes suggested that the analysis of short-term changes in stock prices should be based more on the psychological expectations of the relevant investors, rather than on the intrinsic value of the investment. Therefore, one can fully consider the complex intrinsic value of stocks and only analyze and predict short-term stock trends based on the market behavior of stocks. In summary, due to the characteristics of the technical analysis method itself, it is more suitable for the research conducted in this article and meets the requirements of students concerning the related research results. In this paper, technical indicators are used as the predictive features. The long-term trend of the stock market, according to the leading role of the big capital index in the overall market trend and the stock index futures market, chooses the rise and fall of the big capital index as the output variable, that is, the future is predicted according to the characteristic input, and the rise and fall of the equity index, in order to create a suitable predictive model [32, 33].

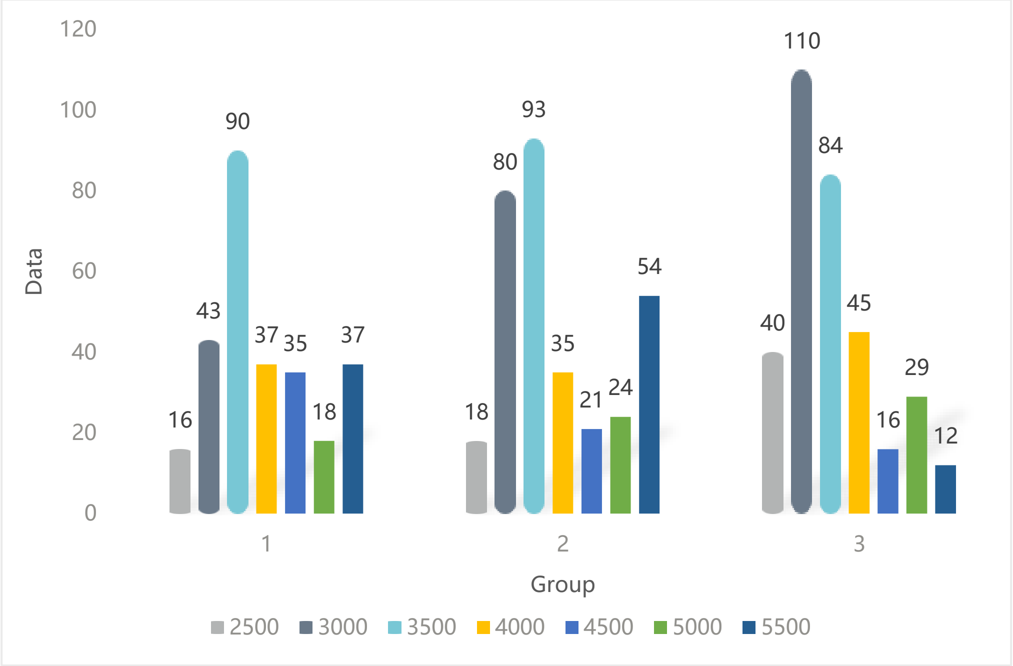


Fig. 6. Histogram of the Shanghai composite index.

5.2 Based on PCA-LSSVM and NSGA-II Hybrid Intelligent Algorithm

The anaerobic ammonia oxidation effluent ammonia nitrogen prediction model and the total nitrogen (TN) removal prediction model based on the PCA-LSSVM intelligent algorithm are yet to be established by the research institute. The basic process steps are as described above. When the parameters are selected, the radial basis function is still selected as the kernel function, and the initialization is based on the minimum selection of the parameters of the two-multiplication SVM; and the regularization parameter γ and the kernel parameter are shown in Table 2.

Table 2. Prediction performance of the PCA-LSSVM model for effluent NH_4^+-N and TN removal concentration

Model type	Type of data	MAPE (%)	RMSE	R
PCA-LSSVM NH_4	Training data	47.62	12.38	0.9926
N removal model	Forecast data	9.93	15.07	-
PCA-LSSVM TN	Training data	3.47	12.48	0.9849
Remove model	Forecast data	3.41	13.66	-

Comparing the simulated value given by the model and the actual value obtained in the experiment, there is little difference between the two, indicating that the multi-objective optimization model of the anaerobic ammonia oxidation denitrification system based on the PCA-LSSVM and NSGA-II hybrid intelligent algorithm established in this paper is more reliable. The optimal solution set has guiding significance for the actual process.

Further, Table 3 shows the distribution of the influent NH_4^+-N, NO_2^--N, chemical oxygen demand (COD) concentration and the pH parameters of each generation in the target iteration process with the change of the effluent ammonia nitrogen concentration. With the increase in concentration of effluent ammonia nitrogen, the influent pH value, influent ammonia nitrogen concentration, influent nitrite nitrogen and influent COD concentration all show a gradual upward trend. Among these, the influent pH value is distributed between 7.48 and 7.62. NH_4^+-N and NO_2^--N are distributed between 184–192 mg/L and 29–350 mg/L, and the influent COD concentration is between 50–300 mg/L [34].

Table 3. Distribution of the influent NH_4^+-N, NO_2-N, COD concentration and pH parameters with the change of the effluent ammonia nitrogen concentration

Serial number	Influent pH value	NH_4-N (mg/L)	NO_2 (mg/L)	COD (mg/L)
A1	7.51	184.61	301.11	74.58
A2	7.52	186.49	305.77	96.37
B1	7.56	188.94	313.15	132.30
B2	7.54	188.19	319.88	157.67

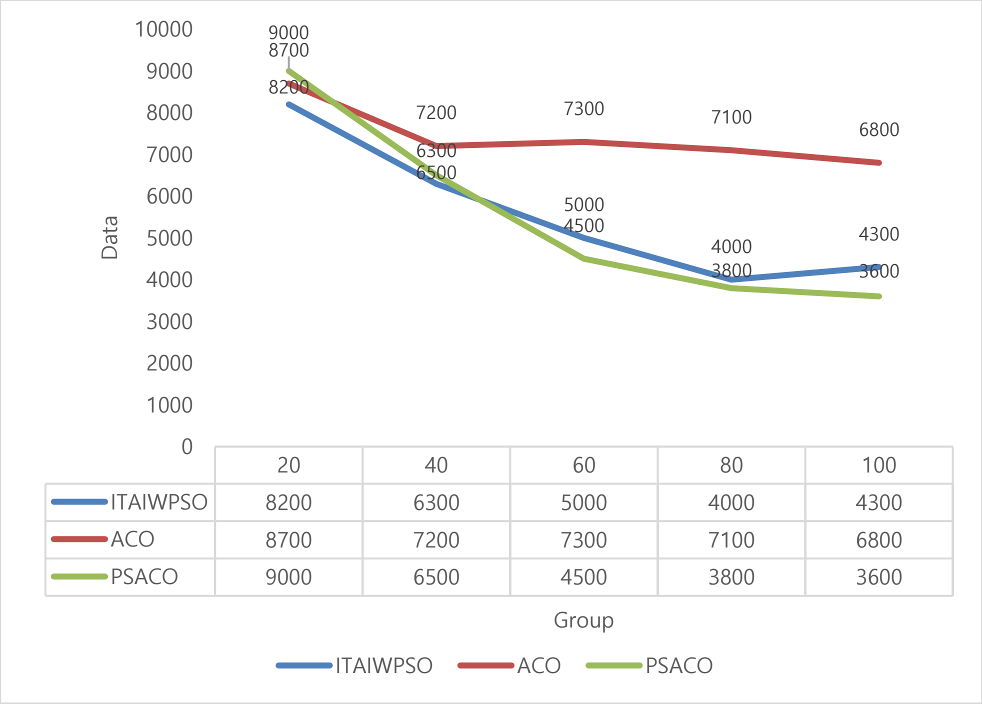


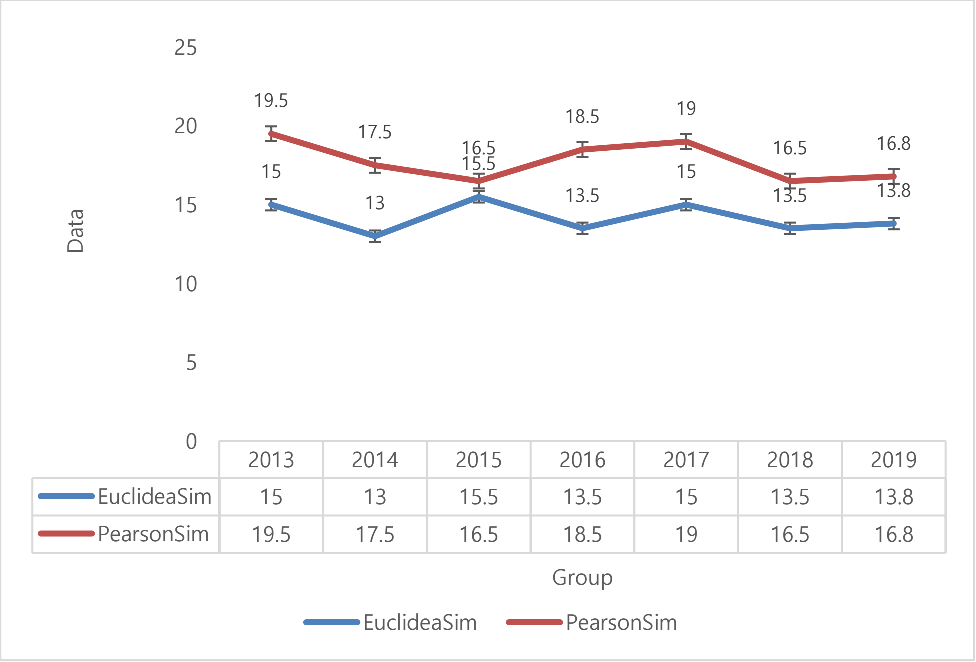
Fig. 7. Graph of the running results with the number of tasks set at 50.

Table 4. ITAIWPSACO scheduling algorithm parameters

Parameter name	Symbol	Value
Population size	s	100
Number of resources (number of virtual machines)	r	5
Number of tasks	tn	50–300
Maximum inertia weight	ωmax	1
Minimum inertia weight	ωmin	0

Fig. 7 shows the fusion scheduling algorithm (ITAIWPSACO), the improved particle swarm scheduling algorithm (ITAIWPSO), the ant colony algorithm (ACO), and the running results of these three task-scheduling algorithms when the number of tasks is 50. It can be clearly seen that the task completion time curve of the IPACO2 algorithm starts to converge faster when the number of iterations is 60. When the number of iterations ranges from 80 to 200, the ITAIWPSACO algorithm gradually converges and stabilizes to the optimal value when the task is completed, showing superior results to the case where the ITAIWPSO and ACO scheduling algorithms are used alone. Table 4 shows the running results of the three task-scheduling algorithms when the number of tasks is 300. It can be clearly seen that the ITAIWPSACO scheduling algorithm starts from the iteration number of 40 and that the task completion time curve tends to converge, and the iteration number is equal to 60 to 200. The task completion time curve of the second stage gradually stabilizes, almost converging to an optimal value, and shows better results than when the ITAIWPSO and ACO scheduling algorithms are used independently [35, 36].

As shown in Table 4, this experiment still uses Java as the development language, the cloud simulation platform CloudSim as the cloud computing environment, and Eclipse as the development tool. The fusion ITAIWPSACO scheduling algorithm proposed in this paper was compared and analyzed with the standard ACO scheduling algorithm and the ITAIWPSO scheduling algorithm. The parameters required for the experiment were set, and the integrated scheduling algorithm ITAIWPSACO fully absorbed the advantages of the ITAIWPSO algorithm and the ACO algorithm. Thus, the ITAIWPSACO scheduling algorithm performed better than the ACO scheduling algorithm at the initial stage of iteration, and it performed better than both the ITAIWPSO scheduling algorithm and the ACO scheduling algorithm at the later stage of iteration. When a certain number of tasks are completed, the task execution time of the ITAIWPSACO algorithm is quicker, the convergence speed is faster, and the convergence accuracy is higher.



	2013	2014	2015	2016	2017	2018	2019
EuclideaSim	15	13	15.5	13.5	15	13.5	13.8
PearsonSim	19.5	17.5	16.5	18.5	19	16.5	16.8

Fig. 8. Comparison of recommended results of different similarity calculation formulas.

The results of the analysis experiment are shown in Fig. 8. Through the analysis of the experimental data, it can be seen that the traditional collaborative filtering algorithm uses similar formulas based on the Pearson correlation coefficient (PCC) and Euclidean distance to produce recommendation results. There is a difference in the point spread ratio. The point spread ratio of the recommended result using the Pearson similar calculation formula is better than the point spread ratio using the Euclidean similar calculation formula. Therefore, the Pearson (PCC) is used. The recommended accuracy of collaborative filtering algorithms with similar formulas is more accurate. By analyzing the results of experiment one, and according to the experimental plan designed in the subsection, when conducting experiment two, the Pearson (PCC) similarity formula will be used to calculate the degree of similarity between items, and an improved algorithm that introduces a time decay function compared. Make sure that the other conditions remain unchanged, and compare the recommended results before and after the fusion time factor.

This algorithm is also a swarm optimization algorithm, and also has a parameter setting of population size. The function of this parameter in the algorithm is the same as that described in the particle swarm algorithm. In addition, the artificial fish school algorithm has several parameters that need to be determined: artificial fish field-of-view, moving step length, and congestion factor. The artificial fish field-of-view mainly affects the rear-end collision and grouping operations of artificial fish. When artificial fish have a large field-of-view, this will lead them to move to the center of the school uniformly. If the movement of the fish school is too uniform, it is not conducive to the search for the global optimal solution; but if it is too small, the artificial fish always swim blindly in the field-of-view, thus enhancing the randomness of the algorithm. The moving step size is difficult to obtain in this algorithm, because if the value is too large, there is a greater chance that the artificial fish will skip the global optimal solution; and if it is too small, the algorithm will move closer to the greedy algorithm, greatly increasing the convergence time of the algorithm. The crowding factor is a parameter of artificial fish school that is markedly different from the particle swarm algorithm. The existence of this parameter prevents artificial fish from being concentrated in a small area, so it can ensure that the fish school does not always fall into a local optimal solution.

6. Conclusion

When attempting to research a single-species intelligent algorithm, there are bound to be optimization and application defects due to its own shortcomings, so the fusion of two or more single-species intelligent algorithms to form a mixed-group intelligent algorithm can effectively maximize their respective strengths and avoid their weaknesses, and further enhance the specialties of the single-species intelligent algorithm. The PSO has good global search ability, and has advantages in terms of high- and low-dimensional optimization problems, but it can easily fall into the local optimum, while the local refined search ability of the collaborative algorithm is more prominent. Therefore, this paper attempted to improve the particle swarm algorithm and perform a parallel game search. The better result of the search stall and delay was selected as the initial threshold of the improved collaborative algorithm, and then the improved collaborative algorithm was used for a local refined search to form a hybrid swarm intelligence algorithm of two algorithms. The core strategy of this paper consisted in conducting detailed and comprehensive experiments comprising five basic time series data categories, which basically represent all types of time series data.

Through a large number of experiments and illustrations, it has been confirmed that the core strategy of this paper can indeed obtain the optimal parameter set within a reasonable time cost, and overcome the limitations of other classic algorithms where the time cost is too large or which cannot be universally applied to every dataset type. The shortcomings of better solution results are obtained, and then better prediction results are obtained. At the same time, time efficiency can also be controlled within a more appropriate range. Although the fusion algorithm, ITAIWPSACO, proposed in this paper has obtained relatively good experimental results, there are still shortcomings regarding task scheduling in the cloud computing environment, so it needs to be further improved and perfected. In the ITAIWPSACO algorithm proposed in this paper, only the optimization condition of the task completion time is considered. Although the task scheduling cost is added to the ITAIWPSO algorithm at the initial stage of scheduling, the final optimization result is only the task completion time. Therefore, in the real cloud, many factors should be considered in the computing environment, and future studies will be required to improve the algorithm.

Author’s Contributions

Conceptualization, ZM, QW. Funding acquisition ZM. Investigation and methodology, ZM. Project administration ZM, QW. Resources ZM, QW. Supervision QW. Writing of the original draft, QW. Writing of the review and editing, QW. Software, QW. Validation, ZM. Formal analysis, ZM. Data curation, ZM, QW. Visualization, ZM, QW.

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Competing Interests

The authors declare that they have no competing interests.

References

[1] J. Zhou, "Features selection and forecasting method for hot micro-blog based on FA-SVM," *Computer Applications and Software*, vol. 35, no. 12, pp. 107-111, 2018.

[2] J. Sun, P. Wang, Y. Zhang, Z. Feng, and H. Sang, "An improved method for feature selection of the remote sensing image classification based on feature contribution and PCA transform," *Geomatics & Spatial Information Technology*, vol. 41, no. 1, pp. 49-54, 2018.

[3] C. Zhang, H. Wang, J. Zeng, L. Ma, and L. Guan, "Short-term dynamic radar quantitative precipitation estimation based on wavelet transform and support vector machine," *Journal of Meteorological Research*, vol. 34, no. 2, pp. 413-426, 2020.

[4] W. Liu, H. Yang, and S. Liu, "A feature selection algorithm of battery SOH based on ACCA-FCM and SVM-RFE," *Computer and Modernization*, vol. 2018, no. 1, pp. 11-18, 2018.

[5] A. Sukumar, Y. Subramaniyaswamy, V. Vijayakumar, and L. Ravi, "A secure multimedia steganography scheme using hybrid transform and support vector machine for cloud-based storage," *Multimedia Tools and Applications*, vol. 79, pp. 10825-10849, 2020.

[6] K. Li, J. Luo, Y. Hu, and S. Li, "A novel multi-strategy DE algorithm for parameter optimization in support vector machine," *Journal of Intelligent Information Systems*, vol. 54, pp. 527-543, 2020.

[7] J. Wang, P. Du, Y. Hao, X. Ma, T. Niu, and W. Yang, "An innovative hybrid model based on outlier detection and correction algorithm and heuristic intelligent optimization algorithm for daily air quality index forecasting," *Journal of Environmental Management*, vol. 255, article no. 109855, 2020. https://doi.org/10.1016/j.jenvman.2019.109855

[8] W. Li, G. G. Wang, and A. H. Gandomi, "A survey of learning-based intelligent optimization algorithms," *Archives of Computational Methods in Engineering*, vol. 28, pp. 3781-3799, 2021.

[9] M. Singla, D. Ghosh, and K. K. Shukla, "Improved sparsity of support vector machine with robustness towards label noise based on rescaled α-hinge loss with non-smooth regularizer," *Neural Processing Letters*, vol. 52, no. 3, pp. 2211-2239, 2020.

[10] J. Ali, M. Saeed, M. F. Tabassam, and S. Iqbal, "Controlled showering optimization algorithm: an intelligent tool for decision making in global optimization," *Computational and Mathematical Organization Theory*, vol. 25, pp. 132-164, 2019.

[11] F. Cui, H. Hu, and Y. Xie, "An intelligent optimization method of E-commerce product marketing," *Neural Computing and Applications*, vol. 33, pp. 4097-4110, 2021.

[12] L. Lu, X. Ren, K. H. Yeh, Z. Tan, and J. Chanussot, "Exploring coupled images fusion based on joint tensor decomposition," *Human-centric Computing and Information Sciences*, vol. 10, article no. 10, 2020. https://doi.org/10.1186/s13673-020-00215-z

[13] S. W. Kim and J. M. Gil, "Research paper classification systems based on TF-IDF and LDA schemes," *Human-centric Computing and Information Sciences*, vol. 9, article no. 30, 2019. https://doi.org/10.1186/s13673-019-0192-7

[14] Q. Lin, H. Zhang, and Q. Li, "Wrapper feature selection algorithm based on MA-LSSVM," *Journal of Nanjing University of Science and Technology*, vol. 40, no. 1, pp. 10-16, 2016.

[15] Y. Wu and L. Li, "A dual population hybrid intelligent optimization algorithm for combined heat and power economic dispatch," *Systems Engineering*, vol. 36, no. 5, pp. 128-138, 2018.

[16] Y. Shen, J. Song, and Z. Wan, "Improved fireworks algorithm for support vector machine feature selection and parameters optimization," *Microelectronics and Computers*, vol. 35, no. 1, pp. 21-25, 2018.

[17] J. Zhang, S. Ding, and B. Li, "Improved particle swarm optimization algorithm for support vector machine feature selection and optimization of parameters," *Journal of Computer Applications*, vol. 36, no. 5, pp. 1330-1335, 2016.

[18] C. Tang, S. Xu, N. Cheng, Z. Duan, and X. Wu, "Research on collaborative optimization of gait characteristics and SVM parameters based on GA," *Computer Engineering and Applications*, vol. 55, no. 23, pp. 131-135, 2019.

[19] H. Xu and H. Zhang, "Sensory quality prediction of cigarettes based on feature selection and improved SVM algorithm," *Journal of Guilin University of Electronic Technology*, vol. 38, no. 4, pp. 303-307, 2018.

[20] J. Wang, X. Chen, and W. Zhang, "Feature selection algorithm of kernel polarization and its application in LSSVM," *Machinery Design & Manufacture*, vol. 2018, no. 7, pp. 19-22, 2018.

[21] Y. Liu and Z. Zhao, "Recognition of abnormal quality patterns based on feature selection and SVM," *Statistics and Decision*, vol. 34, no. 10, pp. 47-51, 2018.

[22] E. O. Abiodun, A. Alabdulatif, O. I. Abiodun, M. Alawida, A. Alabdulatif, and R. S. Alkhawaldeh, "A systematic review of emerging feature selection optimization methods for optimal text classification: the present state and prospective opportunities," *Neural Computing and Applications*, vol. 33, no. 22, pp. 15091-15118, 2021.

[23] Y. Zhao, R. Chen, and W. Liu, "Research on optimal support vector classifier model of integrating feature selection," *Computer Science*, vol. 43, no. 8, pp. 177-182, 2016.

[24] N. K. Mishra and P. K. Singh, "FS-MLC: feature selection for multi-label classification using clustering in feature space," *Information Processing & Management*, vol. 57, no. 4, article no. 102240, 2020. https://doi.org/10.1016/j.ipm.2020.102240

[25] Y. Li, Z. Wei, and K. Xu, "Hybrid feature selection method of Chinese emotional characteristics based on Lasso algorithm," *Computer Science*, vol. 45, no. 1, pp. 39-46, 2018.

[26] B. Pes, "Ensemble feature selection for high-dimensional data: a stability analysis across multiple domains," *Neural Computing and Applications*, vol. 32, no. 10, pp. 5951-5973, 2020.

[27] G. Ma, C. Wu, and W. Liu, "Research on hybrid feature selection algorithm for gene data sets," *Measurement & Control Technology*, vol. 38, no. 10, pp. 71-75, 2019.

[28] A. Alsahaf, N. Petkov, V. Shenoy, and G. Azzopardi, "A framework for feature selection through boosting," *Expert Systems with Applications*, vol. 187, article no. 115895, 2022. https://doi.org/10.1016/j.eswa.2021.115895

[29] J. Fang and Q. Liu, "Iterative tighter nonparallel hyperplane support vector clustering with simultaneous feature selection," *Acta Electronica Sinica*, vol. 48, no. 1, pp. 44-58, 2020.

[30] Y. Liu, C. Xiang, and H. Wang, "Optimization of feature selection based on mutual information in intrusion detection," *Journal of Northwest University (Natural Science Edition)*, vol. 47, no. 5, pp. 666-673, 2017.

[31] X. Hu and N. Kang, "SVM selective ensemble learning method based on feature selection," *Electronic Technology & Software Engineering*, vol. 2009, no. 18, pp. 143-144, 2019.

[32] G. Wang, X. Huang, X. Wu, and X. Hu, "Algorithm of Chinese sentiment classification of SVM based on optimization information gain feature selection method," *Journal of Chengdu University of Technology (Science & Technology Edition)*, vol. 46, no. 1, pp. 105-110, 2019.

[33] S. Yang and T. Li, "Research on hot issues of college students based on SVM," *Practical Electronics*, vol. 2016, no. 9, pp. 89-92, 2016.

[34] F. Wang and W. Huang, "Research on feature selection of twin support vector machines," *Journal of Zhejiang University of Technology*, vol. 44, no. 2, pp. 146-149, 2016.

[35] C. Qin and Q. Guan, "The research and application of feature selection method based on F-score," *Journal of Yibin University*, vol. 18, no. 6, pp. 4-8, 2018.

[36] S. Zhang and M Zhang, “Study on SVM-based embedded feature selection method,” *Computers and Applied Chemistry*, vol. 33, no. 1, pp. 85-88, 2016.