

Retraction

Retracted: A Classification Method of Network Ideological and Political Resources Using Improved SVM Algorithm

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] W. Wang, "A Classification Method of Network Ideological and Political Resources Using Improved SVM Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 2133042, 10 pages, 2021.

Research Article

A Classification Method of Network Ideological and Political Resources Using Improved SVM Algorithm

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In order to improve the accuracy and efficiency of the classification of network ideological and political resources and promote the efficiency of ideological education, a research on the classification of network ideological and political resources based on the improved SVM algorithm is proposed. We analyze the characteristics and current situation of network ideological and political resources and conclude that the method elements are open and technical. The ontology elements are rich and shared, and the behavioral elements are autonomous and interactive. Three types of network ideological and political resources are proposed: the main resource, content resource, and means resource. The particle swarm algorithm is used to improve the SVM algorithm. In the process of constructing the SVM classifier, the fuzzy membership function is introduced, the classification problem of network ideological and political resources is converted into a secondary planning problem, and the accuracy of network ideological and political resources is finally realized. Simulation results show that the use of improved algorithms to classify network ideological and political resources can improve the accuracy and efficiency of network abnormal data classification.

1. Introduction

At present, ideological and political education resources appear and continue to be enriched with the development of corresponding ideological and political education in a certain class of society. They can be used by ideological and political education activities and can play a very important role in the implementation of corresponding ideological and political education goals. The spiritual and material elements are integrated. In recent years, the rapid development of the Internet has promoted society to enter the era of new media. The way people exchange information has also undergone tremendous changes [1]. The boundaries of knowledge transmission have continued to dissolve, which has had a huge impact on people's lives. In the context of new media, the resources of ideological and political education in colleges and universities have undergone great changes: they bear the responsibility of ideological and political education for students in the network environment, and they also have a profound impact on various spiritual and material elements. It is precisely these. The elements constitute the

network ideological and political education resources of colleges and universities. Therefore, it is particularly important to optimize, integrate, and classify online ideological and political education resources [2].

Classification is a major research field in data mining and machine learning, and support vector machines can better solve the classification problem. However, with the continuous research on the related issues of classification, the data is becoming larger and larger, and the number of features is becoming higher and higher. Although a large number of features provide sufficient information, there are bound to be many redundant features in a huge data object. On the one hand, these redundant features reduce the accuracy of classification, and on the other hand, it will increase the running time and space of the algorithm and reduce the efficiency of the algorithm. Faced with this problem, when classifying network ideological and political resources, it is often necessary to process the data of network ideological and political resources to obtain effective information. Among them, feature selection is an effective means. Through feature selection, we reduce the

dimensionality of the data to reduce the number of features. On the other hand, the selection of parameters also determines the classification ability of the SVM classifier, and a good parameter setting can effectively improve the performance of the classifier. The problem of parameter optimization is also the focus of research in classification problems. So far, there is no particularly effective method for how to obtain the best parameters of SVM.

Reference [3] designed a practical teaching network platform based on the integration of ideological and political teaching resources in colleges and universities, expounding the integration effect of the practical teaching network platform on the human resources, material resources, financial resources, and information resources of college ideological and political practical teaching. This platform can realize the integration of ideological and political teaching resources in colleges and universities, but the accuracy of the classification results of ideological and political resources is low. Reference [4] proposed an ideological and political network classroom mobile learning system based on Android applications, hoping to use this system to effectively promote the development of ideological and political mobile education, but the system is less efficient in classifying network ideological and political resources. Quantum random access memory (QRAM) can use superposition and entanglement to store big data onto qubits logarithmically. QRAM algorithm can design a new QCNN model, which can process massive data effectively. Reference [5] uses the QRAM algorithm to propose a model with higher resource and depth efficiency for large input data and output channel numbers and effectively extract features. In [6], in order to improve resource allocation in remote wide area networks, a standard deviation classification method is proposed. The method assigns diffusion factors (SFs) by considering the mean and standard deviation of RSSI values of terminal devices. Reference [7] proposed a text emotion classification method based on BP neural network.

Aiming at the problems of the above methods, this paper proposes a research on the classification method of network ideological and political resources based on the improved SVM algorithm. This paper proposes an improved SVM feature selection and parameter joint optimization algorithm based on particle swarm optimization, which enables the algorithm to select as few features as possible while improving the classification accuracy. In order to solve the problem that traditional particle swarm optimization is prone to fall into local optimum and premature during optimization, the algorithm introduces the cross-mutation operator in the genetic algorithm (GA) into the PSO to make the particles perform cross-mutation after each iteration. *Action to Avoid This Problem.* Efforts are made to make the particles jump out of the local optimal value currently found, increase the diversity of the group, and find a better value in a larger range. We apply this method to the classification of network ideological and political resources, construct the initial training sample set, and establish the classifier. After labeling different network ideological and political resources, they are directly placed in the training sample set. Assuming that the detection accuracy reaches the set range,

we stop the calculation. Through the above steps, the classification of network ideological and political resources can be realized, which can be divided into subject resources, content resources, and means resources, which provides a certain foundation for network ideological and political teaching.

The contributions of this paper include the following three points:

- (1) We have proposed a research on the classification of network ideological and political resources based on the improved SVM algorithm
- (2) In the process of constructing the SVM classifier, the fuzzy membership function is introduced, the classification problem of network ideological and political resources is converted into a secondary planning problem, and the accuracy of network ideological and political resources is finally realized
- (3) Simulation results show that the use of improved algorithms to classify network ideological and political resources can improve the accuracy and efficiency of network abnormal data classification

2. The Status Quo of Optimization, Integration, and Classification of Network Ideological and Political Resources

2.1. Analysis of the Characteristics and Status Quo of Network Ideological and Political Resources

2.1.1. *Characteristics of Network Ideological and Political Resources.* The so-called ideological and political education resources refer to the ideological and political education that inherits and promotes traditional ideas to a certain extent. Traditional ideological and political education has obvious characteristics of transcendence, practicality, and purpose. Therefore, traditional ideological and political education is a transcendental and purposeful practical activity. The attributes of traditional ideological and political education will definitely have an impact on the network ideological and political education of colleges and universities in the new media era. In addition, the characteristics of sharing, interactivity, reality, virtuality, and immediacy of network education will also appear.

(1) *The Method Elements Are Open and Technical.* The most important feature of online ideological and political education resources in colleges and universities is the openness and technicality of method elements. Its openness is mainly reflected in the following two aspects. First, it must adapt to the rapidly changing information on the Internet in the current new media era. The characteristic is that education methods and methods should be actively updated. Second, traditional education methods must be inherited and developed. When choosing education methods, an open attitude should be adopted. The technical elements of the method are manifested in the development and utilization of the resources of network thought correction education, relying on the corresponding mobile Internet of things

communication equipment and the corresponding network environment. However, if you carefully consider the traditional ideological and political education methods in colleges and universities, you will find that the education method does not have the corresponding technical support, so you will fall into a boring and single situation. At the moment, this kind of atmosphere is difficult to achieve corresponding education. *The Goal.* Because the information exchange in the era of new media has strong immediacy and instantaneity, the transmission boundary of ideological and political education discipline knowledge has been greatly ablated, and it has seriously challenged the authority of the corresponding ideological and political education personnel in the past. Therefore, the educational resources in the elements of the ideological and political teaching methods in colleges and universities must rely on the corresponding virtual reality technology and network communication equipment when carrying on the traditional education methods.

(2) *Ontology Elements Are Rich and Shared.* The richness of ontology elements is mainly manifested in the selection of relatively rich types and quantities in the process of resource development and utilization, such as hidden resources and explicit resources, social resources, and school resources. The sharing of ontological elements is mainly reflected in the logical extension based on the abundance of educational resources. The online ideological and political education resources of colleges and universities are information resources under the background of the network environment, which is different from the physical state storage of natural resources. It is stored through digitalization and has obvious characteristics of reusability and unlimited reproduction. In addition, the online ideological and political education resources of colleges and universities are naturally integrated and can be classified and retrieved without being restricted by the physical environment. We seriously think about the ideological and political education resources formed by the ideological and political education personnel of universities and their books, teaching, education bases, and many other elements. In the process of resource development and use, it is obvious that the characteristics of limitation and scarcity have appeared. Therefore, through the support of corresponding network technology, the sharing and richness of the resources of network ideological and political education in colleges and universities can greatly improve the level of ideological and political education.

(3) *Autonomy and Interactivity in Behavioral Elements.* The behavioral autonomy of higher education subjects is an internal expression of interactivity, and the main manifestation is that the subjects of education can freely choose the corresponding transmission mode. Educational resources can conduct multidirectional, two-way, and one-way communication, as well as asynchronous or synchronous communication, and private or open communication. The interactivity of the subject is mainly manifested in the effectiveness of the transmission of corresponding ideological and political education information resources between the subjects of the college's network ideological and political

education. The subject of traditional ideological and political education in colleges and universities must conduct one-way communication through corresponding media, that is, indoctrinating communication. This interactive method lacks emotional communication between teachers and students, so the education effect is poor. Therefore, the network ideological and political education staff of colleges and universities must actively break through the traditional educational ideas and methods and effectively use the corresponding new media platforms to conduct equal information exchanges with students, so as to reflect the educational nature of colleges and universities.

2.1.2. *Status Quo of Internet Ideological and Political Resources.* At this stage, the development and utilization of online ideological and political education resources in colleges and universities have attracted attention from all walks of life, and the corresponding educational resources have been used to a certain extent. However, due to the influence of traditional ideological and political education, colleges and universities are still relatively extensive in the development and utilization of corresponding educational resources at this stage, and there are several problems in the following aspects:

- (1) The development of educational resources follows the old rules, and the management of network information resources is complex and disorderly. When the network ideological and political education resources of colleges and universities are developed in a disorderly manner, some colleges and universities have problems such as backward development of resources and the development of resources. Those network information resources with strong ideological and political education significance have problems of disorder. Its main manifestation is the simplification and excessive development and utilization of those more mature educational resources, but not paying much attention to those with strong current affairs and new ideas and potential resources, so it is difficult to develop hidden educational resources. Furthermore, it aggravates the boring and boring style of teaching and indoctrination of traditional ideological and political education, which is meaningless to improve the level of ideological and political education. Many colleges and universities have relatively backward methods for developing online ideological and political education resources. For example, the development or use of a hot topic or education module has little effect. When a student party branch of a university conducts online party-building education, the method adopted is very simple, that is, simply downloading or uploading the question bank, and the corresponding party-building video content is not processed from the basic level. When this branch conducts class patriotism education, the above resources are assigned to the network resources of patriotism education under a new name.

- (2) The management of educational resources is disorderly, and the network platform has not yet formed a cohesive force. At present, although some colleges and universities attach great importance to the development and utilization of online ideological and political education resources, there are phenomena of excessive enthusiasm and insufficient organization. Many people cannot reach a consensus on online ideological and political education in colleges and universities. Some people feel that the process of developing and utilizing online ideological and political education resources is to build a corresponding network platform and then fill in the corresponding ideological and political education content. I feel that building a corresponding new media platform is to develop online education resources.

2.2. Classification Goals of Network Ideological and Political Resources. The ideological and political education resources of colleges and universities refer to the sum of various elements that can be included in the ideological and political education activities by the ruling class for development, utilization, and management in a certain class society and then can achieve the goal of ideological and political education. Ideological and political education resources in colleges and universities are mainly divided from three perspectives: the subject of education, the content of education, and the means of education. The use of this classification method is to make the division of ideological and political education resources in colleges and universities more scientific and reasonable, simpler, and clearer.

2.2.1. Subject Resources. The main resources of ideological and political education are individuals, organizations, and social groups that have the responsibility of ideological and political education in the process of ideological and political education. These main resources can be divided into full-time education main resources and part-time education main resources. The main resources of full-time education refer to the team of college counselors and ideological and political theory teachers. The main resources of part-time education include student cadres, college professional course teachers, party and government cadres, logistics service personnel, social ethics and groups, and student family members.

2.2.2. Content Resources. Ideological and political education content resources refer to spiritual and material resources that can help members of society improve their moral qualities, cultivate good behaviors, and establish a correct outlook on life, world outlook, and values. Spiritual resources include the Chinese excellent traditional culture, zeitgeist, national spirit with patriotism as the core, socialist core value system, ethics and legal education, and major historical events and anniversaries. Material resources mainly include natural landscapes, revolutionary sites,

historical cultural relics, and places where major historical events occurred.

2.2.3. Means and Resources. Ideological and political education means resources are the methods and means used in the process of ideological and political education to achieve the purpose of ideological and political education. It can be mainly summarized as traditional educational methods and new educational methods. Traditional education methods mainly include explicit education methods such as classroom teaching and conversation methods. New educational methods are mainly the use of various forms of practical activities, management and services, and other implicit educational methods, as well as new carriers and new educational technologies.

With the continuous development of information technology, the teaching methods and content of colleges and universities have undergone great changes. In the era of new media, students advocate an equal relationship between teachers and students and a harmonious environment for topics. The network ideological and political education of colleges and universities is directly related to the students [8].

Ideological trends and political views, therefore, college administrators, and teachers must attach great importance to the integration and classification of network ideological and political resources, so as to ensure the quality of teaching and improve the level of teaching.

3. Classification Method of Network Ideological and Political Resources Based on Improved SVM Algorithm Optimization

3.1. Feature Selection Based on PSO and Joint Optimization Algorithm of SVM Parameters

3.1.1. Particle Swarm Algorithm. Support Vector Machine (SVM) is a binary classification model. Its basic model is a linear classifier defined in feature space with the largest interval, which distinguishes it from perceptron. SVM also includes nuclear tricks, which makes it a substantially nonlinear classifier. The learning strategy of SVM is interval maximization, which can be formalized as a problem of solving convex quadratic programming, and is equivalent to the minimization problem of the regularized hinges loss function. The learning algorithm of SVM is the optimization algorithm for solving convex quadratic programming.

A particle swarm algorithm is a random optimization algorithm of swarm intelligence. Through the study of the flight of bird flocks, it is found that birds only determine their own movements based on the movements of the surrounding birds, but the overall result is that the entire flock of birds is under the control of a center. The particle swarm algorithm is inspired by the behavior characteristics of this biological population and uses the particle motion model to model the solution process for solving optimization problems. In the particle swarm algorithm, the possible solution of each optimization problem can be imagined as a

data point in the search space, which is called a “particle”. The speed of each particle determines the direction and distance of their flight. The fitness value is determined by the objective function. In the search process, the particles follow the current optimal particles to search in the solution space [9]. The specific process is shown in Algorithm 1.

In the equation, p -best and g -best represent the local and global optimal positions of the particle swarm, respectively. When $c_1 = 0$, it means that there is no ability to adjust according to its own optimal value, which is called the global PSO algorithm [10]. At this time, the particles have the ability to expand the search space. It has a faster convergence speed, but due to the lack of local search, it is easier to fall into the local optimal solution when facing local problems than the standard PSO algorithm. The formula is as follows:

$$v_i = \omega \times v_i + c_1 \times \text{rand} \times (g\text{best}_i - x_i). \quad (1)$$

When $c_2 = 0$, there is no information exchange between particles, which is called a local PSO algorithm. Due to the lack of information exchange between particles, the entire group is equivalent to a completely random search, and the convergence speed is slow, so it is difficult to obtain the global optimal solution. The formula is as follows:

$$v_i = \omega \times v_i + c_1 \times \text{rand} \times (g\text{best}_i - x_i). \quad (2)$$

Among them, the inertia factor ω keeps the particles in motion inertia, so that they have a tendency to expand the search space and have the ability to explore new areas. A lower value allows the particles to search around the target area, while a higher value causes the particles to cross the target area and skip the optimal solution [11].

In the binary PSO algorithm, each particle is encoded as a binary vector, and the particle is determined to take 0 or 1 at the corresponding position according to the speed. The sigmoid function satisfies the above conditions, and the sigmoid function is

$$S(V) = \frac{1}{1 + e^{-v}}. \quad (3)$$

In the particle swarm algorithm, the population initialization method is random initialization. Each individual in the population calculates the fitness value and adjusts the individual according to the fitness value. When dealing with high-dimensional complex problems, it often encounters premature convergence and localization. The problem of optimal value cannot guarantee convergence to the global optimal value. Compared with another optimization algorithm, that is, the genetic algorithm, particle swarm algorithm has memory ability, and the previous memory of genetic algorithm is changed with the continuous iteration of the population. The particles in the particle swarm algorithm only share information through the current search for the optimal solution, while the chromosomes in the genetic algorithm communicate with each other to share information so that the entire population as a whole moves in the optimal direction [12]. In addition, the coding technology and genetic operation of the genetic algorithm are relatively simple, and the particles in the particle swarm

algorithm are updated through the internal velocity, so the implementation is simpler. In summary, the two algorithms have their own advantages and disadvantages, so you can consider combining the two algorithms to improve the efficiency of optimization.

3.1.2. GPSO-SVM Algorithm. The traditional particle swarm optimization algorithm has a good orientation for the update of position and velocity and can continuously approach the optimal solution in space. However, there are some problems, such as easy to fall into the local optimal solution, low search accuracy, and low efficiency of later iterations. The crossover and mutation operations of the genetic algorithm (GA) lack clear guidance and lack the ability to approximate the optimal solution in space [13]. However, it can expand the search space and ensure the diversity of the population, and the searchability for the optimal solution in space is relatively low, strong, and not easy to fall into the local optimum. This chapter combines the two algorithms, introduces the crossover and mutation mechanism of the genetic algorithm into the particle swarm optimization algorithm, and proposes the GPSO-SVM algorithm, which generates new individuals through crossover and mutation operations after each iteration of the particle. The current individuals with low fitness are replaced to expand the search space where the particle swarm is constantly shrinking in the iteration so that the particles jump out of the local optimal value position currently searched and search in a larger space to find a better value [14].

The particles in the GPSO-SVM algorithm adopt binary coding, and the kernel function of SVM adopts the RBF kernel function. There are two parameters that need to be optimized: penalty parameter (penalty parameter) $C > 0$ and nuclear parameter $\gamma > 0$. In addition to optimizing these two parameters, feature selection must be performed simultaneously, so the particle code contains three parts, namely, parameter C , parameter γ , and feature code. Let P_t be the particle of the t -th generation, which can be expressed as

$$P_t = \{\alpha_{it}, \beta_{it}, \delta_{it}\}. \quad (4)$$

Among them, α_{it} is the parameter C bit string, β_{it} is the parameter γ is the bit string, δ_{it} is the characteristic bit string, and the values of the three are 0 or 1. The length w of the feature subset selection bit string is determined by the feature dimension, where each bit represents a feature, 1 represents selected, and 0 represents unselected. The GPSO-SVM algorithm aims at the joint optimization of feature subsets and SVM parameters. It improves the accuracy of SVM classification while minimizing the number of selected features. The highest fitness value means that the particle is optimal. Therefore, the classification accuracy and feature subsets are used as independent variables of the fitness function. The fitness function formula is

$$f = W_a \times j + W_f \times \left(\sum_{i=1}^N C_i f_i \right)^{-1}. \quad (5)$$

Input: particle length and number, dataset.

Output: the best individual.

step:

- (1) Set the population size and initialize the position and speed of the population
- (2) Calculate the fitness of each particle
- (3) For each particle, compare its fitness value with the best position p-best it has passed. If the value is larger, it will be regarded as the best position p-best of the particle
- (4) For each particle, compare its fitness value with its global best position g-best. If the value is larger, it will be regarded as the best global position g-best
- (5) Update the speed and position of each particle according to the values obtained in steps (2), (3), and (4)
- (6) If the end condition is not reached (the predetermined number of iterations or a good enough fitness value is not reached) Go to step (2) to continue running; otherwise, go to step (7)
- (7) Output g-best

ALGORITHM 1: Particle swarm algorithm.

Among them, W_a is the weight of the classification accuracy, j is the classification accuracy, W_f is the weight of the number of features, C_i is the cost value of the i feature of the dataset, the default value is 1, f_i takes 1 to indicate that the i feature is selected, and 0 indicates not. When selected, N is the feature dimension of the dataset.

The inertia weight $v_i = \omega \times v_i + c_1 \times \text{rand} \times (\text{gbest}_i - x_i)$ is the coefficient by which the particle maintains the original speed, which reflects the degree of inheriting the current speed. A larger value is good for global search, and a smaller value is good for local search. In general, $v_i = \omega \times v_i + c_1 \times \text{rand} \times (\text{gbest}_i - x_i)$ is set to 1. In order to better balance the global search and local search capabilities of the algorithm, dynamic inertia weights are used, and a larger inertial weight is set to search a larger area in the initial stage of the iteration, and a smaller inertial weight is set to perform a finer local search in the later stage of the iteration. Different from the general method of linearly decreasing inertia weight, this chapter adopts a nonlinear decreasing method of inertial weight, which makes the inertial weight decrease slowly in the early stage and faster in the later stage so that a more precise search can be performed. The inertia weight update formula is as follows:

$$\omega(k) = \omega_s - (\omega_s - \omega_e) \times \left(\frac{k}{D_m}\right)^2. \quad (6)$$

Among them, $\omega(k)$ is the inertia weight at the k iteration, ω_s is the initial inertia weight, ω_e is the inertia weight at the maximum number of iterations, k is the current iteration number, and D_m is the maximum iteration number.

In the mutation operation, the particles can jump out of the local optimal solution by performing the mutation operation on the particles, expand the search space, and improve the possibility of finding a better value. If a fixed mutation probability is used, too large is not conducive to the retention of outstanding individuals, and too small will weaken the effectiveness of mutation operations. Therefore, different individuals should be given different mutation probabilities. For individuals with high fitness, we set a lower probability of mutation, and for individuals with low fitness, we set a higher probability of mutation [15]. This chapter

adopts the adaptive mutation probability method to obtain different mutation probabilities through the fitness value of each particle. The adaptive mutation probability formula is as follows:

$$M(i) = \begin{cases} M_1 - \frac{(M_1 - M_2) \times (h - h_a)}{h_m - h_a}, & h > h_a \\ M_1, & h < h_a. \end{cases} \quad (7)$$

Among them, $M(i)$ is the mutation probability of the i particle in the population, M_1 and M_2 are the maximum and minimum values of the mutation probability, h is the fitness value of the individual, h_a is the average fitness of all individuals, and h_m is the individual's fitness value. *Maximum Fitness*. It can be seen from the above formula that the optimal individual mutation probability is at least M_2 . When the individual fitness is less than the average fitness, the mutation probability is M_1 .

The algorithm flowchart is shown in Figure 1.

3.2. Classification and Optimization of Network Ideological and Political Resources Integration Based on Improved SVM Algorithm. Before classifying network ideological and political resources, it is necessary to perform a series of processing on the classification samples to be trained and at the same time convert them into easy-to-handle vector forms [16]. Combined with the vector space model, the network ideological and political resources are simplified into vector form $\{W_1, W_2, \dots, W_m\}$ with the weight of the featured item as the component, where W_i represents the weight of the i featured item. The weights are processed using normalized relative word frequencies. The specific calculation formula is as follows:

$$W(t, \bar{d}) = \frac{tf(t, \bar{d}) \cdot \log(n/n_t + 0.01)}{\sqrt{\sum_{t \in d} [tf(t, \bar{d}) \cdot \log(n/n_t + 0.01)]^2}}, \quad (8)$$

where $W(t, \bar{d})$ represents the weight value of the network ideological and political resources; n represents the total number of training samples; and n_t represents the total number of network ideological and political resources

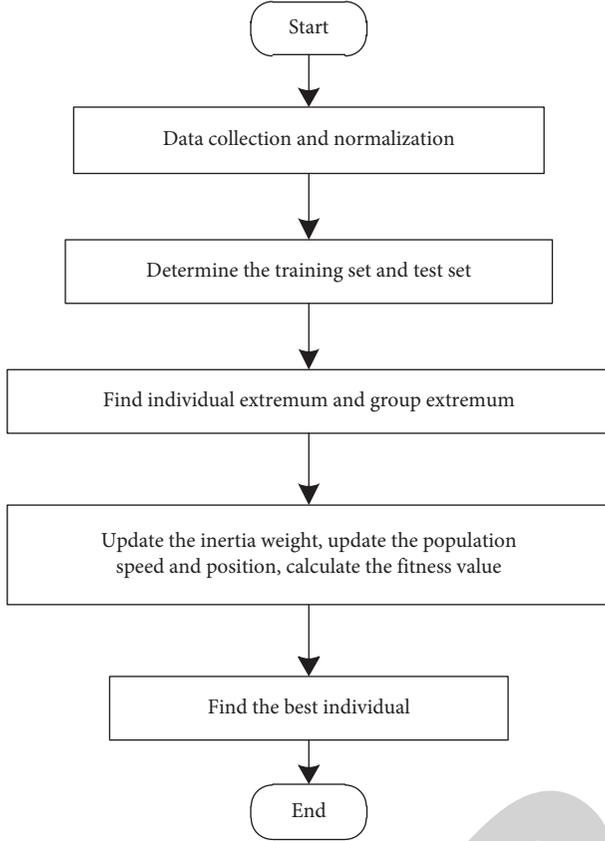


FIGURE 1: GPSO-SVM algorithm flowchart.

appearing in the training samples, which need to be normalized [17]. Through the above processing and calculations, the network ideological and political resource library is expressed as a resource matrix with a specification of $m \times n$. Then, there are

$$A_{m \times n} = [\alpha_{ij}], \quad (9)$$

where m represents the different types of course resources contained in the resource library.

A vector space is a high-dimensional vector space with a maximum dimension of hundreds of thousands. It is difficult to classify and process curriculum resources in such a vector space. Therefore, it is first necessary to reduce the dimensionality of network ideological and political resources to compress the feature dimension to the point that is compatible with the number of training samples. After the dimensionality reduction process, not only can the noise in the course resources be effectively eliminated, but also the classification efficiency and classification accuracy of the network ideological and political resources can be improved. The following uses the mutual feature selection method to calculate the proportion value corresponding to the mutual information of different network ideological and political resources. The specific calculation formula is

$$P(t|C_k) = \frac{1 + \# \sum_{i=1}^{|D|} N(t, d_i)}{|V| + \sum_{j=1}^{|V|} \sum_{i=1}^{|D|} N(t_j, d_i)}, \quad (10)$$

where $P(t|C_k)$ represents the proportion value corresponding to the amount of mutual information of network ideological and political resources; $|V|$ represents the total number of network ideological and political resources; $\sum_{j=1}^{|V|} \sum_{i=1}^{|D|} N(t_j, d_i)$ represents the resource collection of all network ideological and political resources; $P(t)$ represents the value of network ideological and political resources in all training samples. The proportion of the value $|D|$ represents the total number of training samples.

Through the calculation results, the first m features with the largest values can be retained, while other features can be omitted to achieve dimensionality reduction processing.

Set the training set as

$$D = \{(x_1, x_1), (x_2, x_2), \dots, (x_m, x_m)\}. \quad (11)$$

SVM needs to map input space x to feature space first, namely,

$$z = \phi(x). \quad (12)$$

The minimum value of the conversion function of the optimal classification surface problem is

$$\text{Minimize } \phi(w, \xi) = \langle w, w \rangle + C_p \sum_{i=1}^m \xi_i, \quad (13)$$

where C_p represents the penalty parameter.

Since the dimensionality of the feature space is very high, it is difficult to obtain accurate values of w and $\phi(x)$, and the following needs to introduce kernel function technology. As long as the nonlinear mapping function $K(x, x')$ satisfies the Mercer condition, it can be set as a kernel function, and at the same time,

$$K(x, x') = \langle \phi(x), \phi(x') \rangle. \quad (14)$$

At this stage, the speed of the SVM training algorithm is not ideal. It is mainly affected by the dimension of the matrix corresponding to the objective function, which causes the speed of solving the problem to decrease and the dimensionality to increase. In order to effectively solve the above problems, active learning is added to the SVM; the specific steps are as follows.

The SVM active learning machine consists of two independent parts (f, q), where f represents an independent SVM classifier and q represents the query function. The SVM active learning machine mainly determines the final query strategy through the query function and at the same time selects the next sample that needs to be labeled from the candidate set U that has not been labeled.

Analyzing the functional principle, we can see that, in the process of constructing a classifier, the samples that have a greater impact on the classifier are the samples generated during the classification interval. In order to ensure the accuracy of the classification results, each time the classification plane is selected, the sample with the most recent sample closest to the classifier is selected [18]. However, during the entire operation process, the performance of the classifier will still be affected. For this reason, it is necessary to use the SVM active learning algorithm to classify network

ideological and political resources. The specific operation steps are as follows:

- (1) Select i samples from the candidate sample set U , label different sample categories, construct initial training sample set T , and ensure that T contains at least two sample outputs
- (2) Build classifier f through T
- (3) Mark f as (x, \hat{y}) for all samples in U
- (4) In the sample set U , select the sample (x, \hat{y}) that is closest to the classification boundary and has not been labeled
- (5) After labeling different network ideological and political resources, they are directly placed in the training sample set T
- (6) If the detection accuracy reaches the set range, stop the calculation; otherwise, return to step (2) and repeat the above operation

Through the above steps, the classification of network ideological and political resources can be realized, which can be divided into subject resources, content resources, and means resources, which provides a certain foundation for network ideological and political teaching.

4. Experimental Analysis and Results

4.1. Experimental Environment and Parameters. In order to verify the comprehensive effectiveness of the proposed classification system for college English multimedia course resources based on active learning, tests were conducted in the experimental environment shown in Table 1.

As for the parameter setting involved in our improved GPSO-SVM algorithm, we first divided the dataset into training set, verification set, and test set in a ratio of 8:1:1. Then, the training is carried out in the training set, and the result verification is carried out in the verification set. The test set is tested with the result with the highest score in the verification set. At this point, the parameter with the best effect of the verification set is the final parameter setting in this paper.

4.2. Experimental Method and Result Analysis. The experiment uses classification accuracy, recall, and fault tolerance as test indicators. The specific experimental test results are as follows.

4.2.1. Classification Accuracy Rate (%). In order to prove the classification system of the designed system, the systems of [3] and [4] are used as the comparison objects, and the classification accuracy is used to evaluate the classification performance. The classification results are shown in Figure 2.

The analysis of the experimental data in Figure 2 shows that the resource classification performance of the designed method is significantly better than the other two methods. This is because the improved algorithm considers the relationship between network ideological and political resources and the class center and improves the traditional

TABLE 1: Test environment.

Name	Ranges
RAM	8 GB
Processor	Nvidia GeForce
CPU	GTX1080
Programming tools	MATLAB R2016a
Main frequency	3.6 GHz
Operating system	Window 7
Open-source software	DSpace 1.5.2

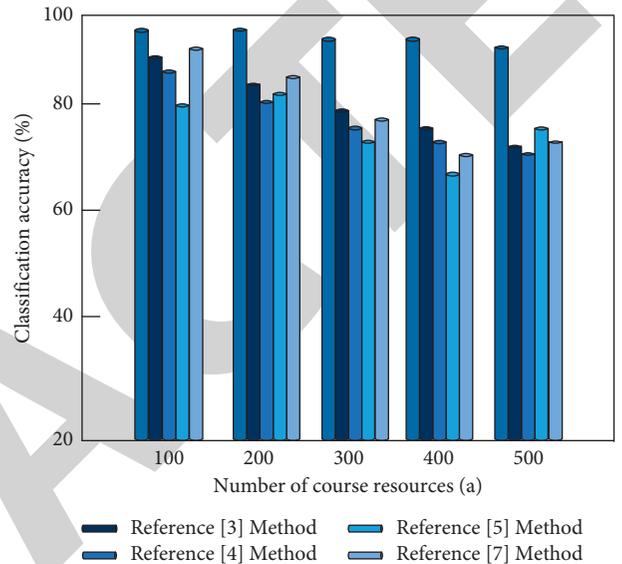


FIGURE 2: Comparison results of classification accuracy of different methods.

SVM. In the process of constructing the SVM classifier, the fuzzy membership function is introduced, the classification problem of network abnormal data is converted for the secondary planning problem, and the accurate classification of network abnormal data is finally realized. This fully reflects the effectiveness of the improved algorithm in the classification of network ideological and political resources.

4.2.2. Fault Tolerance Rate (%). Table 2 gives the comparison results of the recall rates of the three systems.

The analysis of the experimental data in Table 2 shows that the designed method has the highest fault tolerance rate among the three methods; the method of [3] has the second highest fault tolerance rate; the method of [4] has the lowest fault tolerance rate.

4.2.3. Recall Rate (%). In order to further verify the classification performance of the designed system, the following tests compare the recall rates of different systems. The specific experimental results are shown in Figure 3.

The analysis of the experimental data in Figure 3 shows that, compared with the other two methods, the recall rate of the designed method has been significantly improved and has been in a relatively stable state, while the other two

TABLE 2: Comparison results of fault tolerance rate of different methods.

Testing object	Fault tolerance rate (%)				
	Designed method	The method of [3]	The method of [4]	The method of [8]	The method of [10]
01	98.96	97.87	95.97	91.94	92.96
02	97.28	94.36	93.36	93.31	94.46
03	98.17	95.85	94.23	93.13	91.44
04	99.36	93.44	92.43	91.33	94.14
05	97.85	91.56	90.87	90.64	90.56
06	98.33	92.27	91.55	91.11	91.22
07	97.85	92.36	92.74	91.43	94.61
08	98.69	91.78	91.02	91.01	91.04
09	97.66	92.02	91.85	91.61	91.52
10	99.25	94.63	90.74	90.43	90.61

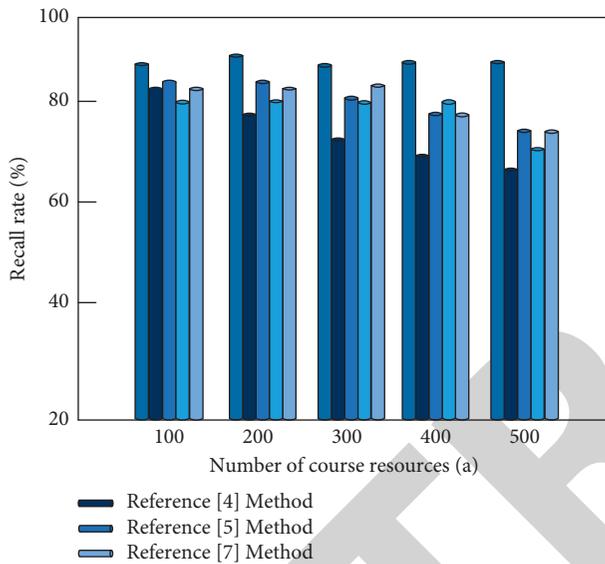


FIGURE 3: Comparison results of recall rates of different classification methods.

methods have shown a straight downward trend. A comprehensive analysis of the above test indicators shows that the classification accuracy, recall rate, and fault tolerance rate of the designed method are higher than the other two methods. The main reason is that, in the actual operation process, the designed method has added active learning where the algorithm classifies network resources, which promotes the effective improvement of the performance of the entire method, and at the same time has strong robustness.

5. Concluding Remarks

This paper mainly focuses on the problem of feature selection and SVM parameter optimization to improve classification accuracy. The feature selection and parameters are optimized simultaneously to reduce the number of features as much as possible while improving the classification accuracy. A classification method of network ideological and political resources based on an improved SVM algorithm is proposed. The algorithm introduces crossover and mutation

operators in PSO to increase the diversity of the population and avoids the problems of premature maturity and local optimality. Experimental results show that the algorithm can obtain a higher fitness value and accurately obtain the feature subset and SVM parameters of the data to be classified, so as to achieve higher classification accuracy. Therefore, it is believed that the GPSO-SVM algorithm performs well in classification ability and feature selection ability and is more efficient. It is an effective algorithm when applied to the classification of network ideological and political resources.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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