

Retraction

Retracted: Research on Classification Method of Network Resources Based on Modified SVM Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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.

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- [1] H. Zhang, J. Hu, and Y. Zhang, "Research on Classification Method of Network Resources Based on Modified SVM Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 5841829, 8 pages, 2021.

Research Article

Research on Classification Method of Network Resources Based on Modified SVM Algorithm

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According to the traditional classification method of network capital resources, there are some problems such as low efficiency, low recall rate, and low precision rate of information. Therefore, this paper proposes a new classification method of network capital resources based on SVM algorithm. Firstly, the original sample data are analyzed by principal component analysis to realize the design of resource classification process. Then, the dimension reduction of network resources data is realized by word segmentation and denoising. Thirdly, the reduced sample data are trained by the SVM classifier, and the best parameters of the reduced data are obtained by the grid search method. Lastly, the search range of SVM classifier parameters based on the original sample data is reset, so as to quickly obtain the best SVM classifier parameters of the original sample data and realize the classification. The experimental results show that this method can improve the recall and precision of network resource information and shorten the classification time of network resources.

1. Introduction

The construction of educational resource platform has been widely concerned, resulting in the gradual strengthening of the friendliness and standardization of educational resource platform. However, the following problems still exist in the process of the construction of educational resources platform. (1) The total number of educational resources is huge, but the quality education resources are relatively scarce. First, the repetition rate of resources in China's educational resources platform is high, the classification method is simple, the utilization rate is low, and a large number of educational resources are redundant. Secondly, due to the reasons of exam-oriented education, the educational resources lack innovation, which cannot spread the learners' thinking well and stimulate the interest of learners. At the same time, the website lacks high-quality navigation mechanism and resource index, and the platform interface is messy, so it is difficult for users to find the resources they need quickly [1–3]. (2) The construction mechanism and standard of educational resources are not perfect. The production and development of

educational resources in our country are in an independent state, and there is a lack of professional design and development teams for collaborative development. It fundamentally ignores the important role of instructional design in resource development, resulting in the low availability of resources [4]. (3) The types and classification of educational resources are single and unreasonable. Most educational resources are presented in the form of courseware, and there is a lack of interaction with learners in the teaching process. The teaching content presented by educational resources cannot stimulate students' interest in learning, and its effect on the improvement of learners is very limited [5]. At present, although the state spends a lot of money to build the national quality curriculum, it still cannot be extended to all kinds of schools at all levels in all provinces and cities, so it cannot really play its due role in the teaching process.

The above problems will have resistance to the sharing of resources, leading to the resources not being used to the maximum and resulting in the low utilization rate of resources, and many resource platforms are ignored. It can be seen that resource classification is a basic problem to be

considered in platform construction. At present, the classification of most resource platforms ignores the feelings of learners, so in the classification of resources, we should start from the perspective of learners, closely link learners' own characteristics, reintegrate resources, and enable learners to conduct active learning better. Relevant scholars have made some progress in this field.

Fowdur et al. proposed a machine learning algorithm for the classification of applications, states, and anomalies [6]. The aim of that paper is to investigate the performance of different network traffic capture tools for extracting features and to evaluate the performance of eight machine learning (ML) algorithms in the classification of (1) applications, (2) states, and (3) anomalies. Six Internet applications were considered along with four PC states and two network anomalies. The network was monitored by three traffic capture tools: PRTG, Colasoft Capsa, and Wireshark, and classification was performed using the Weka Toolkit. The performance of the eight ML classifiers was determined based on several metrics. The Colasoft Capsa feature set gave the highest accuracy for the classification of applications while the same was achieved with features from PRTG for the classification of the four states considered. For anomaly classification, the ML algorithms showed almost similar classification behavior when the Colasoft Capsa or PRTG feature set was used. Khan et al. proposed a burnt human skin segmentation and depth classification method based on deep convolutional neural network [7]. In this paper, the primary goals and objectives were to segment the burnt region of skin from the normal skin and to diagnose the burn depths as per the level of burn. The dataset contains the 600 images of burnt patients and has been taken in a real-time environment from the Allied Burn and Reconstructive Surgery Unit (ABRSU), Faisalabad, Pakistan. Burnt human skin segmentation was carried by the use of Otsu's method and the image feature vector was obtained by using statistical calculations such as mean and median. Using a classifier based on deep learning, burnt human skin can be divided into different depths and different levels according to the degree of burn. Almost 60 percent of images have been taken to train the classifier and the rest of the 40 percent burnt skin images were used to estimate the average accuracy of the classifier. The average accuracy of the DCNN classifier was noted as 83.4 percent and these are the best results yet. By the obtained results of this research task, young physicians and practitioners may be able to diagnose the burn depths and start the proper medication. Lei et al. proposed a tag recommendation by text classification with attention-based capsule network [8]. In this paper, the goal of a tag recommendation system is to provide a set of tags for a piece of text to ease the tagging process done manually by a user. These tags have been shown to enhance the capabilities of search engines for navigating, organizing, and searching content. However, tagging text manually is time consuming and labor intensive. In this paper, we introduce a tag recommendation by text classification. We explore the capsule network with dynamic routing for the tag recommendation task. The capsule network encodes the intrinsic spatial relationship

between a part and a whole constituting viewpoint invariant knowledge that automatically generalizes to novel viewpoints. In addition, an attention mechanism is incorporated into the capsule network to distill important information from the input documents. We conduct extensive experiments on large publication datasets to evaluate the effectiveness of our model. In reference [9], Sabattini et al. proposed a neural network to deal with the classification of the succession stage in the primary forest of the spine in Argentina. The purpose of this work has been to provide technicians an objective tool for the classification of successional status in native forests. In this work, it has been found that there is a relationship between the presence of combinations of different plant species, both arboreal and shrub, related to the classification of forests. This relationship has been analyzed through the application of neural networks in two steps: a perceptron was applied followed by a probabilistic neural network. Through the analysis of these two stages of artificial neurons, we can see that through the presence/absence of 16 species, succession states can be classified objectively. This analysis demonstrated an agreement of 83% with the subjective classification of trained field assessors.

In order to solve the above problems, this paper proposes a network resource classification method based on modified SVM algorithm. This method does not involve probability measure and law of large numbers, so it is different from the existing statistical methods. In essence, it avoids the traditional process from induction to deduction, and it can help to realize efficient "transductive reasoning" from training samples to prediction samples and can greatly simplify the common problems of classification and regression. The motivation of this paper is to take advantage of the SVM algorithm to improve the performance of the classification method of network capital resources. We use the principal component analysis method to analyze the original sample data which can help to realize the design of resource classification process. Then, we use the word segmentation and denoising method to reduce the dimension of network resources. After that, the reduced sample data are trained by the SVM classifier, and the best parameters of the reduced data are obtained by the grid search method. At last, it can reset the search range of SVM classifier parameters based on the original sample data.

The main contribution of this work can be described as follows:

- (1) Introduction of the SVM algorithm to resolve classification method of network capital resources. According to the SVM algorithm, it can effectively reduce the processing complexity and improve the processing performance.
- (2) Analysis of the main steps of the classification method of network capital with the SVM algorithm.

This paper is organized as follows. Section 2 presents the method to obtain the optimal classification function for the output of network information resources. Section 3 gives the method of classification time of network resources based on modified SVM algorithm. Section 4 gives the experiment

and the results. Finally, Section 5 outlines some conclusions and suggests a few future research topics.

2. Obtaining the Optimal Classification Function for the Output of Network Information Resources

2.1. Classification of Network Information Resources. The classification process of network information resources (see Figure 1) can be divided into two processes: indexing and classification. The main purpose of indexing is to preprocess the obtained resource set to make its structure clear and standardized. Then, combined with word segmentation dictionary, the attribute and feature of each resource can be ordered by means of word segmentation and feature extraction, and finally the subject set of resources can be located. At the same time, indexing can also be understood as the process of information extraction, which plays a decisive role in the efficiency and performance of resource information classification [10–13]. In addition, the indexing process can also be used to establish and update the knowledge base, and the feature information generated in the process can play a supporting role for the expansion and improvement of the knowledge base. The resource classification process is shown in Figure 1.

Classification processing mainly refers to the process of establishing a direct association relationship between resources and categories that focus on different topics through certain discrimination rules under the premise of a given classification system. From the mathematical point of view, classification can be understood as the process of category mapping, which is expressed as $F: A \rightarrow B$, where A is the resource set to be classified and B is the known category set. In fact, its main purpose is to connect the network information resources whose categories are not clear with the known categories. Because the characteristics contained in a resource can reflect multiple categories at the same time, there are many mapping relationships: one to one, one to many, and so on. The discrimination rules needed for classification are generally generated in the process of training, and the corresponding rules are formed according to the characteristic law parameters of training output [14].

2.2. Denoising Processing. In view of the semistructured characteristics of web pages, there are many kinds of “junk” information which are not related to the theme. This information will not only interfere with the overall efficiency of the resource classification process but also greatly reduce the accuracy of resource feature extraction. Therefore, before resource feature extraction, it is necessary to filter the resource information. It mainly covers the following filtering methods.

2.2.1. Filtering the Original Noise. The filtering information of the original noise can be divided into two categories: one is network information resources, the main content contains a large number of structural elements, comments, script codes, styles, control tags, and other information used for grammar. The more common ones are HTML component

elements, JavaScript scripts, etc. These tags will not have much help and influence on the positioning of resource topics, but not all markers are meaningless, for example, starting tags such as `<title> </title>`, ` ` may provide some reference information for the classification of network information resources. The other is the controllable spam information, which mainly includes navigation bar, advertisement, picture link, copyright, and other information [15, 16].

2.2.2. Filtering Inactive Words. After word segmentation, it is necessary to filter the stop words which have no influence on the information meaning and have no characteristic value, generally including articles, conjunctions, quantifiers, prepositions, function words, and so on. Stop word filtering will effectively reduce the dimension of vector space and improve the accuracy of classification.

2.3. Word Segmentation Processing. The main function of word segmentation is to preprocess the text and extract the hidden feature set sequence of resources. In view of the fact that there is no obvious distinguishing mark between words in Chinese grammatical structure, word segmentation processing technology has become the primary problem of resource classification. It is not only a necessary work before resource classification but also a key link to improve the quality of resource classification. Inaccurate word segmentation will greatly affect the accuracy of the index database, thus greatly reducing the efficient utilization of resources.

2.4. Classification Processing. Classification processing is the key link of network information resource classification, which can be understood as the mapping process of resource feature set and subject category. Information classification methods can be divided into two categories: one is statistical method, which mainly includes support vector machine method, k -nearest neighbor method, naive Bayes method, neural network, and so on; the other is the rule method, which includes decision tree, rough set, etc.

Support Vector Machine (SVM). Support vector machine combines VC dimension and inductive principle of minimum structural risk in statistical learning and uses simple linear classifier to divide sample space [17]. In this method, the original vector is mapped to the kernel space through a kernel function to become a linearly separable mapping vector, and the distribution range of each sample point is cut into independent small areas. Then, the boundary of each area is divided into corresponding positive and negative categories according to the category of the sample points. Finally, the boundary of the sample point area is merged according to the rule of same direction preservation and reverse cancellation. Then, a series of segmented hyperplanes will be constructed; finally, new samples will be input to calculate the circumferences of these sample points with respect to the above classification curve, and the category of the sample points can be judged according to the

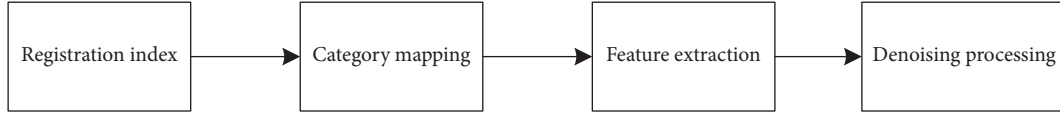


FIGURE 1: Resource classification process.

circumferences, or the category of the sample can be judged by selecting an appropriate ray starting from the point to be determined and using the parity of the intersection number of the ray and the hyperplane. The area is redrawn around the point, and the boundary is reoriented.

Let the given training set be (x_i, y_i) , $i = 1, \dots, n$, $x_i \in R^d$, $y_i \in \{-1, 1\}$, where n is the number of samples and d is the dimension; then, the d -dimensional space is linearly divided by a hyperplane $w \cdot x + b = 0$, and the discriminant function $f(x) = w \cdot x + b$ is normalized, and the classification interval is equal to $2/\|w\|$, so that the maximum interval is equivalent to the minimum $\|w\|^2$ and two kinds of samples satisfy the following conditions:

$$y_i [(w, x_i) + b] - 1 \geq 0, \quad i = 1, \dots, n. \quad (1)$$

If $1/2\|w\|^2$ can reach the minimum value as the measurement standard of the best hyperplane, the support vector is the training sample on the line nearest to the classification line and parallel to the classification line [18]. The general SVM classification algorithm is basically for two kinds of problems. It obtains the value of $w^* \cdot b^*$ through the optimization theory and outputs the optimal classification function.

$$f(x) = \text{sgn}\{(w^* \cdot x) + b^*\}. \quad (2)$$

We then determine the category of the sample. The sum of the above formula is only for the support vector, and b^* is the classification closed value; when $f(x) \geq 0$, x belongs to a known positive category; otherwise, it belongs to a negative category. The results of the comparative study show that SVM has good performance in effect and performance. At present, the method has less participation in evaluation. Therefore, this paper needs to improve this method, and better classification effect of network capital resources will be obtained.

3. Classification Time of Network Resources Based on Modified SVM Algorithm

In view of the shortcomings of traditional SVM classifier, such as low classification efficiency and long calculation time, this paper uses RBF as the kernel function to explore a method to quickly find the best parameters c and γ of the SVM classifier. The method flow is shown in Figure 2.

In this figure, we can see that the original sample data can be dealt with the PCA method, and then the dimension reduction sample data can be obtained. After that, it can be dealt with the SVM network search method. The best parameters c and γ can help to search scope reconstruction. Then, the new parameter range can be obtained. At last, the SVM network search method can be

help to realize the classification results of network resources.

3.1. Optimal Parameter Acquisition of SVM Based on PCA Dimension Reduction Data. In order to solve the problem that the time for grid search method to find the best parameters increases exponentially due to the large amount of sample data and multidimension of object-oriented network resource classification, this paper first uses PCA to reduce the dimension of data and eliminate the correlation between sample attributes and then sets the initial value of the parameter search range based on the reduced dimension data. Then, the first p principal components generated by PCA (to ensure that the information of the first p principal components accounts for more than 99% of the total information, P is generally less than 15) are taken as the new sample attributes. The new samples are trained based on SVM algorithm, and the best parameters of PCA dimension reduction data are obtained by the grid search method. The search scope of grid search method is set as

$$\begin{cases} x = lb & c \quad x \in (-14, 14), \text{step} = 1, \\ y = lb & \gamma \quad y \in (-14, 14), \text{step} = 1, \end{cases} \quad (3)$$

where c and γ are the penalty factor and RBF kernel parameter, respectively, and x and y are coordinate pairs in grid search; the search range is $-14 \sim 14$ by default, and the step size is 1, with a total of 29 values, that is, the best parameters c and γ need to be selected from 841 (29×29) combinations. The classification attributes of the original sample data are generally more than 100. Because the dimension of the sample data is greatly reduced after PCA processing, compared with the best parameter search based on the original data, the parameter search time will be shortened. However, the data processed by PCA lost some information, so the optimal parameters of SVM classifier generated by this process are not the same as the optimal parameters based on the original data, but the approximate range of the latter can be deduced and the search time of the optimal parameters can be reduced.

3.2. SVM Optimal Parameter Acquisition and Classification. According to the optimal parameters of SVM classifier based on PCA dimension reduction data, the search range of original data classifier parameters is delimited, so as to optimize the parameters of grid search method and obtain the optimal combination of parameters based on the original data.

Assuming that the optimal penalty factor and kernel parameter of SVM classifier based on PCA dimension reduction data are, respectively, c_{PCA} and γ_{PCA} , they are

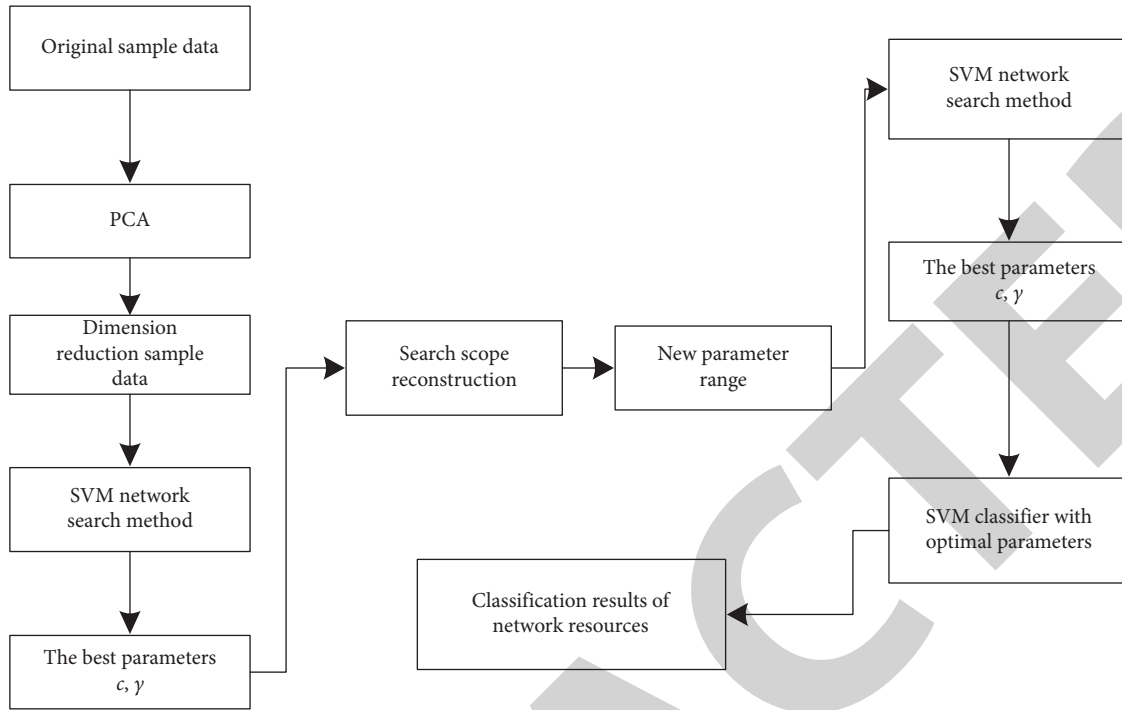


FIGURE 2: Classification process of improved SVM algorithm.

converted into coordinate pairs corresponding to the grid search method, namely:

$$\begin{cases} x_{PCA} = lb, & c_{PCA}, \\ y_{PCA} = lb, & \gamma_{PCA}. \end{cases} \quad (4)$$

This method assumes that the optimal parameters of SVM classifier based on original sample data are near the optimal parameters of classifier based on reduced dimension data. Based on this assumption, taking c_{PCA} and γ_{PCA} as initial values, the original data classifier parameter search range is reset, i.e.,

$$\begin{cases} x_1 \in (x_{PCA} - 2, x_{PCA} + 2), \text{ step} = 1, \\ y_1 \in (y_{PCA} - 2, y_{PCA} + 2), \text{ step} = 1, \end{cases} \quad (5)$$

where x_1, y_1 are the coordinate pairs in SVM parameter search based on the original data, the step size is 1, and they are 5 values, respectively; therefore, the best parameters only need to be obtained from 25 parameter combinations. Based on the new grid search range, the optimal parameter combination c', γ' is obtained by the grid search method for the original sample data. Finally, the SVM classifier is used to classify the original data and verify its accuracy.

3.3. Data Acquisition System. In order to get data, we set up a network data acquisition system. The basic principle of the data acquisition system is shown in Figure 3.

In this figure, the data acquisition terminal is used to collect the data, and the data processing center is used to classify the collected data. There are many data acquisition terminals in this system.

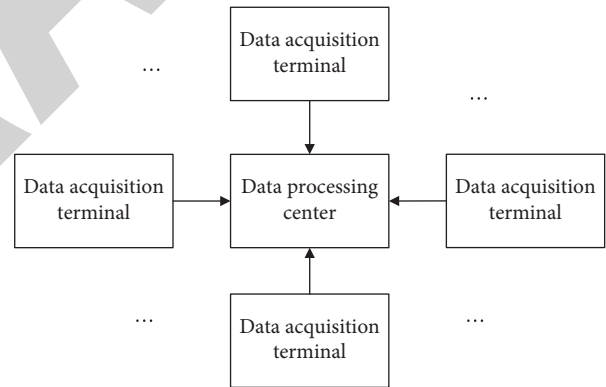


FIGURE 3: Data acquisition system.

4. Experiment

4.1. Experimental Index. At present, there is no complete standard evaluation system for the evaluation of the classification process of network information resources. At present, most of the evaluation standards for the classification effect of network information resources still refer to the result quality evaluation index [20L] of information retrieval, and the more common ones are precision rate, recall rate, F_1 , etc.

- (1) The calculation formula of precision ratio of network information resources is as follows:

$$p(\%) = \frac{a}{a + b}, \quad (6)$$

where p is the calculation result, a represents the number of resources correctly assigned to a certain

TABLE 1: Precision rate of network resource information.

Data volume of network capital resources (GB)	The precision ratio of network resource information (%)			
	Reference [6]	Reference [7]	Reference [8]	Method of this paper
5	73	76	79	92
10	76	72	77	96
15	78	72	73	98
20	66	72	80	90
25	72	69	73	88
30	75	73	81	89
Mean value	73.3	72.3	77.2	92.2

category, and b represents the number of resources wrongly assigned to that category, that is, the proportion of correctly classified texts in all classified texts.

- (2) The recall rate of network information resources is calculated as follows:

$$r(\%) = \frac{a}{a+c}, \quad (7)$$

where r is the calculation result and c is the number of instances that belong to this category but are mistakenly classified into other categories. Recall rate, that is, the proportion of correctly classified text in the text, should be manually classified.

- (3) The calculation formula of F_1 value of network information resources is as follows:

$$F_1 = \frac{2pr}{p+r}. \quad (8)$$

Because there is an obvious correlation between precision and recall, F_1 value realizes the comprehensive evaluation of the above two indicators. In addition, in view of the situation of multitopic categories, different mean methods can be used to obtain the corresponding micro average F_1 value or macro average F_1 value.

At present, most of the performance evaluation criteria are based on time consumption, that is, the time consumption of the whole process when classifying the same set of network information resources.

$$T_s = t_z + t_t + t_y, \quad (9)$$

where T_s is the total time, t_z is the network resource denoising time, t_t is the network resource feature extraction time, and t_y is the network resource category mapping time. In addition, the performance of classification processing can be measured by the number of resources processed per unit time.

4.2. Experimental Scheme. The operating system used in this experiment is Windows Server 2003. The required development tools are as follows: VisualStudio.NET2008 and MATLAB7.0. The programming languages used in this paper are C # and Matlab instructions.

In order to verify the research on the network resource classification method of this paper, we use the methods proposed in reference [6], reference [7], and reference [8] to

compare with the method proposed in this paper to verify the performance.

4.3. Result

4.3.1. Precision Ratio of Classification Methods of Network Resources. In order to verify the accuracy of this method on the information of network resources, the methods of reference [6], reference [7], reference [8], and this paper are used to monitor the accuracy rate of network resources. The specific results are shown in Table 1.

According to the analysis of Table 1, when the data volume of network resources is 5 GB, the precision of reference [6] is 73%, that of reference [7] is 76%, that of reference [8] is 79%, and that of this method is 92%. When the data volume of network resources is 30 GB, the precision of reference [6] is 75%, that of reference [7] is 73%, that of reference [8] is 81%, and that of this method is 89%. The precision rate of this method is always at a high level, which shows that the classification effect of this method is better.

4.3.2. Recall Ratio of Classification Methods of Network Resources. In order to verify the method of this paper, the methods of reference [6], reference [7], reference [8], and this paper are used to monitor the recall rate of network resources. The specific results are shown in Table 2.

Analysis of Table 2 shows that the recall rate of network resource information is different under different methods. When the data volume of network resources is 15 GB, the recall rate of reference [6] is 81%, that of reference [7] is 74%, that of reference [8] is 75%, and that of this method is 96%. The overall analysis of the table shows that the average recall rates of reference [6], reference [7], reference [8], and this method are 79.5%, 75.7%, 76.2%, and 95.8%, respectively. This shows that the method in this paper has a good effect of information retrieval of network resources.

4.3.3. Classification Time of Network Resources. In order to verify the efficiency of this method for the information classification time of network resources, the methods of reference [6], reference [7], reference [8], and this method are used to monitor the classification time of network resources. The specific results are shown in Table 3.

According to the analysis of Table 3, there are differences in the classification time of network resources under different methods. When the data volume of network resources

TABLE 2: Recall rate of network resource information.

Data volume of network capital resources (GB)	Recall rate of network resources (%)			
	Reference [6]	Reference [7]	Reference [8]	Method of this paper
5	83	79	82	99
10	84	72	82	98
15	81	74	75	96
20	76	72	71	90
25	75	76	72	95
30	78	81	75	97
Mean value	79.5	75.7	76.2	95.8

TABLE 3: Classification time of network resources.

Data volume of network capital resources (GB)	Classification time of network resources (s)			
	Reference [6]	Reference [7]	Reference [8]	Method of this paper
5	16	24	23	0.8
10	31	27	29	1.3
15	33	31	35	2.7
20	48	36	39	3.2
25	51	48	45	4
30	59	54	44	4.5
Mean value	39.7	36.7	35.8	2.75

is 10 GB, the classification time of reference [6] is 31 s, that of reference [7] is 27 s, that of reference [8] is 29 s, and that of this method is only 1.3 s. When the data volume of network resources is 30 GB, the classification time of reference [6] is 59 s, that of reference [7] is 54 s, that of reference [8] is 44 s, and that of this method is only 4.5 s. This method always has a lower classification time of network resources, which shows that the classification efficiency of this method is better.

5. Conclusion

In this paper, a classification method of network resources based on modified SVM algorithm is proposed. The classification process of network resources is designed and implemented. The dimension reduction of network resources data is realized by word segmentation and denoising. The SVM classifier is trained on the reduced sample data, and the best parameters of the reduced data are obtained by the grid search method. The best SVM classifier parameters of the original sample data are obtained, and the classification is realized. The results are as follows:

- (1) When the amount of network resource data is 30 GB, the precision of this method is 89%. The precision rate of this method is always at a high level, which shows that the classification effect of this method is better.
- (2) The average recall rate of this method is 95.8%. This shows that the method in this paper has a good effect of information retrieval of network resources.
- (3) The average classification time of this method is only 2.75 s. This method always has a lower classification time of network resources, which shows that the classification efficiency of this method is better.

The SVM can help to avoid the traditional process from induction to deduction, and it can realize efficient “transductive reasoning” from training samples to prediction samples and greatly simplify the common problems of classification and regression. Although the SVM can effectively improve performance, the accuracy and complexity still fail to meet the requirements. In the future, we can try to introduce the artificial intelligence algorithm such as BP network to further improve the performance.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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