Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 9406930, 11 pages
https://doi.org/10.1155/2022/9406930

Research Article

Image Extraction of Tailings Pond Guided by Artificial Intelligence Support Vector Machine

Xiaoyun Wu

Shangluo University, The New Style Think Tank of Shaanxi Universities Shangluo Development Research Institute, Shangluo, Shaanxi, China 726000

Correspondence should be addressed to Xiaoyun Wu; 230023@slxy.edu.cn

Received 29 June 2022; Revised 22 August 2022; Accepted 2 September 2022; Published 22 September 2022

Academic Editor: Kuruva Lakshmanna

The large number of tailings ponds in my country, coupled with various man-made and natural factors in recent years, leads to the frequent occurrence of tailings pond accidents, causing serious harm. Mastering the number and distribution of tailings ponds is of great significance to prevent tailings pond accidents and carry out emergency management of tailings ponds. For the identification and monitoring of tailings ponds, the traditional survey methods are mainly based on ground surveys, and it is difficult to achieve large-scale and high-frequency detection. With the development of artificial intelligence technology, based on the support vector machine (SVM) method, the automatic extraction of remote sensing image (RSI) information has been realized, and remarkable achievements have been made in the field of remote sensing. This paper takes the tailings pond as the research goal, and based on the analysis of the characteristics of the tailings pond in the RSI, the method of SVM target detection is used to realize the rapid and high-precision identification of the tailings pond. The main contents of this paper are as follows: (1) The accident risk of tailings ponds at home and abroad and the status quo of tailings pond monitoring technology are introduced. (2) The relevant theory of SVM is learned, and the kernel function and corresponding parameter selection method of SVM are discussed in a multiclassification problem. (3) On the basis of determining the kernel function, parameters, and features, the trained model is compared with the original model. The results show that the SVM detection model proposed in this paper has excellent performance in tailings pond image recognition.

1. Introduction

In recent decades, my country's economy has developed rapidly, and mining resources have played an increasingly important role in its development. It provides a large number of production materials such as electricity and energy required by industry and agriculture. Tailings refer to the "slag" that is generally sand-like after the concentrates are screened out from metal and nonmetallic ores by concentrators [1]. The tailings sand produced in my country every year reaches about 3×109 tons. However, at present, no new industry has been formed in the redevelopment of tailings in my country, and it is only used in construction and other industries. A large amount of tailing sand is stored in a tailings pond surrounded by mountains, which not only occupies a large amount of mountains. In addition, the use of a large number of chemical liquids in the mineral processing process leads to the discharge of a large amount of toxic liquids containing heavy metal ions, causing pollution of rivers, water sources, and clogging of public drainage systems [2]. Tailings pond refers to a special water conservancy project used for stacking tailings sand and sand dressing wastewater, including tailings accumulation facilities, drainage equipment and pipelines, facilities for transporting tailings sand, safety monitoring equipment, and other auxiliary facilities. According to the topographic features and construction methods of tailings ponds, tailings ponds are divided into river-cut, mountain-side, valley, and flat-terrestrial tailings ponds. Tailings dam refers to a protective facility that blocks tailings sand and a large amount of drainage. It is an initial dam made of hard stones and a subdam made of sand in the later stage. Upstream dam-building methods account for 90% of all tailings dams in my country due to the advantages of easy site selection, simple dam-building methods, strong practicability, and simple management. The method security is the lowest among the three methods [3]. Due to the upstream dam construction method, the subdam is built higher and higher, and the subdam is not built with hard rock but is composed of loose tailings and a small part of plants. This leads to poorer permeability of the tailings dam, higher position of the wetting line, and reduced stability. Most of the tailings dams in western developed countries are mainly midstream and downstream dam construction methods, and the safety monitoring situation of tailings dams in my country is severe [4]. According to the research of the public hazard group of Clark University in the United States, the hazards of tailings pond accidents are ranked 18th after earthquakes, floods, nuclear explosions, poisonous gases, and nuclear radiation. Due to the great difficulty of rescue and the extremely low accident survival rate, the damage caused by the mine dam collapse accident is more serious than that of fire, explosion, and aviation accident. Tailings pond accidents at home and abroad have caused shocking harm. Nearly two-thirds of tailings pond accidents in my country are tailings dam failure accidents. To sum up, the tailings pond is a major source of danger, and the consequences of an accident are unimaginable. Therefore, it is of great significance to master the number, distribution, type, and existing status of tailings ponds to prevent tailings pond accidents and carry out emergency work of tailings ponds [5]. At present, the method of monitoring tailings ponds mainly adopts the method of ground investigation. However, the number of tailings ponds in my country is huge, and the distribution range is wide. At the same time, many tailings ponds are built in remote mountainous areas, and the surrounding environment is very harsh. The information of these tailings ponds is unrealistic. It will consume a lot of manpower and material resources to determine the new situation of tailings ponds and improve the database of tailings ponds frequently, and it is difficult to ensure the accuracy and timeliness. Therefore, the current national security department urgently needs new technical means to conduct large-scale, high-frequency, and rapid automatic monitoring of tailings ponds to improve the level of tailings pond risk management and the ability of tailings ponds to respond to emergencies. Remote sensing technology has the advantages of wide detection range, fast acquisition of data, less restrictions by ground conditions, and large amount of acquired data. It can well make up for the shortage of manual monitoring methods on the ground and is an effective technical means for tailings pond monitoring [6]. The key technology of the above survey content is remote sensing image classification. Commonly used classification methods include K-means, handle recognition, neural network, minimum distance, support vector, object-oriented, maximum likelihood, pattern recognition, and genetic algorithm. SVM is an artificial intelligence algorithm whose basic theory is statistical learning theory. Because the algorithm is suitable for small samples and has the advantages of simple structure, easy training, fast convergence, and high classification accuracy, it is widely used in remote sensing image classification [7]. At present, most of the research on the classification of remote sensing images of mines are multiclassification of the land occupied by mines, and there are few studies on tailings ponds. Considering the large number of tailings ponds in my country and the importance of tailings ponds, this paper uses the support vector machine method to extract tailings pond images and combines the characteristics of tailings ponds to construct a model method suitable for tailings pond detection. The realization of fast and high-precision automatic identification of tailings ponds provides a foundation for the effective management of tailings ponds in my country. This paper creatively proposes the use of support vector machines to achieve pixel-level remote sensing image classification and constructs a complete experimental process. The related theory, feature selection, and parameter selection of support vector machine are discussed. And for the generality of the experiment, seven types of tailings samples were selected. The SVM-OVO classifier was finally selected through experiments, and a good classification effect was obtained.

2. Related Work

The construction of tailings ponds abroad has a long history, and the earlier one was the Brent tailings pond built in 1830 [8]. Reference [9] studied the tailings pond and concluded that the dam failure factors of the tailings pond mainly include the design and construction technology of the tailings dam, the content of tailings, the water level of the tailings pond, and downstream sensitive factors. Reference [10] conducted a comparative study on the tailings leaching of two tailings ponds and found that when the pH value of the tailings is neutral or near neutral, it can effectively prevent the heavy metal elements from entering the surrounding natural environment. Reference [11] pointed out that most of the dam failure accidents in the United States are related to poor basic conditions such as flooding of tailings ponds, unstable dam bodies, and seepage. Reference [12] used a geophysical method to conduct field tests on three tailings dams in Sweden and demonstrated the feasibility of this method in monitoring the physical properties and variability within tailings dams. Reference [13] conducted a statistical analysis of the causes of 147 tailings dam disasters in the e-EcoRisk database and concluded that tailings dam failures are related to dam height. Reference [14] took the tailings pond in the Mediterranean region of the e-EcoRisk project as an example and combined the correspondence analysis method to evaluate the dam failure risk of the tailings pond. Reference [15] used FLAC3D and other software to perform static and dynamic analysis on a typical cross-section of a soil tailings dam. It is concluded that the seismic action has a serious influence on the deformation of the dam body and the bottom input acceleration of the tailings dam has an amplification effect along the dam height. Reference [16] studied the role of capillary water in the stability of tailings dams, found that the stability of the dam body strongly depends on the capillary phenomenon, and proposed that capillary water measurement should be added to the standard monitoring scheme of tailings dams. Reference [17] used fractal geometry that is applied to the study of tailings dewatering and flocculation structure change, and it is proposed to increase the stability of tailings dam by improving the consolidation process and deposition density of fine tailings. The research technology of tailings pond in my country started relatively late. In recent years, with the gradual increase in the country's emphasis on resources and environmental issues, the environmental and safety issues in tailings ponds have also begun to attract the attention of experts and scholars [18]. Many researchers have used remote sensing images to monitor and analyze tailings ponds and their environmental impacts. Reference [19] took an old tin mine tailings pond as an example and completed the research on the site selection of the tailings pond through spatial stacking, buffer analysis, and other methods. Reference [20] explores the detectability of multisource remote sensing data for various types of mine target features based on the characteristics of remote sensing images of mine features, summarizes the status quo, research priorities, and existing problems of remote sensing detection of mine development and mining environment, and proposes the key technical problems that need to be further explored, and the solution ideas are initially proposed. Reference [21] used TM images and a water quality remote sensing monitoring model to study the main water quality indicators in the Hushan tailings pond. It is proved that the use of remote sensing technology and geographic information system technology can effectively monitor the water pollution status of tailings ponds. Reference [22] uses 3S technology to establish the interpretation mark of tailings pond features. The number, area, mineral type, usage, and other information of tailings ponds are extracted, and the monitoring of large-scale regional tailings ponds in a short time is realized. Reference [23] adopted the monitoring method combining remote sensing and geographic information system to establish identification signs of tailings pond location, danger, and harmful factors and classified and extracted three different types of tailings ponds in a certain area. The monitoring status of the tailings pond in this area is presented. Reference [24] sampled 7 tailings ponds in a province and studied the relationship between the color difference of the remote sensing image of the tailings pond and the mineral composition of the tailings pond. Mineral composition is not directly related. Reference [25] used TM remote sensing images and topographic map data to study the ecological image of a tailings pond in a province after the expansion and concluded that the expansion of the tailings pond would have an impact on the surrounding ecological environment. Reference [26] took the iron mine in a city as the research area, combined with the remote sensing image of Gaofen-1, and obtained the best band combination for visual interpretation of tailings pond, which is the remote sensing based on Gaofen-1 and similar resolutions. Image tailings pond research provides the basis. Reference [27] takes a mine tailings pond in a western city as an example and uses domestic high-resolution remote sensing images of multiple periods to extract environmental information of the tailings pond area, and the results show that domestic high-resolution remote sensing images can be applied to tailings ponds monitoring of environmental changes in the reservoir area. SVM was originally used to solve the problem of pattern recognition, the purpose is to find decision rules with good generalization performance, SV is actually a subset of the training set, and the optimal classification of SV is equivalent to the classification of the training set. In recent years, SVM has been widely used in pattern recognition, regression analysis, probability density function estimation, and other fields. Reference [28] uses a mining area as an experimental research area to dynamically monitor the environment in the study area and uses remote sensing methods to monitor the environment in the study area. In this way, the environment of the study area can be protected and the rational development of the mine can be monitored. Remote sensing images of multiple times and multiple resolutions were used, from macro to micro, from whole to part, real-time monitoring of changes in mines in the study area. Reference [29] used Jixi mining area as the experimental research area and used the combination of ERDAS software and MapGIS software to carry out remote sensing processing of the collapse information in the study area. In addition, topographic maps, remote sensing images, and other data are used to verify the study area on the spot to verify whether the extraction of the collapsed area is correct. The interpretation method of the subsidence information in the project area is analyzed, and the application of remote sensing means provides a basis for the extraction and acquisition of coal mine subsidence information. Reference [30] used high-resolution remote sensing images as data sources and used remote sensing images to investigate changes in the surface environment of the mining area, laying a foundation for monitoring the damage to the mining area and its surrounding environment.

3. Method

There are many theories and methods of remote sensing image classification based on machine learning, and the classifiers are too numerous to enumerate, but SVM classification has obvious advantages in many classification methods, and its generalization ability is significantly better than traditional methods, especially for small sample classification. In this chapter, the pixel-level RSI classification is realized based on the SVM theory through the experimental platform. The experimental process is shown in Figure 1. This chapter discusses the related theory, feature selection, parameter selection, and other aspects of SVM.

The basic process of supervised classification of remote sensing images combined with multifeature description and SVM classifier is as follows.

(1) First, mark a certain amount of areas on the image through visual interpretation or in combination with other data, determine the types of ground objects in these areas, and use them as training sample areas to train the SVM classifier

(2) Through a certain algorithm or a combination of certain algorithms, calculate and describe the pixels in the area with the category label obtained in (1), extract the digital features that can effectively

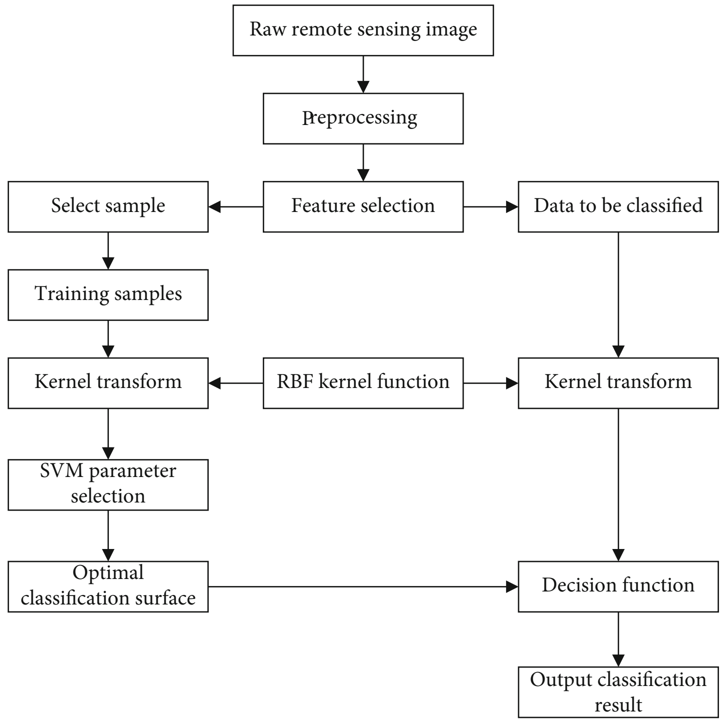

Figure 1: SVM pixel-level classification flow chart.

distinguish the ground objects, and combine these digital features

(3) Preprocess the vector obtained in (2), perform scaling and feature selection in a certain method, and obtain a new feature vector

(4) Use the vector obtained in (3) as the training data of the SVM classifier, select an appropriate method for parameter selection, and use the parameter pair with the smallest generalization error as the SVM and kernel function parameters to train the optimal classifier

(5) Use the feature description algorithm used in (2) to perform feature calculation on the image to be classified, and then use the method used in (3) to scale and feature selection on the result of the feature calculation to obtain the feature vector of the pixel to be classified

(6) The feature vector of each pixel obtained in (5) is used as the input vector, the SVM classifier obtained in (4) is used for classification, and the classification result of each pixel is marked

(7) Count the classification accuracy in (6), and if the classification accuracy meets the requirements, the classification ends; otherwise, check the selection of the training sample area in (1), and reexecute steps (2)-(7) after modifying the sample area

3.1. Support Vector Machine-Related Theory. In the field of machine learning, classifiers such as decision tree, maximum likelihood, random forest, and SVM have been studied and applied by scholars. SVM is a pattern recognition method based on system learning theory proposed in the 1960s, but it was not popularized at that time due to various constraints. In the 1990s, statistical learning theory solved the problems of local minima, overlearning, or underlearning of other classifiers. Therefore, many scholars have studied SVM in depth, making it widely used and developed rapidly. A large number of literatures show that SVM has significant advantages in solving small samples, nonlinear and high-dimensional pattern recognition, etc., and is widely used in remote sensing image classification. Therefore, this paper chooses the SVM method to extract tailings ponds. The ultimate purpose of the SVM is to use a classification hyperplane to completely separate the sample objects, so that the classification accuracy of the sample objects is high and each classification data object has the largest distance from the classification hyperplane. For example, in a hyperplane, there are two types of training samples, H is the classification surface, $H1$ and $H2$ represent the planes farthest from the classification surface and parallel to each other in the two types of samples, and the distance between them is called the segmentation distance. If it can not only separate the two types of samples but also satisfy the maximum blank spacing, we call this plane the optimal classification surface, and the plane in the middle of the optimal classification surface is called the superoptimal classification surface. The problem of finding the superoptimal classification surface is transformed into finding the optimal classification surface. At the same time, the above problem is also transformed into the problem of finding the maximum segmentation distance, so the problem of finding the optimal classification surface can be expressed as a mathematical formula:

$$\min \frac{1}{2}\|w\|^2, \tag{1}$$

$$s.t.y_i(wx_i + p) \ge 1, i = 1, 2, 3, \cdots, n. \tag{2}$$

The above is an idealized situation, that is, the two types of samples can be completely and correctly separated, and there is no empirical risk. In other words, when the classification distance reaches the maximum value, the generalization of the classifier is the best. In reality, most data is nonlinear and cannot be completely separated correctly. Due to various reasons, the samples are misclassified. For this reason, scholars introduce slack variables to balance the empirical risk and generalization performance. The above formula is extended to:

$$\min \left\{\frac{\|w\|^2}{2}\right\} + C\sum_{i=1}^{k} \varepsilon_i, \tag{3}$$

$$s.t.y_i(wx_i + p) \ge 1 - \varepsilon_i, i = 1, 2, 3, \cdots, n, \tag{4}$$

where C is the penalty coefficient, which is an artificially set constant, which represents the punishment for illegal samples in the blank area. In order to solve the above formula, the Lagrangian method is introduced, and the constraints are:

$$\sum_{i=1}^{n} y_i\alpha_i = 0, 0 \le \alpha_i \le C, i = 1, 2, 3, \cdots, n, \tag{5}$$

where α_i is the Lagrange multiplier value corresponding to each constraint condition in the original optimal classification surface solution problem, and the maximum value of the solution function for α_i is:

$$MaxQ(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j (x_i \times y_i). \tag{6}$$

The final formula for classification is as follows:

$$f(x) = \operatorname{sgn}\left\{\sum_{i=1}^{n} \alpha_i^* y_i \left(x_i \times x_j\right) + p^*\right\}, \tag{7}$$

where $sgn()$ is the symbolic function and p^* is the threshold of classification, which can be obtained by taking the median value of any pair of support vectors in the two categories, and x_i is the sample. Since the α_i corresponding to the nonsupport vectors are all 0, the summation in the above formula is actually only performed on the support vectors.

When the SVM is solving the nonlinear separable situation, the key is to use the kernel function to realize the mapping from the input space to the feature space. The commonly used kernel functions are as follows.

The polynomial kernel function is:

$$K\left(x_i, x_j\right) = \left(\gamma\left(x_i, x_j\right) + p\right)^t, t = 1, 2, 3, \cdots. \tag{8}$$

The Gaussian radial basis function (RBF) kernel function is:

$$K\left(x_i, x_j\right) = \exp\left(-\gamma\left\|x_i - x_j\right\|^2\right). \tag{9}$$

The main function of the Gaussian radial basis function is the transformation of the original space and the infinite-dimensional space. It is very flexible to use, so the kernel function is widely used.

The Sigmoid kernel function is:

$$K\left(x_i, x_j\right) = \tanh\left[\gamma\left(x_i \bullet x_j\right) + p\right]. \tag{10}$$

The above theoretical reasoning is aimed at two types of samples, that is, two-classification problems. However, in our real life, most of the classification problems are multiclass recognition. For this, many scholars have conducted in-depth research on the method of extending from two-classification to multiclassification. The literature shows that the multiclassification method of support vector machine has two main ideas: One is to solve all the samples directly, and the classification results are obtained at the same time; the other is to solve the problem of treating the samples as multiple binary classifications based on the binary classification algorithm. Common multivalue classification algorithms are as follows.

(1) One-versus-rest SVM classifier (SVM-OVR): SVM-OVR makes one class as a separate class in the entire training sample, and the rest as one class, which becomes a binary classification problem again. For example, for a sample with K classes, one class is first classified as a separate class, and the remaining $K - 1$ classes are classified as one class. In the decision process, the rule with the largest decision function value is followed. In this way, only K two-class support vector machines need to be trained. Because there are few classification functions, the running speed is fast, which is the advantage of one-to-many classifiers. However, when there are many categories, the training samples will be uneven, which will affect the classification accuracy. In addition, the two-class classifier training must be performed on all samples each time. This training process is very complicated and takes a long time

(2) One-versus-one SVM classifier (SVM-OVO): SVM-OVO was proposed by Kresseh. The classifier is to construct a classifier for each class of all samples. Then vote to decide which class the sample belongs to. For example, in K categories, $K(K - 1)/2$ classifiers are needed, and then each classifier can predict a category of the sample; at this time, the category to which the sample belongs is given a point, and finally, the sample is judged for the class with the

highest score. The advantage of this method is to overcome the imbalance of one-to-many classifier training samples, and the training accuracy is better than SVM-OVR. The disadvantage is that the number of classifiers is large, the training time is long, and there may be times when the same sample has the same number of votes for multiple categories

(3) Direct construction of multivalued classifiers: in the 1990s, scholars such as Weston changed the objective function in the optimization of binary classification based on the theory of binary separability and then reconstructed the classification that satisfies the multivalued situation. However, the objective function of this method is complex, and the calculation is also very complex, which is difficult to implement. When the sample is large, the training time is long. And it cannot significantly improve the classification accuracy, so the practicability is not very strong

(4) Binary tree SVM classifier: the basic idea of this classifier is to use all samples as the root node, then use a method to divide the samples into two categories, and cycle until it can no longer be divided. Train a binary SVM at the nodes to identify samples. The advantage is that it is fast, the disadvantage is that the structure of the binary tree is difficult to design, a misclassification of a node will affect the classification results of the subsequent classifiers, and the cumulative misclassification rate will be misclassified to the end. Therefore, this classifier has not been promoted in practical applications. Based on the analysis of the above several commonly used multivalue classifiers and a large number of experiments by reference scholars, this experiment selects the SVM-OVO classifier to complete the extraction of tailings ponds

(5) Directed acyclic graph SVMs (DAG-SVMs): DAG-SVMs are the same as OVO voting in the training phase. It is also necessary to construct a classification surface between each two categories, that is, there are $K(K-1)/2$ classifiers. But in the classification stage, the method constructs the classifier used as a kind of two-direction directed acyclic graph: including $K(K-1)/2$ nodes and K leaves. Each node is a classifier and is connected to two nodes in the next layer. When classifying an unknown sample, first start from the root node at the top, and continue to classify with the left node or right node in the next layer according to the classification result of the root node until it reaches a certain leaf at the bottom layer. The category represented by this leaf is the category of the unknown sample

3.2. Feature Selection and Fusion. The pixels of the same type of ground objects on the same remote sensing image should have the same or similar characteristics under the same conditions. The classification method based on machine learning is to statistically analyze the characteristic information of each pixel and compare it with the training samples and then classify the same or similar characteristics. The cells of the feature are grouped into one category. Commonly used features are, for example, spectrum, shape, texture, and linearity. Sticking to the selection of a single feature for classification is not very effective, but too much feature selection will increase information redundancy, increase the amount of computation, and may affect the classification accuracy. The rough set feature selection algorithm based on attribute importance reasonably selects and fuses features in the feature set. This method not only simplifies the design of the classifier but also improves the classification accuracy. Therefore, reasonable selection and fusion of features are crucial in the classification process.

3.2.1. Spectral Characteristics. The law of electromagnetic radiation is a characteristic of all things in nature. Certain bands of ultraviolet, visible light, infrared, and microwaves from the outside world can be reflected or absorbed by ground objects, and a few ground objects can also be transmitted by electromagnetic waves. In the process of reflecting, emitting, or absorbing electromagnetic waves, the ground object is represented by a functional relationship, that is, the spectral curve of the ground object. Because of the differences in the internal structure, composition, and state of each feature, its spectral curve has a unique shape. Therefore, spectral features are widely used in classification, and the spectral curve is an intuitive representation of the spectrum of ground objects. The tailings pond has different classification results according to different standards. According to the composition of the raw ore, it can be divided into gold, copper, silver, iron, and other categories. According to the form of tailings, it can be divided into dry tailings pond and wet tailings pond. According to the usage, it can be divided into in use and closed. The reasons for these classifications above will affect the spectral characteristics of tailings ponds.

3.2.2. Texture Features. The spectral characteristics of tailings ponds are analyzed above, and it is understood that the composition and state of ore sands lead to complex spectral characteristics of tailings ponds and obvious spectral differences between different types of tailings ponds. Therefore, only relying on spectral features for classification will definitely cause the phenomenon of "same substance with different spectrum" and "different substance with same spectrum," and it is difficult to obtain the ideal classification effect. Therefore, texture features are introduced to improve the classification accuracy. Texture features can describe the changing laws of objects more clearly and have a strong advantage in embodying edge relationships. It is widely used in pattern recognition, change detection, face recognition, etc. Scholars have deeply studied texture features. Now commonly used texture features include the gray-level cooccurrence matrix, Markov model, Gabor filter, and local binary model. The gray-level cooccurrence matrix can describe the spatial distribution and structural characteristics of the gray level of each pixel of the image, and it has advantages in improving the classification effect of the geoscientific target of the image by using the texture feature of the image.

3.2.3. Feature Fusion. The commonly used multifeature fusion methods include vector superposition and probability fusion. Probabilistic fusion is to combine multiple features with spectral features and then input them into the classifier, respectively, and assign weights to the features through the posterior probability for classification. Among many feature fusion methods, vector stacking is recognized as the simplest and most effective feature fusion method. In terms of computational complexity, vector superposition is simpler than probabilistic fusion. Vector overlay fusion is to linearly combine all features. The advantage of the vector superposition method is that there is no information loss, and the calculation amount is small and the algorithm is simple. The disadvantage is that with the increase of features, there will be more redundant information, and if the features cannot be selected reasonably, the classification accuracy will be affected. In view of the few features selected in this paper, the shortcomings of the vector superposition fusion method have little influence, so this method is selected to fuse the selected features.

3.3. Selection of Parameters and Kernel Function. The relevant principles and basic parameters of SVMs are introduced above, and the commonly used kernel functions are introduced. Combined with the actual situation of the experiment, the SVM-OVO classifier was selected for the experiment after referring to other literatures. In the case of determining the classifier, the choice of penalty parameter C, kernel function, and related parameters will affect the classification accuracy. The relationship between the kernel function, the mapping function, and the feature space is interlocked, and the mapping function and the feature space change with the change of the kernel function. The complexity of the subspace distribution of learning sample features, the maximum VC dimension, and the minimum empirical error vary with the change of the mapping function. In the feature subspace, confidence range and dimension are positively correlated, and empirical risk is negatively correlated. If the dimension of the feature subspace is from high to low, the optimal classification surface will change from complex to simple. These two extreme cases will affect the generalization ability of the learning machine, so the choice of the kernel function will determine the generalization ability of the learning machine. Of course, different kernel functions correspond to different kernel parameters and the performance of the kernel parameter image classifier. The kernel parameter of the Gaussian radial basis kernel function is the width parameter σ. The width parameter σ determines the mapping function, which also determines the complexity of the sample feature subspace, the maximum VC dimension, and the minimum empirical error. In this experiment, the Gaussian radial basis kernel function is selected. The values of the penalty parameter C and the width parameter σ affect the generalization ability of the learning machine and are also parameters that affect the algorithm complexity and sample ratio. Only a reasonable allocation of the confidence range and empirical risk of the classifier can make the learning machine generalize the best. The relevant experiments of parameter selection are described in detail in Section 4.

4. Experiment and Analysis

4.1. Sample Selection and Quantitative Evaluation Indicators. In addition to the importance of classifier selection in supervised classification, sample selection is also a critical step for success or failure. Different training samples will have different classification results. Therefore, the selected samples should express the characteristics of the type as much as possible. The pixels of the selected samples should be pure and uniform in color. At least one sample of a type of ground object should be selected, and if multiple samples of the same type of ground object are selected, the distribution should be as uniform as possible. According to the spectral characteristics and the actual situation, a total of 7 types of samples were selected. Three types of tailings samples were selected, namely valley-type tailings pond, flat-type tailings pond, and dry-draining tailings pond. There is also a class of negative samples of water, bare ground, clouds, and buildings (see Table 1 for details).

The tailings pond object detection task can be classified as a binary classification problem. The image contains tailings ponds and targets that are not tailings ponds, that is, the background. Taking tailings ponds as an example, P represents the number of tailings ponds marked in the sample, and TP represents the tailings ponds marked in the sample, which are also correctly predicted by the model as the target of tailings ponds. FP indicates that the sample belongs to the background but is incorrectly predicted by the model to be the target of the tailings pond, which is a false detection. FN indicates that the sample is marked as a tailings pond but is incorrectly predicted by the model as a background target, that is, the tailings pond that has not been detected belongs to the missed detection. TN indicates that the sample belongs to the background and is also correctly predicted by the model to be the background target. In this paper, the detection performance of the model is mainly evaluated by precision rate, recall rate, and $F1$ score. The accuracy rate refers to the proportion of tailings ponds correctly detected in the prediction results, that is, the ratio of the predicted number of tailings ponds to the predicted number of tailings ponds. This indicator reflects the ability of the model to deal with false detections, and the calculation formula is as follows.

$$Pre = \frac{TP}{TP + FP}. \tag{11}$$

The recall rate refers to the proportion of tailings ponds correctly detected in the prediction results to the total real tailings ponds, that is, the ratio of the predicted number of real tailings ponds to the number of tailings ponds marked in the sample. This metric reflects the ability of the model to handle missed detections. The formula

Table 1: Tailings pond sample set details.

Number	Sample	Number of pixels
1	Valley tailings pond	358
2	Flat-type tailings pond	265
3	Dry discharge tailings pond	85
4	Negative water sample	196
5	Bare ground negative sample	352
6	Cloud negative samples	1579
7	Building negative samples	721

Table 2: Selection of width parameter σ and penalty coefficient C.

Num.	Width parameter σ	Penalty coefficient C	Precision	Recall	$F1$
1	0.5	50	0.968	0.943	0.955
2	0.5	100	0.995	0.986	0.990
3	0.05	50	0.957	0.927	0.942
4	0.05	100	0.962	0.931	0.946
5	0.005	50	0.944	0.884	0.913
6	0.005	100	0.951	0.895	0.922

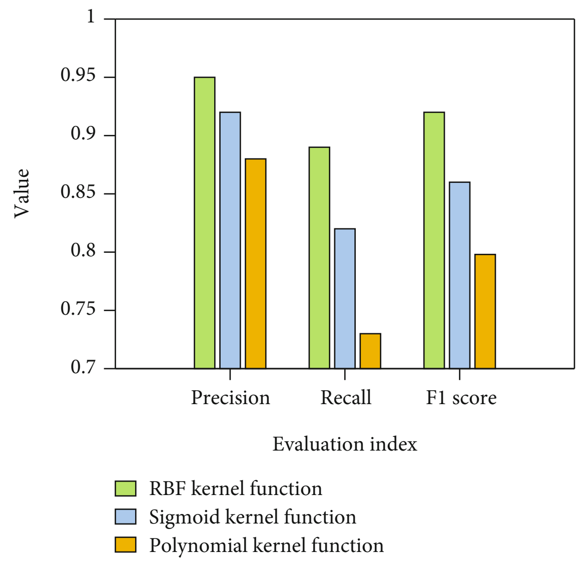

Figure 2: The influence of different kernel functions on each evaluation index.

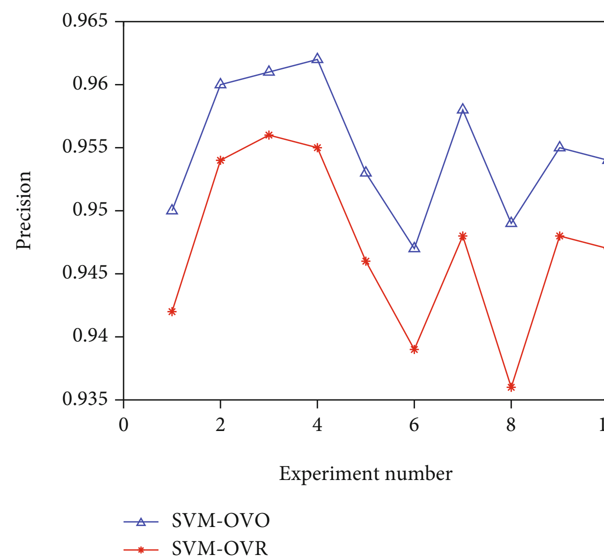

Figure 3: Precision of model accuracy of different classifiers.

for calculating recall is as follows.

$$Rec = \frac{TP}{P}. \quad (12)$$

Precision and recall are two contradictory and unified indicators, and $F1$ score can be used to balance the two. The formula for calculating $F1$ score is as follows.

$$F1 = \frac{2 \times Pre \times Rec}{Pre + Rec}. \quad (13)$$

4.2. Model Parameter Selection

(1) According to the experimental characteristics, the RBF kernel function is selected to form a variety of methods based on the radial kernel function technology for experiments. In order to prove the superiority of this kernel function, an experimental comparison is made with the Sigmoid kernel function and the polynomial kernel function mentioned in this paper, and the experimental results obtained are shown in Figure 2

(2) The width parameter σ and the penalty coefficient C are obtained by cross-validation, and the experimental results are shown in Table 2

The experimental results show that when C and σ are 100 and 0.5, respectively, the effect of each index is the best.

(3) The experimental effect of different classifiers: in this paper, the SVM-OVO classifier is selected, and the SVM-OVR classifier is selected to compare the classification effects of the two classifiers, and the accuracy of 10 experiments is randomly selected as the evaluation index. The results are shown in Figure 3

In addition, Figure 4 shows the time consumption and classification accuracy of the two classifiers in the experiment, and the values in the figure are the average of 10 experimental data.

It can be seen that the SVM-OVO classifier used in this paper has advantages in various performances.

4.3. Model Experiment after Parameter Optimization. After the model training is completed, the detection performance of the model needs to be evaluated. Data samples are used to evaluate the detection performance of the

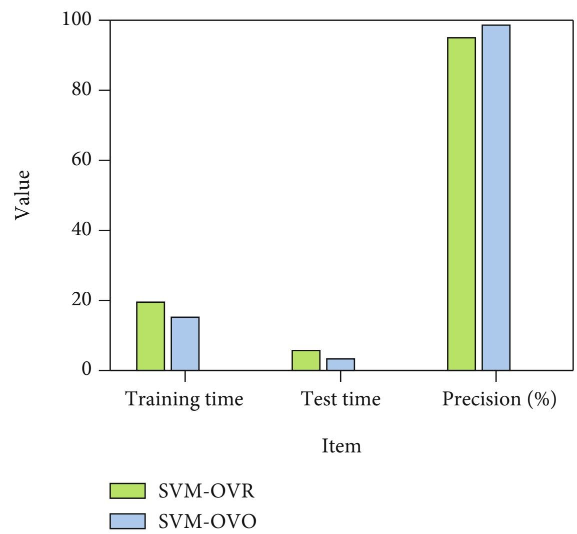

Figure 4: Time and accuracy comparison of the two classifiers.

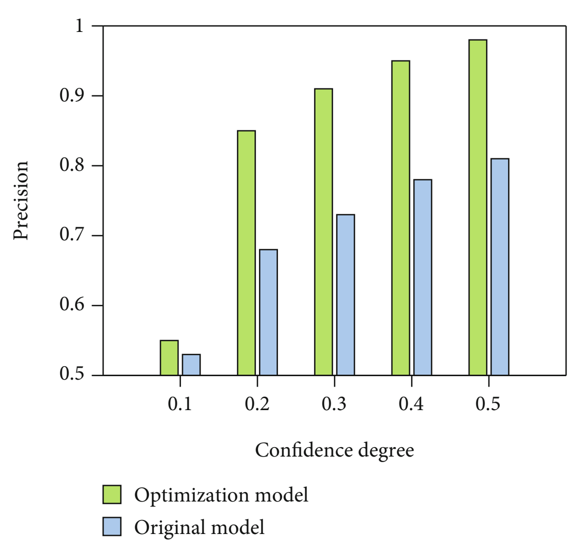

Figure 5: Precision comparison of two models at different confidence levels.

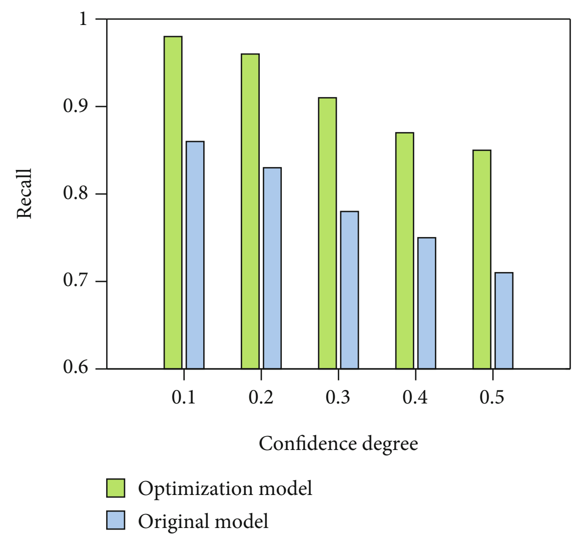

Figure 6: Recall comparison of two models at different confidence levels.

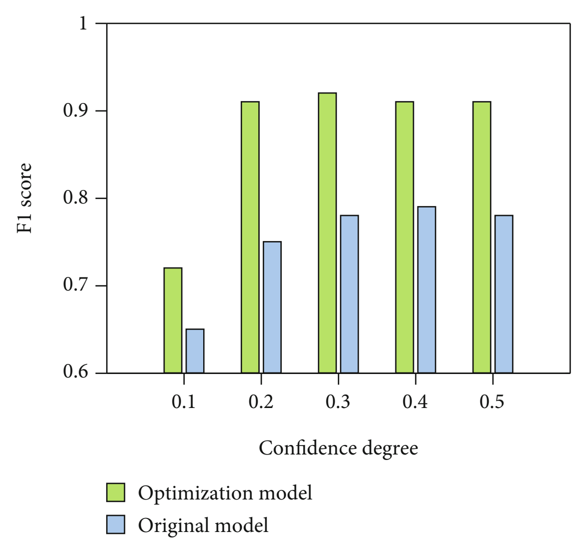

Figure 7: $F1$ score comparison of two models at different confidence levels.

two models before and after parameter optimization. After a sufficient number of iterations, the model with the highest accuracy is selected to detect the tailings pond in the test set. At the same time, set the confidence threshold between 0.1 and 0.5, and record the number of tailings pond detections, the number of correct detections of tailings ponds, the number of false detections of tailings ponds, and the number of missed detections of tailings ponds under different confidence thresholds. Calculate the precision, recall, and $F1$ score at the corresponding confidence thresholds. The detection results of the two models are shown in Figures 5–7.

The following can be seen from Figures 5–7: (1) In the detection results of the two models, with the increase of the confidence threshold, the detection accuracy of the model increases, and the recall rate decreases with the increase of the confidence threshold. (2) When the confidence threshold is set to 0.1, the two models get the highest recall rate, the highest recall rate of the original model is 86%, and the highest recall rate of the optimized model is 98%. When the confidence threshold is set to 0.5, the two models get the highest accuracy, the original model has the highest accuracy of 82%, and the optimized model has the highest accuracy of 99%. (3) The highest $F1$ score of the original model and the modified model are 0.79 and 0.92, respectively. The corresponding precision rate, recall rate, and $F1$ score value of the modified model under each confidence threshold are higher than those of the original model. It can be seen from the above experiments that the

Table 3: The performance comparison of different algorithms on the test data set.

Index	Algorithms			
	Our model	EPF	JSRC	SADL
Precision	97.9%	94.1%	87.9%	89.5%
Recall	96.8%	92.5%	85.8%	88.2%
$F1$	95.2%	90.4%	82.3%	87.6%
Running time (s)	5.32	9.58	52.75	22.39

performance of the modified model is much better than the original model, and the training accuracy and detection performance are greatly improved.

4.4. Comparison with Other Models. In order to prove the superiority of the optimized SVM model proposed in this paper, several other algorithms are selected for comparison with it, and the specific experimental results are shown in Table 3.

Comparing the performance of the model proposed in this paper with other algorithms on the test data set, the results show that the model proposed in this paper is due to other models in various indicators.

5. Conclusion

Tailings ponds are a huge source of environmental risks. Once an accident occurs, it will bring serious harm to the surrounding environment, so it has become the focus of environmental emergency supervision. Especially in recent years, the high incidence of environmental emergencies caused by tailings ponds has made the environmental emergency management situation of tailings ponds grim. At present, the environmental supervision capacity of tailings ponds in my country is weak, mainly relying on ground surveys, and the information and technical support capacity is seriously insufficient. Therefore, in order to meet the work requirements of environmental emergency management, on the basis of analyzing the characteristics of tailings ponds and remote sensing technology, this paper proposes a method for extracting tailings pond images with SVM combined with multiclassification of SVM. The tailings pond is automatically extracted. This paper has done the following work on the extraction of tailings pond images by SVM: (1) The accident risk of tailings ponds at home and abroad and the current status of tailings pond monitoring technology are introduced. (2) The relevant theory of SVM was learned, and the kernel function and corresponding parameter selection method of SVM were discussed in a multiclassification problem. (3) Refer to the experiments of other scholars to select the kernel function and parameters suitable for this experiment. The spectral features and texture features of the tailings pond are analyzed, and the vector stacking method is selected to fuse multiple features. On the basis of determining the kernel function, parameters, and features, the trained model is compared with the original model. The results show that the SVM detection model proposed in this paper has excellent performance in tailings pond image recognition. (4) Comparing the performance of the model proposed in this paper with other algorithms on the test data set, the results show that the model proposed in this paper is due to other models in various indicators.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflict of interest.

Acknowledgments

This work was supported by the Shaanxi Provincial Department of Science and Technology Key R&D Program: Research on Stability Detection Technology of Tailings Reservoir Dam (Number: 2018GY-082).

References

[1] X. L. Liang, "Brief talk on environmental risk of tailings reservoir and countermeasures," *Environmental Science Survey*, vol. 30, no. 3, p. 3, 2011.

[2] F. A. N. G. Liang, Z. H. O. U. Shukui, and L. I. U. Yingjiu, "Study on groundwater pollution risk assessment method in uranium tailings pond," *Environmental Engineering*, vol. 34, no. 1, pp. 100–102, 2016.

[3] W. J. Liao, K. L. Huangfu, Y. He, and Z. Z. He, "Integrated real-time monitoring, analyzing and analyzing pre-warning system for tailings reservoir," *China Safety Science Journal*, vol. 24, no. 8, pp. 158–163, 2014.

[4] Q. S. Li, S. L. Li, and J. J. Chen, "Discussion on the situation and prospect of safeguard for tailing pond," *The Chinese Journal of Geological Hazard and Control*, vol. 22, no. 1, pp. 99–106, 2011.

[5] Z. Xin, X. Xiaohu, X. Kaili et al., "Study on the risk assessment of the tailings dam break," *Procedia Engineering*, vol. 26, pp. 2261–2269, 2011.

[6] X. Rulin, L. Jie, F. Zhuo et al., "The application of remote sensing in the environmental risk monitoring of tailings pond in Zhangjiakou City, China," *Remote Sensing Technology and Application*, vol. 29, no. 1, pp. 100–105, 2014.

[7] M. Pal and P. M. Mather, "Support vector machines for classification in remote sensing," *International Journal of Remote Sensing*, vol. 26, no. 5, pp. 1007–1011, 2005.

[8] K. Babaeyan-Koopaei, E. M. Valentine, and D. A. Ervine, "Case study on hydraulic performance of Brent reservoir siphon spillway," *Journal of Hydraulic Engineering*, vol. 128, no. 6, pp. 562–567, 2002.

[9] W. C. Fontes, J. C. Mendes, S. N. Da Silva, and R. A. F. Peixoto, "Mortars for laying and coating produced with iron ore tailings from tailing dams," *Construction and Building Materials*, vol. 112, pp. 988–995, 2016.

[10] H. Holmström, J. Ljungberg, and B. Öhlander, "Role of carbonates in mitigation of metal release from mining waste. Evidence from humidity cells tests," *Environmental Geology*, vol. 37, no. 4, pp. 267–280, 1999.

[11] C. Strachan, "Tailings dam performance from USCOLD incident-survey data," *Mining Engineering*, vol. 53, no. 3, pp. 49–53, 2001.

[12] A. T. Özer and L. G. Bromwell, "Stability assessment of an earth dam on silt/clay tailings foundation: a case study," *Engineering Geology*, vol. 151, pp. 89–99, 2012.

[13] M. Rico, G. Benito, A. R. Salgueiro, A. Díez-Herrero, and H. G. Pereira, "Reported tailings dam failures: a review of the European incidents in the worldwide context," *Journal of Hazardous Materials*, vol. 152, no. 2, pp. 846–852, 2008.

[14] A. R. Salgueiro, H. G. Pereira, M. T. Rico, G. Benito, and A. Díez-Herreo, "Application of correspondence analysis in the assessment of mine tailings dam breakage risk in the Mediterranean region," *Risk Analysis: An International Journal*, vol. 28, no. 1, pp. 13–23, 2008.

[15] D. Chakraborty and D. Choudhury, "Investigation of the behavior of tailings earthen dam under seismic conditions," *American Journal of Engineering and Applied Sciences*, vol. 2, no. 3, pp. 559–564, 2009.

[16] M. T. Zandarín, L. A. Oldecop, R. Rodríguez, and F. Zabala, "The role of capillary water in the stability of tailing dams," *Engineering Geology*, vol. 105, no. 1-2, pp. 108–118, 2009.

[17] F. Vaezi, R. S. Sanders, and J. H. Masliyah, "Flocculation kinetics and aggregate structure of kaolinite mixtures in laminar tube flow," *Journal of Colloid and Interface Science*, vol. 355, no. 1, pp. 96–105, 2011.

[18] Y. Liang, X. Yi, Z. Dang, Q. Wang, H. Luo, and J. Tang, "Heavy metal contamination and health risk assessment in the vicinity of a tailing pond in Guangdong, China," *International Journal of Environmental Research and Public Health*, vol. 14, no. 12, p. 1557, 2017.

[19] L. Dong, S. Deng, and F. Wang, "Some developments and new insights for environmental sustainability and disaster control of tailings dam," *Journal of Cleaner Production*, vol. 269, p. 122270, 2020.

[20] W. Cai, Z. Wei, R. Liu, Y. Zhuang, Y. Wang, and X. Ning, "Remote sensing image recognition based on multi-attention residual fusion networks," *ASP Transactions on Pattern Recognition and Intelligent Systems*, vol. 1, no. 1, pp. 1–8, 2021.

[21] W. T. Liu, Z. Zhang, and Y. Peng, "Application of TM image in monitoring the water quality of tailing reservoir," *Mining Research and Development*, vol. 30, no. 6, pp. 90–92, 2010.

[22] D. Yan, G. Li, X. Li et al., "An improved faster R-CNN method to detect tailings ponds from high-resolution remote sensing images," *Remote Sensing*, vol. 13, no. 11, p. 2052, 2021.

[23] D. Yan, H. Zhang, G. Li et al., "Improved method to detect the tailings ponds from multispectral remote sensing images based on faster R-CNN and transfer learning," *Remote Sensing*, vol. 14, no. 1, p. 103, 2021.

[24] D. Che, A. Liang, X. Li, and B. Ma, "Remote sensing assessment of safety risk of iron tailings pond based on runoff coefficient," *Sensors*, vol. 18, no. 12, p. 4373, 2018.

[25] Y. K. Shen and W. Zhang, "Prediction and evaluation of ecological impact of Liaoning tailings reservoir expansion project based on "3S" technology," *Forest Inventory and Planning*, vol. 39, no. 1, pp. 5–8, 2014.

[26] Z. Gao, H. Xue, and S. Wan, "Multiple discrimination and pairwise CNN for view-based 3D object retrieval," *Neural Networks*, vol. 125, pp. 290–302, 2020.

[27] S. Ding, S. Qu, Y. Xi, and S. Wan, "Stimulus-driven and concept-driven analysis for image caption generation," *Neurocomputing*, vol. 398, pp. 520–530, 2020.

[28] J. Lyu, Y. Hu, S. Ren et al., "Extracting the tailings ponds from high spatial resolution remote sensing images by integrating a deep learning-based model," *Remote Sensing*, vol. 13, no. 4, p. 743, 2021.

[29] D. Cheng, Y. Cui, Z. Li, and J. Iqbal, "Watch out for the tailings pond, a sharp edge hanging over our heads: lessons learned and perceptions from the Brumadinho tailings dam failure disaster," *Remote Sensing*, vol. 13, no. 9, p. 1775, 2021.

[30] Q. Li, Z. Chen, B. Zhang et al., "Detection of tailings dams using high-resolution satellite imagery and a single shot multibox detector in the Jing–Jin–Ji region, China," *Remote Sensing*, vol. 12, no. 16, p. 2626, 2020.