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Research Article

Classification of Land Cover Remote-Sensing Images Based on Pattern Recognition

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With the development of remote sensing technology, remote sensing image data plays an active role in the dynamic monitoring of global resource changes and land cover utilization. Remote sensing image land cover classification is an important application direction of remote sensing data; how to further improve the accuracy of remote sensing image land cover classification is very important for the effective application of remote sensing data. The traditional remote sensing image land cover classification is mainly to classify remote sensing data according to the spectral data of ground objects. However, due to the complex environment of remote sensing images and the dynamic changes of the environment, traditional classification methods based only on pixel spectral data are often unable to achieve. A satisfactory classification result is achieved. In addition, some researchers have also proposed to combine pixel neighborhood texture information to supplement spectral feature data. Although the traditional classification method based on spectral features solves the problem of time-consuming visual interpretation, to a certain extent, due to the limited semantic expression ability and poor generalization ability of the design features, the classification accuracy is still not very satisfactory. This paper mainly studies the classification method of land cover remote sensing image based on pattern recognition. This paper is based on the experimental results of remote sensing data in Nanjing Yuhuatai District in 2018 and 2019. The ground resolution of the data is 2.5 meters. Data is projected, corrected, and equalized. Half of the images covering 43.75 square kilometers are used as training samples, and the remaining 50 square kilometers are used for detection. In the classification results of this IndianPines data, OA only increased by nearly 10% to 86.2%, AA increased by 13%, r was 82.77%, and Kappa coefficient was 0.84. In the classification results of Salinas data, both OA and AA increase by about 5%, and the optimization effect is not obvious.

1. Introduction

Since the first artificial satellite entered the earth's orbit in 1957, human beings have started space activities [1]. With the continuous update and development of sensor platform technology, satellite remote sensing has also developed rapidly, resulting in different earth observation satellite remote sensing products. In the 1980s and 1990s, the United States and France used Landsat and SPOT satellites to obtain remote sensing image data with a ground resolution of 10–30 m [2, 3]. The Landsat family of satellites has 2 Thematic Mappers (TM) and 4 MSS systems and Enhanced Thematic Mappers (ETM+) [4]. The SPOT series satellites include SPOT-1 launched on February 22, 1986, SPOT-2 launched in 1990, SPOT-3 launched in 1993, and SPOT-4 launched in 1998. The ground resolution is 10 m–20 m. In May 2012, SPOT-5 satellite with a ground spatial resolution of 2.5 m–5 m was launched on September 9, 2012, and SPOT-6 satellite with a ground spatial resolution of 1.5 m was launched on September 9, 2012. On November 14, 1997, the rest were still operating normally. SPOT can be used for stereo shooting, and its ground resolution is getting higher and higher, and it is more widely used in thematic map production than Landsat [5, 6]. At the same time, various joint agencies in Japan, India, Canada, China, South Korea, and other countries are running remote sensing systems with spatial and spectral resolution within a certain resolution range [7, 8]. Remote sensing (RS) is a comprehensive detection technology that emerged in the 1960s, including aerospace, automatic control, computer image processing, and other technologies [9]. According to the electromagnetic wave theory, RS uses various platform sensors to detect surface objects that radiate or reflect electromagnetic wave information at a long distance and performs various processing on the detected electromagnetic wave information to synthesize image data to realize object recognition and classification of actual surface objects [10, 11].

In recent years, the field of robotics research has been increasingly attracted by humanoid robots. Robots have basic characteristics such as perception, decision-making, and execution. They can assist or even replace humans in completing dangerous, heavy, and complex work, improve work efficiency and quality, serve human life, and expand or extend the scope of human activities and capabilities [12]. The design, construction, and application of anthropomorphic robots address many interesting research challenges: bipedal walking, human-robot interaction, and interaction with unstructured and unknown environments. Among them, how to design robots with the same performance as humans is a complex problem. The challenge that developers must face when considering design issues is the design of the manipulator and arm. When designing the hand of a humanoid robot, it is designed through functional guidance. A large number of robot designs have extremely high requirements on finger freedom, size, and human-like appearance [13, 14]. To design a human-sized lightweight arm/hand system, either focus on purely mechanical approaches or employ some anthropomorphic and bioinspired designs [15]. Focus on designing a humanoid arm that is reliable, meets requirements, can ensure safe operation, and has a long standby time. The limited size of the manipulator has a certain influence on the arrangement of the joint brakes. The general solution is to use a new drive system or fluid or cable drive. To handle manipulation tasks in a human-centric environment, visual and tactile sensor information is concentrated in a closed-loop control loop. Visual information is mainly used to recognize and understand the pose and shape of objects. The main goal of control architectures for manipulation tasks is to coordinate a range of actions, introducing learning ideas in sensor-motor coordination and taking inspiration from biology. The goal is to develop a robot that assists humans with everyday tasks, humanoid robots, multimodality, and the ability to cooperate and learn with humans. Operationally, it includes the ability to learn and use high-level cognitive models of objects and tasks from demonstrations. The main concept of machine vision is to use the computer to simulate the human visual function, obtain the input image through the camera, then convert it into a digital image signal, input it into the computer, and obtain the corresponding information through software processing, thus providing a basis for correct judgment. The most basic feature of the machine vision system is to improve the flexibility and automation of production. With the support of digital image processing algorithms, three-dimensional objects can be morphologically recognized, and the actions of field devices can be judged according to the recognition results. According to the specific functions, it can be divided into image acquisition, image processing, motion control, etc., to form the information or multidimensional data that needs to be obtained in the image at work and form an artificial intelligence recognition system. This field is applied in [16].

Machine vision, also known as computer vision, is a popular direction for the rapid development of artificial intelligence in recent years. In layman's terms, machine vision is to simulate the function of the human eye, extract useful information from visual imaging, and provide decisions or services for other systems. Machine vision is a comprehensive technology, including mechanical engineering technology, electric light source lighting, optical imaging, sensors, analog and digital video technology, and computer software and hardware technology [17]. The study of machine vision began with image pattern recognition in the 1950s. The concept of machine vision is proposed by the concept of artificial intelligence technology established in the early 1970s. In the 1990s, machine vision made breakthroughs in many fields, and technologies such as face recognition, fingerprint recognition, iris recognition, and optical character recognition became more and more mature. In the 21st century, with the rapid development of machine learning based on statistical models, the realization form of machine vision has also changed, and statistical methods and machine learning methods have become mainstream. In recent years, the most popular machine learning method in the field of artificial intelligence is nothing more than deep learning. Convolutional neural network (CNN) is a branch of deep learning. It is a learning method specially used in the field of vision, which has greatly promoted the development of machine vision technology. It can perform supervised learning and unsupervised learning. Its hidden layer intraconvolution kernel parameter sharing and the sparsity of interlayer connections make it possible to grid features with less computational effort [18]. Machine vision can improve the automation and intelligence of products in this field, which is of great significance for improving social productivity. Although machine vision has become a hot spot in society, very few people really understand machine vision. For our high school students, whether we can keep abreast of the latest developments in technology is related to our career planning. Therefore, this paper discusses the key technologies and application status of machine vision [19].

Romero considers the use of single-layer deep convolutional networks in remote sensing data analysis. Given the high dimensionality of the input data and relatively little available labeled data, direct application to multispectral and hyperspectral images of supervised (shallow or deep) convolutional networks is very challenging. Therefore, we propose to use greedy hierarchical unsupervised pretraining combined with efficient algorithms for unsupervised learning of sparse features. The algorithm is based on sparse representation while enforcing both overall sparsity and lifetime sparsity of extracted features. They successfully demonstrate the expressive power of the extracted representations in several contexts: aerial scene classification, very high resolution (VHR) land use classification, or land cover classification of multispectral and hyperspectral images. The proposed algorithm significantly outperforms standard principal component analysis (PCA) and its corresponding kernel (kPCA), as well as current state-of-the-art antenna algorithms [20]. Rwang sees remote sensing as a tool that is important for generating land-use and land-cover maps through a process called image classification. For the image classification process to be successful, several factors should be considered, including the availability of high-quality Landsat imagery and auxiliary data, an accurate classification process, and user experience and procedural expertise. The purpose of his research is to classify and map land use/ land cover in the study area using remote sensing and Geospatial Information System (GIS) techniques. His research consists of two parts: (1) land use/land cover (LULC) classification and (2) accuracy assessment. In this study, nonparametric rules are used for supervised classification. The main categories of land use and land use change were agriculture (65.0%), water bodies (4.0%), built-up areas (18.3%), mixed forests (5.2%), shrubs (7.0%), and barren/ bare land (0.5%). The overall classification accuracy of his study was 81.7% with a Kappa coefficient (K) of 0.722. The Kappa coefficient has a high rank, so classified images are suitable for further study. This study provides an important source of information that planners and policymakers can use to help plan the environment sustainably [21]. Liu believes that, with the improvement of the spatial resolution of remote sensing images, the details, geometric structures, and texture features of ground objects have been better displayed. Since the same object type has different spectra or different object types have the same spectrum, the statistical separability of different land cover categories in the spectral domain is reduced, which is a great challenge to the traditional high spatial resolution remote sensing classification methods based on pixel features. By fusing the texture, structure, and shape features of pixels, the classification accuracy of pixel-based classification methods is improved. However, pixel-based multifeature classification methods usually have the disadvantages of "salt and pepper" effect and computational complexity. Object-based image analysis (OBIA) methods have received extensive attention in recent years. The basic feature of OBIA is that the homogeneous area is the processing unit. The OBIA method can solve the "salt and pepper" problem in traditional methods and overcome the shortcomings of pixel-based classification methods [22].

Pattern recognition is the process of interpreting, summarizing, identifying, classifying, and analyzing various forms of information of objective things or phenomena. Pattern recognition is related to and intersects with computer science, statistics, cybernetics, image processing, artificial intelligence and other disciplines. Therefore, pattern recognition is known as multidisciplinary interdisciplinary. The application of pattern recognition in the field of computer refers to the use of computer to identify and discriminate the target entity represented or imitated by a specific objective entity [23]. Pattern recognition focuses on image processing and computer vision, speech and language information processing, brain network group, and brain-like intelligence. It studies the mechanism of human pattern recognition and effective computing methods. A pattern refers to the spatiotemporal distribution of information obtained by observing a specific objective entity. Isomorphic pattern populations or patterns in the same class are called pattern classes, or classes for short. For example, in the field of remote sensing classification, it is called buildings, roads, shrubs, lawns, etc. [24]. That is, the principle of "pattern recognition" is to assign the pattern to be recognized to the pattern class to which it belongs according to a certain measurement method, measurement basis, or measurement index. With the rapid development of sensor technology, computer application technology, automatic control technology, and communication technology, pattern recognition is also widely used in remote sensing image processing [25]. A pattern recognition system refers to a computer system that performs pattern recognition. Research designers design different pattern recognition systems according to their needs and then perform pattern recognition and classification by computer. A complete pattern recognition system goes through five steps: sample information collection, information preprocessing, selection and extraction of useful features, design, and classification of classification decision functions. Every step is very important. The processing degree of the previous step directly affects the performance of the next step. For example, pattern samples may contain a lot of noise and interference information. If the original pattern samples are not preprocessed, this interference information will occupy the feature space and increase the feature dimension. Therefore, the noise interference data is filtered to reduce the feature dimension, while the original pattern sample information is converted into an information format that can be processed by the computer, and then feature selection is performed on the sample information [26]. Because some features do not contribute much to the recognition category, they can be removed, select some useful feature information for the recognition category, learn the recognition model from the favorable feature inference, and finally classify the sample type decision to obtain the recognition classification result [27].

According to the recognition principle, pattern recognition can be divided into the following four recognition modes: pattern recognition based on structure, pattern recognition based on statistics, pattern recognition based on neural network, and fuzzy pattern recognition [28]. Among them, the statistical-based pattern recognition based on the Bayesian decision system based on the principle of statistical probability theory is the most classic recognition mode, which is widely used in the recognition and classification of surface objects in remote sensing images. Bayesian decision-making is based on incomplete intelligence. The subjective probability is used to estimate the partially unknown state, then the Bayesian formula is used to correct the occurrence probability, and finally the optimal decision is made by using the expected value and the modified probability. Statistics-based pattern recognition methods often use a tree-structured pattern of a hierarchical structure of classes and subclasses to complete pattern recognition. The principle of hierarchical recognition is the principle of hierarchical segmentation and classification, so it has always played an important role in image classification or segmentation [29]. The general principle of classical statistics-based pattern recognition is to decompose a pattern into a data analysis process of several pattern categories, including cluster analysis, unsupervised and supervised learning, parameterized and unparameterized probability density statistics (ParametricorNonparametricProbabilityDensityEstimati on), preprocessing., feature selection or extraction (FeatureSelectionorExtraction), postprocessing after recognition classification, classification accuracy evaluation, and performance analysis. Since the 1960s, statistical-based pattern recognition research has developed rapidly. His main research interests are computer interpretation of remote sensing images based on statistical pattern recognition. Remote sensing images processed by computer must be digital images, and analog images obtained by photography must be converted by image scanners. It is characterized by distinguishing different positions in an image based on the spectral statistical properties of a single pixel [30]. The main research achievements include research results after transforming pattern recognition problems into probability density statistics problems, such as Bayesian decision-making, nearest neighbor decision-making, parameter-free pattern recognition research results based on Parzen probability density statistics, and leave-one-out error estimation; for feature evaluation, distance-based metrics and error-boundary-based estimation methods have also been proposed [31]. There are also Fisher discriminants; supervised parameter estimation in classification techniques, unsupervised learning based on decomposition and mixture probability densities, and some ensemble models of classification processors have also been proposed. Neural networks and SVM algorithms are also closely related to the principles of statistical pattern recognition, and their applications are also very extensive. With the increasing abundance of satellite remote sensing image data in various countries, many similar research results based on pixel or regional statistical pattern recognition methods have played a huge role in the processing and classification of remote sensing image data [32].

Problems existing in remote sensing classification based on geographic coverage changes: from the traditional single classifier model to the multiclassifier combination model, the traditional remote sensing image classification method gradually develops towards the object-based and object-oriented classification model and promotes the development of multiclassification model. The fusion of source data enables the effective fusion of RS and GIS and has achieved a lot of research results. However, there are still problems in the following aspects that need further research.

(1) Unification of characteristic factors: the application of traditional remote sensing classification methods, especially in the classification of low- and medium-resolution remote sensing images, is based on the brightness difference between pixels. However, due to the influence of factors such as illumination and terrain, the reflected or radiated electromagnetic wave information of some pixels in the image is not clear enough, resulting in pixel confusion, "homogeneity and heterogeneity" or "heterogeneous objects with the same spectrum" and other phenomena, and there must be a large number of errors. Pixels in the classification result of missing images carry this phenomenon, which affects the classification accuracy. Same-spectrum and same-spectrum foreign objects are based on the phenomenon that the same type of ground objects has different spectral characteristics on remote sensing images or the phenomenon that different ground object types have similar spectral characteristics.

(2) The unity of the classification algorithm: due to the different classification decision principles of different classification algorithms, there is no overlap between different classification algorithms in the classification and classification accuracy sets of different surface objects. Therefore, a single classifier decision function is not enough for complex classification problems, and multiple decision functions are needed to judge together. Therefore, it is most realistic to combine multiple classifiers to achieve complex classification according to certain rules. Classifier is a general term for the methods of classifying samples in data mining, including algorithms such as decision tree, logistic regression, naive Bayes, and neural network. On the basis of giving full play to the advantages of a single classifier, it is particularly important to study and design new classification techniques and new classification models and to enrich the knowledge system of remote sensing classification based on the needs of actual classification problems.

(3) The influence of noise: the appearance of noisy information in remote sensing imagery seems to be an inevitable reality, mainly depending on the degree of processing. The degree of processing directly affects the accuracy of image classification. Therefore, noise information is filtered according to the general law of noise information distribution (generally, high-resolution images are distributed inside the surface, and low- and medium-resolution images are distributed at the edge of the surface). Screening useful data is an important basic work before image classification.

(4) Lack of texture feature extraction: texture refers to a small, semiperiodic, or regularly arranged pattern that exists within a certain range in an image. Texture features are the basis for labeling and extracting object classification features on image surfaces. Texture features are usually represented by geometric patterns, sizes, or shapes. However, the traditional extraction method using $(2n+1)\times(2n+1)$ template is not conducive to the extraction of large-

scale texture gray value. To effectively extract the gray value of image texture or provide benefits for image segmentation or classification and classification reference, further research is required.

(5) The influence of scale selection: scale selection is an important part of the field of remote sensing research. Therefore, in-depth research on scale selection, scale conversion, and scale effects is required in practical applications.

Furthermore, most experimental data for innovative research results in image classification or segmentation are basically based on the use of existing commercial software. With the emergence of high-altitude, hyperspectral, and high-temporal remote sensing image data, the feature information contained in remote sensing images will become more abundant or more complex. Will the data processing performance of existing commercial software be affected? It is necessary to design and develop new taxonomic theories and application software as a powerful complement to existing methods or techniques.

The innovation of this research paper is mainly reflected in the following aspects:

(1) Two optimization and improvement methods of SVM kernel function are proposed. Taking advantage of the inherent characteristics of remote sensing image data, a useful exploration is made on the selection of the support vector machine kernel function and optimal parameters. Two methods of optimizing kernel function are proposed to study the optimization and improvement of SVM kernel function objectively. The method of optimizing the kernel function first realizes the complementary effect of the original kernel function. Secondly, the sample measurement function can consider the characteristics of the brightness difference and the angle difference of the sample at the same time, which effectively overcomes the shortcomings of the traditional kernel function that is extremely sensitive to noise and abnormal data.

(2) Two sample ranging standards and multiclassifier combination techniques are proposed. Based on the research on the traditional remote sensing image classification algorithm, this paper makes a useful exploration on the optimization and improvement of the classification rules of the classification algorithm. Classification algorithms discover class rules and predict classes for new data by computing and analyzing training sets of known classes. Taking the successful application of multiclassifier combination technology in remote sensing image classification as a research clue, two sample distance measurement standards based on mixed discriminant rules are proposed, and the remote sensing image classification task is realized through multiclassifier combination. (classifier technology). The research results not only make full use of the inherent spectral features and spatial geometric feature information of remote sensing image samples, but also effectively overcome the shortcomings of traditional remote sensing image classification algorithms with single discrimination rules and use multiple classifiers. The combination technology effectively solves the problem of data misclassification and omission and improves the classification accuracy.

(3) An automatic segmentation method of remote sensing image pixels based on the combination of FCM and SVM is proposed, and object-oriented remote sensing image classification is realized on this basis. Image segmentation is the technology and process of dividing an image into several specific regions with unique properties and proposing interesting targets. It is a key step from image processing to image analysis. The implementation principle of the segmentation algorithm proposed in this paper is simple, and it effectively solves the shortcomings of the traditional segmentation algorithm that is too harsh. The SVM supervised classification algorithm is used to segment the objects obtained by the FCM algorithm, and the object-oriented remote sensing image classification task is realized, which effectively solves the "salt and pepper" phenomenon that often occurs when performing classification tasks. Traditional remote sensing image classification algorithms improve the classification accuracy of remote sensing images.

2. Suggested Method

2.1. Remote Sensing Image Classification Methods

2.1.1. Maximum Likelihood Classification. Maximum likelihood classification (MLC) is one of the most widely used supervised classification methods. It assumes that various distribution functions are normal distribution, selects training areas, calculates the attribution probability of each sample area to be classified, and performs classification (an image classification method). Its discriminant rule is based on probability. Maximum likelihood assumes that all types of training data for each band are normally distributed and classifies pixels with a pattern metric or feature X into the ith class that may have feature vector X. In other words, it calculates the probability that it belongs to a certain class pixel by pixel and divides the pixel into the class with the highest probability. To obtain probabilistic information on the training data, the probability density function is first calculated. For single-band data, a certain type of probability density function looks like this:

$$\hat{p}(x \mid \omega_i) = \frac{1}{(2\pi)^{1/2}\hat{\sigma}_i} \exp\left[-\frac{1}{2}\frac{\left(x - \hat{\mu}_i\right)^2}{\hat{\sigma}_i^{\,2}}\right]. \tag{1}$$

In the formula, x is the brightness value of the pixel, is the estimated mean value $\hat{\mu}_i$ of all training classes $\hat{\sigma}_i^{\,2}$, and is the estimated variance of the class with observed values.

The Landsat7ETM+ data is multiband remote sensing data; that is, the training data consists of multiband data. The n-dimensional multivariate normal density function can be calculated using the following formula:

$$\hat{p}(X \mid \omega_i) = \frac{1}{(2\pi)^{1/2}\hat{\sigma}_i} \exp\left[-\frac{1}{2}(X - M_i)^T V_i^{-1} (X - M_i)\right], \quad (2)$$

where $|v_i|$ is the determinant of the covariance matrix and is the v_i^{-1}inverse of the covariance matrix and $M_i$is the mean vector.

When classifying the unknown measure pixels of the multispectral data, the maximum likelihood method is used to calculate $\hat{p}(X|\omega_i) \cdot p(\omega_i)$ is the product of each class, and it is divided into the class with the largest product.

$$\hat{p}(X|\omega_i) \cdot p(\omega_i) \geq \hat{p}\left(X|\omega_j\right) \cdot p\left(\omega_j\right). \quad (3)$$

In fact, the maximum likelihood classification is mostly applied under the assumption that the probability of occurrence of each class is equal, that is, the maximum likelihood classification without prior knowledge; formula (3) omits the prior knowledge item and is simplified to

$$p_i \geq p_j, \quad (4)$$

and

$$p_i = -\frac{1}{2}\log_e|V_i| - \left[\frac{1}{2}(X - M_i)^T V_i^{-1} (X - M_i)\right], \quad (5)$$

where M_i is the ith average measurement vector category. $V_i$is the covariance matrix of the ith, kth to l bands.

In most remote sensing applications, certain classes have a higher probability of occurrence than others. At this point, we can weight each class with the appropriate prior knowledge probability $p(\omega_i)$. At this point, formula (4) becomes

$$p_i \cdot p(\omega_i) \geq p_j \cdot p\left(\omega_j\right), \quad (6)$$

and

$$p_i \cdot p(\omega_i) = \log_e p(\omega_i) - \frac{1}{2}\log_e|V_i| - \left[\frac{1}{2}(X - M_i)^T V_i^{-1} (X - M_i)\right]. \quad (7)$$

Equation (6) is called the Bayesian discriminant rule, which applies the prior knowledge probability to the obtained terrain features and terrain to improve the accuracy of remote sensing classification.

2.1.2. Support Vector Machine Classification. Support vector machines (SVM) were proposed by Vapnik. SVM is a class of generalized linear classifiers that perform binary classification on data in a supervised learning manner, and its decision boundary is the maximum margin hyperplane that solves the learning samples. It takes the minimization of the confidence interval value as the optimization objective and the training error as the constraint condition of the optimization problem; that is, SVM is a statistical method based on the structural risk minimization criterion. Its generalization ability is better than some traditional statistical methods. Since the advent of the classic SVM in the early 1990s, it has received extensive attention in the field of machine learning due to its complete theoretical framework and many good results in practical applications.

2.1.3. Nonlinear Separability and Kernel Function. Nonlinear separability was proposed by Boser et al. In 1992, the kernel function was applied to the optimal hyperplane to construct nonlinear classifiers. The kernel function is used to replace the dot product inner product, and the sample space is transformed into a high-dimensional or infinite-dimensional feature space (Hilbert space) with a nonlinear mapping φ to construct the optimal hyperplane.

Kernel function reference solves the linear inseparability problem in classification, and its quality directly affects the performance of support vector machine, so kernel function has become one of the core problems of support vector machine research. The research of kernel function mainly focuses on its model selection and kernel function construction. The commonly used kernel functions are

(1) Polynomial inner product function:

Homogeneous:

$$k\left(X_i, X_j\right) = \left(X_i \cdot X_j\right)^d. \quad (8)$$

Heterogeneous:

$$k\left(X_i, X_j\right) = \left(X_i \cdot X_j + 1\right)^d. \quad (9)$$

The result is a d-order polynomial classifier.

(2) Gaussian radial basis function (RBF):

$$k\left(X_i, X_j\right) = \exp\left(-\gamma \parallel X_i - X_j^2 \parallel\right)\gamma > 0. \quad (10)$$

Each cardinality center corresponds to a support vector, and the algorithm automatically determines the output weight.

Hyperbolic tangent function as inner product function:

$$k\left(X_i, X_j\right) = \tanh\left(kX_i \cdot X_j + c\right). \quad (11)$$

At this point, the SVM implements a multilayer sensor with hidden layers. The hidden layer nodes are automatically determined by the algorithm, which has no local minima.

Among them, γ, d, k, and c (relaxation limit parameters) are the parameters of the kernel function. At present, there is no certain theoretical guidance for the selection of the kernel function, and it is mainly based on experience. Considering whether the choice of the kernel function reasonably affects the generalization ability of the support vector machine, a Gaussian kernel with a single parameter γ is usually chosen. The optimal combination of c and γ is obtained by grid searching the exponentially increasing sequence of c and γ, cross-validating each parameter combination, and then selecting the combination with the highest accuracy. The final model is trained on the training data using these parameter combinations.

2.1.4. Decision Tree Classification. Decision tree learning is a very common method in data mining. Its purpose is to predict the value of the target variable from the value of the input variable. The more mature decision tree algorithms include ID3 algorithm, C4.5 algorithm, C5.0 algorithm, and CART (Classification and Regression Tree) algorithm. The construction of the decision tree is done through top-down recursive divide and conquer. In decision analysis, a decision tree can express the decision-making process explicitly. In data mining, a decision tree expresses data rather than decisions. The ID3 algorithm is an iterative divisor proposed by J. Ross Quinlan in 1986. It calculates the test sample information gain, selects the attribute with the largest information gain as a node to build a decision tree, but cannot handle continuous attributes, and the decision tree is overfitting to the data. The C4.5 algorithm is an improvement to the ID3 algorithm, which overcomes the disadvantage that the ID3 algorithm cannot handle continuous variables. The C5.0 algorithm adds the boost function on the basis of the C4.5 algorithm, which improves the speed and memory utilization. CART was proposed in 1984 by several statisticians. It can handle both highly skewed or polymorphic numerical data, as well as sequential or unordered generic data. This article describes the CART, C4.5, and C5.0 algorithms. This study mainly uses the C5.0 algorithm to construct decision trees.

2.2. Remote Sensing E Estimation Method for Land Development and Integration

2.2.1. Remote Sensing Evaluation of Soil Surface Temperature. Surface temperature was calculated using TM6 data from Landsat. Landsat TM remote sensing image data has been widely used due to its high ground resolution. This data (TM6) thermal band can be used to analyze regional differences in thermal radiation and temperature on the Earth's surface. The wavelength range of this band is 10.45–12.5 μm, and the pixel ground resolution under the zenith viewing angle is $120\,\text{m} \times 120\,\text{m}$. This ground resolution is much higher than the ground resolution of the NOAAZAvHRR remote sensing data ($1.1\,\text{km} \times 1.1\,\text{km}$ from the zenith view). Therefore, TM data is a better choice for accurate surface temperature analysis. However, compared to its wide application in the visible and near-infrared bands, thermal (TM6) data of TM images are rarely used, and most applications use its grayscale value directly or just convert it to pixel b brightness without calculating actual surface temperature. Since the surface thermal radiation is affected by the atmosphere and the radiation surface during the conduction process, the thermal radiation intensity (which has been converted into the corresponding gray value) observed by the TM remote sensor is no longer a simple surface intensity, which is heat radiation. Therefore, the thermal radiation and temperature changes of the surface cannot be expressed intuitively, and the conclusions drawn from the regional analysis directly using the original TM6 value (gray value or brightness temperature) have a large deviation. The magnitude of the bias is directly dependent on the strength of atmospheric and surface influences. Traditionally, so-called atmospheric correction methods are used. Calculate surface temperature from TM6 data, which requires the use of atmospheric models such as LowTRAN or MoDTRAN or simulating the effect of the atmosphere on surface thermal radiation, including estimating the absorption of thermal radiation by the atmosphere and the intensity of thermal radiation up and down and then remotely sensed from satellites. This part of the atmospheric influence is subtracted from the total amount of thermal radiation observed by the monitor (calculated as gray value) to obtain the surface thermal radiation intensity, which is finally converted to convert the thermal radiation intensity into the corresponding surface temperature. Although this method still exists, some problems, such as real-time atmospheric profile data, are relatively complex and accurate, but they can be basically avoided through further research and improvement, such as derivation of the law of heat conduction. In 2019, Hurtado et al. proposed a new atmospheric correction method based on the surface energy balance equation and standard climate parameters is, and the surface temperature is calculated using TM data. This method is very close to the method of calculating surface temperature.

2.2.2. Remote Sensing Evaluation of Soil Organic Matter Content. It has also been pointed out that soil organic matter is an important part of soil and plays a very important role in soil fertility. The organic matter content of different soil types varies greatly, the higher one can reach more than 200 g/kg, and the lower one can reach below 5 g/kg. Therefore, detecting soil organic matter content is an important way to understand soil fertility. Dalal and Henry used near-infrared spectroscopy to predict moisture, organic carbon, and total nitrogen in Australian soils. Their predicted soil organic matter content ranged from 0% to 2.6%, with a 1 74–1 75% bias in the near-infrared predictions when organic matter content was higher or lower. The near-infrared spectroscopy prediction results of the two groups of soil samples with organic matter content of 0%–4% and 4%–4% were inconsistent. For 14%, there is a significant deviation. It is believed that soil can be understood by analyzing the C+ ratio of soil organic matter. The decomposition stage of organic matter improves the accuracy of NIR spectroscopy in predicting soil organic matter. The vF991 ground object spectrometer was used to measure the spectrum of each upper layer on the soil sample profiles formed under 8 different environmental conditions, and the reflection spectrum curve of each upper layer was obtained, and the organic matter content of each upper layer was determined. By studying the relationship between soil organic matter content and soil reflection spectrum Correlation analysis showed that the correlation coefficients between the organic matter content released in the 376.795 nm band, the 616.506 nm band, and the 724.0975 nm band and the soil spectrum were −0.63, −0.64, and −0.645, respectively. Peng Yukui et al. used near-infrared spectroscopy to evaluate soil organic matter content in the loess region of China. The calibration correlation result for 52 samples was 0.938 with a standard deviation of 0.23. The correlation result of the 74 samples was an organic correlation coefficient of 0.921 with an estimated standard error of 0.28, which was close to the chemical analysis of laboratory soil organic matter.

2.3. Supervised C-Classification. Supervised classification, also known as training classification, is to determine the attribute categories of pixels in other regions based on the pixel attribute characteristics of training regions of known categories. Pixel classification of training regions is generally performed through visual interpretation.

In supervised classification, firstly, the training samples of various features are extracted in the training area, and the learning algorithm is trained with these samples to determine the discriminant function, and then the discriminant function is used to classify the image. If the discriminant criterion meets the classification accuracy requirements, this criterion is established; otherwise, the classification decision rules need to be reestablished until the classification accuracy requirements are met.

The key issue in land object classification is the choice of classifier, which is usually determined by comprehensive factors such as the complexity of the target category and the accuracy requirements. The currently used classifiers are based on traditional statistical analysis, neural networks, and pattern recognition. The commonly used parallelepiped method, minimum distance method, Mahalanobis distance method, and maximum likelihood method are methods based on traditional statistical analysis; support vector machines and fuzzy classification are methods based on pattern recognition. In addition, there are spectral angle method (SAM), spectral information divergence, and binary encoding for hyperspectral data. The supervised classification process of remote sensing images is shown in Figure 1.

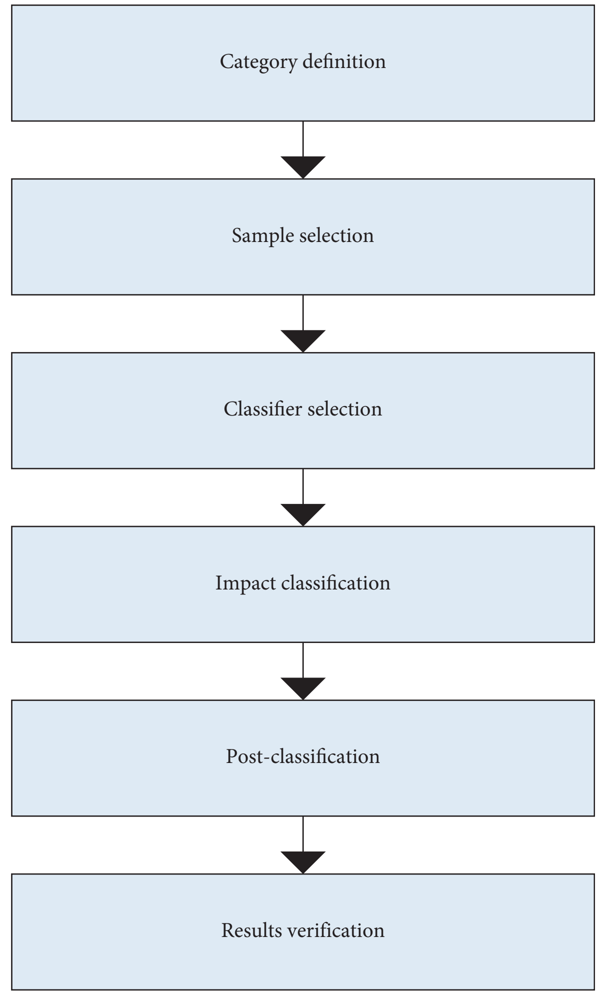

Figure 1: Supervised classification process of remote sensing imagery.

2.4. Unsupervised C Classification. Unsupervised classification, also known as cluster analysis, is characterized by the fact that it does not require training and only uses a specific clustering algorithm to classify features based on their spectral characteristics. The spectral characteristics of the pixels of the same category in the classification results conform to the same rules, but cannot directly reflect the types of ground objects they represent. The spatial distribution of each sample is divided or merged into a cluster according to its similarity, and the types of ground objects represented by each cluster can only be determined by field investigation or comparison with known types of ground objects. Therefore, a visual interpretation of the classification results is required to determine the category of the feature. In the process, categories are often combined. Due to the huge amount of spectral feature data contained in remote sensing image pixels, the supervised classification process requires multiple iterations, and the research on unsupervised classification algorithms pays great attention to the efficiency of algorithm operations.

(1) The K-means method randomly finds the similar position of the cluster, that is, the central position. When the maximum number of iterations is reached, the central position is used to iterate to complete the classification. The general process of unsupervised classification of remote sensing images is shown in Figure 2.

    The K-means classification method is a continuous algorithm, which gradually moves each cluster center through an iterative method to achieve the best clustering effect. The algorithm principle is also very simple. The flow chart of K-means algorithm is shown in Figure 3.

(2) Self-organizing iterative data analysis method:

    ISODATA is an improvement based on the K-means algorithm, which allows the adjustment and change of the number of classes and classification results based on the K-means algorithm, mainly based on the specified parameters (thresholds) to check the clustering situation of the previous cycle. Therefore, decide to redecompose, merge, or cancel some cluster decomposition: (1) The parameter "maximum standard deviation" can be set. When the standard deviation of a band in a class exceeds this

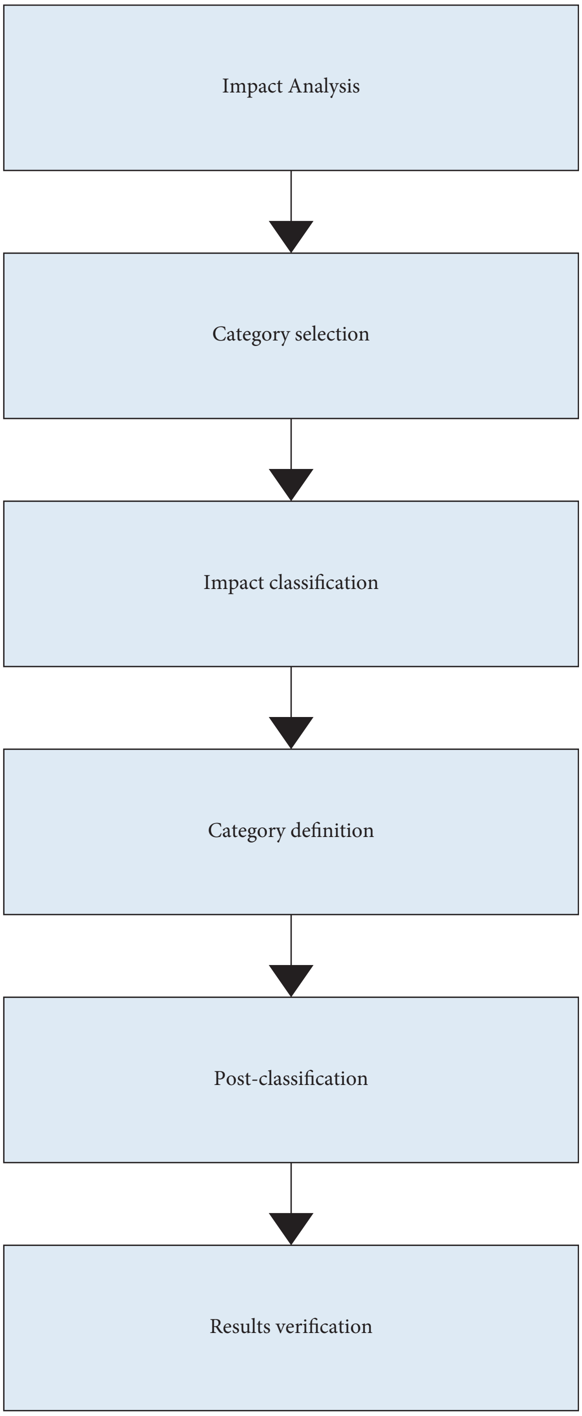

Figure 2: Remote sensing image supervised classification process.

threshold, it is decomposed into two classes. (2) Merge: you can set the “minimum distance between classes” parameter. When the distance between two classes is less than this minimum distance, they are merged. (3) Cancel: when the number of pixels in a class is too small and less than the parameter “minimum number of pixels in a class,” the class is cancelled and the pixels in it are reassigned to adjacent clusters. The algorithm flow chart is shown in Figure 4.

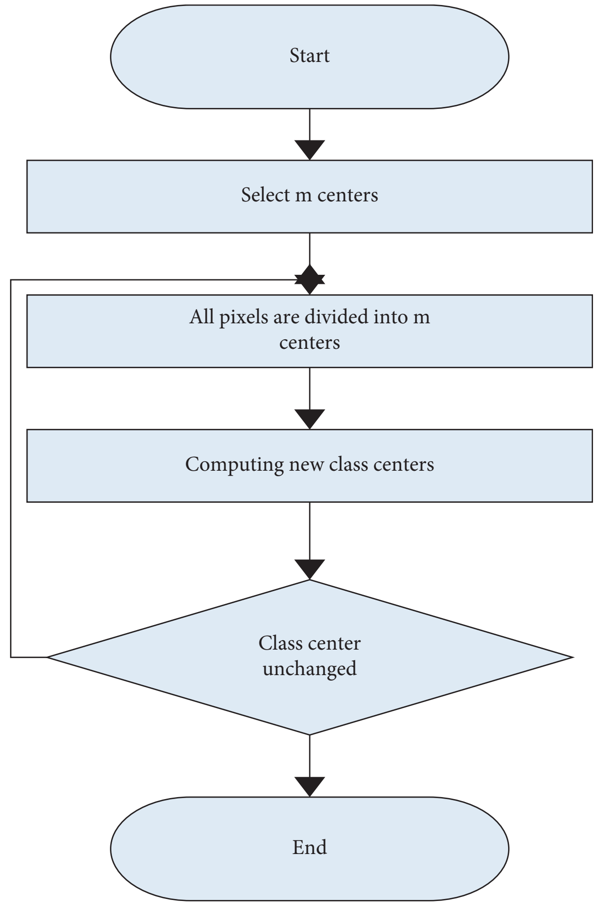

Figure 3: Flow chart of K-means algorithm.

3. Experiment

3.1. Subject. The remote sensing data of Yuhuatai District in 2018 and 2019 used the QT-DMTF change detection method, and the ground resolution of the data was 2.5 meters. Data is projected, corrected, and equalized. Half of the images covering 43.75 square kilometers are used as training samples, and the remaining 50 square kilometers are used for detection. Artificially drawn ground-truth images, including open spaces, buildings, roads, rivers, and ponds, change from open space to buildings and from buildings to open spaces.

3.2. Experimental Design

3.2.1. Data Preparation. Remote sensing data: ground satellite data +1, 2 + 13 have high spatial, spectral, and temporal resolution. For land use, land cover is an economical and practical data source. Associated graphs, data, and text reports mainly include detailed land survey, land change survey map, basic farmland planning map and data; other thematic maps, such as soil map, vegetation map, land type map, grass resource distribution map; land resource evaluation map and other related pictures, etc., in addition to geometric correction of remote sensing images, vectorization of related data, and unification of coordinates.

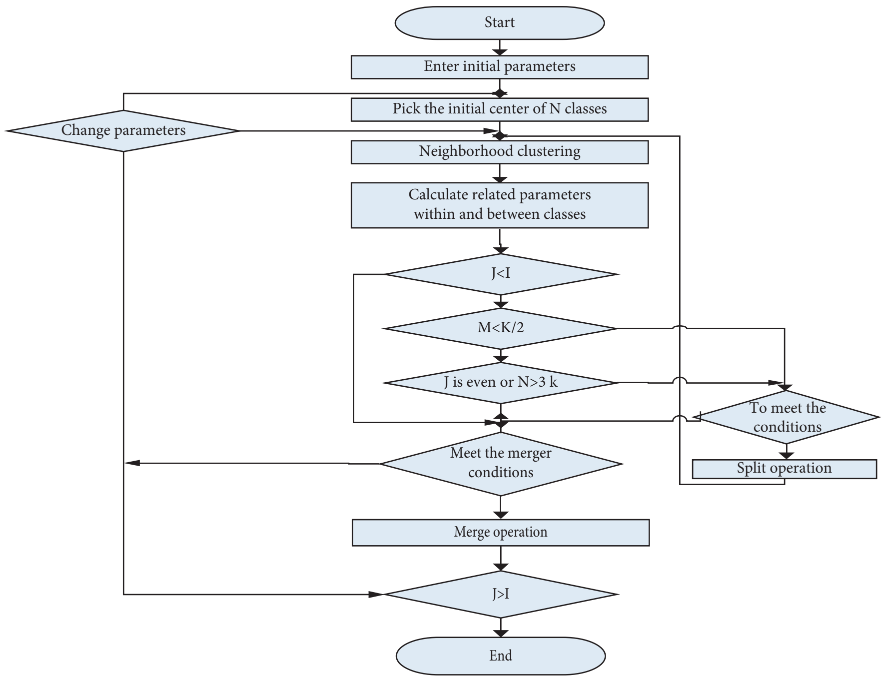

Figure 4: Flow chart of ISODATA algorithm.

3.2.2. Enhance Remote Sensing Information. The enhancement of remote sensing information mainly includes contrast enhancement, including linear expansion, nonlinear expansion, histogram adjustment, color enhancement, *p* pseudocolor enhancement for single-band images, and color synthesis for multiband images (select bands or components using 456 values). Multidimensional orthogonal linear transformation is based on image statistical features: KL transformation (principal component analysis), KL transformation ("hat transformation").

3.2.3. Extraction of Change Information. The methods of extracting the change information of remote sensing images can be divided into two categories in essence: one is based on the spectral value change of a single pixel; the other is based on the spectral value change of a single pixel. The other is classification based on input data. Classification change monitoring is based on first-level classification: firstly, remote sensing classification is performed on the images before and after the time period, and then the images are compared, and the classification results are compared to find out the changes of monitoring indicators. First, they are then subtracted to get the difference image, the change area is determined, then the change area in the difference image is classified, and finally the type of change is determined. Classification change monitoring is based on principal component transformation: fuse the before and after images, and then perform principal component transformation. In general, the first few principal components account for 95% of the variance. The geological significance of these principal components is analyzed, represented by brightness and greenness, to determine the type and scale of land use and land cover changes; classification changes monitoring results are extracted based on remote sensing thematic information.

3.3. Experiment Implementation. This section uses two algorithms, ELM and Ensemble-ELM, to perform classification experiments on IndianPines, PaviaU, and Salinas hyperspectral data. The experimental results of the three datasets are analyzed and evaluated in detail below.

From the analysis of IndianPines classification accuracy, compared with the ELM algorithm, the Ensemble-ELM algorithm proposed in this section improves the classification accuracy by about 10%. The two methods have higher classification accuracy for the 5th, 6th, 8th, and 14th ground features, but lower classification accuracy for the 3rd, 4th, 9th, and 12th ground features. This is because grasslands, pastures, trees, timber, etc. are all homogeneous areas and are easy to label, while categories such as corn and soybeans are also divided into specific subcategories, which are prone to misclassification, and there are too few labeled samples in category 9. The characteristics of the ninth category of features cannot be well characterized, which should be one of the reasons for the poor classification results of this category. But in general, the Ensemble-ELM algorithm improves the classification accuracy of each category, which shows that the application of ensemble learning in ELM classification has achieved good results. When the training sample set is small, the classification accuracy of ELM is low, while the classification accuracy of the Ensemble-ELM algorithm is still higher than 85%, which meets the basic requirements of remote sensing image classification.

The Ensemble-ELM algorithm proposed in this chapter has achieved very good classification effect data when classifying PaviaU. The overall accuracy (OA) of the test samples was above 91%, with a Kappa coefficient of 0.88. Compared with the ELM algorithm, the accuracy is improved by about 20%. Compared with SVM, Ensemble-ELM algorithm shows advantages in classifying PaviaU, both in classification accuracy and in experiment time. Both algorithms have poor classification results for the third category. Compared with the PaviaU ground truth data map in the previous section, it can be analyzed from the classification map that this is because the features of the third and eighth classes are similar and can be easily understood as the eighth class. At the same time, the first category can easily be mistakenly classified as the eighth category. There is a serious confusion between Class 2 grassland and Class 6 bare soil in the ELM classification map, which improves the confusion in the Ensemble-ELM classification map. Meanwhile, the classification map of Ensemble-ELM is smoother than that of ELM.

Compared with ELM, the Ensemble-ELM algorithm proposed in this chapter improves the classification accuracy of Salinas data by 4.4% for AA and 5.1% for OA, but the improvement is not large and the effect is not obvious. In the case of small sample classification, the classification effects of Ensemble-ELM and SVM algorithms are comparable, but have significant advantages in classification speed. It can be seen from the classification effect diagrams of ELM and Ensemble-ELM algorithms that, compared with ELM, the phenomenon that the third category is misclassified as the fifth category in the Ensemble-ELM classification diagram has been significantly improved, and the characteristics of the third category have been significantly improved. The classification accuracy should be smoother and the classification map should be smoother. However, the classification effect of the two algorithms is poor for the 15th category, and the phenomenon of misclassification to the 8th category is more serious. The classification effect after optimization has not been significantly improved.

By comparing the experimental results on the IndianPines, PaviaU and Salinas datasets, it can be found that the Ensemble-ELM algorithm proposed in this chapter has a better classification effect on the PaviaU dataset, and the optimization effect of the ELM algorithm is more prominent. Compared with ELM, Ensemble-ELM algorithm, the classification results of ELM on PaviaU show that OA is increased by 19%, AA is increased by 15%, the classification accuracy rate is over 91%, and the Kappa coefficient is 0.88. In the classification results of IndianPines data, OA only increased by nearly 10% to 86.2%, AA increased by 13% to 82.77%, and the Kappa coefficient was 0.84. In the classification results of Salinas data, both OA and AA increase by about 5%, and the optimization effect is not obvious.

4. Discussion

4.1. Analysis of Indian Pine Results. In terms of classification accuracy, it can be seen from Table 1 that, in the classification results of IndianPines' LBP-KELM method, OA is more than 30% higher than KELM, about 25% higher than SVM, and each class is improved to more than 94%. For example, the classification accuracy of KELM and SVM for the first category is only 4.88% and 17.07%, while the classification accuracy after using LBP-KELM is as high as 97.56%, indicating that the method proposed in this chapter utilizes texture features to achieve good classification results. In terms of classification efficiency, the processing speed is comparable to KELM, and it has a significant advantage over SVM in classification efficiency.

4.2. MODIS Data Analysis. To validate the algorithm, SKM, CKM, SAP, and IS-AP were selected for experiments with labeled samples at different scales. For the IS-AP and SAP algorithms, set the parameter to 0.85, and the self-similarity is the average of all the similarities. Figure 5 shows the quantitative analysis of the four algorithms. As can be seen from Figure 5, MRI reaches the highest value when SKM, CKM, SAP, and IS-AP select sample proportions of 12%, 10%, 10%, and 8%, respectively. Table 2 lists the MRIs of SKM, CKM, SAP, and IS-AP at 12%, 10%, 10%, and 8% of labeled samples, as shown in Figure 5 and Table 2.

4.3. Comparative Analysis of Different Classification Methods. Through research analysis, we know that the classification accuracy of the LCNet-27 model is better. In the method comparison, the article uses LCNet-27 to compare and analyze the traditional method. In terms of sample size selection, for TM images, the classification results obtained by the 5×5 sample size are better than other sample sizes in terms of detail retention and overall classification accuracy. To analyze the effectiveness of the method model, this paper will use the 5×5 sample size as the standard input sample size for the TM image method. The same set of training samples and validation samples were compared with the SVM classifier using spectral features and the SVM classifier using spectral plus texture features. The 7×7 sample size of QuickBird images was compared with traditional methods. The texture feature is selected according to the gray level co-occurrence matrix, and the mean and dissimilarity of the two texture measures of each band are added to obtain an 8-dimensional texture feature. The texture features and spectral features are classified as input features for the SVM classifier. In the quantitative accuracy evaluation, the overall classification accuracy and Kappa coefficient of the three classification methods for TM images and QuickBird images are shown in Figures 6 and 7.

4.4. LCNet: Analysis of the Influence of 27 Samples of Different Sizes on the Classification Results. With LCNet-27, the training accuracy is better than LCNet-13. This section will use the LCNet-27 model to select the optimal sample size and use the optimal sample size to compare and analyze the accuracy of the two models. Each pixel is collected according to the neighborhood size of 3×3, 5×5, 7×7, and 9×9 and then input into the LCNet-27 model trained by the respective sample size, and the pixel-by-pixel category judgment is performed, the accuracy of the classification is evaluated, and the QuickBird data test area is also collected according to the neighborhood size of 5×5, 7×7, and 9×9 for pixel-by-pixel category judgment; TM image classification, QuickBird image classification, and classification accuracy comparisons are shown in Table 3 and Figure 8.

Table 1: Classification results of Indian pine by KELM, SVM, and LBP-KELM algorithm (precision unit: %).

Category	Number of training samples	Quantity testing sample	KELM	Support vector machines	LBP-KELM
1	5	41	4.88	17.07	97.56
2	143	1285	75.10	73.93	98.13
3	83	747	52.07	57.03	99.33
4	24	213	34.27	55.87	95.31
5	48	435	86.67	86.90	99.08
6	73	657	98.33	96.19	99.09
AA			64.03	72.95	98.33
Office automation			77.90	80.22	98.36
Kappa			0.74	0.77	0.98
Training time (seconds)			0.11	$2.66E+04$	0.22
Test time (seconds)			0.61	8.60	1.51

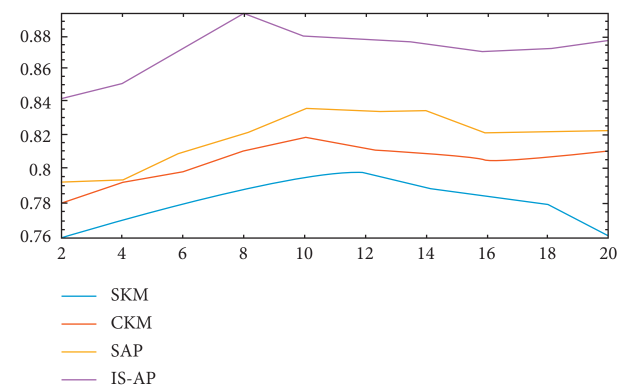

Figure 5: Proportion (%) of labeled samples.

Table 2: SKM, CKM, SAP, and IS-AP clustering results MRI (MODIS data).

Evaluation indicators	SKM	CKM	Sap	Access point
Proportion of labeled samples (%)	12	10	10	8
NMR	0.807	0.825	0.843	0.896

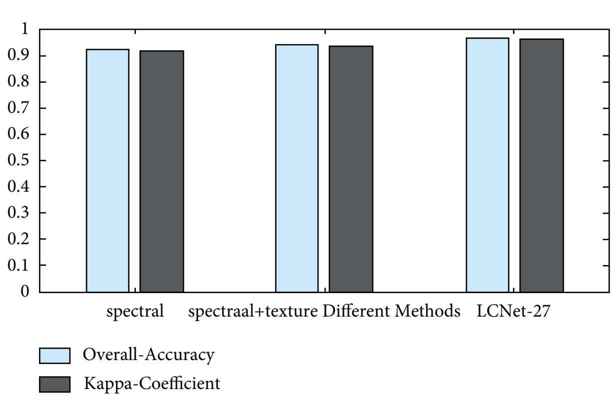

Figure 6: TM overall classification accuracy of different methods.

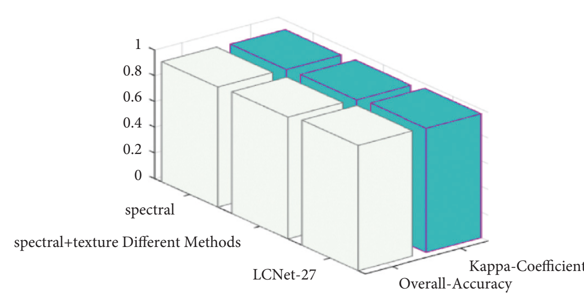

Figure 7: Overall classification accuracy of different QuickBird methods.

Table 3: TM overall classification accuracy for different sample sizes.

	Accuracy
$3*3$	0.7
$5*5$	0.75
$7*7$	0.8
$9*9$	0.7

4.5. Analysis of ELM-SVM Classification Model. To test the performance of the ELM-SVM classification model, the combined model also conducts land cover classification experiments using the following two remote sensing image datasets. Meanwhile, in order to effectively test the performance of the ELM-SVM method, we compare with the SVM and ANN algorithms on the overall classification accuracy and Kappa coefficient. In order to improve the classification accuracy, the internal parameters of all methods are set to the optimal values; the thematic classification effect map is generated for the remote sensing image

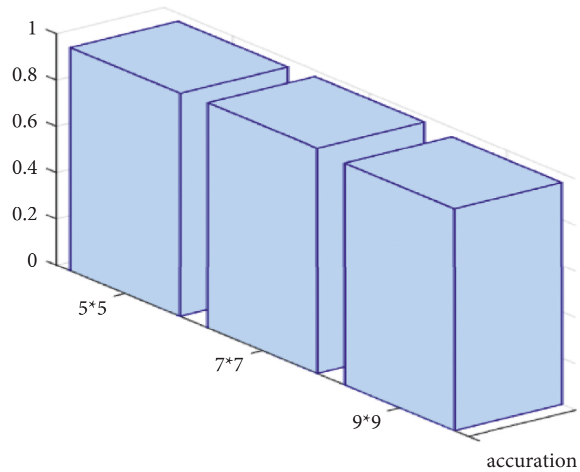

Figure 8: Comprehensive classification accuracy of QuickBird sample of different sizes.

Table 4: Confusion matrix for classification test using SVM.

Class	Water	Put up	Grass, shrub	Bare land	Road	All	User accuracy
Water	1148	2	0	0	25	1328	0.987
Put up	0	444	0	0	266	698	0.852
Grass, shrub	0	0	1294	0	73	1456	0.741
Bare land	0	0	0	82	10	90	0.963
Road	5	1329	30	15	11000	12825	0.9234
All	1155	1764	1409	95	10999	15133	
User accuracy	0.999	0.3	0.997	0.888	0.766		0.872

experimental data, and the visual comparison analysis is carried out with the classification effect map of the SVM and ANN methods; based on ENVI5.0, in the self-made components, the experiments were carried out in the experimental environment, as shown in Table 4.

5. Conclusion

The classification of remote sensing images is the basis and focus of remote sensing image analysis. Based on the characteristics of remote sensing images, this paper attempts to find the combination of pattern recognition methods and thematic classification applications of remote sensing images, aiming to improve the classification accuracy of remote sensing images. Remote sensing images such as ALOS/PALSAR and PSM are used as the main experimental data. Using the spatial and spectral features of remote sensing images, several SVM kernel function fusion methods and remote sensing image classification algorithms based on SVM, KNN, ELM, and other pattern recognition methods are proposed to classify and identify surface objects in remote sensing images. Finally, based on FCM and SVM, combined with remote sensing image segmentation method, object-oriented remote sensing image classification is realized.

The research summarizes the principles of pattern recognition methods commonly used in remote sensing image classification. The concept of pattern recognition and the workflow of pattern recognition system are briefly introduced. The main focus is on the integration of statistical pattern recognition with this study. The identification methods and experimental evaluation index systems commonly used in classification work are deeply studied.

Machine vision mainly studies the use of computers to simulate human visual functions. It extracts information from images of objective things, processes and understands it, and finally uses it for actual detection, measurement, and control. Typical industrial machine vision application systems include light source, optical system, image acquisition system, image digitization module, digital image processing module, intelligent judgment and decision-making module, and mechanical control execution module; machine vision is mainly divided into visual inspection, vision, and robot vision. In other respects, it has been promoted in the fields of medical testing and intelligent transportation, bringing convenience to people's lives. However, the existing technology is still difficult to deal with complex scenes, so this problem has also become the future development direction of machine vision. The main application of machine vision technology at this stage is still to capture visual information, but how to combine it with the perceptron has become a difficult problem in the next stage. The birth and application of machine vision technology have greatly liberated human labor, improved the level of production automation, and improved human living conditions. Its application prospect is very broad. At present, foreign machine vision technology has been widely used in production and life, while our country is still in its infancy, and the joint efforts of scientific and technological workers are urgently needed to rapidly improve the development level of our country's machine vision technology and make progress to make its own contribution to China's modernization.

In the research work and writing process of this paper, due to our limited understanding of the research field and the lack of basic experimental data, many issues related to the research content of this paper need to be further developed, including the following points:

(1) All the research methods proposed in this paper can only be applied to remote sensing images such as ALOS/PALSAR and PSM and cannot be directly applied to the classification or segmentation of remote sensing images from other platforms. Therefore, in addition to optimizing and perfecting the algorithm principle proposed in this paper, we should also try to apply the algorithm principle proposed in this paper to the classification or segmentation of remote sensing image data based on other sensor platforms.

(2) The distance measurement between the sample points of the algorithm proposed in this paper is generally based on the Euclidean distance formula or the Euclidean distance formula. Combining this formula with the spectral angle matching formula, the performance of other distance formulas has not been tested, so the theoretical research needs to be improved, and the research should be applied from different angles as much as possible, such as considering the use of the Markov distance measurement index formula.

(3) All the classification methods proposed in this paper can take into account the extraction of spatial and spectral features of remote sensing data. In order to obtain higher classification accuracy or reasonable classification or segmentation effect, efforts should be made to use richer remote sensing data, data characteristics, feature information, such as the standard deviation and spectral ratio of image objects, the fractal dimension of the image, and the shape features of image landmarks and texture features.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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