Research Article

Remote Sensing Data Processing of Urban Land Using Based on Artificial Neural Network

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With the rapid development of urbanization, the utilization rate of land has become the focus of attention. Remote sensing technology can provide a large amount of data for the prediction of urban land. It is also a thorny problem to find the correlation between the complex data of land change. The neural network technology has obvious advantages in finding the mapping relationship between high-dimensional and nonlinear data. This paper combines the dynamic changes of urban land and neural network methods to analyze the utilization rate and coverage of urban land in the future. In this paper, the data obtained by remote sensing technology is normalized and clustered to classify different types of urban land. Convolutional neural networks and long-short-term memory neural networks are used to extract the spatial and temporal dynamic characteristics of urban land use. The research results show that the clustering method used in this paper can reasonably classify different urban land types, especially the classification of buildings. The method of predicting the future trend of land use is also in line with the dynamic process of land use. The largest prediction error comes from the prediction of the building, and the largest error is only 2.56%, which is a reasonable error range. The smallest error does not exceed 1%, and the correlation coefficient between the real and predicted values of urban land use types reaches 0.9698.

1. Introduction

In recent years, with the development of national policies, the process of urbanization has been accelerating. However, the inherent land area of a city remains unchanged, which leads to serious problems such as traffic congestion, tight housing, and lack of public facilities [1]. At the same time, the land coverage rate and land utilization rate are constantly changing over time. There is a strong correlation between urban land use and other social factors, such as economic development, social policies, etc. It is difficult to develop by relying solely on manpower [2]. This requires strong support from scientific and technological forces. Remote sensing technology can provide a large number of dynamic types of urban land use data, including not only time information of land use but also spatial information. These data contain a large amount of implicit information. Neural network technology is just good at discovering nonlinear relationships between data [3].

Traditional land data acquisition methods have shortcomings such as long periods, poor timing, and low accuracy, and cannot provide useful information data in real time or in a timely manner [4]. The use of land will undergo major changes over time, which requires a technology that can process land data in real time. Land is a very important resource for humans and even organisms, and it is the basis for human production, development, and survival [5]. The changes in land use directly affect the progress and development of human society and also have an important impact on the development and distribution of natural resources. It is also meaningful for the development of the country to grasp and predict information such as land utilization and coverage in a timely manner [6]. Reasonable urban land use classification plays an important role in urban infrastructure planning, socioeconomic improvement, natural disaster prevention, and crisis management [7]. However, we consume a lot of manpower and physics every 10 years to carry out intensive urban land use surveys. This method is not only

time-consuming but also difficult to categorize the data and discover the laws [8]. According to the rapid development of big data technology and scientific information technology in the current era, finding a method suitable for the efficient classification of urban land is a key issue of research.

With the rapid development of artificial intelligence technology and remote sensing technology, greater progress has been made in process of urban land use. Chen et al. [9] used the fuzzy remote sensing data set of the land to extract the affected spectral features and texture features for data preprocessing and then used the support vector machine to classify the feature set to achieve land use classification, and the accuracy and classification index reached very good classification effect. Zhang et al. [10] have used the SMC coding method to extract features and classify the land image data obtained from remote remote sensing technology, and finally verified the accuracy of the SMC coding measurement in the extraction and classification of the land impact from the accuracy of the land classification. Xu et al. [11] made full use of the reasoning application method to study the feasibility of this method in land use classification from the perspectives of land image feature extraction, land weight, and land structure similarity based on the worldview-2 satellite remote sensing image data. Rimal et al. [12] compared the accuracy of support vector machines and maximum likelihood machines in land use classification. The data comes from land satellite remote sensing images. He proved that the support vector machine SVM has higher classification accuracy. Anugraha et al. [13] combined land remote sensing data with the perception behavior of human society for the first time and then used the decision tree and random forest method to evaluate the accuracy of land use classification. The accuracy can reach 83% and 86%. Chu et al. [14] proposed the iterative adaptive superpixel segmentation (LCPP-ISSS) technology for land remote sensing data classification, which can provide high-resolution land cover information. At the same time, he also proposed a land cover classification method with patch complexity. The accuracy of the LCPP-ISSS method is 10% higher than that of the conditional random field method. Zhang et al. [15] proposed a land use classification method for multispectral remote sensing data based on a probability model and combined it with the copula method to study the uncertainty of the land use classification method. The accuracy of this method is increased by 29.4% compared to the traditional maximum likelihood method. Hashim et al. [16] pointed out that supervised learning methods have higher accuracy and feasibility in land use classification tasks than unsupervised learning methods. At the same time, he used the accuracy of the maximum likelihood, support vector machine, and neural network methods in the classification task. This conclusion pointed out that the support vector machine method has better accuracy. Ekim et al. [17] proposed a land remote sensing data classification method based on the semantic segmentation method. Deep neural network technology is used by him in remote sensing data classification, and the data set can come from multiple types of target remote sensing data sources. The data source of

NWPU-RESISC45 shows that this method improves the accuracy of land use classification.

Remote sensing technology can provide real-time land change dynamics with higher resolution and long-distance [18]. It uses neural network technology to classify different types of land in the same period, or to classify land types in different periods in the same category, which has great social significance for the efficient and comprehensive use of land [19]. At the current stage, the classification of land cover and land use is still a hot research topic in the field of remote sensing. Similarly, the rational classification of land use based on remote sensing data is of far-reaching significance for environmental monitoring, analysis of urban space utilization, and prediction of natural disasters [20]. A reasonable and accurate classification of land use and land cover is not only the basis for full utilization of land but also has a greater effect on the overall planning of urban development [21]. However, in terms of remote sensing data, there are problems such as loss of high-frequency details, blurred boundaries, and limited spatial information reconstruction capabilities, which make the boundary accuracy of classification not high [22]. In the field of artificial intelligence, convolutional neural networks can fully extract features, and superresolution technology can reconstruct lost information, which provides greater technical support for remote sensing data in land use classification [23].

This research is composed of five parts. The first part introduces the progress of land use and land cover classification and the importance of remote sensing data for land use classification. The second part introduces the significance of neural network technology to land use classification and the source and composition of the learning data set. The third part introduces the classification methods and neural network models used in land use. The fourth part mainly analyzes the accuracy and error of the classification method in land use. At the same time, statistical parameters such as correlation coefficient are used to quantitatively analyze the accuracy and generalization ability of neural network technology in land use classification. The fifth part is the summary part of the article.

2. The Significance of Artificial Intelligence in Processing Land Remote Sensing Data

2.1. The Significance of Land Use Data for Prediction. Although there is a large amount of remote sensing data of urban land, the classification of remote sensing data is a challenging task [24]. Because remote sensing data has problems such as partial data loss, low resolution, and unobvious boundaries, more advanced learning algorithms are needed to classify and predict future land use trends [25]. Remote sensing data contains complex data such as residential land and wasteland, and there is a certain time correlation, which brings difficulties to the classification of urban land use [26]. Remote sensing technology is a long-distance, noncontact, wide-range, and real-time detection method. It can collect spatiotemporal data of land use in real time, which provides data support for neural network technology in land application classification [27]. Although

there are high-latitude and nonlinear characteristics between remote sensing data, neural network technology can handle the relationship well. And the current classification methods, such as decision tree, clustering, and random forest technology, can classify land use according to distance or density [28]. Compared with a wide area, the use of urban land is more complicated. Real-time classification and prediction also play an important role in government decision-making. Remote sensing technology can provide spatial data that changes over time. It would be more reasonable if these data can be used to find the time and space relationship between land use [29, 30]. Urban land includes residential land, industrial land, and landscape land. It is not only closely related to the spatial distribution of land use but also has an obvious relationship with economic development strategies. And the development of a city's economy is closely related to time, so there is also a time correlation in urban land use. The neural network model has good performance in predicting time characteristics and spatial characteristics [31]. If the advantages of neural network technology's spatiotemporal characteristics prediction can be combined with the remote sensing data of urban land use, urban land types will be more accurately classified, and it will have a better predictive performance for urban land use types. Therefore, it can be seen that the neural network is reliable to predict the future trend of land use and to classify different times and different land types.

2.2. Data Set Composition and Acquisition. A reasonable data set has an important impact on prediction accuracy and generalization ability. Neural network technology is a method of mapping the feature relationship between input and output [32]. If the remote sensing data itself has large defects, it will seriously affect the classification of urban land use. At the same time, the data selection should also be normalized to the features. Otherwise, the weight of the neural network will be more biased towards larger features, which leads to poor generalization ability of land use classification. At present, there are a variety of data for land use information, and there are a large number of constantly updated real-time data, which is beneficial to the research of this article. The geospatial cloud database has rich real-time land data. Landsat 8 OLI_TIRS satellite digital product data was selected to extract remote sensing data. At the same time, in order to more intuitively illustrate the accuracy and generalization ability of the neural network proposed in this article, Beijing is selected as the research data object of this article. The data graph comes from the URL www gscloud cn. Figure 1 and Figure 2 show a schematic diagram of the satellite in Haidian District, Beijing. It can be clearly seen from Figure 1 that the land types in this area are very complex, such as lakes, residential land, educational land, industrial land, and the land use density is also inconsistent. The Beijing area is densely populated and the land-use situation is complex, and the land use types in this area are updated quickly. If this model can better predict the land use trend in this area, it has better generalization ability for other relatively sparse land areas, and it is more convincing. For
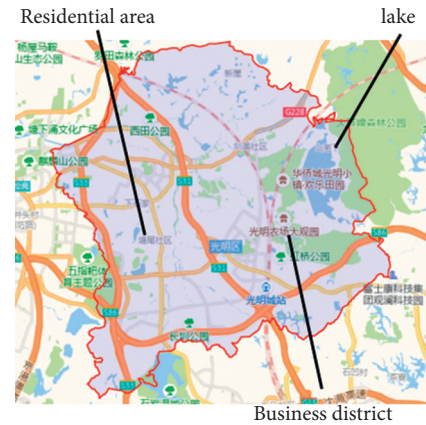

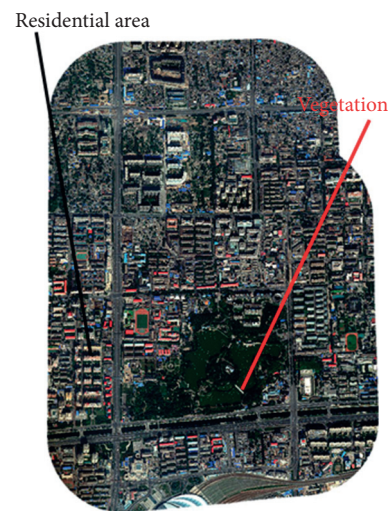Figure 1: Beijing remote sensing satellite image.

Figure 2: Remote sensing satellite image.

such complex data, it is necessary to extract features such as texture through a neural network to extract the types of data that the neural network can need and also to do a good job of labeling.

3. The Introduction of Neural Network Methods and Processes

3.1. The Method of Classification. With the development of machine learning technology, there are many advanced classification methods at this stage, such as decision trees, random forests, clustering, support vector machines, etc. These classification methods can be used in different classification objects according to different classification principles. The most commonly used classification method in urban land use classification is the support vector machine method. For the problem of urban land use classification, this method is to find a hyperplane to classify different types of land types. The hyperplane represents the best accuracy and the best generalization ability. The feasibility of this classification method has been proved in previous documents. In order to combine the advantages of convolutional

neural networks, this paper adopts a clustering method to classify land use types. Clustering is a way to classify based on distance or density, which is also the most widely used classification. K-means is a classification method based on feature distance, which is a simple and widely applicable clustering method. There are big differences in land use in different cities. In order to improve the generalization ability of the neural network model in this paper, the K-means method is used as a classification task of urban land use.

3.2. Convolutional Neural Network.

Convolutional neural network is a special category of BP neural network. It is also mainly composed of two processes of forward propagation and backpropagation. The process of finding the optimal weight is also the process of continuously minimizing the loss function. The difference between a convolutional neural network and a fully connected neural network is the weight sharing stage, which reduces the number of operation parameters, which makes it possible to construct large-scale deep networks. A fully connected neural network requires matrix operations between every two weights, which not only increases the amount of calculations but also increases the consumption of cost resources. Because the data of remote sensing technology is dynamically carried out all the time, and its coverage area is large, the information contained is more complicated. If a fully connected neural network is used, it will inevitably cause a lot of parameter calculations and at the same time, will cause a lot of waste of resources. For the prediction of urban land use, the convolutional neural network can extract useful features for calculation, which reduces the number of parameters. A convolutional neural network has done processing in weight sharing, which is the only selective calculation of weight matrix, which reduces the amount of parameter calculation of neural network, which allows the development of deeper network layers. In recent years, convolutional neural networks have achieved great success in areas such as feature extraction and image recognition. Figure 3 introduces the operating principle of the convolutional neural network. The input of the neural network is the land use type and meteorological information after clustering, and it is a time series containing time information. The input is the land use type for the next stage.

Convolutional neural network is a supervised learning method. The input layer first goes through the convolutional layer, pooling layer, and activation function for forward calculation, and then the predicted value is compared with the true value for the loss function, and finally, through the reverse. The propagation method minimizes the loss function value; that is, it finds the direction of the gradient drop of the loss function. The basic process equation of the perceptron is shown in (1), where the sign is the activation function, and the ω is the weight, and the b is the bias.

$$f(x) = \text{sign}(\omega \bullet x + b), \tag{1}$$

where ω is the neural network weights, and b is the neural network bias. The Sign is the activation function. As shown in (2), it can add the bias parameter b_j^ζ, and the excitation
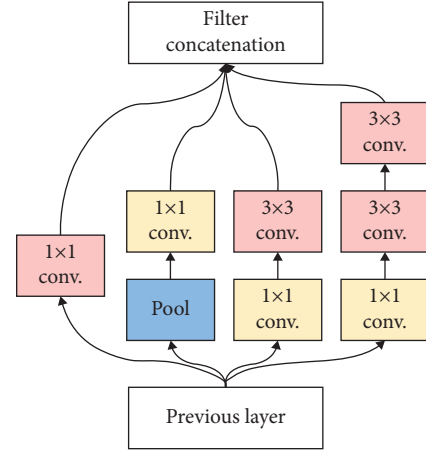

FIGURE 3: Convolutional neural network operation process.

value of the activation function is the output parameter of the convolution layer.

$$x_j = f\left(\sum_{i \in M_j} x_i^{\zeta-1} * k_{ij}^\zeta + b_j^\zeta\right). \tag{2}$$

As shown in (3), the function of this function $\text{up}(x)$ is to reshape the shape of $\delta_j^{\zeta+1}$ into the same shape as δ_j^ζ, so as to facilitate the convolution operation.

$$\delta_j^\zeta = \beta_j^{\zeta+1}\left(f'(u)_l^\zeta \circ \text{up}\left(\delta_j^{\zeta+1}\right)\right). \tag{3}$$

As shown in (4), the function $\text{down}(x_j^{\zeta-1})$ is to sum the eigenvalues. Then it adds a bias to output according to the activation function.

$$x_j = f\left(\sum_{u,v} \beta_j^\zeta \text{down}\left(x_i^{\zeta-1}\right) + b_j^\zeta\right). \tag{4}$$

As shown in (5), where the f' represents the derivative of the above pooling layer function (5). The k_{ij}^ζ is convolution kernel, the $\delta_j^{\zeta+1}$ is the weight parameters.

$$\delta_j^\zeta = f'\left(u_j^\zeta\right) \circ \text{conv2}\left(\delta_j^{\zeta+1}, \text{rot180}\left(k_j^{\zeta+1}\right)\right). \tag{5}$$

As shown in (6), the (6) shows the derivative of the bias parameter k_{ij}^ζ, which is a parameter in the form of a matrix.

$$\frac{\partial E}{\partial k_{ij}^\zeta} = \sum_{u,v} \left(\delta_j^\zeta\right)_{uv}\left(p_i^{\zeta-1}\right)_{uv}. \tag{6}$$

3.3. Long and Short Memory Neural Network.

Through the previous review, it can be found that there is a time correlation in the prediction of land use, and changes in the distribution of time will also affect changes in urban land use and land cover. Although convolutional neural networks have achieved great success in spatial feature extraction, data features also have time correlation, such as in the field of speech recognition.

The correlation between time means that the characteristics of the past moment will affect or even affect the

characteristics of the future moment for a long time, which requires genetic preservation of certain characteristics. The long and short memory loop neural network has achieved great success in dealing with the problem of time characteristics. As the use of urban land changes over time, its use type will change more quickly than rural land or relatively empty areas, which is determined by factors such as economic policies and demographic changes. Therefore, time characteristics should be fully considered when dealing with urban land use and land cover prediction problems. Long-short memory neural network is used to extract the time characteristics of land use, and it maintains the time characteristics with strong correlation, which will further improve the accuracy of urban land use and land cover predictions. Figure 4 shows the operational process of the long and short memory neural network. The time series features of remote sensing data are first extracted through the time characteristics of LSTM, and then spatial features are extracted through CNN.

The core part of LSTM is the cell state. It has the ability to add or delete information to the cell state. This is a gate control state. A gate is a control method that allows partial information to pass through selectively. It is composed of a Sigmoid function and a matrix operation. The calculation process of the forgets is shown in (7), where W_f is the weight matrix of the forget gate, and b_f is the bias matrix of the forget gate.

$$f_t = \sigma\left(W_f \bullet \left[h_{t-1}, x_t\right] + b_f\right). \tag{7}$$

The control variables of the input gate also come from the input and output. Tanh nonlinear function normalizes the input to between -1 and 1, as shown in the following equations:

$$i_t = \sigma\left(\omega_i \bullet \left[h_{i-1}, P_t\right] + b_i\right). \tag{8}$$

$$\widetilde{C}_t = \tanh\left(w_c \bullet \left[h_{t-1}, P_t\right] + b_c\right). \tag{9}$$

After passing the forget gate and memory gate to get the current time variable, which can refresh the variable by the following formula, as shown in (10), where $\overline{C}_{t-1}$ is the characteristic value of the cheap moment, and $\overline{C}_t$ is the characteristic value of the current moment. The i_t is the Information retention factor.

$$\overrightarrow{C}_t = f_t \times \overrightarrow{C}_{t-1} + i_t \times \overrightarrow{C}_t. \tag{10}$$

When the output gate is equal to 0, the output is closed, and the internal memory of LSTM is completely cut off and cannot be used as an output. When the output gate is equal to 1, the output is fully opened, where σ is the activation function, and the ω_0 is the weight, the $\overline{h}_{t-1}$ represents the state value at the previous moment.

$$O_t = \sigma\left(w_o \bullet \left[\overrightarrow{h}_{t-1}, P_t\right] + b_o\right),$$
$$\overrightarrow{h}_t = O_t \times \tanh\left(\overrightarrow{C}_t\right). \tag{11}$$
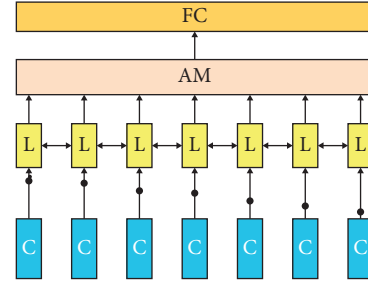

FIGURE 4: The operational process of LSTM.

3.4. Data Preprocessing and Normalization. The data obtained through remote sensing satellites Landsat 8 OLI_-TIRS is a three-channel aviation impact. It can be seen from the Beijing area map that it contains complex features such as vehicles, vegetation, lakes, rivers, and buildings. At the same time, the buildings can be divided into residential areas and industrial areas., Business district, etc. For neural networks, this is a remote sensing satellite data map with complex features. Compared with the classification of buildings, the characteristics of lakes and rivers are relatively obvious, which is easy to classify and distinguish. For the classification of buildings, a preprocessing process of data enhancement is required. This paper uses the model of the final connection for classification training, and all data features of different categories need to be classified. There are obvious magnitude differences between data with different characteristics, which requires data standardization processing, and the data is uniformly processed into input data conforming to the normal distribution, and the size value is between intervals [0,1]. The normalization method StandardScaler is used as the data normalization process in this article. The equation for normalization is shown as follows:

$$z = \frac{x - \mu}{\sigma}. \tag{12}$$

where the μ is the mean of the data set, and σ is the variance of the data set.

4. Analysis and Discussion of the Result

First, it will analyze the feasibility of the clustering method from the perspective of urban land use type classification. Figure 5 shows the predicted value and the real comparison curve at different times. For the urban land use situation, the predicted value of the neural network is in good agreement with the real one. The land use error in the first two months was relatively large, but it was also within the acceptable range. This was mainly due to the error caused by the temporary policy and the uneven sample distribution caused by the relatively sparse data set in this part. In the following two months of urban land use prediction, the error is relatively small, and both the peak change and the downward trend are in good agreement. For the prediction of different land types, the difference is obvious at the peak and valley of the trend. The predicted values are more accurate for land
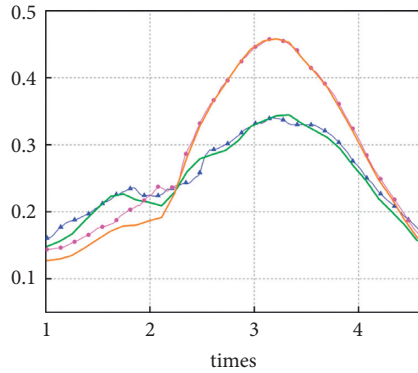
FIGURE 5: The predicted value and the real comparison curve at different times.

FIGURE 6: Contour maps of predicted values in different areas.

types with small dynamic changes such as lakes and vegetation. The relatively poor prediction of land types for buildings is mainly due to the changes in policies and the needs of economic development, as well as the relatively large dynamic changes in residential and industrial areas. In general, the forecast trend of its land types is better. Figure 6 shows the predicted value and the real comparison curve at different times. According to the remote sensing data map and the urban land layout, there are large predicted gradient changes in the residential and commercial areas in the central area. However, in surrounding land use areas such as vegetation and industrial areas, the gradient of prediction differences is small. Generally speaking, although there are differences in the prediction errors of different land types, the errors are generally within an acceptable range. For land types with large dynamic changes such as buildings, more features can be added to improve the prediction accuracy.

Figure 7 shows the predicted value of contour changes in different regions. Similarly, for mountains or vegetation with larger terrain, its dynamics are poor, so its prediction accuracy is higher. As for residential land with low terrain, its dynamics are affected by comprehensive factors such as economic activities and social activities, and its dynamics are relatively strong, so its prediction accuracy is low. The fluctuation of the error over time is more obvious, which further proves that the urban land use has obvious time characteristics. Consistent with the previous conclusions, the errors in the prediction of land use types in the previous few months were relatively small. Still, the errors will continue to increase over time. Figure 8 shows the percentage of errors that deviate from the true value. It can be seen that the errors are basically distributed on both sides of the true value, and the distance of deviation is small, which shows that the predicted value and the true value have reached a good agreement.

Figure 9 shows the urban land use error in different time periods. In general, the errors are within the acceptable range, and the maximum error is only 2.56%, which is convincing enough for the classification and prediction of urban land use. This Figure 9 reflects the change trend of the land types in residential areas over time. It can be seen that the error in the previous few months was relatively small, only about 1%. This may be related to the relatively recent
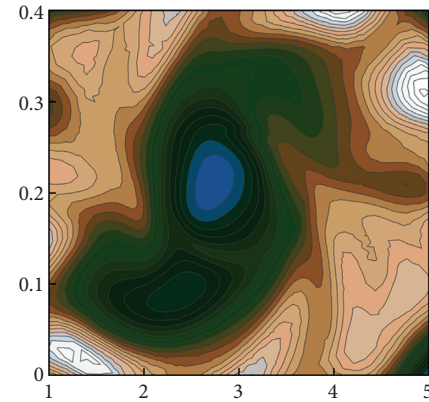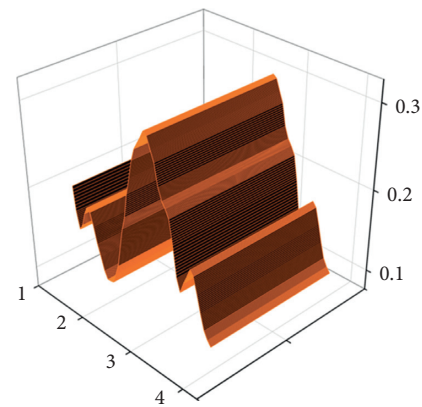

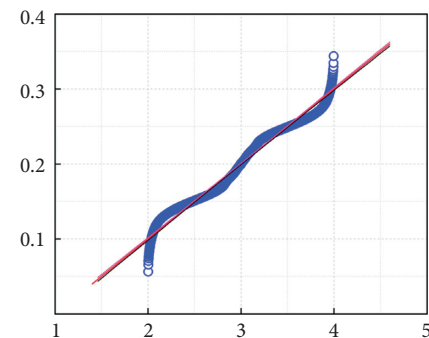FIGURE 7: Prediction of contour changes in different regions.

FIGURE 8: Error normal distribution percentage curve.

development time interval of local government decision-making, economic development, and residents' living standards. However, in the later period of time, the prediction results of land types in residential areas were relatively poor, with errors exceeding 1.5%. This was caused by the cumulative error of time and the strong dynamic changes of land types in residential areas. The prediction accuracy of residential land types can be improved by training this part of the data set separately or through data enhancement. Figure 10 shows the linear correlation coefficient diagram of urban land use type prediction. It can be clearly seen from Figure 10 that the predicted value is in good agreement with
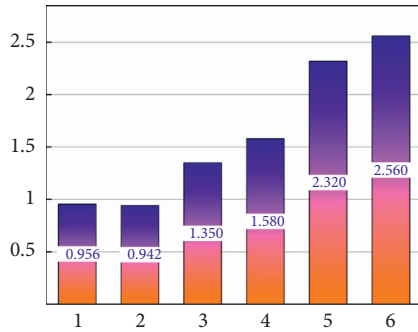
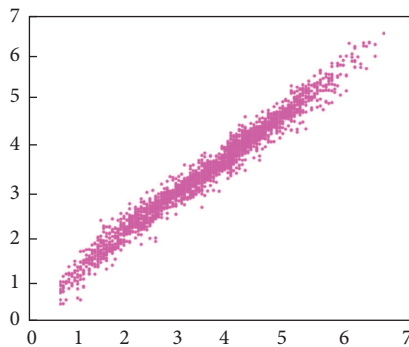Figure 9: Different time intervals of urban land use errors.

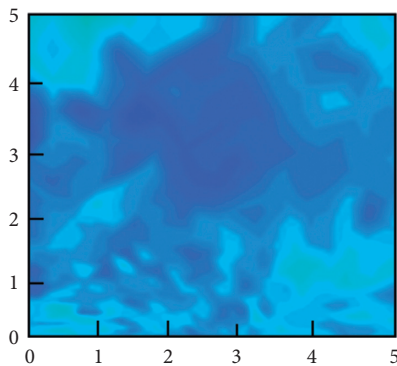Figure 10: Urban land use correlation coefficient curve.

Figure 11: Prediction of lake land types.

better predict the trend of urban land use. This is also directly related to the economic development of residents, the prevention of natural disasters, and the development of society. Remote sensing technology is a real-time, long-distance technical means to monitor the dynamic changes of urban land. It can provide a large amount of data. How to reasonably use remote sensing data to classify and predict urban land use and coverage is the key to using these valuable data.

This paper proposes a spatiotemporal method of using remote sensing data to predict urban land use classification and prediction. First, use the clustering method to classify remote sensing data, especially the classification of buildings, which is also the classification of complex features. Then the convolutional neural network is used to extract the spatial characteristics of land use, the long and short memory neural network is used to extract the dynamic progress of urban land use, and finally the future trend of urban land use is predicted. For land types with obvious characteristics such as lakes, rivers, and vegetation, the accuracy of classification and prediction results is high because these land types have a relatively small dynamic process. Although the classification and prediction of building land types have large errors, the maximum error is only 2.56%, which is an acceptable prediction error. This is mainly due to the relatively large dynamic process of the building. The smallest error is only 0.942%, which appears in the prediction of smaller land types such as lakes and vegetation. From the perspective of error, the classification and utilization of urban land use types have achieved very good results, which has a good reference significance for the decision-making of functional parts. From the perspective of the linear correlation coefficients of statistical parameters, their values all exceed 0.96, which is trustworthy enough for the prediction of urban land use. The clustering method and spatiotemporal prediction neural network model proposed in this paper for the dynamic use of urban land have a high degree of credibility.

Data Availability

The data used in this article can be obtained upon reasonable request.

Conflicts of Interest

There are no conflicts of interest in the study.

Acknowledgments

the actual land type, and the numerical points are distributed on both sides of the linear function. Its linear correlation coefficient even reached 0.96, which shows that this neural network model has good accuracy and feasibility in predicting urban land use prediction, and it is a convincing network structure. Figure 11 shows the prediction of lake land types, which the error is also relatively small.

5. Conclusion of the Research

With the continuous deepening of urbanization, the use of urban land has been shown to be particularly important. The data obtained through remote sensing technology contains a large amount of nonlinear, high-dimensional data, which is difficult to process by manual methods. Neural network technology can better process these nonlinear data and

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