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Retraction

Retracted: A Graph Neural Network (GNN) Algorithm for Constructing the Evolution Process of Rural Settlement Morphology

Security and Communication Networks

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Security and Communication Networks has retracted the article titled "A Graph Neural Network (GNN) Algorithm for Constructing the Evolution Process of Rural Settlement Morphology" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

References

[1] Z. Hu, K. Chen, and X. Xie, "A Graph Neural Network (GNN) Algorithm for Constructing the Evolution Process of Rural Settlement Morphology," *Security and Communication Networks*, vol. 2022, Article ID 7517347, 10 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2020, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

A Graph Neural Network (GNN) Algorithm for Constructing the Evolution Process of Rural Settlement Morphology

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Traditional statistical methods were mainly used to study the evolution process of rural settlement form and scale from a qualitative perspective, but it was difficult to quantitatively analyze the evolution process of the rural settlement form. Therefore, this paper proposed an intelligent monitoring method of rural settlement morphology evolution process based on the graph neural network (GNN) algorithm. Firstly, the specific working process of image feature extraction, analysis, and processing based on the graph neural network (GNN) algorithm was described. Secondly, combined with the change characteristics of rural settlement morphology evolution and scale development, the graphical neural network algorithm was used to effectively extract the morphological characteristics of rural settlements, and the monitoring information characterizing the dynamic changes of rural settlement morphology and scale was obtained through feature clustering. Finally, through experiments and using the graph neural network algorithm, the evolution process of rural settlement morphology was monitored in real time. The experimental results showed that the monitoring data obtained by this method were basically consistent with the actual statistical results, which showed that the intelligent monitoring method of the rural settlement form evolution process based on graph neural network algorithm can better reflect the dynamic change process of the rural settlement form and scale development. This study will provide some theoretical reference and guiding significance for the quantitative analysis of the evolution process of the rural settlement morphology and its influencing factors.

1. Introduction

With the acceleration of urbanization, some rural settlements have developed rapidly; especially, the form, function, and scale of settlements have been greatly developed. Compared with plain areas and traditional agricultural areas, the shape and distribution of rural settlements in mountainous areas are complex and changeable [1]. Therefore, it is of certain guiding significance for the rational guidance, regulation, and optimization of the scale of rural settlements to study the change process of temporal and spatial characteristics of rural settlements in mountainous areas and deeply explore the evolution law and influencing factors of rural settlements.

According to the theory of geography, rural settlements are important places for farmers' production, life, and socialization. From the perspective of geographical composition and morphological changes, rural settlements are patches of interaction between farmers and land. Therefore, at rural settlements, people are interdependent and have certain regional structural characteristics and functions. The morphological evolution of rural settlements is affected by the conditions of natural resources and the level of economic and social development [2]. There are some differences in the morphological evolution characteristics, speed, and process of different rural settlements. Therefore, through the exploration of the evolution process of the rural settlement form, scholars at home and abroad have revealed the relationship between the evolution of rural settlement spatial pattern and different regions and development backgrounds, which is also one of the research hotspots of rural settlement.

The form and functional structure of rural settlements are dynamic, sustainable, and long-term, and their evolution process is a complex and changeable process. Many years ago, some scholars conducted an in-depth research on the relationship between the temporal and spatial structure of rural settlements and the external environment [3, 4]. With the deepening of rural settlement research, the research on the evolution of rural settlement morphology and structure has been extended to population migration, urban-rural integration, land development, and cultural life. In the 21st century, with the improvement of rural settlement research methods, many scholars turn their research focus to the evolution mechanism and prediction of rural settlement morphology. The research shows that the continuous development of the rural settlement form is closely related to the external natural environment and social stage. The development scale, form, and structure of the rural settlement can fully reflect the internal relationship between residents' life and nature. In addition, from the perspective of landscape ecology of rural settlements, some scholars use the change of landscape index to analyze the landscape pattern and dynamic change of rural settlements, so as to reveal the development process of the evolution of rural settlements. Traditional methods are usually used to explore the development process of rural settlement evolution from a qualitative perspective, but cannot quantitatively reflect the rural settlement form and its dynamic changes.

2. Related Works

As early as the 19th century, people began to study rural settlements and their functional structure. In 1841, German scholars analyzed the reasons for the formation and development of rural settlements, which provided a theoretical basis for the later study on the evolution of settlement form. Forman put forward the central geography theory for the change of rural settlements, and expounded that the scale and distribution of rural settlements are related to economic, transportation, and administrative factors [5]. French scholar Blanches and Wesolowska expounded the correlation between the formation of rural settlements and natural environmental factors and historical and cultural factors, and found that the settlement form and its development change with the change of geographical location [6]. According to the types of rural settlements in different regions of Germany, German scholars put forward the basic theories and methods of settlement geography. With the extensive study of settlement area and morphology, many scholars have carried out an in-depth research on rural settlements from different aspects and made some progress.

From the research status and future development trend of rural geography, some scholars in the United States and Britain analyzed the geography, history, and their relationship with rural settlement areas, and explored the relationship between rural settlement morphological structure adjustment, economic and social development, and landscape change in the industrial age [7, 8]. In addition, some scholars have studied the relationship between the morphological structure of rural settlements and other adjacent disciplines. The scale and evolution of rural settlements can usually be analyzed and extracted by means of system analysis, quantitative and deductive analysis, combined with mathematical model and geographic information system, to reproduce the evolution process of rural settlements in an intuitive way.

In recent years, 3S technology has been gradually applied to the study of rural settlements. For example, GIS technology can effectively obtain various remote sensing image information such as geographical and spatial location. In addition, the quantitative analysis method based on GIS technology provides an effective means for the study of rural settlements. For the research on the evolution of rural settlement spatial form and its influencing factors, the early stage mainly explored the influence law of natural geographical factors on the distribution of rural settlements based on the results of field investigation and analysis and from a qualitative point of view [9, 10]. With the increasing development of geographic information system and 3S technology, the way of data acquisition has been improved, and the accuracy of data obtained has been improved. People began to use the method of landscape ecology to study the pattern characteristics of rural settlements and the evolution characteristics of settlement patches. At the same time, mathematical statistics was used to study the influence of natural and human factors on settlement evolution. Since then, people's research on rural settlements has changed from qualitative description to quantitative analysis.

In exploring the evolution process of rural settlement morphology, most of the existing methods only process the image appearance features obtained from remote sensing images, and these features usually lack in-depth information, which makes it difficult to obtain ideal prediction results when processing complex image information [11, 12]. In recent years, depth neural network model has been greatly popularized in the field of vision. Among them, some scholars have studied the image segmentation method based on depth learning model, which can be effectively applied to the processing and analysis of remote sensing images. Inspired by the research results in other related fields, some scholars apply graph neural network model to image feature extraction and processing, and combine semantic enhancement and network segmentation methods to express different features. Using the attention mapping mechanism, the image features at different positions can be weighted to obtain the feature map, but this method requires more computing resources and storage space [13]. The method of graph neural network is usually to segment the collected image to form multiple small regions, then use the traversal method to reorganize the two regions with the largest correlation, and re aggregate the image into one region until all relevant pixels are concentrated in one candidate region. Then, the image feature points are selected from the candidate regions, stretched, and enlarged into pictures of the same size, and the pictures are sent to CNN model for processing to obtain the required image feature points.

Compared with other image processing methods, the method based on graph neural network can subdivide and fuse the image. Therefore, it can be better applied to the real-time dynamic analysis of the image.

3. Working Principle of Graphical Neural Network

3.1. Structure and Function of Graph Neural Network. According to the application requirements of structured and unstructured scenes, some researchers proposed using graph neural network (GNN) to process the structure information of graphs and achieved good results. GNN network can not only realize the problems that are difficult to be solved by other neural network methods but also make the deep learning theory widely used in the fields of recommendation system, graph clustering, and so on. Compared with other network structures, GNN network structure is simpler [14]. It mainly adopts graph convolution and graph pooling to complete relevant operations, and uses the full connection layer and output layer to form the whole network structure, as shown in Figure 1.

When the GNN network structure is applied to image processing, the initial image matrix is generally transmitted to the input layer as the input object of the GNN network structure, and then the graph convolution, graph pooling, and other operation modules are used for correlation processing. Finally, the processing results are output through the output layer. The main task of graph convolution is to linearly combine each feature point in the graph with its adjacent feature points, use the adjacency matrix to process the relevant feature information and propagate the results to different network layers. Using nonlinear layer to transform different morphological feature points, similar morphological feature points can be associated.

In order to realize the mapping of different images, the feature extraction can be carried out through the graph volume kernel, and the pooled method can be used to reduce the dimension of the extracted features. Therefore, multilayer clustering algorithm can be used to reduce the dimension, which is also called graph pooling. The data types processed by the pooling layer are generally regular morphological features. In order to make the features extracted from any region applicable to other different regions, the features of different local regions can be aggregated and represented by larger dimensional morphological features. For example, in convolutional neural networks, maximum pooling algorithm and average pooling algorithm are often used to obtain the feature sizes of different regions, respectively, and expressed by the maximum or average value of the image features of the region.

The graph convolution operation of graph neural network is used to process the image features and output the results. The image features processed by the graph pooling layer are in the same neighborhood, and the feature points in this field form a cluster. Because the output results generated by graph convolution operation will cluster the feature points in the same field, graph neural network uses graph convolution operation to generate many graph features, and outputs graph feature information of different dimensions through feature clustering operation. Therefore, clustering algorithm can be used to process the features, so that the output feature dimensions are different.

In order to speed up the processing speed of the graph pooling layer, when the graph pooling operation is carried out on the graph features, it is necessary to use the adjacency matrix to calculate the graph feature pixels, and make the graph pooling layer and the upper layer connect orderly in the graph feature processing [15]. Among them, the discontinuous feature points formed during the graph pooling operation on the graph features do not affect the pooling output results. The pool operation process is shown in Figure 2.

3.2. Graph Neural Network Method. From the above structure and function of graph neural network, it is known that when using the graph neural network model to process image features, it is mainly to optimize the convolution kernel parameters of the network model, and make it reach the best value through repeated intensive training. Therefore, in this paper, polynomial expansion is applied to convolution kernel operation. When strengthening network model training, the optimization of convolution kernel parameters is transformed into continuous optimization of polynomial coefficients. Therefore, each optimization of the polynomial coefficients is based on the output of the previous model training [16]. The loss function used in this paper as the benchmark for training and evaluation of network model parameters is expressed as follows:

$$l = -\frac{1}{m} \sum_{x} y_x \ln b_x. \tag{1}$$

The above function can represent the relationship between the output result b of the input image sample x processed by the graph neural network model, the predicted image y, and the number of samples. When the error between the output result and the actual value is large, the loss function can be used and the parameters of graph neural network can be optimized quickly through the intensive training of the model. The GNN network model algorithm used in this paper mainly includes two parts: forward processing and backward processing. The image features are processed forward based on the GNN network model. The purpose is to process the image structure features by Fourier transform, and then take them as the input object of image convolution for subsequent processing [14]. The processing function of image features in the image convolution layer can be expressed as follows:

$$z^2 = \lambda\left(y_{x,i} + a\right) = \lambda\left(\sum_{k}^{j} g\omega_{k,i}(l) z_{x,i} + a\right), \tag{2}$$

where z^2 represents the output result of the image feature after the image convolution operation, λ is the activation function used by the image convolution, $y_{x,i}$ represents the output result of the image feature after the image convolution operation, and a is the constant parameter of the

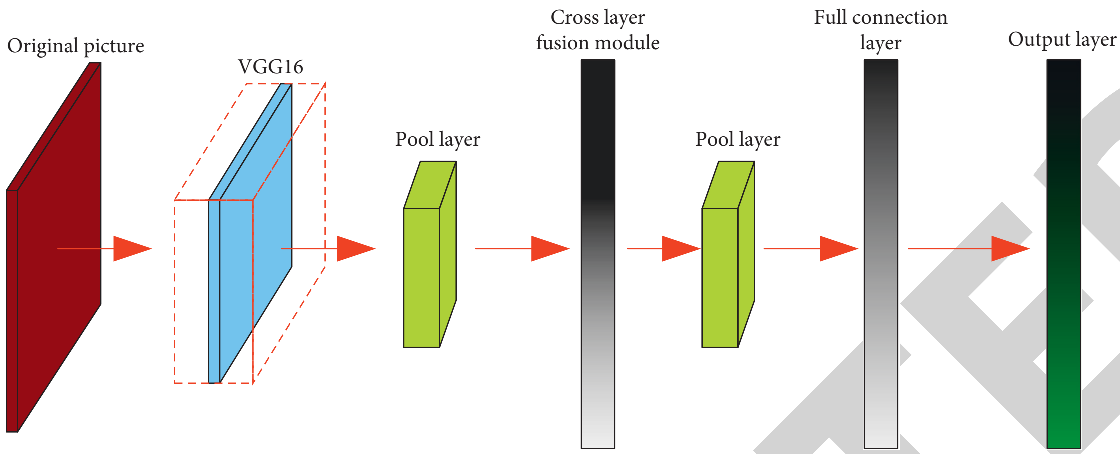

Figure 1: Structure diagram of graph neural network.

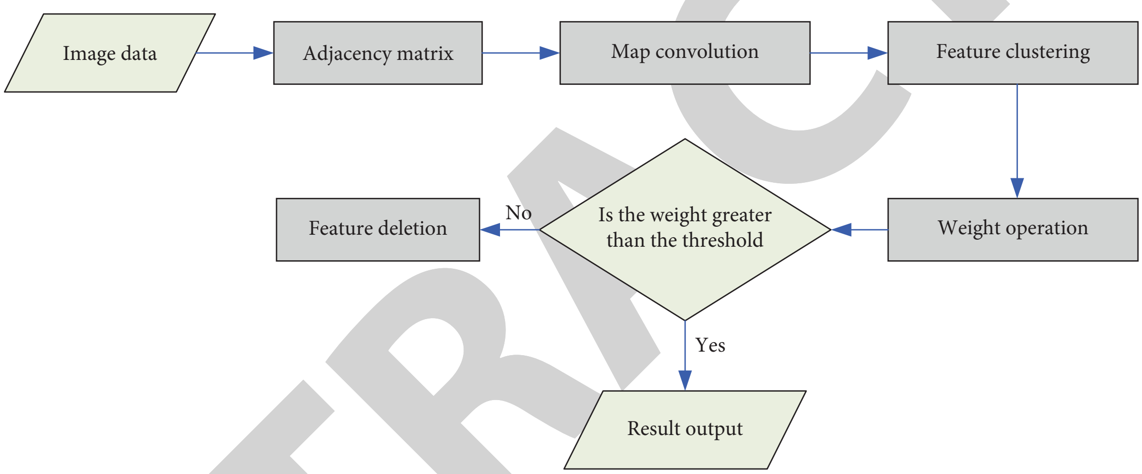

Figure 2: Diagram of pool layer operation process.

image convolution. Using the graph pooling layer of graph neural network model for graph pooling operation is mainly to cluster the feature points of the input image and transform them into one-dimensional feature images. The graph convolution processing in the network model is to input the one-dimensional graph features after the graph pooling operation to other layers, to further complete the graph feature extraction operation. By reducing all graphic features and transforming them into one-dimensional graphic feature vectors, one-dimensional graphic feature vectors are spliced and integrated as the input object of the whole connection layer of the graphic neural network model [16, 17]. The expression of splicing and integration of graph feature vectors in the full connection layer of graph neural network model is as follows:

$$z^{ih} = \lambda\left(q^{ih} z^{2c} + a^{ih}\right), \tag{3}$$

where λ is the activation function used by the full connection layer, z^{2c} represents the image feature processing result of the image pooling layer and takes it as the input processing object of the full connection layer, z^{c2} represents the weight coefficient of the image pooling layer, z^{c2} is the constant parameter of the layer, and z^{ih} represents the image feature output result after splicing and integration. The relevant model parameters are modified by activation function, and the output results are obtained by graph neural network model processing [18]. The forward processing algorithm flow is shown in Figure 3.

For the reverse processing algorithm in graph neural network, the best model parameters and weights are obtained mainly through the learning, training, and optimization of network model. In the graph neural network model, the forward processing algorithm is used to obtain the loss function, and then the loss function is used to calculate the error value, which is fed back from the lower layer of the network model to the upper layer in turn. Finally, the gradient method is used to optimize the parameters of the graph convolution.

Taking the collected image samples as the input object of the model, the network model is used to preprocess the input image. According to each pixel of the image, a graphic feature adjacency matrix is established to make the output of the model closer to the prediction target. Then, the graph features of graph convolution operation are checked by graph convolution. After the response processing of the

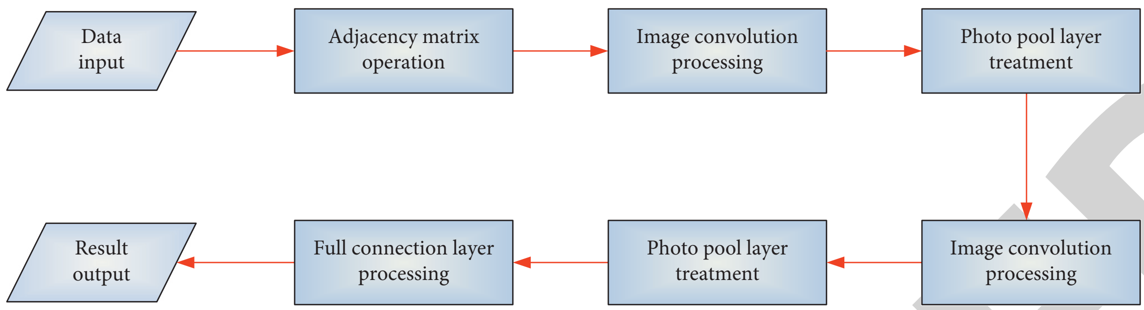

Figure 3: Flow diagram of the forward processing algorithm.

activation function, the graph feature adjacency matrix is used to aggregate different graph feature pixels. By aggregating the adjacent features of the current feature points, all feature pixels and their adjacency matrixes are continuously updated, to reflect the relationship between all graph features and their pixels. Finally, the clustering algorithm is used to classify the relevant features in the graph pool layer.

The model training mainly uses the experimental test results to verify the GNN network model, and the forward processing algorithm is used to obtain the output results. Because the algorithm trains and learns many sample images through GNN network model, and repeatedly uses the new model to forward process the image samples of the test set until the ideal prediction image is output, the continuous optimization of graph neural network model is the guarantee of outputting the ideal result [19]. In order to make the output of the model close to the real image samples, GNN reverse processing algorithm can be used and network training standards can be set. If the error obtained by the loss function cannot reach the preset standard, the error value needs to be continuously fed back to the network model, and then the network model parameters are adjusted through repeated training until the error obtained by the loss function meets the requirements, the network will not be trained and learned, and the finally trained network model will be used for image processing. The training process of graph neural network model is shown in Figure 4.

4. Analysis of Rural Settlement Form and its Scale Change

4.1. Analysis on the Change of Rural Settlement Form. Taking the typical rural mountainous areas with diverse topographic characteristics as the research object, this paper analyzes the morphological characteristics and evolution law of rural settlements in mountainous and hilly areas by using the methods of spatial analysis and econometrics. According to the spatiotemporal evolution characteristics of rural settlements, this paper mainly uses models such as land change index, nearest neighbor index, and nuclear density index to analyze the spatiotemporal change characteristics such as land scale and morphological distribution in the evolution process of rural settlements in this mountainous area, and combines the relevant characteristics from multiple angles in order to construct the evolution process of rural settlement morphology [8, 9]. Land change index can better describe the change speed of land types and the evolution law of regional characteristics in rural settlements, and can be used to reflect the law of land use and change in this area. The land change index of rural settlement area can be expressed by the following formula:

$$M = \frac{R_t - R_e}{R_e} \times \frac{1}{u}, \tag{4}$$

where R_e and R_t represent the total scale of rural settlements in the initial stage and later stage in turn, u is the time length of rural settlements, and M is the scale of rural settlements. $M < 0$ indicates that the residential land in the rural settlement area has been transformed into other land, reflecting that the scale of rural settlement has decreased, while $M > 0$ indicates that other land has been transformed into rural settlement land, reflecting that the scale of rural settlement has increased.

In order to analyze the gap of land change in rural settlements between different regions, it can be expressed by the relative land change rate, and its calculation formula is as follows:

$$r = \frac{\left|R_t - R_e\right|}{R_t} \times \frac{S_d}{\left|S_p - S_d\right|}, \tag{5}$$

where R_e and R_t represent the scale of rural settlements in the initial and final stages in turn, r and S_p represent the total scale of rural settlements in the initial and final stages, r represents the relative change rate of rural settlement land, $r > 1$ represents that the change rate of local area is greater than that of the whole; otherwise, it represents that the change rate of local area is smaller than that of the whole.

The spatial distribution of the morphological characteristics of rural settlements can be described by the nearest neighbor index, which is expressed by the ratio of the observed value to the expected value of the distance between adjacent points [20]. It can reflect the mutual proximity between different patches of rural settlements, which is expressed as follows:

$$K = \frac{H_v}{H_u} = \frac{\sum_{i=1}^{n} g_i/n}{\sqrt{n/S}} = \frac{\sqrt{\omega}}{n} \sum_{i}^{n} g_i, \tag{6}$$

where S represents the distance between point i and its nearest neighbor in the rural settlement area, H_v represents the average nearest neighbor distance between different

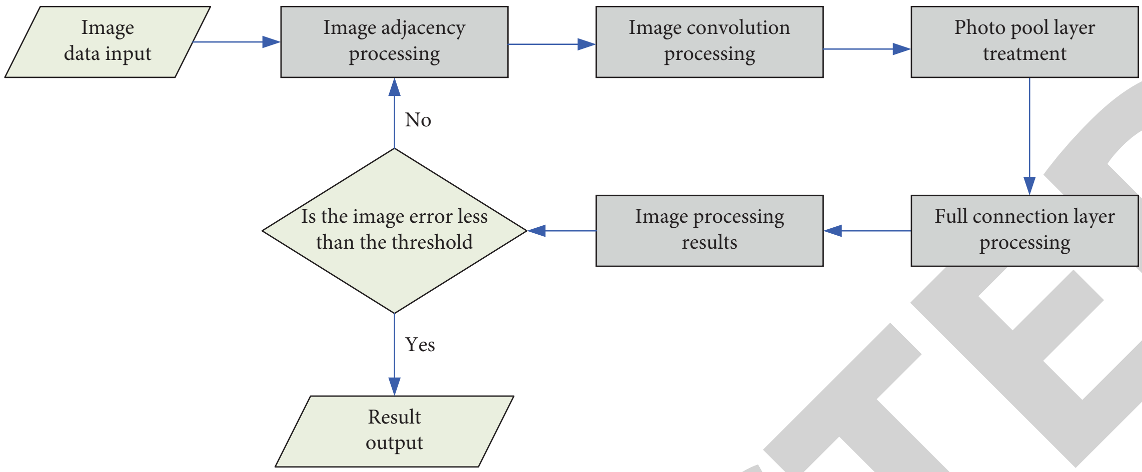

Figure 4: GNN network training update flow chart.

points, S represents the expected distance, and n represents the number of patches in the rural settlement, S represents the distribution density of each point in the rural settlement area, and S represents the minimum external rectangular area of different rural settlements. K is the nearest neighbor index. $K < 1$ indicates that the settlement patches are clustered, and $K > 1$ indicates that the settlement patches are randomly distributed.

Nuclear density index can reflect the morphological distribution characteristics of rural settlements and describe the spatial distribution of rural settlements [3]. Its calculation formula is as follows:

$$F(x_i, y_i) = \frac{1}{nd^2} \sum_{i=1}^{n} E\left(\frac{g_i}{n}\right), \tag{7}$$

where $F(x_i, y_i)$ is the predicted value of kernel density at a certain point of rural settlement at (x_i, y_i), g_i is the number of samples at different points of rural settlement, d is a constant, E is the kernel function, and $F(x_i, y_i)$ is the distance from point (x_i, y_i) to point i.

4.2. Analysis on the Change of Rural Settlement Scale. According to the existing research, the scale of rural settlements is a complex dynamic change process, mainly including the changes of the scale and morphological characteristics of rural settlements, as well as the changes of the regional structure and function of rural settlements. The evolution of rural settlement scale is not only related to the local economic and social development level but also changes with the changes of rural settlement structure and morphological characteristics, and leads to corresponding changes in rural settlement functions and services.

In the evolution process of rural settlement scale, the settlement function shows a certain law with the development of rural economy and society. It usually changes from homogeneous isomorphism to heterogeneous diversity, that is, from the original living farming state to the type of composite function. Because there are many types of rural settlements, the scale and evolution speed of rural settlements are related to the types of rural settlements. The traditional rural settlement land is mainly homestead, and the settlement function is usually small-scale cultivated land, enclosure, or breeding land around the homestead [5, 6]. With the rapid development of the rural economy and society, the scale of rural settlements is expanding, and the functions of settlements are also diversified. For example, the land for handicraft, commerce, and storage in the settlement area is gradually increasing. Due to the influence of various natural resources, and economic, social, and cultural factors, the scale, morphological structure, and function of rural settlements are constantly changing. The complexity, diversity, and dynamics of rural settlement functions are the main characteristics of rural settlement evolution in recent years.

4.3. Morphological Structure and Distribution Characteristics of Rural Settlements. The distribution of rural settlements is not only an important part of the evolution of rural settlements but also the main object of studying the changes of regional morphological characteristics of rural settlements [10]. The evolution characteristics of rural settlements mainly reflect the relationship between the morphological structure and function of rural settlements and time from the aspects of regional land type, form, scale, and agglomeration degree. The type and distribution of rural settlement land can reflect the change of regional land use. The change of rural settlement land use type and its area can reflect the change law of rural settlement form in land use.

Based on the statistical analysis of the land use data of a rural settlement area in 2000, 2010, and 2020, through the data and research, it is known that the land-use types of the rural settlement include forest land, cultivated land, water area, grassland, urban land, and rural settlement land. Figure 5 and Table 1 show the land-use types and land-use change results of the rural settlement area in 2000, 2010, and 2020.

According to the statistical results in Table 1, the land type of the rural settlement area is mainly forest land, followed by grassland, and cultivated land, indicating that the

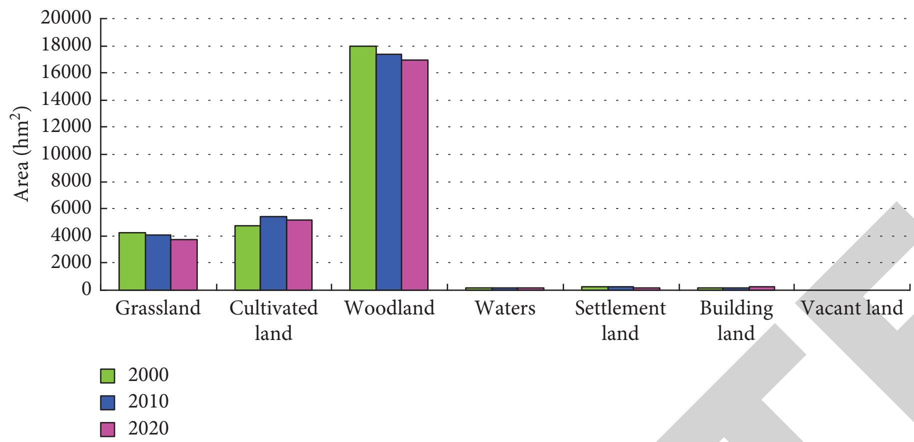

Figure 5: Statistics of land types in settlement areas from 2000 to 2020.

Table 1: Dynamic changes of various types of land use in rural settlements from 2000 to 2020.

Item	Rate of change (%)	Transfer out rate (%)	Transfer in rate (%)
Cultivated land	10.13	0.35	10.48
Woodland	−0.14	1.79	1.65
Grassland	−12.47	13.28	0.81
Waters	4.25	0.83	5.08
Settlement land	−1.29	1.64	0.35
Building land	8.36	8.29	16.65
Vacant land	−37.61	38.27	0.66

natural ecological environment of the settlement is good, the vegetation density is large, and the degree of land development is not high. Over time, from 2000 to 2020, the occupied area of grassland and forest land decreased, the water area was relatively stable, and the cultivated land area still showed a slight growth trend, but the construction land has been increasing significantly.

4.4. Analysis on the Morphological Characteristics of Rural Settlements. Studies have shown that rural settlements can be divided into four categories: living alone, small, medium, and large according to different patch forms. In order to describe the changes of rural settlement scale and its morphological characteristics, the patch number, patch proportion, patch area size, total patch proportion, average patch area, and other parameters in rural settlement area are selected for statistics, as shown in Tables 2 and 3.

The statistical results in Table 2 reflected that the morphological characteristics of rural settlements in 2000 were mainly medium-sized and large patches, which were 52.29% and 45.96%, respectively. Among them, the total area and proportion of medium patches were lower than large patches, the proportion of large patches was 75.55%, and the average area of patches reached 10.47 hm^2, which was higher than other settlement types. The number and proportion of patches in solitary and small settlements were 0.45% and 1.31%, respectively, and the total area and proportion of patches in solitary and small settlements were only 0.01% and 0.19%, respectively. The above analysis shows that in 2000, the distribution types of large settlements accounted for a large proportion, and the number of small settlements was small, which shows that the scale of rural settlements is significantly different. On the other hand, the statistical results in Table 3 reflected that the change of the scale of the rural settlement was not obvious from 2000 to 2010. The patch index of large-scale settlements decreased compared with 2000, indicating that the patch area of large-scale settlements had little impact on the change of the rural settlement form. The number of living alone patches increased to a certain extent, the number of small patches remained basically unchanged, and the number and total area of medium-sized and large patches were lower than those in 2000. This shows that the change of rural settlement form in 2010 is not significant compared with 2000.

5. Dynamic Monitoring of Morphological Changes of Rural Settlements based on Graph Neural Network

5.1. Monitoring Method of Rural Settlement Morphology based on Graph Neural Network. From the abovementioned changes in the morphological structure and function of rural settlements, in order to explore the evolution process of rural settlements, the graph neural network (GNN) algorithm can be used to dynamically monitor the change process of rural settlements. From the above analysis of the morphological characteristics of rural settlements, it is known that the morphological image of rural settlements has local characteristics, so it belongs to the local map structure. Because

Table 2: Statistical table of rural settlement scale in 2000.

Type	Area scope (hm^2)	Patch number	Patch proportion (%)	Patch area size (hm^2)	Total patch proportion (%)	Average patch area size (hm^2)
Alone	<0.2	23	0.45	2.07	0.01	0.09
Small	0.2–2	67	1.31	61.24	0.19	0.91
Medium	2–5	2684	52.29	7926.53	24.25	2.95
Large	>5	2359	45.96	24692.51	75.55	10.47

Table 3: Statistical table of rural settlement scale in 2010.

Type	Area scope (hm^2)	Patch number	Patch proportion (%)	Patch area size (hm^2)	Total patch proportion (%)	Average patch area size (hm^2)
Alone	<0.2	28	0.55	2.52	0.01	0.09
Small	0.2–2	68	1.34	62.35	0.19	0.92
Medium	2–5	2627	51.87	7479.24	23.36	2.85
Large	>5	2342	46.24	24468.65	76.43	10.45

the morphological structure of the local graph can obtain the relationship between the layers of the neural network by using the local mean operation method, the morphological characteristics of rural settlements can be used as the input characteristic graph and processed by the local mean operation. The morphological characteristics of rural settlements can be the combination of elements such as space, time, or time and space [15, 16]. The use of local map structure can reflect the internal relationship between the morphological characteristics of rural settlements from different angles. The partial diagram structure can be defined by the following formula:

$$Z_M = \frac{1}{G(x)} \sum_{M=1}^{n} F(x_M, y_M) H(y_M), \tag{8}$$

where M is the spatial position of the output image, and its value can be calculated by x_M and each corresponding point y_M of other images. x is each morphological feature of the input image, and y is the output image feature corresponding to x. The correlation function $G(x)$ can calculate the correlation between various image morphological features. The function H is mainly used for scaling the input image, and the function $G(x)$ is mainly used for normalizing the output morphological features.

The correlation function F can be expressed as follows:

$$F(x_M, y_M) = \sigma(x_M)^T \zeta(y_M), \tag{9}$$

where $\sigma(x_M)$ can be expressed as $\sigma(x_M) = Q_\sigma x_M$ and Q_ζ can be expressed as $\zeta(y_M) = Q_\zeta y_M$. The parameters Q_σ and Q_ζ can be corrected by convolution operation and training. The function H can be expressed in the following form:

$$H(y_M) = P_L y_M. \tag{10}$$

Function H is mainly used for linear transformation of the input feature H, and parameter P_L is processed by convolution operation and modified by training and learning. In order to facilitate each local image feature to be added to the neural network for processing, the output layer can be processed by residual operation, which can be expressed as follows:

$$B_M = P_A y_M + x_M, \tag{11}$$

where $P_A y_M + x_M$ represents a residual operation module. This residual processing method can input the local image feature into the pretrained network model and make the original model unaffected.

5.2. Result and Analysis. From the above analysis of the morphological characteristics of rural settlements, it is known that the morphological image of rural settlements has local characteristics, so it belongs to the local map structure. In order to explore the evolution process of the rural settlement form, the rural settlement form can be reconstructed by the graph neural network (GNN) algorithm. The local graph structure can use the local mean operation method to get the relationship between each layer of the neural network. Therefore, the morphological characteristics of rural settlements can be used as the input characteristic graph and processed by the local mean operation. The Comparison between settlement image processed by GNN and original image obtained by remote sensing is shown in Figure 6.

Because the morphological characteristics of rural settlements are mainly composed of space, time, or space-time and other elements, the use of this local map structure can reflect the internal relationship between the morphological characteristics of rural settlements from different angles. The statistical results of the evolution process of rural settlement morphology in 2020 are shown in Table 4. The evolution process of rural settlement morphology in 2020 is monitored based on the graph neural network algorithm, and the results are shown in Table 5. The monitoring results of various parameters in Table 5 are basically consistent with Table 4, which shows that the prediction model of the rural settlement form evolution process based on the graph neural network algorithm can better truly reflect the development and change process of the rural settlement form and scale.

From the above analysis results of the evolution process of the rural settlement form, it is known that the driving force for the formation and development of rural settlement mainly comes from external natural environmental factors,

(a) (b)

Figure 6: Comparison between settlement image processed by GNN and original image. (a) Remote sensing image of rural settlement. (b) Settlement image map based on GNN.

Table 4: Actual statistical results of rural settlement scale in 2020.

Type	Area scope (hm^2)	Patch number	Patch proportion (%)	Patch area size (hm^2)	Total patch proportion (%)	Average patch area size (hm^2)
Alone	<0.2	26	0.57	2.34	0.01	0.09
Small	0.2–2	15	0.33	10.18	0.03	0.68
Medium	2–5	2248	49.26	6426.35	21.65	2.86
Large	>5	2275	49.85	23247.36	78.31	10.22

Table 5: Monitoring results of rural settlement scale in 2020 obtained by using this method.

Type	Area scope (hm^2)	Patch number	Patch proportion (%)	Patch area size (hm^2)	Total patch proportion (%)	Average patch area size (hm^2)
Alone	<0.2	25	0.55	2.25	0.01	0.09
Small	0.2–2	14	0.31	9.35	0.03	0.67
Medium	2–5	2235	49.10	6372.25	21.45	2.85
Large	>5	2278	50.04	23326.47	78.51	10.24

and it is regional location factors that promote the evolution of the rural settlement form, and it is economic and social development factors that play a leading role in the evolution process of the rural settlement form. There is a significant correlation and interaction between the external natural environmental factors represented by regional location and the economic and social development factors represented by farmers' per capita income. The natural environmental factors have a great influence on the evolution of the rural settlement form and last for a long time [6, 7]. Due to the urbanization factors, the production and life of rural settlements are affected, which accelerates the evolution of the form and scale of rural settlements. With the reorganization of rural population, land, social life, and industry, the scale and morphological structure of rural settlements will also change, which provides an internal driving force and conditional basis for the continuous change of rural settlements, which also promotes the dynamic and periodic evolution of rural settlements. Compared with 2010, the morphology of rural settlements changed significantly in 2020, among which the morphology of small settlements changed the most, and the number, proportion, area, and proportion of small patches decreased significantly compared with 2010. The number and area of medium-sized patches also decreased compared with 2010, but the average area of medium-sized patches increased, and the number and area of large patches increased compared with 2010. This shows that the form of rural settlements has changed greatly from 2010 to 2020, in which most small settlements have gradually changed to medium and large ones, and the form of rural settlements has changed significantly.

6. Conclusion

Due to the influence of various factors, the morphological structure and scale of rural settlements in mountainous areas were very complex. In order to track the evolution process of rural settlements in real time, an intelligent monitoring method of rural settlements morphological evolution process based on graph neural network algorithm was proposed in this paper. The traditional mathematical statistical method can only explore the evolution law of the rural settlement form from a qualitative point of view, but cannot quantitatively analyze the evolution process of the rural settlement form. Therefore, this paper used the graph neural network algorithm to extract and analyze the remote sensing image features of rural settlement morphology, to realize the dynamic monitoring of the relevant information of rural settlement morphology and scale change. Finally, through experiments and using the graph neural network algorithm, the evolution process of rural settlement shape and scale was dynamically monitored. The experimental results showed that the monitoring values of the rural settlement form change obtained by this method were basically consistent with the actual statistical results, which showed that the intelligent monitoring method of the rural settlement form evolution process based on the graph neural network algorithm can quantitatively reveal the dynamic change process of the rural settlement form and scale. In addition, the intelligent monitoring method of the rural settlement form evolution process based on the graph neural network algorithm proposed in this paper can provide a certain theoretical reference and guiding significance for an in-depth discussion of the rural settlement scale change and its influencing factors.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Zhe Hu and Kexin Chen contributed to the writing of the manuscript and data analysis. Xiaofei Xie supervised the work and designed the study. All the authors have read and given their consent to the final version to be published.

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References

[1] N. M. Argent, P. J. Smailes, and T. Griffin, "Tracing the density impulse in rural settlement systems: a quantitative analysis of the factors underlying rural population density across south-eastern Australia, 1981-2001," *Population and Environment*, vol. 27, no. 2, pp. 151–190, 2005.

[2] M. Sevenant and M. Antrop, "Settlement models, land use and visibility in rural landscapes: two case studies in Greece," *Landscape and Urban Planning*, vol. 80, no. 4, pp. 362–374, 2007.

[3] L. Hualou, L. Yansui, W. Xiuqin, and D. Guihua, "Spatio-temporal dynamic patterns of farmland and rural settlements in su-xi-chang region: implications for building A new countryside in coastal China," *Land Use Policy*, vol. 26, no. 02, pp. 322–333, 2009.

[4] Q. Yanbo, J. Guanghui, Y. Yuting, Z. Qiuyue, L. Yuling, and M. Wenqiu, "Multi-scale analysis on spatial morphology differentiation and formation mechanism of rural residential land: a case study in Shandong Province, China," *Habitat International*, vol. 71, pp. 135–146, 2018.

[5] R. Forman, "Some general principals of landscape ecology," *Landscape Ecology*, vol. 11, no. 3, pp. 133–142, 1996.

[6] J. Banski and M. Wesolowska, "Transformations in housingconstruction in rural areas of Poland's Lubli nregion-Influence on the spatial settlement structure and landscape aesthetics," *Landscape and Urban Planning*, vol. 94, no. 2, pp. 116–126, 2010.

[7] A. F. Alam, R. Asad, and M. Enamul Kabir, "Rural settlements dynamics and the prospects of densification strategy in rural Bangladesh," *SpringerPlus*, vol. 5, no. 1, pp. 254–311, 2016.

[8] I. Bassi, S. Zaccarin, and D. De Stefano, "Rural inter-firm networks as basis for multifunctional local system development: evidence from an Italian alpine area," *Land Use Policy*, vol. 38, no. 2, pp. 70–79, 2014.

[9] G. A. Wilson and R. J. F. Burton, ""Neo-productivist" agriculture: spatio-temporal versus structuralist perspectives," *Journal of Rural Studies*, vol. 38, pp. 52–64, 2015.

[10] A. Gren and E. Andersson, "Being efficient and green by rethinking the urban-rural divide-combining urban expansion and food production by integrating an ecosystem service perspective into urban planning," *Sustainable Cities and Society*, vol. 40, pp. 75–82, 2018.

[11] X. Guan, H. Wei, S. Lu, and H. Su, "Mismatch distribution of population and industry in China: pattern, problems and driving factors," *Applied Geography*, vol. 97, pp. 61–74, 2018.

[12] H. Long and Y. Qu, "Land use transitions and land management: a mutual feedback perspective," *Land Use Policy*, vol. 74, pp. 111–120, 2018.

[13] D. Teney, L. Liu, and A. V. D. Hengel, "Graph-structured representations for visual question answering," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3233–3241, Honolulu, HI, USA, July, 2017.

[14] S. Ryu, Y. Kwon, and W. Y. Kim, "A bayesian graph convolutional network for reliable prediction of molecular properties with uncertainty quantification," *Chemical Science*, vol. 10, pp. 3192–3203, 2019.

[15] J. Lim, S. Ryu, K. Park, Y. J. Choe, J. Ham, and W. Y. Kim, "Predicting drug-target interaction using a novel graph neural network with 3D structure-embedded graph representation," *Journal of Chemical Information and Modeling*, vol. 59, no. 9, pp. 3981–3988, 2019.

[16] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[17] P. J. Ballester and J. B. O. Mitchell, "A machine learning approach to predicting protein-ligand binding affinity with applications to molecular docking," *Bioinformatics*, vol. 26, no. 9, pp. 1169–1175, 2010.

[18] M. M. Stepniewska-Dziubinska, P. Zielenkiewicz, and P. Siedlecki, "Development and evaluation of a deep learning model for protein-ligand binding affinity prediction," *Bioinformatics*, vol. 34, no. 21, pp. 3666–3674, 2018.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, no. 9, pp. 1904–1916, 2015.

[20] L. Ma, W. Cheng, and J. Qi, "Coordinated evaluation and development model of oasis urbanization from the perspective of new urbanization: a case study in Shandan County of Hexi Corridor, China," *Sustainable Cities and Society*, vol. 39, pp. 78–92, 2018.