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EVALUATION OF SOIL ROCKY DESERTIFICATION IN KARST REGION BASED ON DEEP BELIEF NETWORK

Abstract: Dynamic features from remote sensing photos may be successfully extracted using deep learning and symmetric network structure, which can then be used to direct them to carry out accurate classification. The DBN model can more effectively extract features from photos since it uses unsupervised learning. It can be reduced to the many symmetric Restricted Boltmann Machines (RBM) training problem. In this paper, a soil rocky desertification (RD) assessment model based on a deep belief network (DBN) is created in light of the complicated influencing aspects of Karst RD risk assessment encompassing several geographical elements. The model builds upon the conventional RBM framework and incorporates the influence layer of related elements as an auxiliary requirement for retrieving Geographic Information System (GIS) score data. Then, in order to forecast the level of soil rocky desertification, it learns the features of many elements. The experimental results show that the proposed model proposed in this paper has better prediction performance and faster convergence speed, and its classification results for different degrees of RD are more consistent with the actual risk assessment results.

Keywords: Karst region, rocky desertification, DBN, GIS

Introduction

Deep learning involves many disciplines with a wide range of disciplines, including statistics, probability theory, algorithm analysis and design, optimisation and other related disciplines and fields. Through recent research and development, DBN (deep belief network) model has been able to effectively solve some complex problems in reality, such as object recognition, language understanding and so on. RBM (Restricted Boltmann Machines) is a kind of stochastic neural network model with two-layer structure, symmetric connection and no self-feedback, with fully connected layers and no connection within layers.

Karst environment is an integrated system in which the atmosphere, hydrosphere, biosphere and lithosphere interact and interact with each other, that is, the balance of ecosystem is maintained through water cycle, carbon cycle, trace element cycle and biological cycle in Karst region. The fragile ecological balance of Karst is not only the premise of the formation of rocky desertification (RD), but also the symbol of the difficulty degree of RD land management. Due to the inherent shortage of soil forming materials, the process of soil erosion is very hidden and complex. The water bearing medium is double

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layered, the vegetation site conditions are bad, and the natural recovery of community ecosystem is slow. Therefore, Karst region is the most typical fragile area in the terrestrial ecosystem of the earth, and the fragile Karst habitat is a hot research area in the field of geography, and the Karst ecological environment has become one of the focuses in the field of contemporary international geology research. RD has always been a major problem affecting the economic development of Southwest China. It is mainly distributed in most areas of Southwest China with high air humidity. Due to the strong and complex Karstification in this area, it is very developed, especially in Guizhou and other areas, and the total area has reached 67,900 km^2. Among them, the coverage of carbonate strata in Guizhou is as high as 130,000 km^2, accounting for 73 % of the total area of Guizhou, which is higher than that of Karst landforms, which account for 63.8 %. In terms of the area, grade and damage degree of RD, the current situation of RD is quite severe.

In the past, the discussion and evaluation of green environment often adopted statistical methods [1, 2]. Through early warning, the possibility and harm degree of farmland RD can be reflected qualitatively, quantitatively and directionally, and then the effective control and scientific prevention of farmland RD can be carried out to provide scientific basis for the rational utilisation of agricultural land resources. The traditional methods such as regression analysis and time series prediction are difficult to accurately predict it [3]. Due to the limitation of subjective and objective factors, the existing multi index evaluation methods of RD degree rely too much on expert experience and simple mathematical models, such as linear weighting, regression analysis, fuzzy synthesis and so on, which are difficult to process the highly nonlinear RD evaluation index data, and cannot meet the objective requirements of RD degree and risk assessment. Therefore, it is necessary to introduce the machine learning theory and pattern recognition method into the field of RD evaluation, and transfer the evaluation method of RD degree from the traditional multi factor evaluation method which only relies on experience knowledge to the self-learning method or self-correction method based on the actual small sample data, so as to make the evaluation work of RD degree and risk more intelligent. The artificial neural network is easy learning and training, and has a wide range of applications in pattern recognition, image processing, control and optimisation, intelligent information management, prediction and other fields [4, 5]. Therefore, this study is committed to introducing the DBN into the evaluation of RD in Karst regions and constructing its risk assessment model.

Related works

Genesis of RD in Karst

The research on Karst development, ecological environment, Karst forest ecology, soil erosion and vegetation restoration is closely related to the study of RD. It not only provides rich basic data and theoretical basis, but also is an important basis for further spatial analysis of RD. The research angle mainly includes the concept connotation, occurrence mechanism, spatial distribution and classification, evolution process, degradation mechanism, control technical measures and modes, and evaluation of control benefits.

The research on RD can be divided into two parts: the study of causes and the study of monitoring methods. In terms of the causes of rock desertification, most scholars believe that there are different degrees of land RD landscape in Karst regions even without human intervention. Therefore, natural factors are the root cause of rock desertification, and human factors only play a catalytic role in the occurrence of rock desertification. Wu et al. [6] believed that the difference between lithology and external natural factors resulted in different grades of RD; Peng et al. [7] believed that the specific natural surface environment has a significant regulatory mechanism for the formation of RD. But even so, some scholars believe that human factors are closely related to the causes of RD. Hou and Gao [8] systematically concluded the relationship between human land relationship and RD control in Karst region. He et al. [9] concluded that the factors affecting the formation of RD include natural conditions and human activities, among which natural conditions are the premise basis, and human unreasonable activities are the most important reason.

Evaluation method

In the aspect of monitoring RD, the main monitoring methods are human-computer interaction interpretation, supervision classification, knowledge-based model construction, comprehensive analysis and feature-based information. Liao et al. [10] used remote sensing and Geographic Information System (GIS) technology to monitor the RD in Yunnan Province, and obtained different degrees of RD information; Pu et al. [11] extracted vegetation coverage and bedrock exposure in Karst region through GIS technology, and applied the monitoring results to the RD landscape pattern in the area to evaluate the environment. Although this method relies on the prior knowledge of the human-computer interaction, it is difficult to guarantee the accuracy of the human-computer interaction.

With the continuous research of deep learning, many domestic scholars have introduced deep learning into remote sensing image classification. In the current research, because DBN model has unsupervised learning and can better extract features from images. Liu et al. [12] extracted aircraft from high-resolution remote sensing images by using the characteristics of DBN model autonomous learning and back propagation parameter adjustment, and proved that the experimental results are better than the traditional classification methods; Zhao et al. [13] proposed to transform the image feature selection into using DBN to reconstruct the image features, which was applied to the classification of dataset. After verification, the overall classification accuracy reached 77 %. In the current research, because DBN model has unsupervised learning and can better extract features from images.

In the aspect of simulation and prediction of evolution trend, many scholars have different research focuses and research areas. The methods used by them are mainly using cellular automata, Markov chain or a combination of the two methods, using more than two periods of remote sensing image data to predict the evolution and development trend of RD in the next 10 years, 20 years or even 50 years.

RD evaluation model based on DBN

Model structure

DBN is composed of two parts: multi-layer RBM and one layer back propagation network. The specific structure of DBN includes inputting data for pre training and automatically making small adjustments. The data input is unsupervised by training unlabelled samples. After the pre training, the BP (Back Propagation) neural network is trained by means of supervised learning, and the error is propagated layer by layer, and the weight of the whole DBN is adjusted reversely. At this time, the DBN model can be regarded as a common neural network model, but the last layer BP network of DBN adjusts the weight value of each layer randomly according to the error of the output result of the last layer, which is different from the weight value of each layer set in advance by the traditional neural network.

Energy function model

RBM is a typical energy function model, which can be expressed as follows:

$$E(v,h) = -\sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}v_i h_j - \sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j \tag{1}$$

where w_{ij} represents the weight between the i-th visible layer connection point v_i and the j-th hidden layer connection point h_j, a_i and b_j represent the bias value of v_i and h_j, respectively. With the above function, the joint probability distribution function of the visible layer connection point v and the hidden layer connection point h can be obtained as follows:

$$EK(v,h) = \frac{e^{-E(v,h)}}{\sum_{v,h} e^{-E(v,h)}} \tag{2}$$

DBN model has a strong feature learning ability, which can learn the next feature of different factors by using the score data of GIS, so as to predict the degree of soil RD. However, in the actual GIS soil scoring matrix, there are a lot of unknown scores. If the DBN model only considers the score data of a certain feature, it may not be able to accurately learn the degree of soil RD. Therefore, this paper introduces similar factor influence layer to improve the traditional DBN model, named SRBM-DBN.

Extraction of RD information

For each pixel to be classified in the image, its spectral features can be expressed by the rectangular region composed of itself and its surrounding domain pixels. Assuming that the size of the neighbourhood window is L, a spectral feature vector of size L x L can be constructed for each pixel. Spectral characteristics calculation when the window size set L is 5, each level direction number of 4, 4, 3, get the spectral characteristic vector dimension for 16 + 16 + 8 = 40, respectively in the study of statistics of the three band spectrum characteristic vector, reorganising the three characteristic vectors into a vector classification as input, the dimension of the input vector is 3 × (5 × 5 + 40) = 195.

Parameter setting

In the DBN model, we set the initial learning rate n as 0.01. In the process of data training, we dynamically adjust the learning rate *N* through the reconstruction error, that is, when the reconstruction error becomes larger or unchanged, the quotient of *N* and 2 will be made, and the learning rate *N* in other cases will remain unchanged. *W* can initialise a random number from the gaussian distribution N (0,0.01). The offset value *B* of the hidden layer is reset automatically and the reset value is 0, and the hidden layer is 3 layers. The sample set is set as 200 and input training is carried out. Since the number of nodes in the input and output layers is 195 and 5 respectively, the study takes [5, 195] as the range and takes 5 as the step to calculate the reconstruction error corresponding to the node.

Since RD is divided into five levels and output in this study, a softmax layer is added after the DBN model, and 5 neurons are set.

Experiment and analysis

Data acquisition

In this risk assessment of Karst rocky desertification, grids were used as the calculation unit, and the size of each grid was 50 m × 50 m. The study area was divided into 372,311 grids. Among them, the bedrock exposure rate and planting data of 200 samples were selected in this paper. According to the field investigation, the risk degree of Karst rocky desertification was divided into five levels.

Results and discussion

In this experiment, we compared the improved SRBM-DBN (Stacked Restricted Boltzmann Machines - Deep Belief Network) model with other traditional recommended models to verify the effect of epochs on the experimental results. During the experiment, the number of hidden layer units is set to 160, and iterative training is carried out in M3000R50-100 dataset. The results are shown in Table 1.

Table 1

RMSE of DBN optimisation results

Epochs	RBM	DBN	SRBM-DBN
10	0.896	0.863	0.832
50	0.830	0.796	0.758
100	0.779	0.757	0.737
130	0.764	0.747	0.728
160	0.757	0.741	0.722
200	0.755	0.738	0.719

Table 1 shows the change of Root Mean Square Error (RMSE) value of different recommendation models with the increase of training times. With the increase of training times, the value of RMSE decreases and the prediction accuracy of the model is improved. while with the increase of the number of iterations, the RMSE changes significantly. The model uses the local user similarity method based on project characteristics to calculate similar users, and takes the data of similar users as the input of RBM. For RBM, the data set needs 130 iterations, which tends to converge. SRBM-DBN model is better than that of other models. When the iterations are about 100 times, the prediction accuracy of SRBM-DBN model is almost no longer affected by the number of iterations. It also shows that the proposed SRBM-DBN model has better prediction performance and faster convergence rate.

Table 2

Evaluation comparison of different RD grades

Risk level	Logistic	SRBM-DBN	BP	SVM (Support Vector Machine)
A (none)	0.10	0.11	0.16	0.12
B (potential)	0.22	0.13	0.21	0.15
C (mild)	0.22	0.18	0.25	0.21
D (moderate)	0.60	0.23	0.29	0.23
E (intensity rocky desertification)	0.08	0.53	0.30	0.36

This study selected 10 indexes closely related to RD in farmland as input variables, which are lithology, surface relief index, soil type, vegetation coverage rate, bedrock exposure rate, land reclamation index, slope farmland index, agricultural population density, per capita cultivated land area, etc. that is, the number of neurons in input layer is 10. In addition, considering the spectral characteristics of the ground objects, it is divided into five grades: none (A), potential (B), mild (C), moderate (D) and intensity RD (E). The spectral feature vector which can express the information of RD is constructed and classified as the input of DBN classifier.

According to the proportion distribution data of RD assessment grade in Table 2, the total proportion of no desertification risk or low risk is 24 %, which is better than 27 % of Support Vector Machine (SVM) and 37 % of Back Propagation (BP). In SRBM-DBN model, the proportion of high RD risk is 60 %, which is much higher than that of SVM and BP, showing that the zoning results of SRBM-DBN are more consistent with the actual risk assessment results. In addition, in the densely distributed areas, the results of SRBM-DBN zoning are determined as risk prone areas, which reveals that SRBM-DBN has better data mining ability.

Conclusion

In this study, a soil RD evaluation model is built using the DBN model that SRBM has optimised. The degree of soil RD in the Karst region is categorised into five grades based on the spectral properties of ground objects, and a spectral feature vector that can convey the RD information is built. The DBN classifier uses ten integrated indices as input for classification, including lithology and surface relief index. The outcomes demonstrate the superior data mining capabilities of SRBM-DBN. Densely populated areas are identified as risk-prone zones as a result of zoning. The evaluation's proposed model, which accurately reflects the distribution status of RD degrees across the entire Karst region and can serve as the foundation for RD control in the region, can be seen to have high credibility through the model assessment and field inquiry.

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