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Risk Zoning Method of Potential Sudden Debris Flow Based on Deep Neural Network

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Abstract: With the continuous increase in global climate change and human activities, the risk of sudden debris flow disasters is becoming increasingly severe. In order to effectively evaluate and zone the potential hazards of debris flows, this paper proposes a method for zoning the potential sudden hazards of debris flows based on deep neural networks. According to hazard identification, ten risk indicators of potential sudden debris flows are determined. The risk indicators of a potential sudden debris flow in each region were used as the input factors of a deep trust network (DBN) composed of a back propagation (BP) neural network and a restricted Boltzmann machine (RBM). The DBN is pre-trained using the contrast divergence method to obtain the optimal value of the parameter set of the DBN model, and a BP network is set at the last layer of the DBN for fine-tuning to make the network optimal. Using the DBN model with the best parameters, the risk probability of debris flows corresponding to each region is taken as an output. The risk grade is divided, the risk degree of potential sudden debris flow in each region is analyzed, and the potential sudden debris flow risk in each region is divided individually. The results show that this method can effectively complete the risk zoning of sudden debris flow. Moreover, the cumulative contribution of the indicators selected by this method is significant, and the correlation of indicators is not significant, which can play a role in the risk assessment of potential sudden debris flow. This study not only provides new ideas and methods for risk assessment of sudden debris flow disasters, but also fills a gap in the field of geological hazard susceptibility mapping.

Keywords: deep neural network; BP neural network; debris flow risk; hazard level classification; hazard source; hazard indicators

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1. Introduction

Under the influence of global climate change and human activities, sudden mudslides have become an increasingly serious problem, posing a huge threat to human life and property safety. In order to effectively address this challenge, the accurate assessment and zoning of potential sudden debris flow hazards have become crucial [1,2]. However, existing evaluation methods often appear inadequate when dealing with complex geological environments, ever-changing natural conditions, and a large number of influencing factors. Therefore, how to use advanced technological means to achieve accurate prediction and zoning of potential sudden debris flow hazards has become an important scientific problem that urgently needs to be solved in the field of geological disaster prevention and control.

There are many methods for risk zoning a potential sudden debris flow domestically and internationally. Karel Kováík et al. [3] developed a local meshless numerical model of the granular debris flow. The possibility of avalanche movement and rapid slope movement was simulated by the local meshless method to predict the risk degree of extensive damage caused by mountain infrastructure, and the dry granular soil movement model of debris flow was established by the weighted square local method to realize the regional division of debris flow. This method does not consider all the indexes, so the prediction accuracy is not high. The artificial neural network model proposed by Lee et al. [4] was used to predict a debris flow area in central Korea. An artificial neural network (ANN) model based on 63 historical events was established to predict the debris flow volume. By adjusting the R-2 value of ANN, 94% of the debris flow volumes observed by the ANN model were within the 1:2 and 2:1 lines of the predicted volume, which could predict the debris flow-prone areas in Korea. This method does not repeatedly train and learn the network to achieve the best performance, so the prediction result is not ideal. Duarte et al. [5] proposed the debris flow prediction of a subset of the common spatial domain after wildfires in the United States. After a wildfire, the possible debris flow in burn scars was evaluated using the Wildfire Elaine algorithm. In order to use this tool effectively, the object encapsulation problem was defined. Burn scars were represented by single-cell objects in the grid domain, the circular buffer was built around them, and the linear programming (LP) model was established. The best result produced by using this model was not only suitable for the simplified synthetic dataset, but also suitable for the burn scar subset produced by severe wildfire, and it successfully predicted whether there was the possibility of debris flow in the burn scar area. This method is not supported by a large number of evaluation index data, resulting in relatively low prediction accuracy. The application of UAV images was proposed by Kim et al. [6] in the stability analysis of urban rainfall-induced debris flow. The images were collected in UAV of the upper part of the slope that cannot be directly identified. Through image analysis, the digital elevation model of the slope surface was established, and the rainfall flow direction and the area, width, and length of the cutting area were calculated. Through numerical analysis, the influence of rainfall on slope instability ten days before the collapse, with time, was analyzed. Through the above methods, the regional disasters of debris flow were predicted. This method is only based on image analysis, and it is not supported by a large number of specific evaluation index data, resulting in a relatively low level of prediction accuracy. XU T. J et al. [7] used the maximum entropy principle and Wigner Ville distribution to identify micro ancient river channels. Based on the principle that the maximum entropy power spectrum is equivalent to the AR model power spectrum, they used the Burg algorithm and Levinson Durbin recursive rule to obtain the prediction error and autoregressive coefficients of the AR model. This method achieves precise identification of ancient river channels. However, this method may have sensitivity to noise and may not perform well in dealing with complex terrain, requiring further refinement and improvement.

Therefore, this study proposes a risk zoning method of potential sudden debris flow based on the deep neural network to accurately predict the risk area of potential sudden debris flow and reduce the occurrence of debris flow disasters. This article chooses DBN as the basic model, which is a multi-layer network structure that can extract deep features of data through layer-by-layer training. Compared with traditional models, DBN can more comprehensively consider various factors that affect the occurrence of debris flows, and has stronger adaptability, which can be adjusted and optimized according to actual situations. The contrastive divergence method was used to train DBN in terms of training methods. This is a fast learning algorithm that can greatly improve training efficiency compared to traditional Gibbs sampling methods, and is particularly suitable for processing high-dimensional debris flow hazard evaluation index data. After completing the training of DBN, the BP neural network is further used to solve the probability error of danger. The BP neural network has better generalization ability and can better handle complexity and uncertainty in practical applications.

2. Design of Deep Neural Network Model for Risk Zoning of Potential Sudden Debris Flow

2.1. Risk Assessment of Potential Sudden Debris Flow Based on Deep Neural Network

Through long-term repeated verification and research, a deep neural network model is established based on multiple observation data of existing debris flows, which involves the complex nonlinear relationship between potential sudden debris flow hazard evaluation indicators (input factors) and hazard level (output factors). The trained network is used to predict new observation data and further train the deep neural network to improve the learning and generalization performance of the network. The input potential to evaluate the risk level includes sudden debris flow risk assessment indicators such as terrain factors, soil factors, water factors, and human factors. Through high-precision geographic information system (GIS) input, it is possible to accurately reflect actual terrain, climate, soil type, and the data of other conditions, which should have sufficient spatial resolution to capture the specific environment and terrain details of debris flow occurrence. Effective feature sets are generated through data cleaning, feature scaling, and feature filtering and selection. The risk assessment structure of potential sudden debris flow based on the deep neural network is shown in Figure 1.

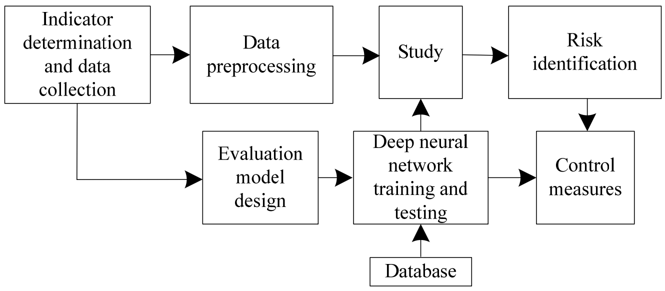

Figure 1. Risk assessment structure for potential sudden debris flow.

2.2. Hazard Source Identification

The formation of debris flow and the severity of disasters mainly have the following reasons: topographic factors, soil factors, water factors, and human factors [8,9].

2.2.1. Slope Factor and Height Factor

A debris flow mainly occurs in mountainous areas, and it is suspected that the mechanism of its occurrence or formation is related to its drop and angle [10]. Several samples with the same mass (500 g), humidity, and soil quality are taken. Tables 1 and 2 show details of the influence of the angle and height on a mud-rock slide and the destructive power of a debris flow by its impact distance on light objects (averaged by many measurements).

Topographic factors consist of an angle and a drop. For the same drop, increasing the angle makes it easier to slide down and results in a higher final kinetic energy, which increases its destructive power. However, the damaged area decreases after the angle exceeds 75 degrees. When the angle remains constant, an increase in the drop leads to a corresponding increase in the gravitational potential energy and destructive power. When the two factors are merged, their destructive power is significantly increased.

Table 1. Influence of angle (sample middle–end and horizontal height 30 cm) on mud slide.

Angle of Slope to Horizontal Plane (°)	Is It Easy to Slide?	The Impact Distance to a Horizontal Light Mass (cm)	Frictional Coefficient	Soil	Initial Speed (m/s)
0	No	0	0.3	clay	0
10	No	0	0.3	clay	0
20	No	0	0.3	clay	0
30	Hard to slide	5.2 cm	0.35	clay	1.5
40	Slippable	7.6 cm	0.38	clay	2.2
60	Easier to slide	10.8 cm	0.42	clay	3.0
80	Very easy to slide	7.9 cm	0.45	clay	4.0
90	Particularly easy to slide	5.4 cm	0.48	clay	4.8

Table 2. The impact of the drop on the mud slide (slope angle is 60 degrees).

Sample with Horizontal Height	The Impact Distance to a Light Mass	Frictional Coefficient	Soil	Debris Flow Rate $(m)^3/S$	Debris Flow Velocity (m/s)
15 cm	3.8 cm	0.32	sand	0.02	2.5
30 cm	6.9 cm	0.35	sand	0.04	3.5
45 cm	13.5 cm	0.38	sand	0.12	5.5
60 cm	18.2 cm	0.42	sand	0.21	7.2
75 cm	24.4 cm	0.45	sand	0.35	9.5

Theoretical analysis: As the angle between the sample and the horizontal plane increases, the force in the opposite direction of friction (a component of gravity) also increases. That leads to a greater combined force in the direction of motion, resulting in higher acceleration, higher final velocity, and increased destructive power. However, when the angle is between 80 and 90 degrees, almost all of the impact force is consumed in the vertical direction, and its destructive power is considerably diminished due to the accumulation buffer. According to the law of conservation of energy, the higher the position of the sample with the same mass, the greater the gravitational potential energy and kinetic energy at the end. Therefore, debris flows mainly occur in mountainous areas with low vegetation coverage.

2.2.2. Soil Factor and Water Factor

The influence of soil quality on debris flow generally includes the softness, water absorption, and quantity of soil quality. According to the difficulty level of excavation, the classification of soil engineering generally includes eight types of soil: Class I soil (soft soil), Class II soil (ordinary soil), Class III soil (hard soil), Class IV soil (gravel hard soil), Class V soil (soft stone), Class VI soil (secondary hard stone), Class VII soil (hard stone), and Class VIII soil (special soil). As the soil water absorption rate increases, the gravitational potential energy of the same mass of soil will also increase, resulting in more adverse effects. For two samples with the same angle and height, spray one of them gradually to increase its water content. It was found that samples with a lower moisture content are more prone to sliding. When the water volume continues to be uniformly increased until the sample slides, its effect on the lightweight block is further away, indicating greater potential harm. This indicates that the viscosity and water absorption of soil have a significant impact on its sliding behavior. In addition, as the amount of water increases, the viscosity of the soil first increases and then decreases. When the weight of the soil reaches a certain value, it will rapidly slide, leading to landslides. After the soil gradually saturates, the continuous addition of water will form debris flows, which have stronger fluidity and energy, and the greatest destructive power. Therefore, for this type of soil, special attention should be paid and measures should be taken to monitor it.

Water factors are mainly divided into reservoir, glacier impact, and rain impact. The primary source of kinetic energy in debris flows caused by glacier melting and reservoir dam breakage is derived from the kinetic energy of water. Debris flows are mainly caused by rain, which increases the gravitational potential energy of soil. When water content exceeds a certain value, it will reduce its friction and increase its fluidity.

2.2.3. Human Factors

Human factors mainly include the following factors: First, an insufficient understanding of debris flows. People generally lack knowledge about debris flows, have weak safety awareness, poor prevention and coping abilities, and miss the escape route, thus causing huge losses. Second, life and production activities contribute to the formation of debris flows. The destruction of vegetation by production and life, random stacking of slag, or mining and digging provide conditions for the outbreak of debris flows. Third, we can minimize production and life activities in a debris flow damage area by preventing production and life in the area where debris flow disasters will inevitably occur and where the protection is not enough.

2.3. Risk Assessment Index System of Potential Sudden Debris Flow

According to hazard identification, the risk index of a potential sudden debris flow is determined. The risk of debris flow refers to the possibility of a disaster-causing geological process [11], and the core is the activity degree of such a process. Based on the qualitative analysis, the higher the activity degree of geological processes causing disasters, the greater the danger, resulting in more serious disaster losses. In the quantitative evaluation, the danger of debris flow disasters needs to be reflected by specific indicators. After identifying the hazards and clarifying the impact of the activity level of the geological processes that cause disasters on the risk of debris flows, in order to more accurately evaluate the potential danger of sudden debris flows, a potential sudden debris flow risk evaluation index system with three levels (comprehensive indicators, main indicators, and group indicators) is constructed. This system will provide important guidance for subsequent model design and application (Figure 2).

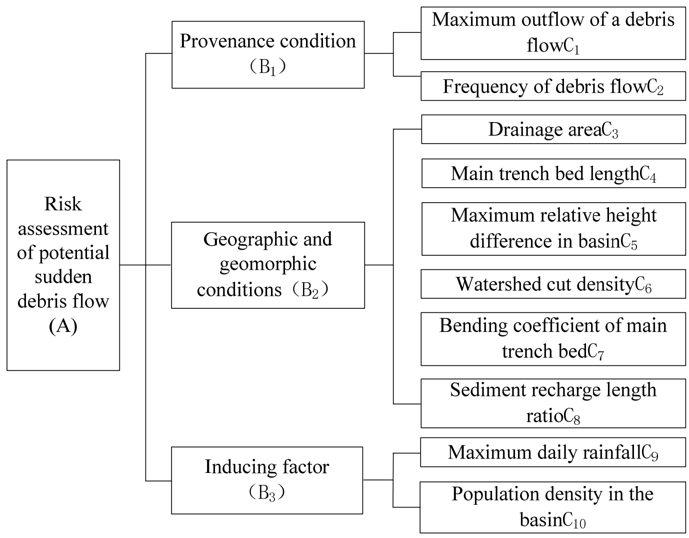

Figure 2. Risk assessment system of potential sudden debris flow.

(1) Comprehensive indicators

This level is the overall index, reflecting the final risk assessment result of a potential sudden debris flow.

(2) Main indicators

The risk of a potential sudden debris flow is analyzed and investigated from three aspects: material source conditions, landform conditions, and inducing factors. Among them, rainfall is one of the important factors affecting debris flows. Rainfall can increase soil moisture and reduce soil friction and adhesion, thereby promoting the formation and flow of debris flows. Generally speaking, the greater the rainfall and the longer the duration, the greater the likelihood of debris flows occurring.

(3) Group indicators

Specific indicators to measure the risk of a potential sudden debris flow include 10 indicators, such as the maximum amount of debris flows and the frequency of debris flows. On the basis of the comprehensive analysis of relevant research results, following the principles of science, practicality, and brevity, several specific evaluation indexes are shown in Table 3.

Table 3. Risk evaluation index system of potential sudden debris flow.

Subject Index	Population Index	Remark
Provenance condition B_1	Maximum outflow of a debris flow C_1	10^4 m^3
	Frequency of debris flow C_2	Next/A hundred years
Geographic and geomorphic conditions B_2	Drainage area C_3	km^2
	Main trench bed length C_4	km
	Maximum relative height difference in basin C_5	km
	Watershed cut density C_6	km/km^2
	Bending coefficient of main trench bed C_7	Actual length of trench bed/Straight length of trench bed
	Sediment recharge length ratio C_8	Cumulative length of sediment recharge along the way/Length of main ditch
Inducing factor B_3	Maximum daily rainfall C_9	mm
	Population density in the basin C_{10}	Number of people /km^2

Due to the different dimensions of the indexes involved in the evaluation, the magnitude differs significantly. In order to facilitate the calculation, the indexes that affect the risk of geological disasters must be dimensionless. The dimensionless method is shown in (1):

$$X\text{dimensionless value} = \frac{X_{\text{actual value}} - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where $X_{max}= [X_{\text{actual value}}]_{max}$, $X_{min}= [X_{\text{actual value}}]_{min}$.

Every single index in the risk assessment index system of potential sudden debris flows reflects the risk degree of a debris flow disaster from different aspects, so it is necessary to comprehensively evaluate the overall situation (debris flow risk) by using the deep neural network. The risk assessment index of potential sudden debris flow in every region as the deep neural network model must be inputted. Then, the probability value of a debris flow disaster in every region should be outputted, showing the possibility of debris flow in that region. The model output can be used to judge whether the area is dangerous. Additionally, based on the probability value, the risk degree of a debris flow in this area can be divided into five levels: slight risk, low risk, medium risk, high risk, and extremely high risk. With the data of different areas as the input data of the deep neural network, the risk degree of potential sudden debris flow in different areas can be obtained. Then, the results of the risk degree of a potential sudden debris flow in each area can be presented with visualization technology, such as marking the dangerous areas with GIS.

3. Risk Zoning of Potential Sudden Debris Flow Based on DBN

3.1. DBN Model

The deep belief network (DBN) is a kind of deep neural network that utilizes a greedy learning method in deep learning [12], which has been widely studied and has promoted the development of neural networks. The DBN has achieved extraordinary success in image recognition, handwriting recognition, speech recognition, and other related areas. Structurally, as shown in Figure 3, the DBN consists of a layer of unsupervised learning BP neural network and a layer of unsupervised learning restricted Boltzmann machine (RBM). In this study, the DBN model is used to complete the risk zoning of a potential sudden debris flow based on the risk evaluation index obtained above.

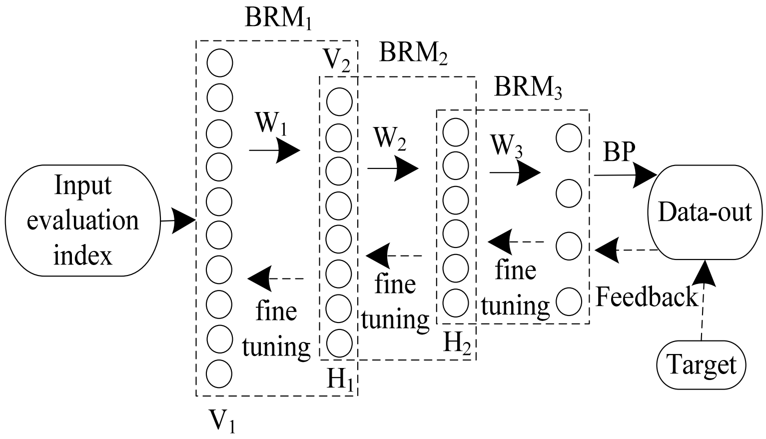

Figure 3. Network diagram of DBN.

DBN gradually forms an abstract evaluation index [13] in the process of accepting the evaluation index of potential sudden debris flow risk by the bottom neural network. That index is further refined by increasing the number of network layers [14], allowing the last neural network to form the most easily classified evaluation index vector. That vector is used to realize the risk zoning of a potential sudden debris flow. Because RBM can only ensure the optimal evaluation index of each layer and cannot completely delete the error information, it cannot make the whole DBN evaluation index optimal [15]. However, the multi-layer neural network is able to reduce the error information generated by the upper layer and obtain the optimal evaluation index. Therefore, the accuracy of the deep neural network is higher than that of a single-layer neural network [16].

The training of DBN in the risk zoning of potential sudden debris flows mainly includes pre-training of unsupervised learning and fine-tuning of supervised learning, as follows:

(1) Pre-training. Initialize the confidence network parameters and train each layer parameter from bottom to top using uncalibrated data of a potential sudden debris flow risk evaluation index. Because of the sparsity constraint, the model can achieve a more accurate evaluation index while inputting a potential sudden debris flow risk evaluation index. Then, take the hidden layer output from the first layer as the visible layer input from the upper layer, et cetera. However, when the risk evaluation index of potential sudden debris flow is mapped to different spaces, the risk evaluation index information of a potential sudden debris flow in each layer should be kept.

(2) Fine-tuning. The BP network is set at the last layer of DBN, and the error between the actual output and the expected output of the potential sudden debris flow risk level is supervised and propagated downward layer by layer. DBN is a method of learning and inputting the risk evaluation index data for a potential sudden debris flow [17]. Thus, the whole situation can be optimized, and the weights of each layer can be trained. As long as a few iterations are carried out, the expected effect can be obtained, and the risk classification of potential sudden debris flow can be realized.

3.2. Restricted Boltzmann Machine

RBM plays an important role in DBN, enabling DBN to gradually form abstract evaluation indicators from the underlying neural network through layer-by-layer greedy learning, thereby achieving the zoning of debris flow hazards. DBN is composed of multiple layers of restricted Boltzmann machines (RBMs). By adjusting the weights between neurons in each layer, the whole neural network can generate training data composed of potential sudden debris flow risk assessment indicators according to the maximum probability [18]. This is performed to extract the best potential sudden debris flow risk assessment indicators and divide the debris flow risk. A typical RBM structure is a two-layer network that consists of a visible layer v and a hidden layer h, as shown in Figure 4. The visible layer is used to receive the input data, which are the risk evaluation index of potential sudden debris flow. The hidden layer is used to extract the evaluation index. The neurons in the visible layer and the hidden layer are interconnected to complete the information transmission when extracting the evaluation index. In contrast, the neurons in each layer are independent of each other.

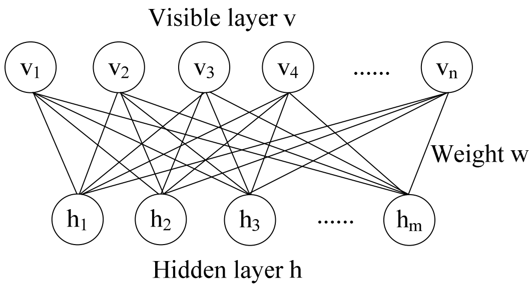

Figure 4. Structure of the restricted Boltzmann machine.

In Figure 4, $v = [v_1, v_2, ..., v_n]$ is the input node of the n potential sudden debris flow risk evaluation index of the visible layer unit; $h = [h_1, h_2, ..., h_m]$ is the output node, extracted for the m potential sudden debris flow risk evaluation index of the hidden layer unit; $w = \left[w_{ij}\right]_{n \times m}$ is the connection weight matrix from the input layer to the output layer, where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$; $B = [b_1, b_2, \ldots, b_n]$, in which b_i is the bias of the i-th visible cell v_i; $C = [c_1, c_2, ..., c_m]$, in which c_j is the bias of the j-th implied cell h_j.

For a given visible layer, the risk evaluation index is the input of potential sudden debris flow v, and the output is the extraction result of the risk evaluation index of the potential sudden debris flow in the hidden layer h. The energy function of restricted Boltzmann machine $E(v, h|\omega)$ is:

$$E(v, h|\omega) = -\left(\sum_{i=1}^{n} b_i v_i + \sum_{j=1}^{m} c_j h_j + \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j\right) \tag{2}$$

Formula $\omega = \left\{w_{ij}, b_i, c_j\right\}$, which is the parameter set of the RBM model.

Energy function $E(v, h|\omega)$ can be regarded as the energy value between the input node of a potential sudden debris flow risk evaluation index of each visible layer and the output node of a potential sudden debris flow risk evaluation index extraction result of the hidden layer under the current node distribution state of the visible layer and hidden layer. Assuming that each node of the visible layer and hidden layer has two states of 0 and 1, the nodes of the visible layer and hidden layer can compose $t = 2^{n+m}$ state pair. Via the exponentiation and regularization of the energy function, we can obtain the joint probability distribution $P(v, h|\omega)$ of the set of nodes $\{v, h\}$ in the visible and hidden layer in a certain state pair, and obtain Formula (3):

$$P(v, h|\omega) = exp(-E(v, h|\omega)) \times Z^{-1} \tag{3}$$

Among them, $Z = \sum_{\{v,h\}_1}^{\{v,h\}_t} exp(-E(v, h|\omega))$ is a normalized factor (also called partition function), which represents the sum of possible states of all potential sudden debris flow risk assessment indicators in the nodes of the visible layer and hidden layer. According to Formula (3), the joint probability distribution $P(v, h)$ in any state can be obtained theoretically. However, Z is complicated to calculate by the joint probability distribution, so the Gibbs sampling method is generally used to approximate the joint probability distribution and characterize the possible state of the risk assessment index of a potential sudden debris flow. By summing all the binary states of the m nodes in the hidden layer h, the edge probability distribution $P(v)$ of the visible layer v nodes set is obtained as follows:

$$P(v) = \frac{1}{Z}\sum_{i=1}^{n}\exp(b_i v_i)\prod_{j=1}^{m}\left[1+\exp\left(c_j+\sum_{i=1}^{n}v_i w_{ij}\right)\right] \tag{4}$$

Similarly, the edge probability distribution $P(h)$ of the hidden layer h is:

$$P(h) = \frac{1}{Z}\sum_{j=1}^{m}exp(c_j h_j)\prod_{i=1}^{n}\left[1+exp\left(b_i+\sum_{j=1}^{m}h_j w_{ij}\right)\right] \tag{5}$$

Edge distribution is often called likelihood function, for example, the probability that the set of nodes in the $P(h)$ hidden layer is under a certain state distribution. According to $P(h)$, the conditional probability distribution $P(v|h)$ of the visible layer can be obtained.

$$P(v|h) = \frac{P(v,h)}{P(h)} = \frac{exp(-E(v,h|\omega))}{\sum_v exp(-E(v,h|\omega))} \tag{6}$$

Similarly, the conditional probability distribution of hidden layer $P(h|v)$ is:

$$P(h|v) = \frac{P(v,h)}{P(v)} = \frac{exp(-E(v,h|\omega))}{\sum_h exp(-E(v,h|\omega))} \tag{7}$$

According to the structural characteristics of no connection in the RBM layer and full connection between the layers, for a given visible cell state v, through the conditional probability distribution function of the hidden layer $P(h|v)$, the probability of implicit units is $P\left(h_j = 1|v\right)$ of the j-th activation:

$$P\left(h_j = 1|v\right) = \frac{P\left(v, h_j = 1\right)}{P(v)} = \beta\left(c_j + \sum_i w_{ij} v_i\right) \tag{8}$$

In the formula, $\beta(x) = \frac{1}{1+\exp(x)}$ is the sigmoid function.

For a given implied cell state h, the i-th activation probability of visible units $P(v_i = 1|h)$:

$$P(v_i = 1|h) = \frac{P(v_i = 1, h)}{P(h)} = \beta\left(b_i + \sum_j w_{ij} h_j\right) \tag{9}$$

3.3. DBN Training of Multi-Layer Structure Based on Contrast Divergence

The DBN model can obtain accurate results of potential sudden debris flow hazard zoning, which is inseparable from DBN model training. During training, multiple RBMs are trained in a bottom–up way, and the hidden layer of each RBM is used as the input layer of the next RBM. The final multi-layer structure is obtained through layer-by-layer accumulation, which is used to complete the potential sudden debris flow hazard zoning.

The goal of training RBM is to obtain the parameter set $\omega = (w, b, c)$ to fit the existing data and improve the accuracy of DBN in obtaining the risk zoning results of potential sudden debris flow. By finding the RBM in the training set (assuming the number of samples is T), Formula (10) can then be obtained:

$$\omega^* = argmaxR(\omega) = argmax\sum_{t=1}^{T} logP\left(v^{(t)}|\omega\right) \tag{10}$$

The traditional method is to obtain the parameter ω optimal value using Gibbs sampling [19]. However, when the dimension of the risk assessment index of a potential sudden debris flow is very high, a large number of sampling processes are needed, resulting in the low efficiency of RBM training. Therefore, in 2006, Hinton proposed a fast learning algorithm for RBM, called contrast divergence [20], which differs from the traditional Gibbs sampling method. A training sample is composed of risk assessment indicators, and a potential sudden debris flow v is composed of visible units. The activation probability of the j-th hidden unit can be obtained using Equation (8). Assuming that the hidden layer is known, the activation probability of the i-th visible unit can be obtained using Equation (9). This allows for the reconstruction of the visible layer, which is composed of the extraction results of the potential sudden debris flow risk evaluation index v_k. If v_k and v are the same, it can be explained that the hidden layer is another expression of the visible layer. Then, the parameters of RBM are adjusted to reduce the reconstruction error between the state of training samples and the state of visible layers v and v_k. Finally, the updating rules of each parameter RBM are obtained as shown in Formula (11):

$$\begin{cases} \Delta w_{ij} = \mu < v_i h_j >_{data} - < v_i h_j >_{recon} \\ \Delta b_i = \mu < v_i >_{data} - < v_i >_{recon} \\ \Delta c_i = \mu < h_j >_{data} - < h_j >_{recon} \end{cases} \tag{11}$$

Among them, μ is the learning rate; $<>_{data}$ represents the positive correlation expectation of inputting the training data of potential sudden debris flow risk evaluation index; $<>_{recon}$ represents the reverse correlation expectation of reconstructing the risk evaluation index data of potential sudden debris flow. Reconstruction error is the basis for DBN to judge the learning effect of evaluation indicators in the pre-training stage. A lower reconstruction error indicates a better learning effect and higher reliability of the results of potential sudden debris flow hazard zoning.

After completing the pre-training of DBN, taking the risk evaluation index of potential sudden debris flow in each region as input, the probability value of the debris flow disaster corresponding to each region is output. The corresponding risk level is obtained according to the probability value. The risk level of each region is displayed by means of a visualization method to realize the risk zone of a potential sudden debris flow in each region.

3.4. Risk Probability Error Resolution Based on BP Network Algorithm

After completing the training of the multi-layer-structured DBN based on contrast divergence, the BP network algorithm is further used to solve the probability error of danger in order to improve the accuracy of zoning. The deep belief network is a BP neural network entity classifier. First, the high-level potential sudden debris flow risk evaluation index vector obtained by several restricted Boltzmann machines is used as the input of the BP neural network for supervised learning. Second, the network adjusts the parameter values between networks according to the BP algorithm ω. Finally, the depth belief network with the best parameter value is constructed to complete the risk classification of a potential sudden debris flow.

The BP neural network is a supervised classifier. In the process of forward propagation, the trained risk probability of potential sudden debris flow is compared with the actual output risk probability of potential sudden debris flow, and an error value is obtained. The error value is used to estimate the error of the previous layer's output layer. The parameters of the whole DBN are optimized by backward propagation and fine-tuning, improving the accuracy of the risk classification of a potential sudden debris flow.

For each training sample constructed by the potential sudden debris flow risk evaluation index, it is assumed that the actual output debris flow risk probability of the output node is g_i and the ideal output debris flow risk probability is f_i, whereby the error gradient between them is Equation (12):

$$\psi_i = g_i(1 - g_i)(f_i - g_i) \tag{12}$$

In the same way, the error gradient of the k-th hidden layer is given by Equation (13):

$$\psi_i^k = y_i^k \left(1 - y_i^k\right) \sum_j w_{ij}^k \psi_j^k \tag{13}$$

Combining Equations (12) and (13), after the total error gradient ψ is obtained, it is used to update the weight of DBN, which is expressed as (14):

$$w'_{ij} = w_{ij} + \eta g_i \psi \tag{14}$$

Among them, η is the learning ratio; w_{ij} and w'_{ij} are the weights before and after the update; experiments need to be conducted to confirm g_i, ψ. After calculating the new weight, repeat the above steps until the probability error of a potential sudden debris flow risk is small enough.

The traditional BP network randomly initializes the bias value and connection weight and then uses the BP algorithm to optimize it until it converges. Then, the DBN network based on the BP algorithm is used to initialize the weights of each layer of the BP network by the weights of DBN instead of randomly. Lastly, the DBN is expanded into a BP network, and the parameters of the whole DBN network are optimized to achieve optimal performance. The obtained risk probability error is input into the multi-layer structure of the deep neural network, which outputs the final zoning result to realize a more accurate risk grade zoning of a potential sudden debris flow.

4. Prevention and Control Countermeasures

(1) Conduct a general survey of four factors in various regions, especially in areas where debris flows frequently occur. All the factors of debris flows are recorded electronically, and the data are analyzed. Then, a computer is used to form a key monitoring area, and the responsibility lies with people and departments. The flood season is from May to September, and the main flood season is from June to August. During this period, it is crucial to pay close attention to the weather forecast, strengthen the inspection and elimination of various factors, and enhance measures to ensure controllability. Moreover, focus on regional monitoring, time period monitoring, risk factor monitoring and inspection, and targeted protection.

(2) Enhance the publicity and education of the fundamental knowledge of debris flow disasters, especially in debris flow-prone areas, so that personnel can qualitatively judge the possibility and severity of debris flow disasters and learn the necessary escape and self-help methods.

(3) Strengthen the downward resistance of debris flow movement. On the one hand, by strengthening the protection of vegetation, the branches and leaves of vegetation can reduce the water absorption of rock and soil, and the roots of vegetation increase the downward resistance of the soil. On the other hand, in special areas where vegetation cannot grow, protective nets are added to increase the downward resistance of rocks and soil, especially in steep walls near roads and railways. Build artificial debris flow prevention facilities, such as building concrete barriers in mountain gullies.

(4) Avoid creating hazards and refrain from exposing oneself to danger. Avoid digging and placing excavated soil randomly. Avoid participating in activities related to industry and daily living in areas prone to frequent debris flows. If it is inevitable, it is imperative to set up safe and reliable protection to ensure that the danger is minimized.

From the perspective of risk analysis, various factors are interrelated, and the improvement of one or more factors can reduce the likelihood of debris flow occurrence. Therefore, comprehensive prevention and control strategies are crucial. Through risk assessment and monitoring warning systems, potential risk sources can be identified and addressed in a timely manner. By combining engineering measures (such as building drainage systems, strengthening protective facilities, etc.) with non-engineering measures (such as developing emergency plans, organizing evacuation drills, etc.), we can comprehensively enhance the ability to prevent and control debris flow disasters.

5. Experimental Analysis and Related Discussion

In order to validate the feasibility and effectiveness of the method employed in this study, a specific area was chosen for conducting experiments. This area is located at the edge of the plateau and exhibits characteristics such as loose soil, poor vegetation conditions, frequent heavy rains, storms, floods, and easy-to-form water-collecting terrain, making it susceptible to debris flow formation. According to the risk assessment indicators of a potential sudden debris flow shown in Table 3, a total of 25 groups of sample data in this area were collected for experiments. The samples included 10 groups of index data as training samples and 15 groups of index data as test samples. Initially, the evaluation index data of 10 groups of training samples are input into the network and trained. Afterward, the evaluation index data of 15 groups of test samples are input into the trained network after dimensionless processing. The prediction results are shown in Table 4.

Table 4. Division results of 15 groups of test samples.

Sequence Number of Debris Flow	Minor Hazard	Lower Risk	Medium Risk	High Risk	Extremely High Risk	Prediction Result of This Paper	Expert Judgment
1	0.981	0.011	0.003	0.001	0.002	Minor hazard	Minor hazard
2	0.003	0.004	0.010	1.000	0.001	High risk	High risk
3	0.004	0.001	0.005	0.012	0.980	Extremely high risk	Extremely high risk
4	0.001	1.000	0	0.004	0.002	Lower risk	Lower risk
5	0.006	0.004	0.990	0.025	0.014	Medium risk	Lower risk
6	1.000	0.002	0.021	0.006	0.014	Minor hazard	Minor hazard
7	0.015	0	0.007	0.013	0.992	Extremely high risk	Extremely high risk
8	0.015	0.006	0.976	0.004	0.017	Medium risk	Medium risk
9	0.002	0.954	0.004	0	0.001	Lower risk	Lower risk
10	0.987	0.001	0.011	0.013	0.003	Minor hazard	Minor hazard
11	0.014	0	0.004	0	0.968	Extremely high risk	High risk
12	0.004	0.996	0	0.001	0.004	Lower risk	Lower risk
13	0.994	0.012	0.003	0.006	0.014	Minor hazard	Minor hazard
14	0	0.954	0.020	0.004	0.011	Lower risk	Lower risk
15	0.978	0.001	0.014	0	0.004	Minor hazard	Minor hazard

As can be seen from Table 4, the results of this method are compared with the risk zoning identified by experts in the basic database. It is found that the results of other samples are consistent with the results determined by experts, except for the results of samples N5 and N11. Using contrast divergence method to pre-train DBN to obtain the optimal values of the DBN model parameter set, and setting a BP network in the last layer of DBN for fine-tuning to make the network optimal, this approach is novel and can meet the risk zoning needs of potential sudden debris flows.

Various methods, shown in Table 4, are used to predict the samples N1–N9: the method used in this study, the genetic neural network method, the IBRF neural network method, the radial basis function neural network method, and the fuzzy neural network method. Figures 5–8 show the comparison between the methods used in Table 4 and the results judged by experts.

Analyzing Figure 5, it can be seen that the prediction results of samples N2 and N7 in the genetic neural network method are low, the prediction results of sample N5 are high, and the prediction of three samples is inaccurate. Analyzing Figure 6, it can be seen that the prediction results of sample N7 in the IBRF neural network method are relatively low, while the prediction results of samples N1 and N5 are relatively high, and the predictions of three samples are not accurate. From Figure 7, it can be seen that the prediction results of samples N2, N3, and N8 in the radial basis function neural network method are low, while the prediction results of sample N5 are high, and the prediction of four samples is inaccurate. From Figure 8, it can be seen that the prediction results of sample N9 in the fuzzy neural network method are low, while the prediction results of samples N4 and N8 are high, and the predictions of three samples are inaccurate. From Table 4, it can be seen that the method proposed in this article only yields higher results for N5 in the prediction of N1–N9 samples. By comparing the five methods, it is concluded that the method proposed in this paper has higher prediction accuracy and can accurately predict potential sudden debris flow hazard zoning in order to improve the safety of residents and property.

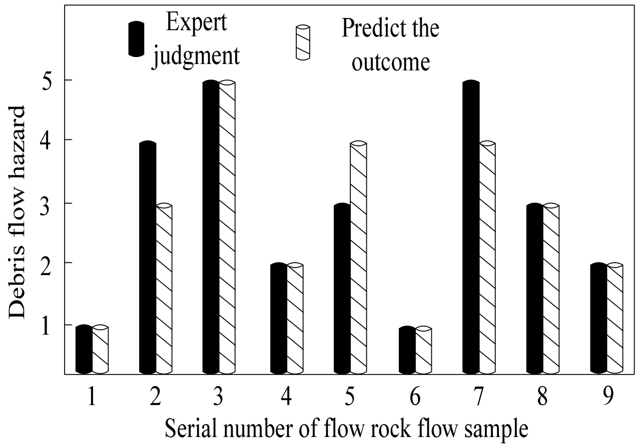

Figure 5. Prediction results of genetic neural network method.

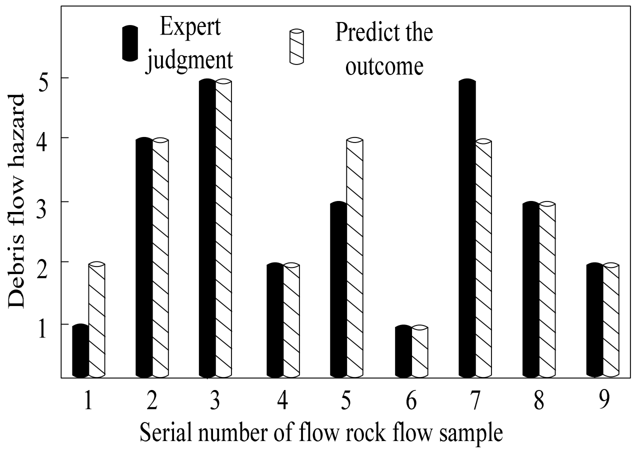

Figure 6. Prediction results of IBRF neural network method.

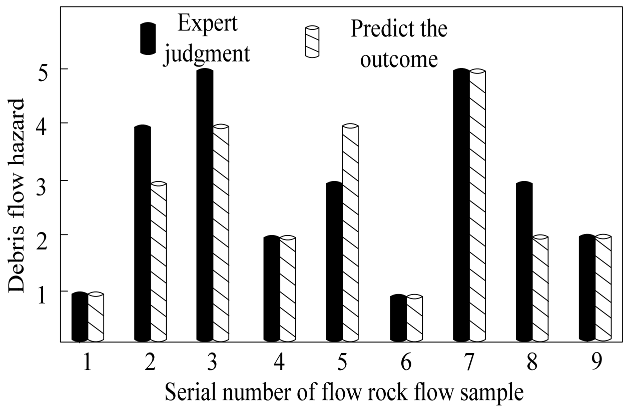

Figure 7. Prediction results of radial basis function neural network method.

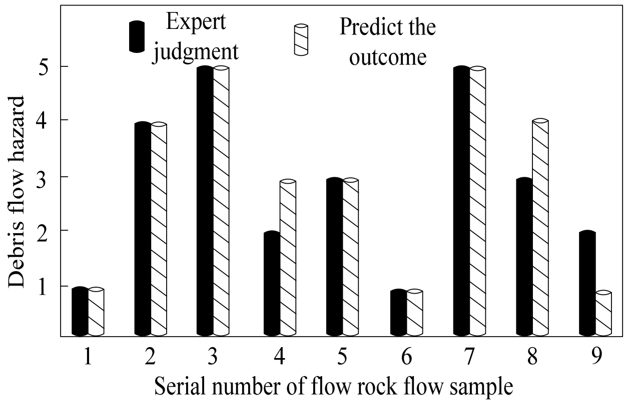

Figure 8. Prediction results of fuzzy neural network method.

In order to verify the convergence speed of the deep neural network in this method, the genetic neural network method, IBRF neural network method, radial basis function neural network method, and fuzzy neural network method are compared to show the training convergence curve of each method when the network performance reaches the optimal level, as shown in Figure 9.

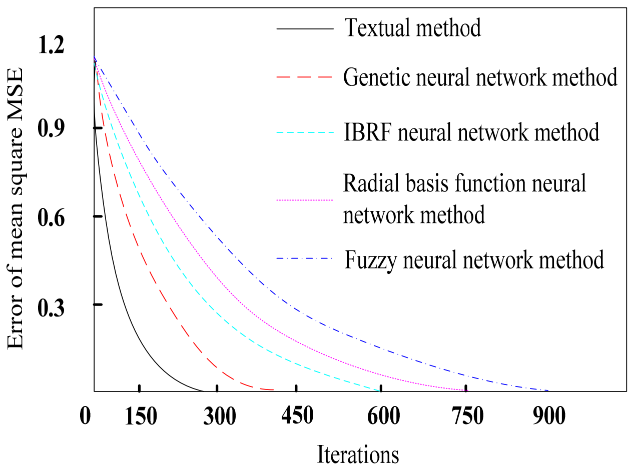

Figure 9. Training convergence curves of 5 kinds of neural networks.

Analyzing Figure 9, it can be seen that the genetic neural network method completed training after 400 iterations, the IBRF neural network method completed training after about 600 iterations, the radial basis function neural network method completed training after 750 iterations, and the fuzzy neural network method completed training after about 900 iterations. However, the method proposed in this paper completed training after 250 iterations. By comparison, it is demonstrated that the method proposed in this article has a higher efficiency in completing network training and can complete potential sudden debris flow hazard zoning in the shortest possible time.

In order to validate the efficacy of the evaluation model used in this study, the cumulative contribution degree of the risk evaluation index of a potential sudden debris flow is analyzed. Suppose the cumulative contribution degree of the risk evaluation index of a potential sudden debris flow exceeds 85%. In that case, the selected index can be effectively used as the risk evaluation index of a potential sudden debris flow. The cumulative contribution of each potential sudden debris flow risk assessment index in Figure 2 is counted, and the result is shown in Figure 10.

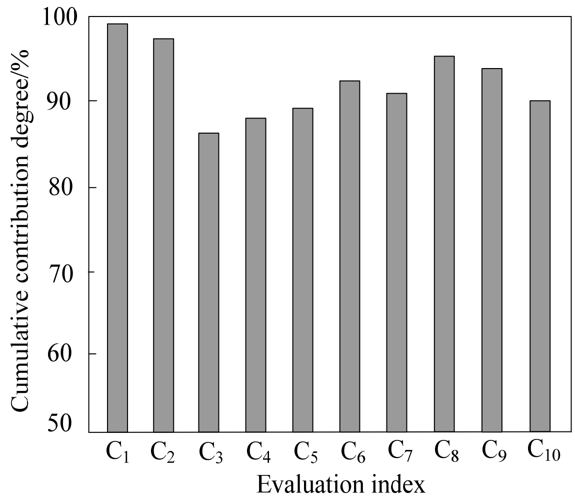

Figure 10. Cumulative contribution of risk assessment indicators of potential sudden debris flow.

As shown in Figure 10, the cumulative contribution degrees of ten potential sudden debris flow risk assessment indicators all exceed 85%, among which six assessment indicators exceed 90% and three assessment indicators are close to 100%. The experiment shows that the 10 evaluation indexes in this evaluation model can play the role of risk evaluation of a potential sudden debris flow. This is because the method uses a DBN model with the best parameters, which outputs the probability of debris flow risk corresponding to each region, more sensitively reflecting the key factors related to potential sudden debris flow risk. At the same time, it proves the effectiveness and reliability of these 10 evaluation indicators in the assessment of potential sudden debris flow risk. By using these indicators for potential sudden debris flow risk assessment, it is possible to more accurately predict and evaluate the risk of potential sudden debris flows, which helps to take corresponding prevention and response measures.

By analyzing the correlation of indicators, the information non-overlapping degree of the risk evaluation index system of a potential sudden debris flow constructed by the method used in this study is tested and compared to the index correlation of the genetic neural network method, IBRF neural network method, radial basis function neural network method, and fuzzy neural network method. The lower the index correlation, the lower the degree of information non-overlapping, and the better the comprehensiveness of index system construction. An interval of [1, 0.75] represents high correlation; an interval of [0.75, 0.5] represents significant correlation; an interval of [0.5, 0.25] represents weak correlation; and a [0.25, 0.0] interval represents irrelevant. The analysis results are shown in Figure 11.

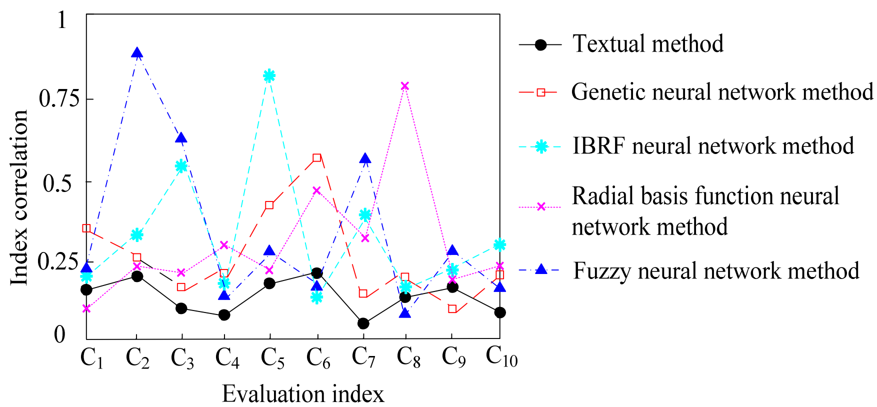

Figure 11. Analysis results of the construction effect of potential sudden debris flow risk assessment index system.

According to Figure 11, the correlation of 10 evaluation indexes in the risk evaluation index system of potential sudden debris flow constructed by the textual method is lower than 0.25, indicating that all indexes are irrelevant. There are three weak correlations and one significant correlation in the genetic neural network method. There are two weak correlations, one significant correlation, and one high correlation in the IBRF neural network method. There are three weak correlations and one high correlation in the radial basis function neural network method. There are two weak correlations, two significant correlations, and one high correlation in the fuzzy neural network method. The above results show that the index system of risk assessment of potential sudden debris flow constructed by this method has a low correlation and a low non-overlapping degree of index information, and the index system has excellent comprehensiveness. The proposed method performs better in the risk assessment of debris flows because it comprehensively considers multiple physical factors, such as material sources, topography, and triggering factors. The evaluation indicators are closely related to the physical mechanism of debris flow occurrence. This method utilizes neural network models for dynamic prediction, which has high efficiency and accuracy, and each indicator has clear physical meaning and interpretability.

6. Conclusions

In this study, a method based on a deep neural network is proposed for the risk zoning of potential sudden debris flows. Based on the analysis of debris flow hazards, the risk assessment index system of a potential sudden debris flow is established. Furthermore, in conjunction with the related characteristics of debris flow disasters, a group of 10 risk assessment indexes of a potential sudden debris flow are proposed as input factors of the deep neural network. This study introduces the training process of the deep neural network (DBN). The network achieves optimality by reducing the reconstruction error and determination of optimal parameter values. Then, the network improves the accuracy of a potential sudden debris flow risk classification. After completing the pre-training of DBN, each output node corresponds to a certain category and outputs five grades of potential sudden debris flow risk classification. Finally, this study gives the prevention countermeasures to make the prevention measures more targeted and effective, avoiding excessive waste of resources in debris flow disaster prevention. Thus, the risk assessment model of potential sudden debris flows based on the deep neural network is completed.

Experiments show that the deep neural network can be successfully applied to the risk zoning of a potential sudden debris flow. The risk assessment model of a potential sudden debris flow based on the deep neural network has high reliability, which provides an effective new method for the risk zoning of potential sudden debris flow. The deep neural network has a self-adaptive ability and can retrain or further train the network according to the actual situation of debris flows in the region until the purpose of accurately zoning a potential sudden debris flow risk is realized.

However, this article still has some limitations. Although this article has comprehensively considered various physical factors and the characteristics of debris flow disasters to select evaluation indicators, the selection of indicators still has a certain degree of subjectivity and may have certain errors. When applied to larger areas in practice, the generalization ability of the model still needs further verification. Future research will further expand and improve the evaluation index system, enhance model generalization ability, and consider the impact of environmental changes. At the same time, strengthen data collection and organization, continuously improve and update the basic database, and provide more comprehensive data support for the model.

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