

## *Retraction*

# **Retracted: Integration and Fusion of Geologic Hazard Data under Deep Learning and Big Data Analysis Technology**

### **Complexity**

Received 19 December 2023; Accepted 19 December 2023; Published 20 December 2023

Copyright © 2023 Complexity. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] F. He, C. Liu, and H. Liu, "Integration and Fusion of Geologic Hazard Data under Deep Learning and Big Data Analysis Technology," *Complexity*, vol. 2021, Article ID 2871770, 10 pages, 2021.

## Research Article

# Integration and Fusion of Geologic Hazard Data under Deep Learning and Big Data Analysis Technology

Feng He,<sup>1</sup> Chunxue Liu ,<sup>1</sup> and Hongjiang Liu<sup>2</sup>

<sup>1</sup>School of Urban and Environmental Sciences, Yunnan University of Finance and Economics, Kunming, Yunnan 650221, China

<sup>2</sup>School of Tourism, Leshan Normal University, Sichuan, Leshan 614000, China

Correspondence should be addressed to Chunxue Liu; [chunxueliu@ynufe.edu.cn](mailto:chunxueliu@ynufe.edu.cn)

Received 26 April 2021; Accepted 17 June 2021; Published 12 July 2021

Academic Editor: Zhihan Lv

Copyright © 2021 Feng He et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

To discuss the analysis and evaluation of highway landslides, the application of data mining methods combined with deep learning frameworks in geologic hazard evaluation and monitoring is explored preliminarily. On the premise of optimizing the processing of landslide images, first, the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) based on the natural statistical characteristics of the spatial domain is introduced, which is initially combined with Super-Resolution Convolutional Neural Network (SRCNN). Then, the AlexNet is fine-tuned and applied to highway landslide monitoring and surveying. Finally, an entropy weight gray clustering evaluation method based on data mining analysis is proposed, and the performances of several methods are verified. The results show that the average score of the BRISQUE algorithm in Image Quality Assessment (IQA) is above 0.9, and the average running time is 0.1523 s. The combination of BRISQUE and SRCNN can improve the image quality significantly. After fine-tuning, the recognition accuracy of AlexNet for landslide images can reach about 80%. The evaluation method based on gray clustering can effectively determine the correlation between soil moisture content and slope angle and thereby be applied to the analysis and evaluation of highway landslides. The results are beneficial to the judgment and assessment of highway landslide conditions, which can be extended to research on other geologic hazards.

## 1. Introduction

With the prompt development of advanced technologies, the quality of human life has been improved significantly. In the meantime, the excessive utilization of natural resources has caused a series of problems, such as geologic hazards and other natural disasters. Of all the kinds of geologic hazards, landslides cause the greatest losses to human society [1, 2]. According to official data, in 2016, there were 7,403 landslides across China, and the resulting economic losses were even more serious. Therefore, it is of great significance to evaluate, predict, and prevent landslide disasters. To analyze the landslides effectively, higher requirements are put forward for the quality of images involved. It is extremely difficult to understand the actual disaster situations only by visual observation. Therefore, applying image enhancement technology to the monitoring and survey of geologic hazard is necessary [3, 4].

Meanwhile, effective assessment of disasters is also the key to preventing and mitigating disasters.

At present, experts and scholars have researched the prevention and evaluation of landslide disasters. Darya et al. (2017) employed remote sensing technology to quantitatively assess regional-scale landslide disasters under the premise of insufficient data; through an automatic identification method, the susceptibility and damage of landslides with 30-year time series obtained by satellite remote sensing data were evaluated; finally, the results suggested that satellite remote sensing had huge potential in acquiring temporal and spatial information about landslides, which could improve landslide hazards effectively, especially in areas with insufficient data such as Kyrgyzstan [5]. Su et al. (2017) tested the influence of coal mining on landslides in coal-mining areas by comparing the landslide sensitivity maps drawn by three nonlinear methods; the results revealed that the Support Vector Machine (SVM) model had better

prediction efficiency; several major factors, including rock nature, distance from the highway, slope angle, elevation, and land-use types, were the most suitable condition factors affecting the mapping of landslide susceptibility [6]. Liu et al. (2018) adopted Tianshui City in Gansu Province, China, as the research object to analyze and discuss the assessment of potential earthquake landslide disasters; through the empirical attenuation relationship, the peak ground acceleration of two specific earthquake scenarios was estimated, and the results showed that an earthquake with a magnitude of 7.0 would cause more slope instability around Tianshui City [7]. For the natural disasters of debris flows and landslides caused by heavy rainfall, Fan et al. (2017) proposed a simplified physics-based debris flow runoff model and a new hydraulic and mechanical trigger model, which provided a temporal and spatial resolution framework for real-time disaster assessment [8]. Many scholars have analyzed and discussed the landslides, but research on applying big data mining and analysis methods to landslides is rare. In the meantime, there is less research that combines big data technology and deep learning on landslides.

On this basis, to explore the evaluation and analysis of highway landslides, the Image Quality Assessment (IQA) algorithm of deep learning without image reference set is introduced. Similarly, the gray clustering assessment method based on data mining analysis is introduced to study the monitoring and survey of highway landslides. The results are expected to provide an effective method for the prevention and control of highway landslide geologic hazards.

## 2. Method

**2.1. Image Processing Optimization Algorithm Based on Mobile Machine Vision.** Position and imaging are the two major imaging applications of machine vision. The camera completes imaging through the projection method. The distance between the camera and the detected object determines the clarity and affects the brightness of the final image [9]. For related objects, the brightness value of the image formed on the surface of the object is affected by the microstructure composition of the object surface, the change in the incident light distribution, and the relative orientation between the object and the light source. This induces the difference in the radiation intensity received by the machine vision; in addition to the influence of environmental factors, the final image quality will be damaged. This is especially common in geologic hazards such as highway landslides; therefore, the defogging of the image is more important. At present, the referenceless evaluation of defogging algorithms based on image quality enhancement has no unified standards. Generally, the methods include subjective evaluation and objective scoring. Among the evaluation indicators for images, the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) based on the natural statistical characteristics of the spatial domain is a referenceless IQA method. It assesses image quality by extracting Mean Subtracted Contrast Normalized (MSCN) coefficient from the image, thereby fitting the Gaussian distribution model and calculating the relevant feature values; consequently, the

referenceless IQA is realized [10, 11]. The equation for MSCN is

$$\text{MSCN} = \frac{I(i, j) - u(i, j)}{\sigma(i, j) + C}. \quad (1)$$

In (1),

$$u(i, j) = \sum_{k=-K}^K \sum_{l=-L}^L w_{k,l} I_{k,l}(i, j), \quad (2)$$

$$\sigma(i, j) = \sqrt{\sum_{k=-K}^K \sum_{l=-L}^L w_{k,l} (I_{k,l}(i, j) - u(i, j))^2}. \quad (3)$$

In (2) and (3),  $i$  and  $j$  represent the coordinates of the corresponding image, where  $C = 1$  and  $K = L = 3$ .

The equation for the generalized Gaussian distribution is

$$f(x; \alpha, \sigma^2) = \frac{\alpha}{2\beta\Gamma(1/\beta)} \exp\left(-\left(\frac{|x|}{\beta}\right)^\alpha\right). \quad (4)$$

As for highway landslides occurring in mountains, since the environment of mountains is often foggy, noises will exist in images directly captured by Unmanned Aerial Vehicles (UAVs). Therefore, the dark channel defogging algorithm is introduced. In this algorithm, the equation for dark channel  $J^d$  is expressed and calculated as

$$J^d(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} J^c(y)). \quad (5)$$

In (5),  $J^c$  represents the various channels in the RGB image and  $\Omega(x)$  shows the size of the filter window with pixel  $x$  as the center. After the minimum value of the three channels is obtained by the above equation, the image is displayed as a grayscale image. Then, the grayscale image is subjected to a minimum filtering process. The radius corresponding to the filtering can be expressed as

$$J(x) = \frac{I(x) - A}{\max(p(x), p^0)} + A. \quad (6)$$

In (6),  $I(x)$  represents the originally input image,  $J(x)$  represents the final output clear image,  $A$  represents the light component corresponding to the atmosphere, and  $p(x)$  represents the projection rate.

On this basis, the image super-resolution reconstruction technology is applied. The principle of this technology depends on low-quality images to obtain high-quality images through calculations, thereby improving the accuracy of image recognition. In this method, the Super-Resolution Convolutional Neural Network (SRCNN) is one of the typical representative algorithms. SRCNN is composed of three convolution layers. By using low-quality images as input, it can directly output high-quality images [12, 13]. Specifically, the structure of the algorithm mainly includes image feature block extraction, nonlinear feature mapping, and image reconstruction. The equations for reconstructing the overall high-quality image are as follows:

$$F_1(Y) = \max(0, W_1 * Y + b_1), \quad (7)$$

$$F_2(Y) = \max(0, W_2 * F_1(Y) + b_2), \quad (8)$$

$$F(Y) = W_3 * F_2(Y) + b_3, \quad (9)$$

$$L(\theta) = \frac{1}{n} \sum_{i=1}^n \|F(Y_i, \theta) - X_i\|^2. \quad (10)$$

In (7)–(10),  $b$  represents the weight,  $W_1$  represents the filter with a size of  $64 * 9 * 9$ ,  $W_2$  represents the filter with a size of  $64 * 1 * 1$ ,  $W_3$  represents the filter with a size of  $32 * 5 * 5$ ,  $L(\theta)$  represents the mean square loss function,  $n$  represents the total number of training samples, and  $X_i$  represents the reconstructed image.

**2.2. Highway Landslide Monitoring Based on Fine-Tuning AlexNet Deep Learning Network.** At present, most of the surveying and mapping works are realized with the aid of remote sensing technology. For highway landslides, the overall conditions can be understood through this technology. Furthermore, experts in this field can assess the disaster situation and propose corresponding countermeasures based on the photos obtained by remote sensing technology. However, the overall application of remote sensing technology takes a long time, and each image needs to be confirmed by experts before measure implementation. This is detrimental to the timely assessment of road safety. Chen used a deep learning framework to achieve rapid identification of landslides. Web crawler is a targeted program that can quickly obtain information such as images or information [14]. The application of this technology can significantly reduce the workload [15, 16]. According to the corresponding crawler rules, the necessary images or information can be obtained by entering the keywords of “aerial photography + geologic hazard + road landslide” in the search engine. However, in the meantime, the web crawler has the problem of more interference information. Therefore, it is necessary to remove the noise, eliminate the invalid images, and retain the higher-quality images.

AlexNet is a deep learning model. The overall structure of the network model includes five convolution layers, three pooling layers, and one fully connected layer [17, 18]. In the survey and monitoring of highway landslides, the corresponding image input size in AlexNet is  $224 * 224 * 3$ . The first convolution layer contains 96 convolution kernels with a size of  $11 * 11 * 3$ , and the corresponding step size is 4. Then, the ReLU function is adopted for activation, and the corresponding equation is

$$f(x) = \begin{cases} 0 & x < 0 \\ x & x \geq 0 \end{cases} \quad (11)$$

The next step is the pooling operation and the normalization operation. Findings of Gao et al. (2018) proved that, through the pooling operation, the dimensionality reduction of the feature area can be realized, which helps avoid the appearance of overfitting [19]. The normalization

operation is the unified processing of the data. The goal of this operation is to reduce the amount of data calculation and improve the generalization and overfitting of data. The size of the second convolution layer is  $5 * 5 * 3$ , after which the activation processing repeats, followed by the same pooling and normalization operations. The size of the third to fifth convolution layers is  $3 * 3 * 3$ . Specifically, the third and fourth layers use 384 convolution layers, and the fifth layer uses 256 convolution layers. The last is the output of the fully connected layer, and the final output is 1000. However, since there are few authoritative samples on highway landslides, if the deep learning framework is used directly, overfitting will occur during the training process. Therefore, the fine-tuning method is introduced to adjust the relevant parameters in AlexNet. Specifically, it is mainly the adjustment of the parameters in the fully connected layer. Since the image types in the database only include landslides and nonlandslides, the output of the AlexNet fully connected layer is adjusted to 2. After fine-tuning, the specific settings of AlexNet parameters are shown in Table 1.

**2.3. Gray Clustering Disaster Assessment Method Based on Data Mining.** Gray theory has good applicability in the solution of uncertainty problems. Gray clustering is a data mining method for classifying unclear data systems, which has been widely used in the era of big data [20, 21]. Highway landslides are affected by many factors; meanwhile, these factors are closely connected. Due to the difficulty in data collection, the slope, lithology, vegetation coverage, and height are chosen as indicators for clustering analysis, and the geologic hazard of highway landslides is divided into four danger levels: normally dangerous, moderately dangerous, highly dangerous, and extremely dangerous.

In statistical analysis, entropy is a measurement used to express variable uncertainty [22]. Assuming that there is a discrete random variable of  $X$ , the corresponding probability distribution can be expressed as

$$P(X = x_i) = P_i, \quad i = 1, 2, \dots, n. \quad (12)$$

On this basis, the entropy is

$$E(X) = - \sum_{i=1}^n P_i \log P_i. \quad (13)$$

A larger entropy value corresponding to the variable indicates a higher degree of its existence uncertainty. Therefore, in the process of highway landslide disaster assessment, the entropy weight theory can be adopted to determine the feature weight. Combining entropy with the gray clustering method can calculate the landslide clustering coefficient. Through the objective data information and gray attribute characteristics contained in each feature value, the disaster level corresponding to each landslide can be obtained, which can provide a good reference for disaster assessment. In summary, the proposed evaluation content and system of highway landslide disaster based on entropy weight and gray clustering are shown in Figure 1.



TABLE 1: Parameter setting of fine-tuned AlexNet.

Parameter composition	Iterations	Test interval	Initial learning rate	Learning rate change	Learning rate adjustment	The maximum number of iterations	Weight decay
Corresponding value	9	25	$1 \times 10^{-3}$	0.1	200	2500	$5 \times 10^{-4}$

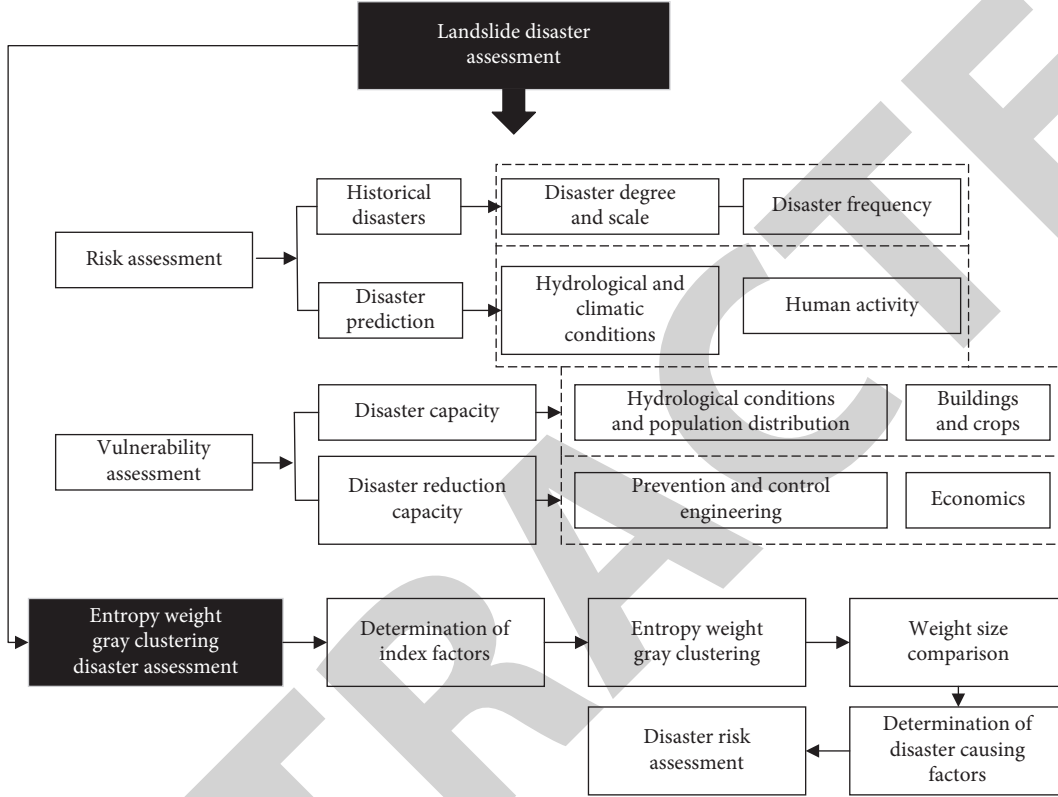


FIGURE 1: The evaluation content and system of highway landslide disaster based on entropy weight and gray clustering.

**2.4. Simulation and Result Analysis.** To evaluate the effect of the BRISQUE algorithm, the score and running time for different image distortion types are utilized as benchmarks, and the common IQA methods are compared and analyzed. Here, the peak signal-to-noise ratio (PSNR), structural similarity (SSIM), generalized regression neural network (GRNN), and natural image quality evaluator (NIQE) are chosen. For image indicators of different quality, the JPEG compression (JPEG), White noise (WN), JPEG 2000 compression (JP2K), fast fading (FF), and Gaussian blur (BLUR) are chosen. The average running time of several image quality evaluation algorithms is compared and analyzed.

Although highway landslides are affected by multiple factors, water has the greatest impact on landslides. The increase in soil moisture content changes the soil structure of the rock and soil, and the instability of highway slopes increases. In general, landslide disasters occur only on slopes, and the possibility of disasters on slopes with different slopes is also different. The SLIDE model is applied to the calculation of slope stability in the evaluation. The expression and calculation corresponding to this model are

$$FS = \frac{\tan \phi}{\tan \alpha} + \frac{c + c(t)}{\gamma_s Z_t \sin \alpha \cos \alpha}. \quad (14)$$

In (14), FS represents the stability coefficient,  $Z_t$  represents the infiltration depth corresponding to time,  $c(t)$  represents the cohesive force of the soil surface at time  $t$ ,  $\gamma_s$  represents the soil capacity per unit,  $\phi$  represents the soil friction angle, and  $\alpha$  represents the slope.

The stability indicator of landslide can be expressed as

$$SI = FS_{\min} = \frac{C'_{\min} + [1 - \min(X_{\max}(a/\sin \theta), 1) \cos^2 \theta \cdot t_{\min}]}{[1 + \min(X_{\max}(a/\sin \theta), 1) \cos \theta \cdot \sin \theta]}. \quad (15)$$

In (15),  $C$  represents the cohesion of the soil,  $\theta$  corresponds to the inclination of the sliding surface, and  $a$  represents the catchment area.

During the experiment, the flying height of the UAV is set to 6.5 m, and the height of the simulated landslide is set to 1.5 m; as for the main parameter of the camera, the shutter is set to 200, and the imaging magnification is 2 times. Given that the landslide has the same water content, the landslide slope is set to 1°, 4°, 10°, 16°, 22°, and 28° for photo-taking.

Given that the landslide has the same slope, the soil moisture content is set to 7.3%, 15.1%, 18.6%, 21.7%, 26.2%, and 30.7% for photo-taking. The overall shooting environment is under the shade of trees. This is to simulate a bad weather scene. The shooting time is chosen to be a day with a good view. During the experiment, the image enhancement method used is the proposed mobile machine vision method. Based on the fine-tuned AlexNet highway landslide survey model and entropy weight gray clustering analysis under data mining, the landslide slope and soil moisture content are taken as indicators to evaluate and predict the landslide disasters. The research results are universal for landslides so that the research method proposed is suitable for data image analysis of geologic hazards.

### 3. Results and Discussion

**3.1. IQA Results Based on Mobile Machine Vision.** Among the different types of image distortion, the comparison results of the BRISQUE algorithm based on machine vision and the common image quality evaluation are shown in Figure 2.

The distribution changes of the score results and the results of the average running time of the algorithm indicate that the score corresponding to the BRISQUE algorithm is very close to that of the PSNR method and the SSIM method; meanwhile, its average running time is slower, which is about 0.1 s, but this is within the acceptable fluctuation range. Among the various image distortion types, the average score of BRISQUE is above 0.9, and the final average running time is 0.1523 s. In terms of the IQA results, BRISQUE is better than the NIQE method. In general, the BRISQUE algorithm has better results than other conventional methods in IQA.

The above results show that, under the premise of no reference, this IQA method exhibits excellent performance compared with the traditional full-reference IQA method. Therefore, it is feasible to use the IQA algorithm as an indicator. Moreover, combining this method with the SRCNN algorithm based on image super-k reconstruction can obtain high-quality and clear images. Therefore, it plays a guiding role in analyzing highway landslide conditions and evaluating geologic hazards. Figure 3 demonstrates the actual effect of the image before and after processing using the machine vision image optimization combining dark channel dehazing and super-resolution reconstruction based on the BRISQUE algorithm.

**3.2. Highway Landslide Monitoring Effect Based on Fine-Tuning AlexNet Deep Learning.** For some of the highway landslide photos in the Baidu image library, the AlexNet deep learning highway landslide monitoring method will be fine-tuned to verify the generalization ability of the deep learning model. The corresponding relationship between the obtained photos and the recognition situations is shown in Figure 4.

The correspondence between the highway landslide photos and the recognition results of the fine-tuned AlexNet deep model suggest that, for Figure 4(a), among the

recognized results by the fine-tuned AlexNet deep learning model, 65.06% is landslide; for Figure 4(b), 48.34% is landslide; for Figure 4(c), 94.4% is landslide; for Figure 4(d), 94.32% is landslide. In general, the accuracy of the fine-tuned AlexNet deep learning model for highway landslide recognition is about 80%.

AlexNet is a deep learning model. The special structure of this model gives it special performance. It completes the training process based on big data analysis, and the application of nonlinear activation function enables the model to have a faster convergence speed. After fine-tuning, the model can effectively avoid the occurrence of overfitting in the application process. Through the adjustment of the parameters in the fully connected layer, the deep learning model is given stronger pertinence, thereby expanding the scope of application in actual scenarios. Its high recognition accuracy can effectively identify the actual condition of highway landslides, which is beneficial to the analysis, evaluation, and prediction of the geologic hazard. Although there may be misjudgments for photos that are yellowish or have a wide shooting range, the recognition and judgment of the images will not be affected.

**3.3. Analysis of Monitoring Results of Highway Landslides.** The soil moisture content and landslide slope are the baselines. The fitting regression results of the relative error of highway landslide survey under the premise of different angles and different moisture contents are shown in Figures 5(a)–5(d).

According to the curve changes of several data regression fittings, the regression fitting corresponding to the first time has the optimal effect, and the proportion of relative error corresponding to this regression fitting is also at a low level. There are some differences at different angles. For example, when the slope angle is  $10^\circ$ , the relative error of the first regression fitting is about 7.5%; when the slope angle is  $22^\circ$ , the relative error of the first regression fitting is about 24.8%. For the first regression fitting, if the remaining differences can be removed, a better fitting effect may be obtained, but at the same time, the overall fitting effect will decrease. Under the premise of different slope angles, the relative error obtained by the fitting is distributed in a relatively stable range; specifically, it is in the range of 1% to 22%.

For the geologic hazard of highway landslides, soil moisture content and slope angle are the two most significant influencing factors; therefore, it is necessary to analyze the relationship between them [23, 24]. The effectiveness of the gray clustering evaluation algorithm based on entropy weight is analyzed by the method of four-fold regression fitting. According to the overall distribution and changes of the model error obtained by linear fitting, the relationship between the soil moisture content and the slope angle can be judged, which is close to linear. On this basis, the slope angle of highway landslides can be detected quickly so that the soil moisture content will also be controlled, which is critical for the evaluation and analysis of highway landslide conditions.

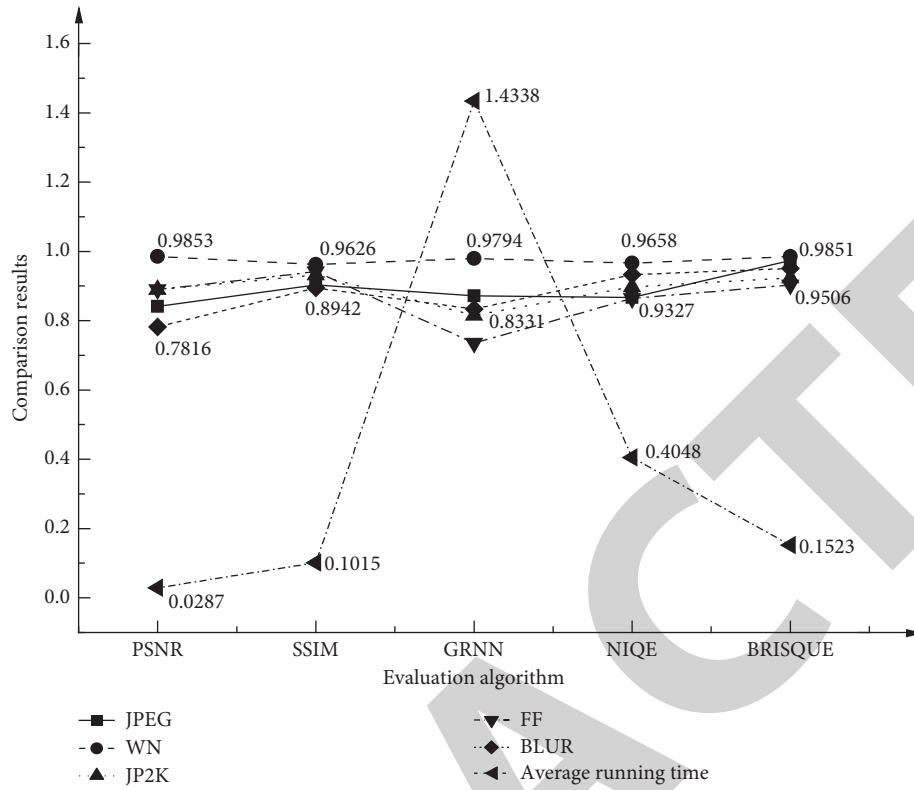
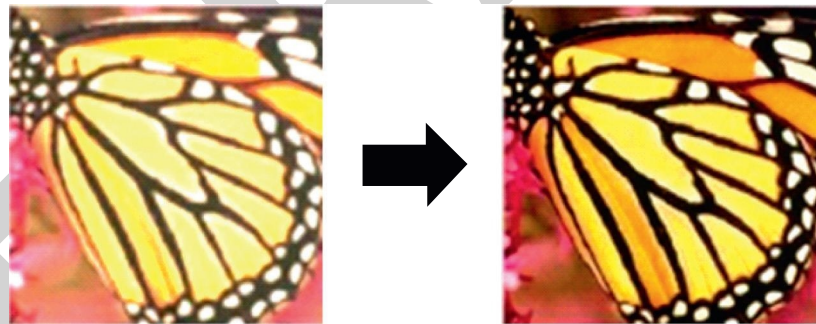


FIGURE 2: Comparison results of several image quality evaluation algorithms.



Input image: blur

Reconstructed output image: clear

(a)

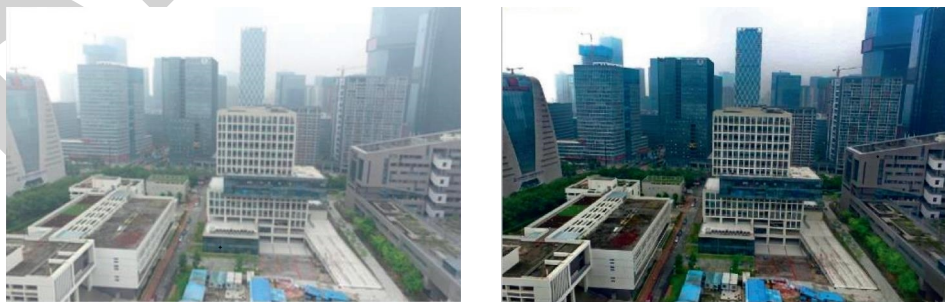


Image before processing

Processed image

(b)

FIGURE 3: Comparison of actual image effects before and after optimization reconstruction.

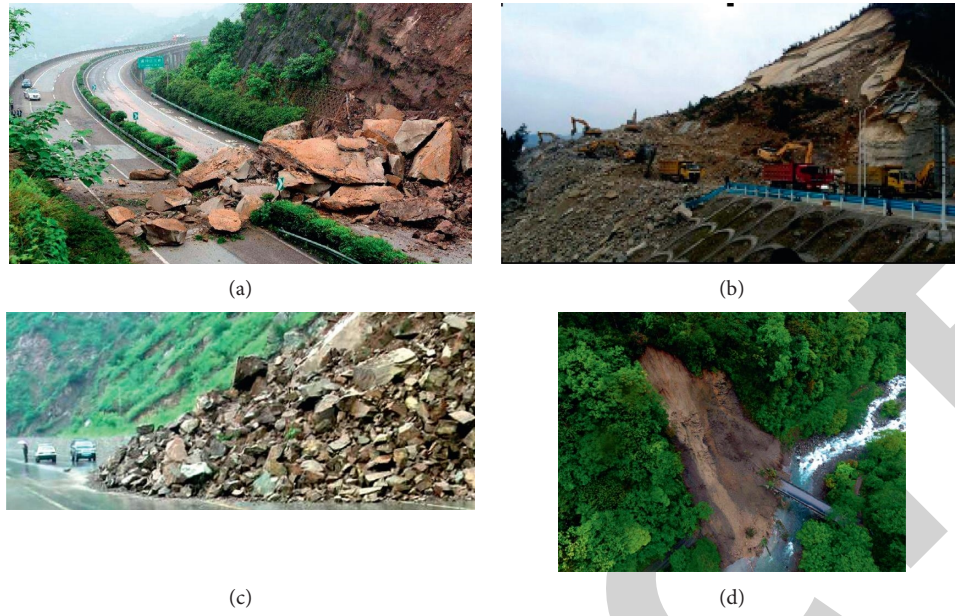


FIGURE 4: Fine-tuning the recognition results of the AlexNet deep learning model. (a) 65.06%, (b) 48.34%, (c) 94.4%, and (d) 94.32%.

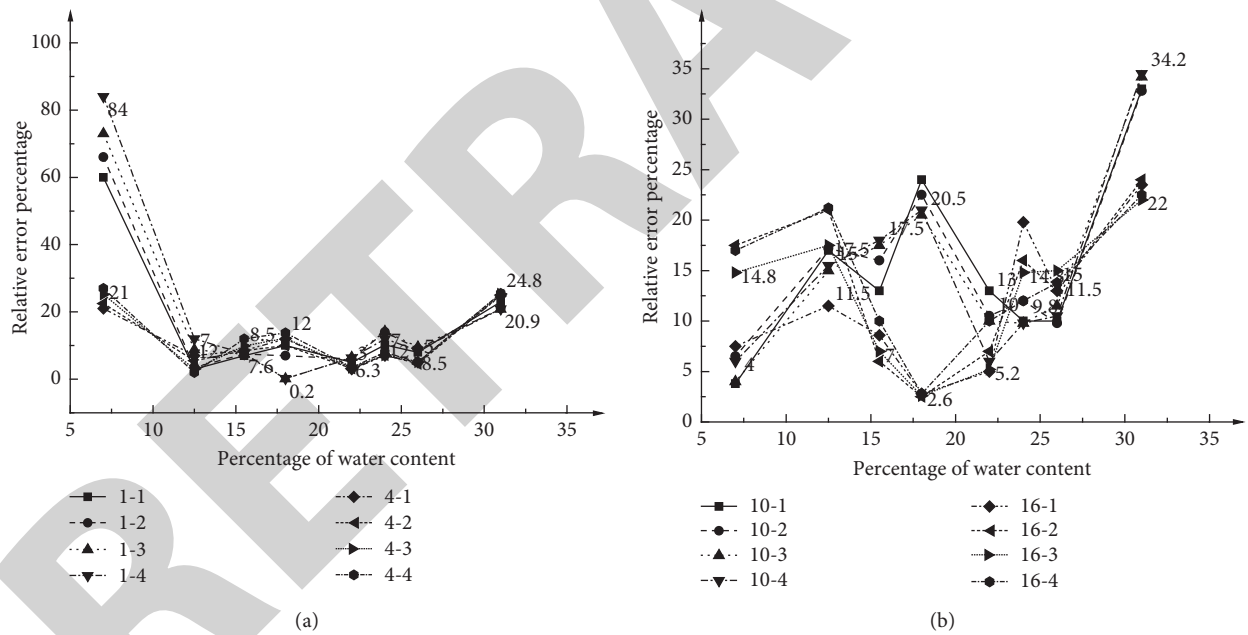


FIGURE 5: Continued.



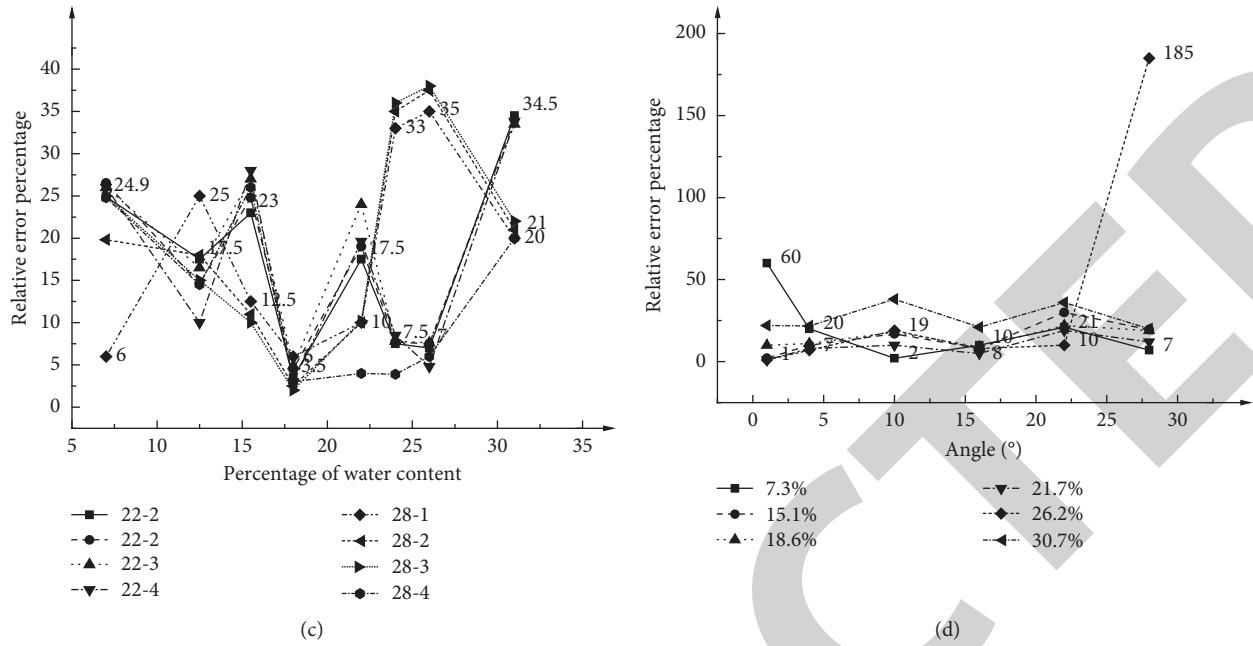


FIGURE 5: The fitting regression results of the relative error of highway landslide survey under different angles and moisture content: (a) slope angles are  $1^\circ$  and  $4^\circ$ ; (b) slope angles are  $10^\circ$  and  $16^\circ$ ; (c) slope angles are  $22^\circ$  and  $26^\circ$ ; (d) angle-error under different moisture content (1-1 represents the first regression fitting result when the slope angle is  $1^\circ$ , 1-2 represents the second regression fitting result when the slope angle is  $1^\circ$ , 7.3% indicates the soil moisture content, and the rest may be deduced by analogy).

#### 4. Result Analysis and Discussion

Under the condition of natural dead weight, the mountain is in an understable-stable state, and it is easy to shear and damage at the toe of the slope under heavy rain conditions, forming a landslide. At present, the principle of landslide treatment measures in China is to increase the antisliding force and reduce the sliding force to increase the stability coefficient. The following engineering measures are recommended for landslide treatment [25, 26]. (1) All-round drainage: the surface water is led out, including the surface drainage outside the sliding area and the underground drainage, to reduce the groundwater level in the sliding area. Such drainage measures often use drainage ditches and intercepting ditches. Underground drainage can greatly reduce the pore water pressure and, simultaneously, improve the sliding resistance by increasing the effective normal stress. (2) Slope cutting and load reduction: slope cutting and load reduction is an inexpensive method. Similarly, soil landslides and bedding landslides are widely used. By cutting the slope of landslide bodies, the sliding force can be reduced and the stability of the slope can be improved. However, the antislip part at the slope foot cannot be reduced. The following methods are commonly used: one is to reduce the slope by grading to leave the platform; the other is to directly reduce the slope; the third is to reduce the slope through the balance of excavation and filling, and simultaneously, drainage can be set for the backfill part if necessary. (3) Supporting and retaining structure: if the slope cannot be stabilized by changing the geometry and drainage of the slope, the supporting and retaining structure can be used, such as building retaining walls (anchors,

retaining walls, gravity retaining walls, and anchor cable retaining wall), passive antislid piles, wooden cage block stone walls, reinforced gabion retaining walls, retaining walls with polymer or metal strips or plates and other reinforced materials (reinforced soil retaining walls), slopes surface ecological protection system, in situ concrete continuous wall pouring on the side slope, and flexible slope protection structure (steel rope net to intercept falling rocks). (4) Internal reinforcement of the slope: internal reinforcement measures for the slope include micropiles, lattice anchors with the same structure, soil nails, rock anchors, reinforced soil, anchor cables (with or without prestress), grouting, soil anchors, and cement piles. The piles that penetrate the sliding body and deep into the sliding bed are called antislid piles, which can support the sliding body. The antislid piles are required to provide enough shear resistance. There are two types of antislid piles: single piles and pile groups. Piles can control shallow landslides. However, in deep landslides, the pile driving may deviate in other directions instead of along the vertical direction, which will disturb the adjacent and underlying materials and eventually lead to further development of the pile tip sliding surface. Antislid piles should be provided with drainage, and the drainage ditch can be filled with sand and drained by pipes with holes. Projects that use antislid piles as antislip support require a short construction period, save labor and materials, bring less damage to the mountain, and are safe and convenient. (5) Planting trees and grasses: planting trees and grasses in the landslide area also plays a good protective role in landslide management. The most important thing for planting trees is to prevent shallow landslides. Besides, planting trees and grasses will also reduce the penetration of

surface water into the slope, which will reduce the sliding on the deep sliding surface, thereby contributing to the stability of the landslide.

## 5. Conclusion

The highway landslide, a representative geologic hazard, has been explored. The mobile machine vision image quality optimization method is introduced, and the AlexNet deep learning monitoring framework is fine-tuned. The entropy weight gray clustering analysis based on big data mining is introduced into the landslide condition assessment. The results show that the BRISQUE algorithm without image reference has good results in IQA. The fine-tuning of the AlexNet deep learning framework has high recognition accuracy in highway landslide surveys. The application of the entropy gray clustering evaluation method can analyze the correlation between soil moisture content and slope angle effectively, which provides an effective method for the survey, monitoring, analysis, and evaluation of geologic hazards.

However, due to the influence of actual experimental conditions, the authenticity and effectiveness of road landslide simulation are lacking, and there are some errors during data processing. In addition, the big data mining and analysis method, as well as the deep learning framework, are only in a preliminary combination. The soil moisture content and slope angle have not been calculated subsequently. Future explorations will deepen and strengthen these aspects.

## Data Availability

All data are fully available without restriction.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This work was supported by the Scientific Research Fund Project of Yunnan Provincial Department of Education “Earthquake relief asymmetric information game dynamics model in complicated landforms” (no. 2020J0381).

## References

- [1] C. W. Chen, T. Oguchi, Y. S. Hayakawa et al., “Sediment yield during typhoon events in relation to landslides, rainfall, and catchment areas in Taiwan,” *Geomorphology*, vol. 303, pp. 540–548, 2017.
- [2] W. M. Abdulwahid and B. Pradhan, “Landslide vulnerability and risk assessment for multi-hazard scenarios using airborne laser scanning data (LiDAR),” *Landslides*, vol. 14, no. 3, pp. 1057–1076, 2017.
- [3] K. Wang, S. Zhang, R. Delgadotellez et al., “A new slope unit extraction method for regional landslide analysis based on morphological image analysis,” *Bulletin of Engineering Geology and the Environment*, vol. 78, no. 6, pp. 4139–4151, 2019.
- [4] C. Y. Chiu, T. S. Quah, S. C. Hsu et al., “Site investigation and analyses of landslide range using particle image velocimetry,” *Journal of Testing and Evaluation*, vol. 45, no. 1, pp. 196–207, 2017.
- [5] G. Darya, R. Sigrid, B. Robert et al., “Evaluation of remote-sensing-based landslide inventories for hazard assessment in southern Kyrgyzstan,” *Remote Sensing*, vol. 9, no. 9, p. 943, 2017.
- [6] Q. M. Su and S. M. Zhao, “Comparative assessment of three nonlinear approaches for landslide susceptibility mapping in a coal mine area,” *ISPRS International Journal of Geo-Information*, vol. 6, no. 7, p. 228, 2017.
- [7] J. Liu, J. Shi, T. Wang et al., “Seismic landslide hazard assessment in the Tianshui area, China, based on scenario earthquakes,” *Bulletin of Engineering Geology and the Environment*, vol. 77, no. 3, pp. 1263–1272, 2018.
- [8] L. Fan, P. Lehmann, B. Mcardell et al., “Linking rainfall-induced landslides with debris flows runout patterns towards catchment scale hazard assessment,” *Geomorphology*, vol. 280, pp. 1–15, 2017.
- [9] Q. Mark, S. Emanuele, and R. David, “Miniaturisation of pressure-sensitive paint measurement systems using low-cost, miniaturised machine vision cameras,” *Sensors*, vol. 17, no. 8, p. 1708, 2017.
- [10] L. S. Chow and H. Rajagopal, “Modified-BRISQUE as no reference image quality assessment for structural MR images,” *Magnetic Resonance Imaging*, vol. 43, p. 74, 2017.
- [11] B. Bauman and P. Seeling, “Spherical image QoE approximations for vision augmentation scenarios,” *Multimedia Tools and Applications*, vol. 78, no. 13, pp. 1–23, 2019.
- [12] K. Umehara, J. Ota, and T. Ishida, “Application of super-resolution convolutional neural network for enhancing image resolution in chest CT,” *Journal of Digital Imaging*, vol. 31, no. 4, pp. 441–450, 2018.
- [13] L. Mukherjee, H. D. Bui, A. Keikhosravi et al., “Super-resolution recurrent convolutional neural networks for learning with multi-resolution whole slide images,” *Journal of Biomedical Optics*, vol. 24, no. 12, pp. 1–15, 2019.
- [14] Y. Chen, “Application of the best evacuation model of deep learning in the design of public structures,” *Image and Vision Computing*, vol. 102, Article ID 103975, 2020.
- [15] Y. Zheng, J. Zhu, and C. Lai, “A SEIQR model considering the effects of different quarantined rates on worm propagation in mobile internet,” *Mathematical Problems in Engineering*, vol. 2020, Article ID 8161595, 16 pages, 2020.
- [16] H. Zhou and W. Guo, “A stochastic worm model,” *Telecommunication Systems*, vol. 64, no. 1, pp. 135–145, 2017.
- [17] X. Dai, H. Yin, and N. K. Jha, “NeST: a neural network synthesis tool based on a grow-and-prune paradigm,” *IEEE Transactions on Computers*, vol. 68, no. 10, pp. 1487–1497, 2019.
- [18] H. K. Suh, I. Joris, H. J. Willem et al., “Transfer learning for the classification of sugar beet and volunteer potato under field conditions,” *Biosystems Engineering*, vol. 174, pp. 50–65, 2018.
- [19] X. Gao, S. C. Zhao, and Y. B. Shao, “An analysis of the current status and countermeasures of bike-sharing in the background of Internet,” in *Proceedings of the International Conference on Virtual Reality and Intelligent Systems (ICVRIS)*, pp. 469–472, Hunan, China, August 2018.
- [20] G. Liu, J. Yang, Y. Hao et al., “Big data-informed energy efficiency assessment of China industry sectors based on K-means clustering,” *Journal of Cleaner Production*, vol. 183, pp. 304–314, 2018.

- [21] S. Park, S. J. Lee, and S. Jun, "Patent big data analysis using fuzzy learning," *International Journal of Fuzzy Systems*, vol. 19, no. 4, pp. 1158–1167, 2017.
- [22] C. Hur and S. Kang, "Entropy-based pruning method for convolutional neural networks," *Journal of Supercomputing*, vol. 75, no. 6, pp. 2950–2963, 2019.
- [23] M. M. Crawford, L. S. Bryson, E. W. Woolery et al., "Long-term landslide monitoring using soil-water relationships and electrical data to estimate suction stress," *Engineering Geology*, vol. 251, pp. 146–157, 2019.
- [24] H. Y. Lo and L. F. Liu, "On the analytical solutions for water waves generated by a prescribed landslide," *Journal of Fluid Mechanics*, vol. 821, pp. 85–116, 2017.
- [25] J. H. Luo, D. C. Mi, H. F. Huang et al., "Intelligent monitoring, stability evaluation, and landslide treatment of a carbonaceous mudstone and shale slope in Guangxi, China," *International Journal of Safety and Security Engineering*, vol. 10, no. 3, pp. 373–379, 2020.
- [26] F. Xu, X. Yang, and J. Zhou, "Dam-break flood risk assessment and mitigation measures for the Hongshiyuan landslide-dammed lake triggered by the 2014 Ludian earthquake," *Geomatics, Natural Hazards and Risk*, vol. 8, no. 2, pp. 803–821, 2017.