Research Article

Slope Shape and Edge Intelligent Recognition Technology Based on Deep Neural Sensing Network

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In order to solve the problem that the slope surface diseases cannot be accurately identified, which cannot be repaired in time and cause serious slope disasters, a slope intelligent recognition technology based on deep neural network is proposed. Based on convolutional neural network (CNN) theory, the technology adopts the transfer learning method to solve the overfitting problem of slope surface samples, which is difficult to obtain a large number of marked samples, and verifies the proposed model by experiment. The results are as follows: the recognition results of various slope surface diseases by ResNet-18 network are higher than AlexNet and VGG-16, with an average accuracy of 84.1%, and the recognition effect of cracks is the best. Under the same migration strategy, the detection accuracy of ResNet-18 is 96.3%, which is much higher than the other two, and the detection time is reduced by 15% on average. It is proved that the ResNet-18 model proposed can identify slope changes very effectively, so that workers can be timely dispatched for maintenance, reducing the possibility of disaster, which has great significance.

1. Introduction

Expressways play an important role in China’s land transportation and meet the basic travel requirements of residents [1]. The continuous acceleration of highway construction is followed by a large number of slope engineering. In remote mountainous areas with large area, highway is still the main transportation choice, and highway slope disaster will lead to casualties and loss of a lot of economic property of people [2].

Due to the slope surface disease that is not timely and effective governance caused by more serious disasters and accidents, endangering people’s lives and property losses often occur. Phase of the overall condition of the slope surface detection, so as to targeted, timely, and effective prevention and control of its disease, to avoid causing greater slope disasters is particularly important. In this case, the detection and identification of slope surface disease is an important prerequisite to avoid slope disaster effectively [3, 4].

At present, most people still choose the way of artificial inspection of the slope, focusing on the damage of the slope (retaining wall, drainage hole). In the environment where the slope is located in complex terrain, the slope angle is too steep, the slope is high, the inspection personnel can only choose to check the slope state on foot, which occupies a lot of manpower, and the work progress is slow but also has the potential of high risk [5]. With the modernization of highway construction, all kinds of signs show that the contradiction between the rapid growth of the demand for the effectiveness and rapidness of slope surface image recognition and the shortage of staff of slope experts and the lag of slope surface disease recognition and detection technology is becoming more and more serious. Therefore, it is urgent to find a new effective and feasible method of slope surface disease identification and detection to solve slope detection and prevention.

2. Literature Review

Conventional slope detection means are displacement monitoring, artificial observation, GPS measurement, and neural network detection [6].
Bao et al. proposed a GA-SVM model for edge prediction of slope stability. The optimization function of the genetic algorithm is used to expand the parameter search of support vector machine. Using the function of support vector machine, very good description of nonlinear, etc., to establish a prediction model, the example proves that the prediction effect is ideal. This is a simple, effective, and easily extended slope stability model [7]. Lin et al. take kinetic energy, resistance, and slope as input and input them to BP neural network. Full display of all the exploration skills of genetic algorithm can optimize the original weight and threshold of its network [8]. At the same time, for the analysis of the principal components, the multiple regression prediction model is constructed. Finally, the two predicted results are compared. BP can predict the movement distance of slope accurately and stably by using the genetic method to expand network optimization [9]. The prediction errors of the maximum horizontal and vertical movement distances less than 10% accounted for 86.67% and 93.33%, respectively. Based on the improved BP neural network, a prediction neural network model for slope stability is constructed for analysis by Kumar and Tiwari and Villaseor-Reyes et al., and the prediction accuracy of the model network is verified. The results show that there is little difference between the expected output and the real output, the constructed BP network can be applied to the stability detection of a mine slope, and excellent results have been achieved [10, 11].

In recent years, with the continuous progress of neural network technology, deep learning has been successfully applied to many applications in computer vision, such as image recognition. This technique has also been applied in the classification, identification, and detection of slope hazards [12].

In order to overcome the problem of handwritten digit recognition in bank check, Nanda et al. applied back propagation in neural network and further constructed LeNet-5 [13]. It includes the input layer and other basic structural layer models [14]. Held et al. used AlexNet to win the photo contest classification [15]. Since then, deep learning has developed rapidly and steadily in the key visual part of the computer. However, increasing the depth of CNN without hindrance is of no use to improving network fitting skills. Instead, it will backfire and cause the dilemma of network degradation. To overcome this dilemma, residual network proposed the identity mapping between modules in 2016, which can deepen the network to more layers and ensure the performance does not degrade [16, 17].

After continuous improvement, the theoretical basis of deep learning becomes more stable. The application of work in every field is very good, and the effect is very good [18]. Poulose et al. proposed the application of a new recursive CNN (RCNN) to face detection and recognition in color images [19]. The use of radial basis function neural network (RBFN) and its feedback application creates a very powerful CNN for facial recognition. The loop CNN first receives the image database as a 3D matrix, and after training, selects the closest faces with acceptable accuracy. In the experimental analysis, the comparison between cyclic CNN and traditional CNN shows the effectiveness of the proposed recursive CNN [20]. Sharma proposed the convolutional nerve with residual connection to perform the task of automatically identifying tree species from the scan image of wood core [21]. In these tasks, the correct recognition rate of the proposed model is 93% and 98.7%, respectively, which is 9% and 3% higher than the most advanced CNN-based model. With the continuous development of transfer learning means, scholars have gradually explored its application in real life scenes. In 2021, research on the correlation between photo identification and land has been continuously produced. Scholars have explored its application in real life scenarios, and there has been considerable research in image recognition, such as advocating a framework based on 50 layers of ResNet-50 for in-depth supervision of the screening of HEP-2 cell photographs. Select two publicly available photo sets and prelearn the ICPR2012 photo set to fine-tune the ICPR2016 photo set in the DSRN model, as the two are similar to the photo set. It proved to be state-of-the-art and superior to the ancient deep CNN (DCNN) method.

On the basis of the current research, this paper takes five common state types of slope surface collected as the research object and uses AlexNet, VGG-16, and ResNet-18 networks to conduct a preliminary study on slope surface image recognition. In order to solve the problem of network overfitting caused by insufficient number of slope surface data sets, transfer learning is used to solve this problem and improve the accuracy of classification recognition, so as to achieve the goal of accurate recognition of slope surface image.

3. The Research Methods

3.1. Image Recognition. Image processing and image recognition are the two most important parts of slope surface image disease recognition, as shown in Figure 1 [22]. The first step is the acquisition of slope surface image, especially for the identification of slope surface disease, which requires comprehensive collection of image data [23]. In order to better identify the images of cracks, water seepage, rockfalls, and landslides, it is necessary to collect the images containing these diseases. On the basis of the original image pretreatment to improve the image quality, so that the original image with representative features more prominent performance, feature extraction of image is the premise of slope surface disease recognition, which is very important for the whole slope surface disease recognition process. Slope surface image classification recognition is the last step, and there are a variety of classification operations, to combine with the actual problems of slope surface image for experimental analysis and selection.

3.2. Convolutional Neural Network. CNN was proposed in the 1990s. It is a kind of feedforward neural network. It not only has strong feature extraction performance but also the neurons only affect some of the surrounding neurons. Local perception and weight sharing are used to reduce the difficulty of CNN operation and improve the operation
respectively. The number of elements contained in the con-

The two most important operations of CNN are convo-

The shallow image features extracted from the pretrained con-

AlexNet’s model is the most classic and basic model in

speed. CNN is generally composed of the input layer, which

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Figure 1: Process of image recognition and classification.

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(2) Use the 5 subsets included as the training set of the network and save the remaining 1 as the test set.

(3) Training the slope surface recognition model and showing the accuracy of the model test set $P_1$.

(4) Select different test set data for each training and repeat the above (2) and (3) 5 times.

(5) The values of $P_1$-$P_6$ are obtained in turn to obtain the average value, that is, the correct accuracy of the $P$ model.

4. Results Analysis

4.1. Image Sets of Slope Surface Are Classified and Compared with Different Network Models. Before the slope surface image is input, the unified resize and padding are used to process the image. The input image of the model is $224 \times 224$ GBR size. Adam optimizer was selected for gradient
descent operation, and then parameters were set. Finally, AlexNet, VGG-16, and ResNet-18 model structures were trained, and the accuracy of the detection model was verified.

Figures 4–6 show the accuracy of slope surface disease detection in all AlexNet, VGG-16, and ResNet-18 experiments. In this experiment, in the same slope surface disease data set, ResNet-18 network is superior to AlexNet and VGG-16 in identifying all kinds of slope surface diseases. The recognition accuracy of ResNet-18 can reach 84.1% on average, and it has the best recognition effect on cracks, followed by undamaged ones, and the lowest recognition accuracy on landslides. This phenomenon may be caused by the complex background of landslides, which increases the difficulty of network identification. AlexNet VGG-16 network has a weak effect on the identification of various slope surface diseases. It may be that AlexNet and VGG-16 are not suitable for the identification of slope surface diseases, because the model cannot well learn and grasp the deeper characteristics of slope surface training samples.

4.2. Comparison of Detection Performance of Different Networks. Under the same migration strategy, all network structure layers were selected to participate in the training, and the detection results of AlexNet network, VGG-16 network, and ResNet-18 network were compared. Table 1 illustrates the experimental results of different network models.

It can be seen from Table 1 that the detection accuracy of VGG-16 network is 90.1%, while that of AlexNet network is 88.5%, 1.6% lower than the former. However, the detection accuracy of ResNet-18 is 96.3%, which is far higher than the former two. Furthermore, the accuracy of surface slope surface disease image increases with the increase of network model depth, which indicates that the recognition result of slope surface image disease is affected to a certain extent by the number of layers of CNN.

5. Conclusion

It is very important to study the automatic identification method of slope surface diseases in the actual outdoor environment for intelligent highway slope management and security situation. The disasters caused by highway slope occur frequently, which cause the blockage of the road at least and the death of the masses at the most serious. In order to avoid a series of safety accidents caused by highway slope disaster, it is necessary to test the surface of highway slope quickly and accurately on a regular basis. The existing method of slope surface disease detection is mainly manual, assisted by UAV, which is highly subjective. At present, more and more machine learning techniques are used in slope stability analysis. However, the deep neural network’s expertise in image classification and recognition has not been brought into full play, mainly because of the lack of a huge open slope surface image data set, which cannot provide the deep neural network with the image data set required for training. Therefore, there are some limitations in image processing for the recognition of slope surface diseases. In view of the above dilemma, the CNN algorithm is used in this paper to carry out recognition research on slope surface disease. The results are as follows:

(1) In view of the lack of open and sufficient slope surface image data set, this paper makes slope surface image data set required by deep learning. Therefore, this paper adopts the combination of UAV and camera to complete the slope surface image collection and image processing on the MATLAB platform.

| Network Structure | Training Time (s) | Validation Accuracy | Test Accuracy |
|-------------------|-------------------|---------------------|--------------|
| AlexNet           | 13095             | 90.5%               | 88.5%        |
| VGG-16            | 22651             | 93.3%               | 90.1%        |
| ResNet-18         | 16245             | 98.9%               | 96.3%        |
In order to discuss the influence of different network structure types on the accuracy of slope surface disease identification results, AlexNet and ResNet-18 based on slope surface image samples were, respectively, trained in this research. Slope surface images constructed in (1) were used as the input of these two networks, and images were classified according to extracted features.

On the basis of the slope surface disease recognition model, in order to find a better image disease recognition model, a comparative experiment was designed to compare the effects of different training mechanisms, different migration strategies, and different network structure types of neural networks on the slope surface disease recognition structure.

Data Availability
The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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