A DL-Based Approach for Evaluating Mine Slope Instability

Paulo Lopes[1]
Hernani Lima[2]

Abstract

Open pit mining is the most important technique for extracting mineral resources from the earth's crust. However, steep slope angles lead to an increased risk of slope collapse, the consequences of which could affect mining operations. Therefore, continuous assessment of excavation slope stability is an important part of open pit design and operation. The scientists used the Rock Engineering System (RES) paradigm, the limit equilibrium method, the artificial neural network (ANN), respectively and other methods to quantitatively analyze mine slope instability. However, these methods have problems such as difficulty in obtaining prior information, simple calculation model, and weak fitting ability, which make it difficult to apply to actual layered soil slopes and rock slopes. This research utilizes the powerful fitting ability of Deep Learning (DL) to construct a workflow of dataset construction - DL network training - DL network testing. In the process, the DL network is trained using the dataset of slope expert features. We provide a DL-based Classification Network model that can efficiently fit and evaluate slope states. Local environmental protection agencies and governments can use it to monitor slope instability in mines and mountainous areas, and effectively improve mine production efficiency.

Keywords

Deep learning; Slope stability; Classification network.

[1] Co-founder - Beyond Mining - paulo@beyondmining.tech
[2] Researcher and Professor - UFOP - hernani.lima@ufop.edu.br

Introduction

Ramp failures occur repeatedly in many situations, leading to serious hazards and consequences. For example, landslides in urban environments can be large in scale and affect large residential areas (Santos et al., 2019). In road cuts, slope failures can lead to accidents and traffic disruptions. In open pit mines, steeper slopes are highly desirable due to the positive economic impact on the cash flow of large projects (Tao, Zhu, Zheng, & He, 2018). However, steep tilt angles lead to an increased risk of failure (Abdulai & Sharifzadeh, 2019).

Although the theory of slope instability analysis has been relatively mature, in the past few decades, slope failure is still one of the key factors that induce other geological disasters (López-Vinielles et al., 2020). According to statistics, in 2014, a huge landslide suddenly erupted in a remote mountainous area in Badakhshan Province, Afghanistan, resulting in the destruction of at least 300 houses, the death of more than 2,100 people, and the disappearance of 2,000 people (Cheng, Chen, Chen, Chen, & Zhong, 2018). In 2017, floods and landslides caused by heavy rainfall in Sri Lanka killed 164 people and left 104 missing (Ghorbanzadeh, Meena, Blaschke, & Aryal, 2019).

The stability of the slope mainly depends on various factors such as the physical and mechanical properties of the rock and soil, external loads and failure modes (Wang et al., 2020). Due to the discreteness of bulk materials, the uncertainty of external loads and the limitations of test conditions, their values are often fuzzy, random and uncertain, which makes it difficult to accurately study the stability of slopes, as shown in Fig. 1., brings great difficulties (Asteris et al., 2022). The traditional slope stability analysis methods can be mainly classified into deterministic analysis methods and uncertainty analysis methods. The deterministic analysis method mainly includes the limit equilibrium method and the numerical analysis method. The limit equilibrium method is based on the deterministic model. The mean value of the relevant parameters is used to evaluate the safety degree of the slope through the median safety factor. The calculation is simple and the result is intuitive. It has been widely used in engineering and accumulated rich practical experience (Zheng et al., 2018), but the uncertainty of parameters cannot be considered when calculating the safety factor of slopes. Numerical analysis methods are usually used to deal with heterogeneous and complex boundaries. This method can obtain the stress-strain relationship of the rock and soil mass, and can simulate the excavation, support and groundwater seepage of the slope to analyze the interaction between the rock and soil mass and the supporting structure. Numerical analysis methods require a huge computational workload, and when encountering nonlinear problems and problems with large parameter variability, the numerical method will produce large errors.

Among the uncertainty analysis methods, the most representative reliability analysis method is the probability and statistics method, which is based on probability theory and reliability theory to evaluate the stability of slopes (Wang et al., 2020). This method can fully consider the engineering uncertainty caused by the discreteness of rock and soil mass, the uncertainty of external force loads, and the uncertainty of human decision-making caused by limited knowledge and information uncertainty. Thus, This method can more fully analyze and consider the uncertainty and risk in engineering (Liu, Li, Cao, & Wang, 2020). However, compared with the traditional stability coefficient design method, the reliability design method uses the reliability index or failure probability to represent the stability of the slope, which is not convenient to apply in practical engineering (D.-Q. Li, Wang, Cao, & Qi, 2019).

Fig. 1 A large-scale slope failure at a porphyry copper mine in South America

DL is an algorithm in machine learning based on representational learning of data (LeCun, Bengio, & Hinton, 2015). An observation (e.g. an image) can be represented in a variety of ways, as a vector of intensity values for each pixel, or more abstractly as a series of edges, regions of a specific shape, etc. (Kamilaris & Prenafeta-Boldú, 2018). Instead, it is easier to learn tasks from examples (e.g., face recognition or facial expression recognition) using some specific representation. The benefit of DL is to replace handcrafted features with efficient algorithms for unsupervised or semisupervised feature learning and hierarchical feature extraction. With the rapid development of DL technology, DL has become a research hotspot in various disciplines, and has been widely used in text (Mondal, Malakar, Barney Smith, & Sarkar, 2022), speech (Hu et al., 2021), image recognition (Fujiyoshi, Hirakawa, & Yamashita, 2019) and other fields have achieved remarkable results. DL does not require manual extraction of target features, which greatly improves the fitting ability of the model, and its classification ability in large labeled natural image datasets (such as ImageNet (Krizhevsky, Sutskever, & Hinton, 2012)) is far superior to traditional methods. The following sections describe common problems found in the literature when using DL for the stability assessment of slopes and

Rock images have been studied by many experts using intelligent algorithms. A technique for classifying rock images using the Naive Bayes K-neighbor algorithm is proposed (Guojian & Peisong, 2021). The images are classified using a softmax multi- classifier and multi-class support vector machine (SVM) (Zhang, Li, Han, Ren, & Shi, 2019). A method for segmenting and quantifying rock CT images using a cluster analysis algorithm (Alzubaidi, Mostaghimi, Swietojanski, Clark, & Armstrong, 2021). Partial transfer learning method is used to train sandstone image classification, resulting in a more accurate sandstone image classification model (J. Li et al., 2020).

However, after an extensive literature review, it is found that the above studies have some shortcomings: The image is processed by standard rock slices, thus the recognition rate of the network is not high enough. At the same time, if the boundary, it is impossible to determine the extent of all rock types on the slope.

This project proposes a DL-based method for rock slope classification, where the dataset uses Expert Feature Dataset (Santos et al., 2019). The project will first load the expert feature dataset and build the corresponding DL network, so that the input data can be adapted to the DL network. Subsequently, a DL network is constructed and trained to realize slope stability classification. Finally, the rock image test set is used to test the reliability of the DL network in this project (Fig. 2).

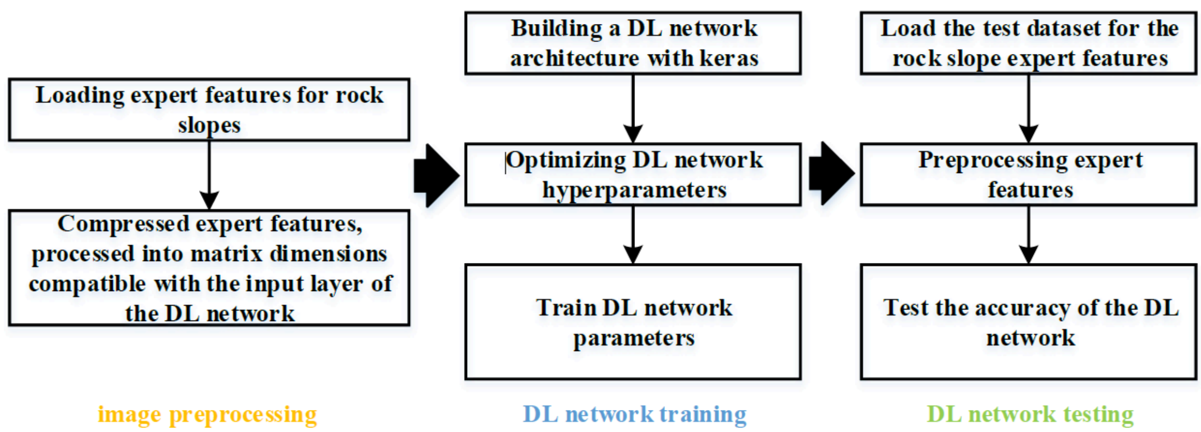

Fig. 2 The keras-based workflow implemented by this project

Methodology

Slope stability can be classified into three categories: stable (ST), overall failure (OF), and failure in a set of benches (FSB). Considering that the problem involves classification of three different classes, we adopt a DL-based multi-class network framework to implement the slope state classification. Table Ⅰ shows the variable symbols used in this paper.ϕ

TABLE 1 List of notations

Symbol	Variable
X	Expert features, i.e. network input
W	Network weights for feature extractor
ϕ	Nonlinear transformation of feature extractor
F	Features mapped by feature extractor
L	Cross entropy loss function
S	Status classification results

Proposed network architecture

We address the slope state classification problem by developing a DL-based feature extractor and classifier, as shown in Fig. 2. The proposed method uses expert features as network input, realizes feature extraction through two fully connected layers, and finally achieves state classification through one fully connected layer. For the feature extractor, the Relu activation function is adopted. For multi-classifiers, the softmax activation function is employed.

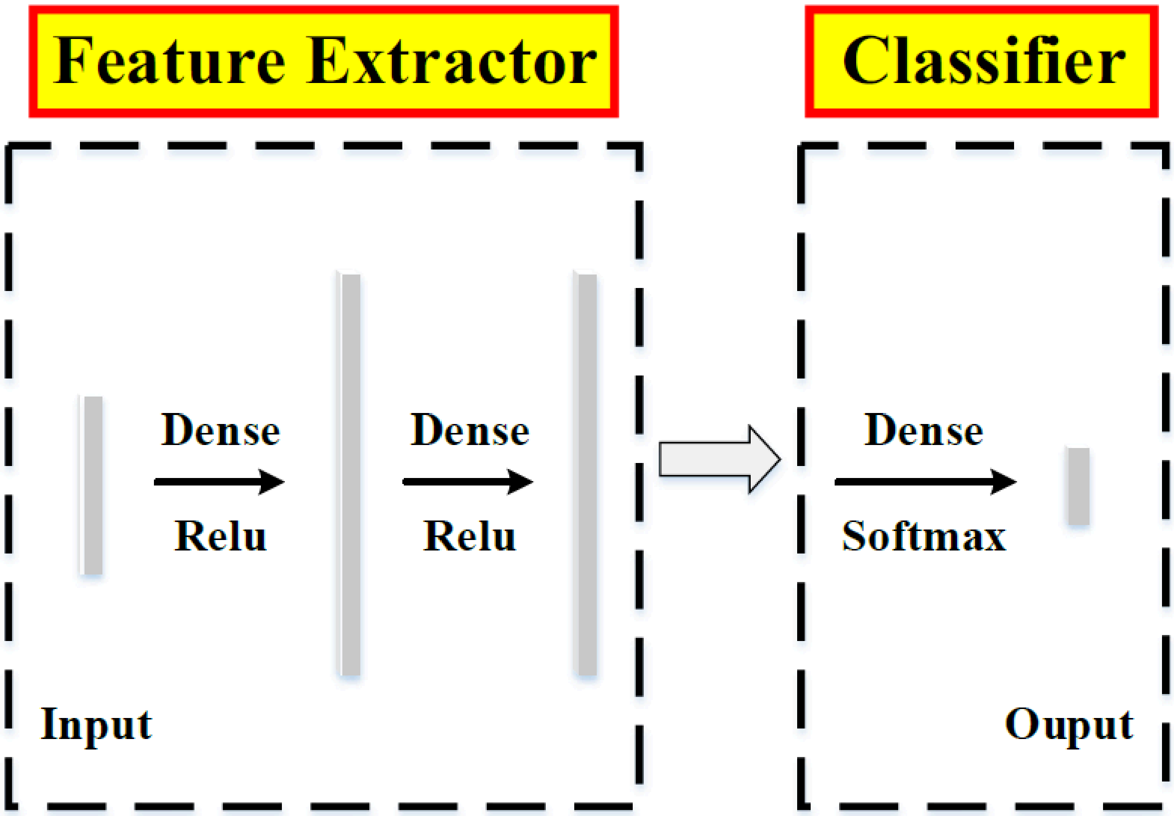

Fig. 3 The feature extractor and classifier of the DL network used in this project The network input can be represented as

$$X = \left[x_1, x_2, \ldots, x_n\right] \tag{1}$$

where x_i is the expert feature and N is the number of expert features.

The purpose of the feature extractor is to achieve feature sparseness and main feature extraction by training the network to learn the weights of different expert features. The feature extractor maps the input into the feature space, and the mapped features can be expressed as

$$F = \Phi(X, W) \tag{2}$$

where x is the set of expert features, φ is the nonlinear transformation of the feature

extractor, w is the network weight of the feature extractor, and F is the feature mapped by the feature extractor.

The purpose of the classifier is to achieve multi-classification by calculating the probability that the current sample belongs to each classification. On the basis of feature extraction, the classifier uses the softmax activation function to achieve state classification. The classification result can be expressed as

$$S = argmax\left(\frac{e^{i}}{\sum_{j=1}^{M} e_{j}}\right) \tag{3}$$

where e is the output result of the fully connected layer of the classifier.

Network training phase

The expert feature dataset is used as the network input, and the weights of the DL network are obtained by back propagation (BP) training. Specifically, based on expert feature samples, the cross entropy L is used as the loss function of the network as follows

$$L =- \sum_{i=1}^{N} y^{i} * log\widehat{y}^{i} \tag{4}$$

where y is the true label, y is the predicted label, and L is the loss function. Taking the fully connected layer D2 as an example, the cost function L calculates the partial derivative of as follows w^2 , and the BP algorithm is used to update the network weight parameters as follows

$$W^{2} \leftarrow W^{2} - \beta\frac{\partial}{\partial W^{2}}E\left(W^{2}\right) \tag{5}$$

where β is the learning rate. On this basis, the network weights are updated layer by layer in the reverse direction, and iteratively iterates until the specified conditions for stopping iteration are met.

We summarize the solutions for DL-based ramp state classification as follows. Backpropagation (BP) algorithm is used in the optimization process.

DL-based slope_stability state classification:
Input: Set of expert features , :1, i x i N
Output: Classification result S
Initialize W^{0}
$t \leftarrow 0$
while (no convergence achieved) do
    Find W^{t+1} → Optimize Equation 8 using BP.
    $t \leftarrow t + 1$
end
$W = W^{t}$
Compute Classification result S → Calculate Equation 3.
return S

Code Metadata

A dataset used to evaluate the performance of the proposed model as well as the implementation is detailed in this section.

Development Environment

The software environment for DL-based slope state classification is windows11@python3.6. The DL network architecture is built from the keras dependency library. In addition, the import of datasets and the storage of output results are implemented through numpy and scipy dependent libraries. At the same time, drawing and picture output are realized through the matplotlib dependency library.

Module overview

The main program mainly includes the init function and the fit function, which are described as follows.

- def init: initializes network hyperparameters and loads raw data.
- def fit: builds training and testing datasets, and builds DL networks. Furthermore, the parameters of the DL network are trained and optimized. At the same time, analyze the performance of the DL network, draw the loss curve, the recognition rate curve and the confusion matrix.

Dataset and implementation details

A dataset used to evaluate the performance of the proposed model as well as the implementation is detailed in this section.

Dataset settings

The database used in this research was presented by Zare Naghadehi (Santos et al., 2019). The authors have used published articles and books which encompass many worldwide open pit slope stability case histories to build an extensive database. Zare Naghadehi pointed out that the selection of the collected information was based on Hudson (1992), which had proposed an atlas of the parameters that directly influence the stability of rock slopes. The selection of the parameters among those proposed by Hudson was made based on recommendations from the literature and on the experience of the authors in open pit mine slope stability. The authors also reported that the selection of the parameters took into account the facility of surveying them at the field. The database organized by Zare Naghadehi contains 84 slopes located in different mines around the world, with 18 expert features, collected in each mine listing the names of every mine and their respective countries.

A total of eighteen variables comprise the database organized by Zare Naghadehi et al. These variables are: rock type (lithology), intact rock strength, rock quality designation (%), weathering, tectonic regime, groundwater condition, number of major discontinuity sets, discontinuity persistence, discontinuity spacing, discontinuity orientation, discontinuity aperture, discontinuity roughness, discontinuity filling, slope (pit-wall) angle, slope (pit-wall) height, blasting method, precipitation, previous instability. Besides the eighteen variables, the stability condition is known. Zare Naghadehi used three types of stability conditions; stable slopes (ST), unstable inter- ramp slopes and unstable global slopes.

Implementation details

Random mutually exclusive array indices are generated from seeds, and the dataset mentioned in the previous section is divided into two completely different subsets, the training dataset and the test dataset. A sample of expert features with a vector length of 18 is used as input to the model. The model is trained in an unsupervised manner to learn common factors of normal signals. The Adam optimizer (Kingma & Ba, 2014) is a gradient-based optimizer used for all stages of training with a learning rate of 0.0001. The model has been trained for 300 epochs and takes about 30 seconds to train on an x86 PC device. The recognition rate and confusion matrix are used as indicators to evaluate the performance of the algorithm.

The recognition rate is as follows

$$P_d = \frac{N_t}{N_a} \tag{6}$$

where N_t is the total number of correctly identified samples, and N_a is the total number of detected samples.

Results and discussion

Through the above data sets and evaluation indicators, the influence of the hyperparameters of the DL network on the recognition performance is simulated and analyzed.

Influence of hyperparameters of DL network on recognition performance

The hyperparameters of the DL network will directly affect the results of feature extraction and classification. Among them, the length of the hidden layer of the network determines the network capacity, so parameters such as the length of the hidden layer are optimized. Taking the hidden layer length N_D as 16, 32, 64 and 128, the validation loss of the DL network during the training process is shown in Fig. 4. As can be seen from the figure, when $N_D = 64$ or $N_D = 128$, the verification loss of the DL network is the lowest. Therefore, for the method in this paper, the longer the hidden layer length N_D , the larger the network capacity and the higher the recognition accuracy, but the computational complexity of the DL network also increases. Comprehensively, this paper selects the number of sampling points $N_D = 64$.

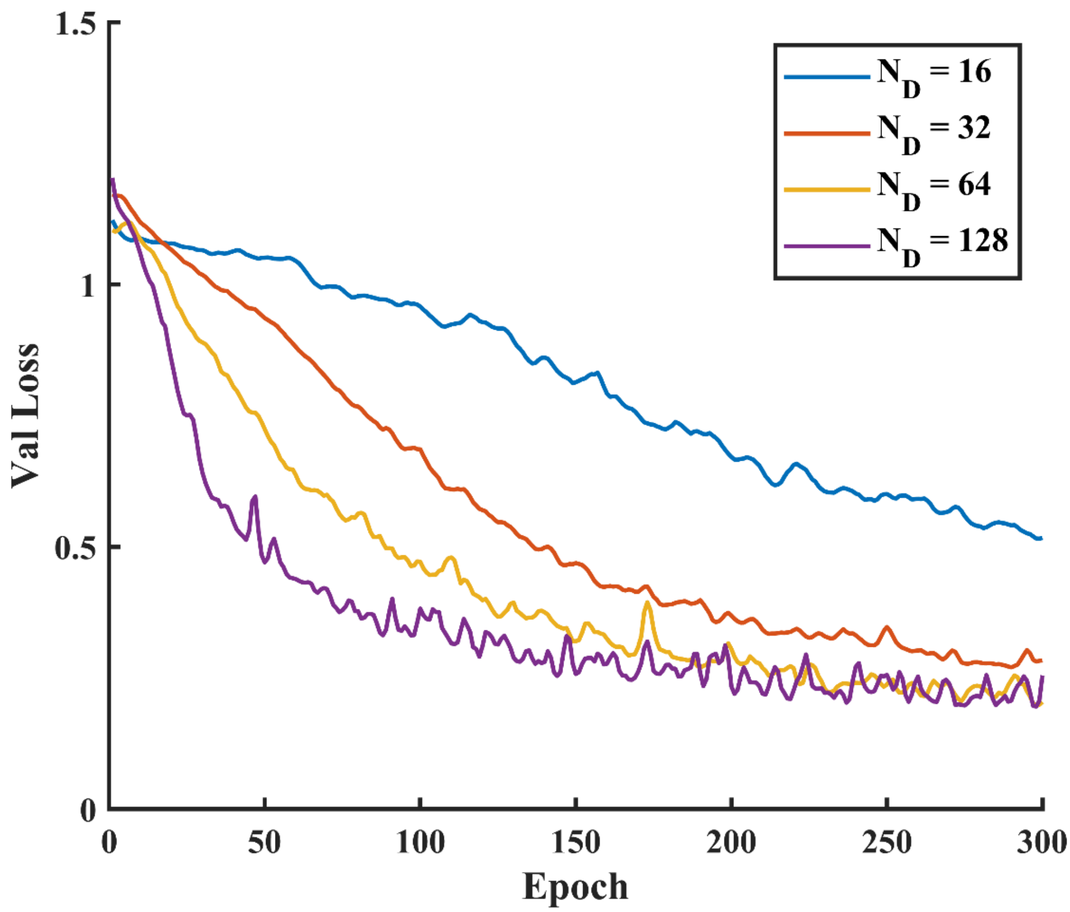

Fig. 4 Comparison of signal detection performance under different hidden layer lengths

DL network training and testing performance

When $N_D = 64$, the loss of the DL network is shown in Fig. 5. As the Epoch increases, the basic trend of DL network loss and validation loss is decreasing. At the same time, when the Epoch is 280, the loss curve of the DL network basically converges.

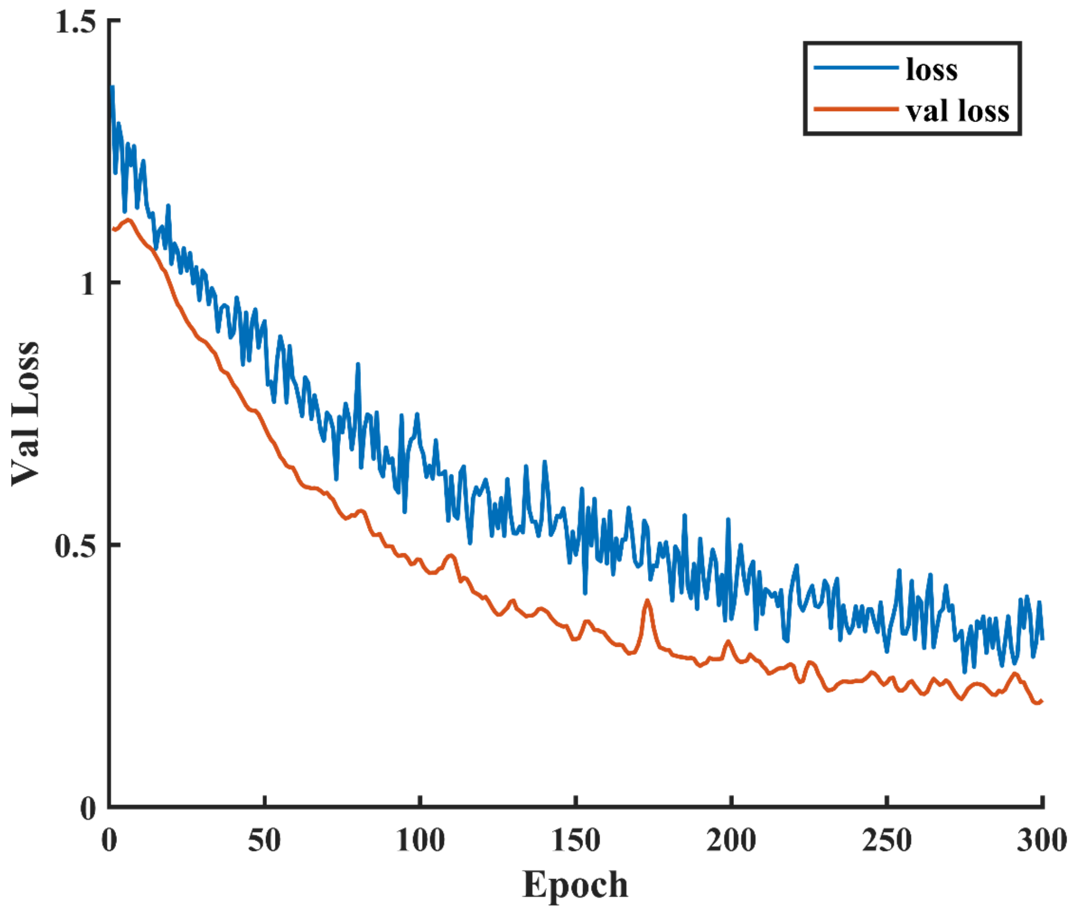

Fig. 5 Variation curve of DL network loss and validation loss during training process

When $N_D = 64$, the recognition rate of the DL network is shown in Fig. 6. With the increase of Epoch, the basic trend of recognition rate and verification recognition rate of DL network is rising. At the same time, when the Epoch is 150, the recognition rate curve of the DL network basically converges.

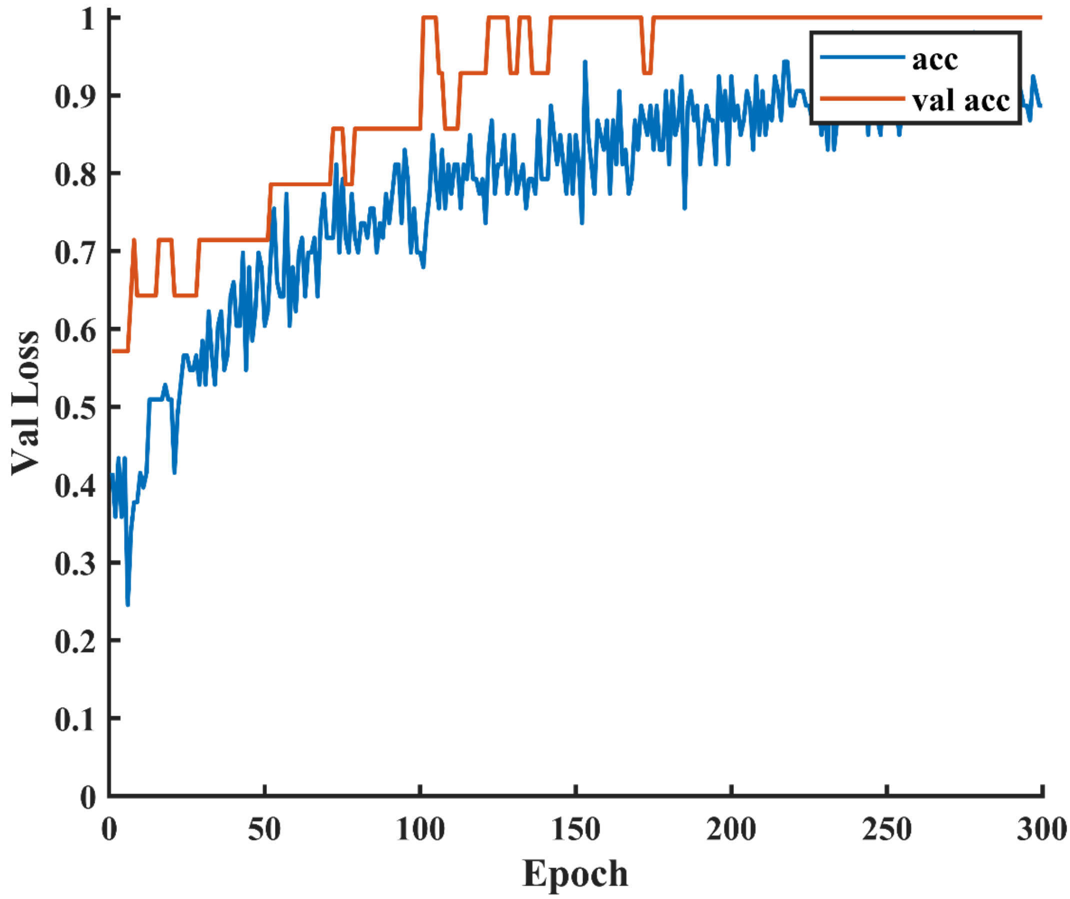

Fig. 6 Variation curve of DL recognition rate and validation recognition rate during training process

Using the testing dataset, the confusion matrix of the DL network is shown in Fig. 7. It can be seen from the figure that the DL network can accurately classify the slope stable states ST/OF and OF/FSB. But for ramp steady state ST/FSB, there is a small amount of confusion in the DL network. At this time, the test recognition rate of the network is 94.12%.

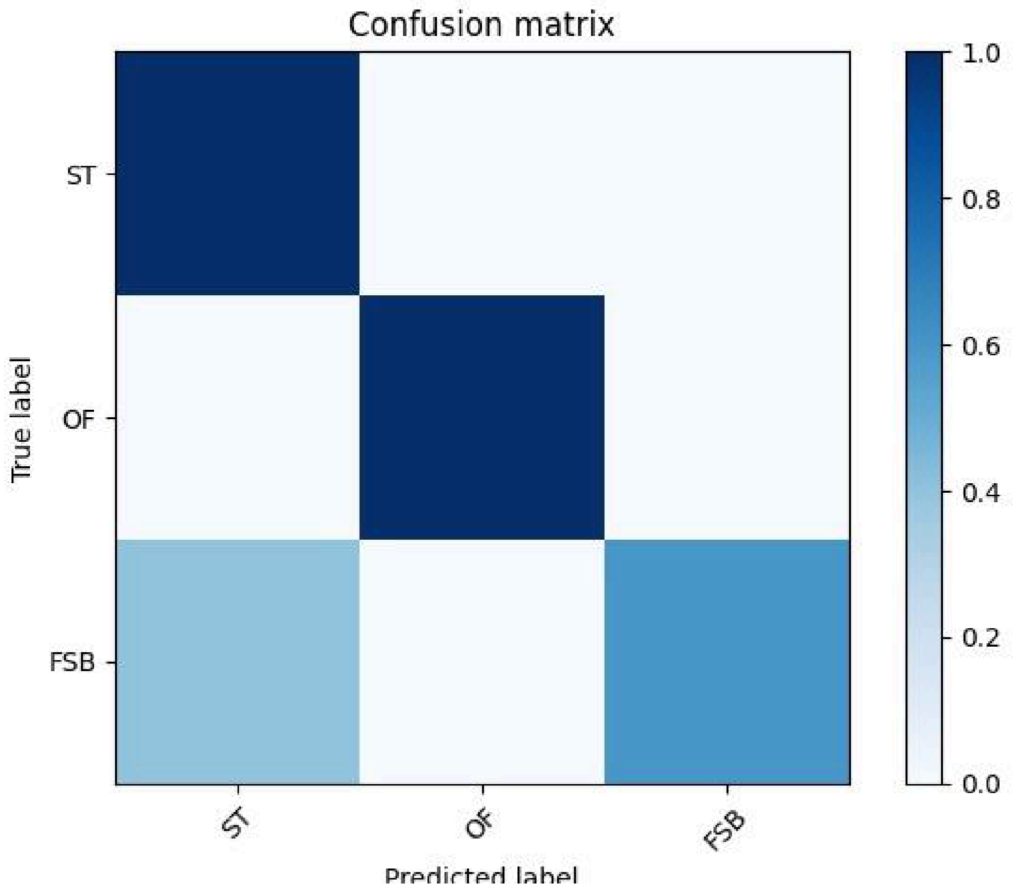

Fig. 7 Confusion matrix of the algorithm in this paper for the testing dataset

Conclusion

In this study, a DL network-based method for identifying the steady state of slopes is proposed. In this paper, the powerful fitting ability of deep learning is used to train the DL network using the dataset of slope expert features to achieve accurate evaluation of the steady state of the slope. The simulation results show that the recognition rate of the DL network is 100% in the training dataset. In the testing dataset, the recognition rate of the DL network can also reach 94.12%. The resulting framework is intended for use by environmental agencies and governments to reduce economic and human costs from slope instability. In future research, the robustness of our method can be further improved by constructing a larger ramp steady state dataset.

References

Abdulai, M., & Sharifzadeh, M. (2019). Uncertainty and reliability analysis of open pit rock slopes: a critical review of methods of analysis. Geotechnical and Geological Engineering, 37(3), 1223-1247. doi:https://doi.org/10.1007/s10706- 018-0680-y

Alzubaidi, F., Mostaghimi, P., Swietojanski, P., Clark, S. R., & Armstrong, R. T. (2021). Automated lithology classification from drill core images using convolutional neural networks. Journal of Petroleum Science and Engineering, 197, 107933. doi:https://doi.org/10.1016/j.petrol.2020.107933

Asteris, P. G., Rizal, F. I. M., Koopialipoor, M., Roussis, P. C., Ferentinou, M., Armaghani, D. J., & Gordan, B. (2022). Slope stability classification under seismic conditions using several tree-based intelligent techniques. Applied Sciences, 12(3), 1753. doi:https://doi.org/10.3390/app12031753

Cheng, H., Chen, J., Chen, R., Chen, G., & Zhong, Y. (2018). Risk assessment of slope failure considering the variability in soil properties. Computers and Geotechnics, 103, 61-72. doi:https://doi.org/10.1016/j.compgeo.2018.07.006

Fujiyoshi, H., Hirakawa, T., & Yamashita, T. (2019). Deep learning-based image recognition for autonomous driving. IATSS research, 43(4), 244-252. doi:https://doi.org/10.1016/j.iatssr.2019.11.008

Ghorbanzadeh, O., Meena, S. R., Blaschke, T., & Aryal, J. (2019). UAV-based slope failure detection using deep-learning convolutional neural networks. Remote Sensing, 11(17), 2046. doi:https://doi.org/10.3390/rs11172046

Guojian, C., & Peisong, L. (2021). Rock thin-section image classification based on residual neural network. Paper presented at the 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP).

Hu, H.-C., Chang, S.-Y., Wang, C.-H., Li, K.-J., Cho, H.-Y., Chen, Y.-T., Lee, O. K.-S. (2021). Deep learning application for vocal fold disease prediction through voice recognition: preliminary development study. Journal of medical Internet research, 23(6), e25247. doi:10.2196/25247

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and electronics in agriculture, 147, 70-90. doi:https://doi.org/10.1016/j.compag.2018.02.016

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25. doi:https://doi.org/10.1145/3065386

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. doi:https://doi.org/10.1038/nature14539

Li, D.-Q., Wang, L., Cao, Z.-J., & Qi, X.-H. (2019). Reliability analysis of unsaturated slope stability considering SWCC model selection and parameter uncertainties. Engineering Geology, 260, 105207.

Li, J., Zhang, L., Wu, Z., Ling, Z., Cao, X., Guo, K., & Yan, F. (2020). Autonomous Martian rock image classification based on transfer deep learning methods. Earth Science Informatics, 13(3), 951-963. doi:https://doi.org/10.1007/s12145-019-00433-9

Liu, X., Li, D.-Q., Cao, Z.-J., & Wang, Y. (2020). Adaptive Monte Carlo simulation method for system reliability analysis of slope stability based on limit equilibrium methods. Engineering Geology, 264, 105384. doi:https://doi.org/10.1016/j.enggeo.2019.105384

López-Vinielles, J., Ezquerro, P., Fernández-Merodo, J. A., Béjar-Pizarro, M., Monserrat, O., Barra, A., . . . García-Davalillo, J. C. (2020). Remote analysis of an open-pit slope failure: Las Cruces case study, Spain. Landslides, 17(9), 2173- 2188. doi:https://doi.org/10.1007/s10346-020-01413-7

Mondal, R., Malakar, S., Barney Smith, E. H., & Sarkar, R. (2022). Handwritten English word recognition using a deep learning based object detection architecture. Multimedia Tools and Applications, 81(1), 975-1000. doi:https://doi.org/10.1007/s11042-021-11425-7

Santos, A. E. M., Lana, M. S., Cabral, I. E., Pereira, T. M., Zare Naghadehi, M., de Fátima Santos da Silva, D., & Dos Santos, T. B. (2019). Evaluation of rock slope stability conditions through discriminant analysis. Geotechnical and Geological Engineering, 37(2), 775-802. doi:https://doi.org/10.1007/s10706-018-0649-x

Tao, Z., Zhu, C., Zheng, X., & He, M. (2018). Slope stability evaluation and monitoring of Tonglushan ancient copper mine relics. Advances in Mechanical Engineering, 10(8), 1687814018791707. doi:https://doi.org/10.1177/1687814018791707

Wang, L., Wu, C., Tang, L., Zhang, W., Lacasse, S., Liu, H., & Gao, L. (2020). Efficient reliability analysis of earth dam slope stability using extreme gradient boosting method. Acta Geotechnica, 15(11), 3135-3150.doi:https://doi.org/10.1007/s11440-020-00962-4

Zhang, Y., Li, M., Han, S., Ren, Q., & Shi, J. (2019). Intelligent identification for rock- mineral microscopic images using ensemble machine learning algorithms. Sensors, 19(18), 3914. doi:https://doi.org/10.3390/s19183914

Zheng, Y., Chen, C., Liu, T., Zhang, H., Xia, K., & Liu, F. (2018). Study on the mechanisms of flexural toppling failure in anti-inclined rock slopes using numerical and limit equilibrium models. Engineering Geology, 237, 116-128. doi:https://doi.org/10.1016/j.enggeo.2018.02.006