Spatial prediction of highway slope disasters based on convolution neural networks

Chao Yin · Zhanghua Wang · Xingkui Zhao

Received: 5 June 2021 / Accepted: 25 February 2022 / Published online: 29 March 2022
© The Author(s), under exclusive licence to Springer Nature B.V. 2022

Abstract
In order to clarify the spatial differentiations of highway slope disasters (HSDs) in Boshan District, spatial prediction was carried out based on ECG-CNN with the support of GIS. Spatial prediction factors of HSDs were selected, and the stabilities of the 147 highway slopes in Boshan District were determined. The spatial prediction model of HSDs was established by ECG-CNN, and the spatial susceptibility map of HSDs in Boshan District was plotted. Influences of the prediction factor combinations and the drill sample and verification sample combinations on the prediction success rates were verified. The results show that low susceptible areas, medium susceptible areas and high susceptible areas account for 56.92%, 28.46% and 14.62% of the total areas of Boshan District, respectively. Some sections of Binlai Expressway, G205, G309, S210 and S307, pass through high susceptible areas. The surface cutting depth has a small impact on the prediction success rate, while the elevation and gradient have great impacts on the prediction success rate. When the drill samples are small, network drill’s maturity has a great impact on the prediction success rate, while when there are many drill samples, the model’s logical structure itself has a large impact on the prediction success rate.

Keywords Highway slope disaster (HSD) · ECG-CNN · Prediction factor · Prediction success rate

1 Introduction
Highway slope disasters (HSDs) include collapse, landslide, debris flow and slope erosion that often occur on natural or artificial slopes along highways to damage subgrade, pavement, bridges, tunnels and other structures (Li and Xie 2013). The prevention and control of HSDs can improve the disaster resistance of highway network and accelerate the construction of “traffic power” (Yin et al. 2020). Spatial prediction is the prerequisite...
for disaster monitoring and early warning based on the fusion of diverse and heterogeneous geographic, geological and hydrological information, which is of great significance to reduce economic losses and casualties (Sezer et al. 2017; Hong et al. 2018; Wang et al. 2019; Yin 2020). Traditional spatial prediction models of HSDs include statistical prediction models (information quantity method, logistic regression method, analytical hierarchy process, frequency ratio model, etc.) and pattern recognition models (artificial neural network (ANN), support vector machine (SVM), decision tree, Kalman filter method, weights of evidence model, kernel-based Gaussian process model, random forest model, Bayesian network, DBN and stacked auto-encoder network, etc.) (San 2014; Zhou et al. 2016; Chen et al. 2017; Zhu et al. 2018; Ali et al. 2021; Sun et al. 2021a). Among them, ANN is widely used; however, shallow networks have problems such as local optimization, overfitting, low learning efficiency and slope diffusion, which decrease the accuracies of the prediction results to a certain degree (Cui et al. 2013; Yang et al. 2019).

Convolutional neural network (CNN) based on the neurocognitive machine model is a type of feed-forward neural network that includes convolutional calculations and has a deep structure (Kiranyaz et al. 2016). As a way to overcome the shortcomings of traditional shallow networks, it has been widely used in image classification, facial recognition, audio retrieval, target location detection and other fields (Li et al. 2018). For instance, in order to further improve the accuracies of pavement disease statistics using two-dimensional images, Sha et al. (Sha et al. 2018) used CNN to carry out pavement disease recognition and measurement based on image classification. Zhang et al. (Zhang et al. 2020a) proposed a cucumber disease leaf segmentation method based on multi-scale fusion convolutional neural networks (MSF-CNNs), which were composed of coding networks (ENs) and decoding networks (DNs). In recent years, with the advancements of deep learning and intelligent computing researches, some scholars have introduced CNN into disaster spatial prediction. For example, Shu et al. (Shu et al. 2017) designed an automatic identification system for HSDs based on CNN, the system was developed in Caffe open-source environment, integrated with the AlexNet and GoogleNet and used a large amount of highway slope data to complete the model training. Bragagnolo et al. (Bragagnolo et al. 2020) took the r.landslide database as the research object, carried out landslide susceptibility assessment based on CNN and compared the assessment results with the data published by the Brazilian Geological Survey Bureau (BGSB) to verify the accuracy of the CNN model. Mandal et al. (Mandal et al. 2021) used the classical CNN model to analyze the landslide susceptibility in Sikkim Himalaya, and constructed the basic CNN model of single convolution, pooling layer and full connection layer. Sameen et al. (Sameen et al. 2020) applied one-dimensional CNN model based on Bayesian optimization to landslide susceptibility assessment, and used Bayesian method to optimize the hyperparameters of CNN. Wu et al. (Wu et al. 2020) used the synthetic minority oversampling technology (SMOTE) to establish the drill samples and conducted landslide susceptibility mapping (LSM) in Wanzhou District, Chongqing City based on CNN. Due to the short history of CNN used in disaster spatial prediction, only a few classic derivative networks (e.g., AlexNet, VGG16, GoogleNet and ResNet) have been verified for their prediction effects (Sahin et al. 2020). In contrast, researches on the use of ECG-CNN and other networks to carry out disaster spatial predictions have not been reported.

Boshan, a district in Zibo City, is located in the northern part of mountain areas of central Shandong Province. Due to the serious surface erosion and growth of gullies, the rapid development of highway construction has produced many unprotected highway slopes (Peethambaran et al. 2020). Combined with the severe weathering and intensification of human engineering activities, HSDs occur frequently, causing serious personal injuries and economic
losses. The spatial prediction of HSDs in Boshan District, which is based on the ECG-CNN network, is to adopt the ROC (receiver operating characteristic) method to explain the network structure with the highest prediction success rate, plot the susceptibility map based on GIS and verify the influences of the prediction factor combinations and the drill sample and verification sample combinations on the prediction success rates. The aim is to provide a theoretical basis for improving highway disaster resistance and regional disaster prevention and mitigation capabilities.

2 Investigation of HSDs in Boshan district

2.1 Disaster overview

As of the end of 2020, the highway mileage of Boshan District reached 982.37 km, including one expressway, two national highways and four provincial highways, the highway density was 143.26 km/100km² (Guo et al. 2021). HSDs in Boshan District are characterized by rockfall, slope erosion and slope instability. Rockfalls often occur on anti-dip layered and loose broken slopes with high weathering degrees, which vary in scales and often occur suddenly. They are easy to trigger the destruction of pavement, subgrade and security facilities. Cut slopes are prone to erosion and damages due to precipitation, resulting in slope soil erosion, formation of slope gullies, slope toe erosion, road shoulder gaps, etc. The unreasonable excavation of highway slopes will destroy the natural environment’s original stability and cause slope instabilities, such as avalanche, landslide and collapse, with collapse being the most common (Zhu et al. 2017). For example, on August 3, 2015, a rockfall disaster occurred on a slope of X236, and two people were injured; on August 23, 2016, the Xiejiadian-Shiquan Highway suffered from a landslide disaster due to continuous rainfall, causing the highway to erode for more than 40 days (Sun and Shi 2020).

2.2 Disaster investigation results

HSDs are the results of the factors of disaster-pregnant environment exceeding certain thresholds. The primary task of disaster spatial prediction is to analyze the intensities, frequencies and densities of disasters in different regions, that is, to analyze the impacts of the prediction factor combinations on the probabilities and scales of disasters (Yin and Zhang 2018). A comprehensive investigation of 147 highway slopes was conducted in Boshan District from October 2 to 7, 2020. The investigation results showed that the total areas of the 147 highway slopes was about 1.231km², the largest slope area was 0.11km², and the smallest slope area was 45m². There were 27 highway slopes with an area of more than 1,000m². The safety factors \( (F_s) \) of the 147 highway slopes were calculated by limit equilibrium analysis, of which 64 were in a stable state \( (F_s > 1) \) and 58 were in an unstable state \( (F_s \leq 1) \). Due to space reasons, the specific calculation processes are not listed here. The distribution of the 147 highway slopes is shown in Fig. 1, and some representative highway slopes are shown in Fig. 2.

2.3 Disaster prediction factors

According to the interaction mechanism of HSDs with the disaster-pregnant environment in the process of incubation, evolution and outbreak, the prediction factors of HSDs include
topographic and geomorphic factors (elevation, gradient, surface cutting depth, surface cutting density), vegetation factors (NDVI, Normalized Difference Vegetation Index), hydrological factors (distance from river) and geotechnical factors (lithology) (Sun et al. 2021b). Although precipitation factors such as the average annual precipitation and average annual rainstorm days have significant impacts on the occurrences of HSDs (Yi et al. 2020), such factors are evenly distributed in Boshan District and have little effect on revealing the
spatial differentiations of HSDs. Therefore, precipitation factors are not considered in the spatial prediction of HSDs in Boshan District.

### 2.3.1 Topographic and geomorphic factors

Topographic and geomorphic factors were extracted from the Digital Elevation Model (DEM) in Boshan District. Elevation and gradient are the basic topographic and geomorphic factors, which play essential roles in HSDs. The elevations of the 147 highway slopes in Boshan District are between 162.5 and 497.3 m, and the gradients are between 25° and 90°. Surface cutting depth is an indicator of the degree of vertical surface fragmentation in a small scale, usually measured by the relative height difference of a particular catchment area, while surface cutting density is mainly related to the size of the study area and the length of the gully system, which is generally measured by the total length of the gullies above a certain level in a particular catchment area (He et al. 2021; Li et al. 2021; Huang et al. 2022). The method proposed by Jia et al. (2012) was adopted to calculate the surface cutting depths and surface cutting densities of the 147 highway slopes. Non-depression treatment and small plain treatment were conducted on DEM data by using ArcGIS hydrological analysis module. After obtaining the flow direction matrixes and confluence accumulation matrixes on the non-depression DEM, the watershed lines were further delineated to obtain the catchment areas. The surface cutting depth was obtained by calculating the difference between the highest and lowest elevations in the catchment area of each highway slope. Considering the actual situation of highway slopes, the calculation unit was divided into two cases: when the catchment area was less than 0.04 km², the catchment area was taken as the calculation unit; when the catchment area was larger than 0.04 km², 0.04 km² was taken as the calculation unit. The calculation of surface cutting density was also carried out by ArcGIS hydrologic analysis module. The calculation process of the first half was consistent with the surface cutting depth, and after obtaining the confluence accumulation matrixes, the gully systems were extracted by setting a reasonable threshold (5000), and then the lengths of the gully systems and the surface cutting densities of all highway slope unit areas (1.0 km²) were calculated by using ArcGIS Engine and .Net programming. The results show that the surface cutting depths of the 147 highway slopes are between 9.1 m and 75.2 m, and the surface cutting densities are between 0 and 0.327 km/km².

### 2.3.2 Vegetation factor

Vegetation factor was extracted from Digital Vegetation Coverage Data in Boshan District. Vegetation roots can fix loose rocks and soils. Areas with high vegetation coverage are able to withstand weathering and reduce risks of HSDs (Ghebrezgabher et al. 2020; Jiang et al. 2021). Vegetation is quantified by measuring the difference between near infrared (strong vegetation reflection) and red light (vegetation absorption). NDVI is a normalized vegetation index, which can be used to reflect vegetation growth condition and spatial distribution density. The calculation method of NDVI is shown in Eq. 1.

\[
NDVI = \frac{NIR - R}{NIR + R}
\]

where NIR is the reflectivity of near infrared band, and R is the reflectivity of red band. The results show that the minimum value of NDVI of the 147 highway slopes is −0.649, and the maximum value is 0.854.
2.3.3 Hydrological factor

Hydrological factor was extracted from Digital Precipitation Data in Boshan District and its surrounding areas. The closer the highway slope to the river, the higher the water content of rock and soil, the stronger the erosion, and the higher the probabilities of HSDs (Dehnavi et al. 2015). The results show that the minimum distance of the 147 highway slopes from river is 5 m, and the maximum is 1090 m.

2.3.4 Geotechnical factor

Geotechnical factor was extracted from Digital Lithology Data in Shandong Province. Lithology provides material basis for HSDs and is one of the controlling factors of HSDs (Dou et al. 2019). Lithology in Boshan District includes hard rock, sub-hard rock, soft rock, gravel soil, cohesive soil, sandy soil, silty soil and loess soil.

Due to the different dimensions of the prediction factors and the large differences in the data ranges, data normalization proposed by Yin et al. (2020), Yin (2020) was conducted before disaster spatial prediction. The details will not be repeated here.

3 Spatial prediction models of HSDs in Boshan district

3.1 Building of the prediction models

3.1.1 Structural design of the prediction models

ECG (Electrocardiogram) is a widely used clinical diagnostic feature of cardiovascular system diseases (Li et al. 2020). The data form processed by CNN has the relationship between local and global. The combination of low-level features (local) can form high-level features (global), and the spatial correlation between different features can be obtained. This relationship between local and global can also be regarded as a feature of different frequency information. Many signals also have such characteristics, such as ECG signals composed of PQRST waves in different frequency bands and amplitudes, and their waveform changes are also closely related to the corresponding symptoms. Therefore, it is feasible to use CNN to process signals represented by ECG (Zhou and Tan 2020; Zhang et al. 2021a, b). To realize the computer-aided diagnosis for cardiovascular system diseases, Zhu (2013) proposed the ECG-CNN network, which consisted of an input layer, a convolutional layer, a pooling layer, a fully connected layer and an output layer. The convolutional layer and pooling layer generally appear in pairs and can be taken several pairs. Zhao et al. (2020) optimized the ECG-CNN network based on wavelet transform, and used 24-layer CNN to extract features hierarchically. The ECG-CNN network was introduced into the spatial prediction of HSDs in Boshan District. The factors that have significant impacts on the prediction success rates are the network structure depth (the number of convolutional layers and pooling layers), the number of convolutional kernels and the number of fully connected layers (Zhang et al. 2020b, 2021).

To verify the prediction success rates of different network structures, four levels of the above three factors were selected for orthogonal experimental design (Liu et al. 2010). Orthogonal experimental design is a design method that uses orthogonal table
to arrange and analyze multi-factor experiments. Some representative combinations are selected from all combinations of experimental factors for experiments (Vild et al. 2016; Kang et al. 2021; Xiong et al. 2021). In this paper, three-factor and four-level orthogonal experiment was adopted to generate 16 representative ECG-CNN network structures. Each network structure was calculated based on the 147 highway slope data, and the four levels selected for each factor are as follows:

1. The network structure depth: [first level, second level, third level, fourth level] = (Li and Xie 2013; Yin et al. 2020; Sezer et al. 2017; Hong et al. 2018);
2. The number of convolutional kernels: [first level, second level, third level, fourth level] = (Yin et al. 2020; Hong et al. 2018; Yin 2020; Zhou et al. 2016);
3. The number of fully connected layers: [first level, second level, third level, fourth level] = (Li and Xie 2013; Yin et al. 2020; Sezer et al. 2017; Hong et al. 2018).

The three-factor, four-level orthogonal experimental design scheme of the ECG-CNN network structures is shown in Fig. 3.

3.1.2 Conversion of model input format

The input of the ECG-CNN model adopt multi-lead electrocardiographic signals, which is one-dimensional data and is quite different from the prediction factors of HSDs. For the sake of the conversion and applicability of data format, and the accuracy of the model, a line chart is available herein for the model input, with the serial number of each prediction factor as the horizontal ordinate and the normalized value of each prediction factor as the vertical ordinate. For example, Fig. 4 is the line chart of the prediction factors of the highway slopes #1, #2 and #3. Among them, for the highway slope #1, the normalized value of elevation was 0.41, and the normalized values of other prediction factors were marked one by one and connected to a broken line diagram. In addition, the 147 highway slopes were coded as 0 or 1, where stable slopes were coded as 0 and unstable slopes were coded as 1.

![Fig. 3 Orthogonal experimental design scheme](image-url)
3.2 Verification of the prediction models

3.2.1 Computation process

With 64 stable slopes and 21 unstable slopes being used as drill samples and the remaining 62 unstable slopes being used as verification samples, 16 ECG-CNN network structures were analyzed and computed under the following computing environment: CPU i7-6700, 8G memory, GTX1050 Ti-4G, Caffe open-source framework (Zhang et al. 2021c). The following took the first structure as an example to illustrate the calculation process. The network structure included one convolutional layer C1, one pooling layer C2, and four fully connected layers F1, F2, F3 and F4. Among them, the convolutional layer C1 contained eight convolutional kernels, as shown in Fig. 5.

Input the line charts of the 85 drill samples into the network, performed convolutional processing in the convolutional layer, and obtained the output feature matrixes through the activation function Sigmoid. The eight convolution kernels had different weights and thresholds, and the obtained output feature matrixes were also different (Xie et al. 2021). The operation of a single convolution kernel is shown in Eq. 2.

Fig. 4 Line chart of the prediction factors of the highway slopes #1, #2 and #3

Fig. 5 First ECG-CNN network structure
where \( l \) is the number of network structure layers, \( i \) is the serial number of convolutional kernels, \( j \) is the serial number of highway slopes, \( x^l_j \) is the line chart of the \( j \)-th highway slope, \( W^l_i \) and \( b^l_i \) are the weight matrix and threshold matrix of the \( i \)-th convolutional kernel in the \( l \)-th layer, \( f(x) \) is the activation function, as shown in Eq. 3.

\[
f(x) = \frac{1}{1 + e^{-x}}
\]  

C1 has eight convolutional kernels, which can obtain eight disaster features. The function of the pooling layer C2 is to aggregate and count the above features to avoid overfitting. The pooling operation is shown in Eq. 4.

\[
x^{l+1}_j = \beta^l_j D\left(x^l_j\right)
\]  

where \( \beta^l_j \) is the multiplicative threshold matrix of the pooling operation, \( D() \) is the down-sampling function, which reduces the pooling feature matrix by 50% in both dimensions.

The function of the fully connected layer is to establish the mapping relationship between the pooling aggregation features and highway slopes’ stabilities so that the outputs of the stable slopes are 0 and the outputs of the unstable slopes are 1 (Sha et al. 2018). After completing the above drill, input the 62 line charts of the verification samples into the trained network, and output the susceptible probabilities after iterative calculation. The values were in the range of 0 to 1, where 0 meant that the disaster would not occur, and 1 meant that the disaster would occur inevitably. Set the mean square error of the prediction results of the 62 highway slopes as \( M_0 \). When \( M_0 \leq 0.1 \), the model has better prediction ability. The computation method of \( M_0 \) is shown in Eq. 5.

\[
M_0 = \frac{\sum_{i=1}^{62} (O_j - T_j)^2}{62}
\]

where \( O_j \) is the susceptible probability of the \( j \)-th highway slope, and \( T_j \) is the stability code of the \( j \)-th highway slope. Since the verification samples are all unstable slopes, \( T_j = 1 \). Figure 6 shows the \( M_0 \) corresponding to each iteration in the calculation process. When the number of iterations was less than 40, \( M_0 \) fluctuated significantly. When the iteration reached 84 times, \( M_0 \) dropped below 0.1, and the computation ended.

### 3.2.2 Selection of the network

To select the optimal network structure, apply the ROC method to verify each network’s prediction success rate. AUC is the area under the ROC curve. The larger the AUC is, the more accurate the evaluation result is. When the AUC is 1, the evaluation result is completely correct. The prediction success rate curve of each ECG-CNN network is shown in Fig. 7.

Based on Fig. 7, compute the prediction success rates corresponding to different network structure depths, number of convolutional kernels and number of fully connected layers, as shown in Table 1.

Table 1 shows that the number of convolutional kernels has the most significant impact on the prediction success rate, followed by the number of fully connected layers, and the
network structure depth has the least impact. The ECG-CNN network with the highest prediction success rate is composed of one network structure depth, six convolution kernels and three fully connected layers. The network was used to establish a spatial prediction...
model for HSDs in Boshan District, and 83 unstable slopes were predicted, with the success rate curve being plotted. The area under the curve was calculated to be 0.912, as shown in Fig. 8.

According to Shu et al. (2017), when AlexNet was used for HSDs’ recognition, the success rates of the four types of test sets were 73.88%, 86.50%, 87.13% and 86.38%, with an average of 83.47%, while the success rates of GoogleNet were 79.13%, 89.88%, 90.25% and 91.63%, with an average of 87.72%. According to Kumar et al. (2017), the accuracy rate of CNN used in evaluating landslide disaster susceptibility in Wanzhou District of the Three Gorges Reservoir was 89.50%, while according to Mandal et al. (2021), the accuracy rate of landslide susceptibility evaluation using classical CNN model was 90.3%. The accuracies of these four types of networks are lower than the ECG-CNN network proposed in this study, which proves ECG-CNN’s feasibility for the spatial prediction of HSDs.

### 4 Spatial prediction results of HSDs in Boshan district

Spatial prediction of HSDs in Boshan District was based on GIS, with the susceptible map being plotted. The available data included:

| Orthogonal experimental analysis results | Network structure depths | Number of convolutional kernels | Number of fully connected layers |
|-----------------------------------------|--------------------------|---------------------------------|---------------------------------|
| First level                             | 0.76900                  | 0.70925                         | 0.70225                         |
| Second level                            | 0.75350                  | 0.72225                         | 0.77325                         |
| Third level                             | 0.75600                  | 0.85150                         | 0.79450                         |
| Fourth level                            | 0.71550                  | 0.71100                         | 0.72400                         |

**Fig. 8** Prediction success rate curve
For the spatial prediction of HSDs in Boshan District based on GIS, the normalized value distribution map of each prediction factor was plotted by setting the grid unit to 30 m × 30 m. Load the C# language on ArcGIS Engine, and perform secondary programming development on the established prediction model. After running for about 144.5 h, the computation of more than 7.758 × 10^5 grids were completed, and the susceptible probabilities of all grids were obtained. The results show that the largest susceptible probability is 0.963, while the smallest is 0.082.

According to the regional differences of the natural landforms of Boshan District and the controlling effect of each prediction factor on the occurrence of HSDs and other disaster regionalization boundaries (Huang and Zhao 2018; Zhang et al. 2019), the susceptible probabilities of HSDs in Boshan District were divided into low susceptible, medium susceptible and high susceptible, and the classification boundaries were: Low susceptible: [0.082, 0.357); Medium susceptible: [0.358, 0.691); High susceptible: [0.692, 0.963]. According to the above classification method, the susceptible map of HSDs in Boshan District was plotted based on GIS, as shown in Fig. 9.

The following conclusions can be drawn from Fig. 9:

1. Low susceptible, medium susceptible and high susceptible areas account for 56.92%, 28.46% and 14.62% of the total areas of Boshan District, namely, 397.3016, 198.6508 and 102.0476 km², respectively. Baita Town and Yucheng Town in the north of Boshan District are mostly in high susceptible areas. Among the 83 unstable slopes, three are located in low susceptible areas, 29 are located in medium susceptible areas and 51 are located in high susceptible areas, accounting for 3.61%, 34.94% and 61.45% of the total, respectively. This indicates that the spatial prediction results of HSDs in Boshan District are reasonable and correct.

2. The susceptible probabilities of HSDs in Boshan District are gradually decreasing from north to south. Apart from the apparent regional differentiations of the combination features of prediction factors, another important reason is that the engineering construction as well as population and economic density in Boshan District, that is, the damage degree to the natural environment caused by the human engineering activities decreases from north to south (Gao et al. 2012).

3. Binlai Expressway, G205, G309, S210 and S307, contain sections that pass through high susceptible areas. Therefore, in addition to strength, daily maintenance, compile emergency plans and reserve emergency supplies, disaster prevention and control measures should be taken on these sections, and the main measures include: Carry out a comprehensive investigation of HSDs and establish a spatial database and attribute database; Establish a disaster monitoring, assessment, prediction and early warning system based on the Internet of Things and rainfall forecast information, with real-time dynamic display of disaster information on GIS; Carry out risk assessment of HSDs; and carry out engineering protection for HSDs with unacceptable risks based on the assessment results.
5 Discussions

5.1 Influences of the prediction factor combinations on the prediction success rates

Reasonable selection of prediction factors is a prerequisite for improving prediction success rates of HSDs. Too few prediction factors will lead to a lack of disaster information and inaccurate prediction results. When there are too many prediction factors that are not completely independent, multicollinearity may occur, making it easy to fall into “curse of dimensionality” (Wen et al. 2013; Charles et al. 2019; Doerr and Mayer 2021; Grüne 2021). After the collinearity analysis, the rationality of the number of prediction factors was discussed in this paper. Five prediction factor combinations (including the combination in Sect. 2.3) were proposed to verify the influences of different combinations on the prediction success rates, as shown in Table 2.

Taking the 64 stable highway slopes and 21 unstable highway slopes as drill samples, line charts of the prediction factor combinations #2 to #5 were plotted and input to the selected ECG-CNN network, and the corresponding verification samples were predicted to obtain the susceptible probability of each highway slope. ROC method was used to verify the prediction results and the prediction success rate of each combination was obtained, as shown in Fig. 10.

The following conclusions can be drawn from Table 2 and Fig. 10:
(1) The more the prediction factors, not necessarily the better. For example, the prediction success rates of the prediction factor combinations #3 and #4 (6 factors) are lower than that of the prediction factor combination #5 (5 factors).
(2) The prediction success rate of prediction factor combination #2 is only slightly lower than that of the prediction factor combination #1, indicating that the surface cutting depth has little effect on the prediction success rate.
(3) The prediction success rates of the prediction factor combinations #3 and #4 are low, indicating that the elevation and gradient factors are important for HSDs, and have more significant impacts on the prediction success rates.

5.2 Influences of the drill sample and verification sample combinations on the prediction success rates

Drill sample and verification sample combinations have great impacts on the studding abilities of ECG-CNN networks. Four sets of drill sample and verification sample combinations (including the combination in Sect. 3.2) were proposed to verify their prediction success rates respectively, as shown in Table 3.

Line charts of the drill sample and verification sample combinations #2 to #4 were proposed and input to the selected ECG-CNN network, and the corresponding verification samples were predicted to obtain the susceptible probability of each highway slope. ROC method was used to verify the prediction results and the prediction success rate of each combination was obtained, as shown in Fig. 11. The following conclusions can be drawn from Table 3 and Fig. 11:

(1) When the drill samples increase, the prediction success rate increases, but the magnitude is not large, indicating that the network drill has matured at this time, and the prediction error is caused by the limitation of the model’s logical structure itself.
(2) When the drill samples decrease, the prediction success rate decreases significantly, indicating that network drill’s maturity has a larger impact on the prediction success rate.

6 Conclusions

(1) Spatial prediction factors of HSDs were selected and spatial prediction models were built on the basis of ECG-CNN in Boshan District. Susceptible map of HSDs in Boshan District was plotted on the basis of GIS. The results show that low susceptible areas, medium susceptible areas and high susceptible areas account for 56.92%, 28.46% and 14.62% of the total areas of Boshan District, namely, 397.3016, 198.6508 and 102.0476 km², respectively. Baita Town and Yucheng Town in the north of Boshan District are mostly in high susceptible areas. Some sections of Binlai Expressway, G205, G309, S210 and S307, pass through high susceptible areas.
(2) Influences of the prediction factor combinations and the drill sample and verification sample combinations on the prediction success rates were verified. The results show that the surface cutting depth has a small impact on the prediction success rate, while the elevation and gradient have great impacts on the prediction success rates. When the
| No. | Number of prediction factors | Prediction factor combination                                                                 | Prediction success rate |
|-----|------------------------------|-------------------------------------------------------------------------------------------------|------------------------|
| #1  | 7                            | Elevation, Gradient, Surface cutting depth, Surface cutting density, NDVI, Distance from river, Lithology | 0.912                  |
| #2  | 6                            | Elevation, Gradient, Surface cutting density, NDVI, Distance from river, Lithology              | 0.907                  |
| #3  | 6                            | Elevation, Surface cutting depth, Surface cutting density, NDVI, Distance from river, Lithology | 0.601                  |
| #4  | 6                            | Gradient, Surface cutting depth, Surface cutting density, NDVI, Distance from river, Lithology  | 0.596                  |
| #5  | 5                            | Elevation, Surface cutting depth, Surface cutting density, NDVI, Lithology                      | 0.701                  |
Fig. 10  Prediction success rate curve of each prediction factor combination

Table 3  Drill sample and verification sample combinations and corresponding prediction success rates

| No. | Drill samples                  | Verification samples | Prediction success rate |
|-----|--------------------------------|----------------------|-------------------------|
| #1  | 64 stable slopes, 21 unstable slopes | 62 unstable slopes   | 0.912                   |
| #2  | 64 stable slopes, 35 unstable slopes | 48 unstable slopes   | 0.915                   |
| #3  | 50 stable slopes, 15 unstable slopes | 68 unstable slopes   | 0.804                   |
| #4  | 40 stable slopes, 8 unstable slopes | 75 unstable slopes   | 0.535                   |

Fig. 11  Prediction success rate curve of each drill sample and verification sample combination
drill samples are small, network drill’s maturity has a great impact on the prediction success rate, while when there are many drill samples, the model’s logical structure itself has a large impact on the prediction success rate.

Acknowledgements This research is supported by the National Natural Science Foundation of China (Grant No. 51808327) and Natural Science Foundation of Shandong Province (Grant No. ZR2019PEE016). I would like to thank Han Zhang for his contribution to the revision process.

Funding Funding was provided by National Natural Science Foundation of China (Grant No. 51808327) and Natural Science Foundation of Shandong Province (Grant No. ZR2019PEE016)

Declarations

Conflict of interest The authors have not disclosed any competing interests.

References

Ali SA, Parvin F, Vojtekova J, Comulus R, Linh NTT, Pham QB, Vojtek M, Gigovic L, Ahmad A, Ghorbani MA (2021) GIS-based landslide susceptibility modeling: A comparison between fuzzy multi-criteria and machine learning algorithms. Geosci Front 12(2):857–876
Bragagnolo L, Silva RV, Grzybowski JMV (2020) Landslide susceptibility mapping with r. landslide: A free open-source GIS-integrated tool based on Artificial Neural Networks. Environ Modell Softw 123:104565
Charles V, Aparicio J, Zhu J (2019) The curse of dimensionality of decision-making units; a simple approach to increase the discriminatory power of data envelopment analysis. Eur J Oper Res 279(3):929–940
Chen W, Pourghasemi HR, Kornejady A, Zhang N (2017) Landslide spatial modeling: Introducing new ensembles of ANN, MaxEnt, and SVM machine learning techniques. Geoderma 305:314–327
Cui P, Xiang LZ, Zou Q (2013) Risk assessment of highways affected by debris flows in Wenchuan earthquake area. J Mt Sci 10(2):173–189
Dehnavi A, Aghdam IN, Pradhan B, Varzandeh MHM (2015) A new hybrid model using step-wise weight evaluation ratio analysis (SWARA) technique and adaptive neuro-fuzzy inference system (ANFIS) for regional landslide hazard evaluation in Iran. CATENA 135:122–148
Doerr B, Mayer S (2021) The recovery of ridge functions on the hypercube suffers from the curse of dimensionality. J Complex 63:101521
Dou J, Yunus AP, Bui DT, Merghadi A, Sahana M, Zhu ZF, Chen CW, Khosravi K, Yang Y, Pham BT (2019) Assessment of advanced random forest and decision tree algorithms for modeling rainfall-induced landslide susceptibility in the Izu-Oshima Volcanic Island, Japan. Sci Total Environ 662:332–346
Gao XM, Qin ZL, Wang LJ, Chen LX, Ma SQ, Yang KD (2012) The climatic characteristics of geological calamity in the mountainous area of the middle part of Shandong Province. Sci Technol Rev 30(4):55–60 (in Chinese)
Ghebrezgabher MG, Yang TB, Yang XM, Sereke TE (2020) Assessment of NDVI variations in responses to climate change in the Horn of Africa. Egypt J Remote Sens Space Sci 23(3):249–261
Grüne L (2021) Overcoming the curse of dimensionality for approximating Lyapunov functions with deep neural networks under a small-gain condition. IFAC-PapersOnLine 54(9):317–322
Guo QY, Bai WY, Zhao XY, Guo LY, Wang XH, Geng CM, Wang XL, Wang J, Yang W, Bai ZP (2021) Source and health risk assessment of PM2.5-bound metallic elements in road dust in Zibo City. Environ Sci 42(3):1245–1254
He Y, Zhao ZA, Yang W, Yan HW, Wang WH, Yao S, Zhang LF, Liu T (2021) A unified network of information considering superimposed landslide factors sequence and pixel spatial neighbourhood for landslide susceptibility mapping. Int J Appl Earth Obsv Geoinform 104(15):102508
Hong HY, Liu JZ, Bui DT, Pradhan B, Acharya TD, Pham BT, Zhu AX, Chen W, Ahmad BB (2018) Landslide susceptibility mapping using J48 decision tree with AdaBoost, Bagging and rotation forest ensembles in the Guangchang area (China). CATENA 163:399–413
Huang Y, Zhao L (2018) Review on landslide susceptibility mapping using support vector machines. CATENA 165:520–529
Huang FM, Yan J, Fan XM, Yao C, Huang JS, Chen W, Hong HY (2022) Uncertainty pattern in landslide susceptibility prediction modelling: Effects of different landslide boundaries and spatial shape expressions, Geosci Front 13(2):10131
Jia XL, Xu JL, Yang HZ, Zhao LP (2012) Calculation of broken index of surface based on GIS. J Chongqing Univ 35(11):126–130 (in Chinese)
Jiang R, Sanchez-Azofeifa A, Laakso K, Wang P, Xu Y, Zhou ZY, Luo XW, Lan YB, Zhao GP, Chen X (2021) UAV-based partially sampling system for rapid NDVI mapping in the evaluation of rice nitrogen use efficiency. J Cleaner Prod 289:125705
Kang PC, Zhao QQ, Guo SQ, Liu H, Chao ZL, Jiang LT, Wu GH (2021) Optimisation of the spark plasma sintering process for high volume fraction SiCp/Al composites by orthogonal experimental design. Ceram Int 47(3):3816–3825
Kiranyaz S, Ince T, Gabbouj M (2016) Real-time patient-specific ECG classification by 1D Convolutional Neural Networks. IEEE Trans Biomed Eng 63(3):664–675
Kumar D, Thakur M, Dubey CS, Shukla DP (2017) Landslide susceptibility mapping & prediction using Support Vector Machine for Mandakini River Basin, Garhwal Himalaya, India. Geomorphology 295:115–125
Li YJ, Xie QL (2013) Study on discriminant criterion of highway landslide disaster. Appl Mech Mater 275–277:2735–2739
Li X, Jie ZQ, Feng JS, Liu CS, Yan SC (2018) Learning with rethinking: Recurrently improving Convolutional Neural Networks through feedback. Pattern Recogn 79:183–194
Li RF, Hou CL, Zhou H, Dai YS, Jin LQ, Xi Q (2020) Comparison on radiation effective dose and image quality of right coronary artery on prospective ECG-gated method between 320 row CT and 2nd generation (128-slice) dual source CT. J Appl Clin Med Phys 21(8):1–7
Li ZQ, Allegre O, Li QL, Guo W, Li L (2021) Femtosecond laser single step, full depth cutting of thick silicon sheets with low surface roughness. Opt Laser Technol 138:106899
Liu RJ, Zhang YZ, Wen CW, Tang J (2010) Study on the design and analysis methods of orthogonal experiment. Exp Technol Manag 27(9):4 (in Chinese)
Mandal K, Saha S, Mandal S (2021) Applying deep learning and benchmark machine learning algorithms for landslide susceptibility modelling in Rorachu river basin of Sikkim Himalaya. India Geoscience Frontiers 12(5):17
Peethambaran B, Anbalagan R, Kanungo DP, Goswami A, Shihabudeen KV (2020) A comparative evaluation of supervised machine learning algorithms for township level landslide susceptibility zonation in parts of Indian Himalayas. CATENA 195:104751
Sahin EK, Colkesen I, Acmali SS, Akgun A, Aydinogu AC (2020) Developing comprehensive geocomputation tools for landslide susceptibility mapping: LSM tool pack. Comput Geosci 144:104592
Sameen MI, Pradhan B, Lee S (2020) Application of convolutional neural networks featuring bayesian optimization for landslide susceptibility assessment. CATENA 186:104249
San BT (2014) An evaluation of SVM using polygon-based random sampling in landslide susceptibility mapping: the Candir catchment area (western Antalya, Turkey). Int J Appl Earth Obs Geoinf 26:399–412
Sezer EA, Nefeslioglu HA, Osna T (2017) An expert-based landslide susceptibility mapping (LSM) module developed for Netcad architect software. Comput Geosci 98:26–37
Sha AM, Tong Z, Gao J (2018) Recognition and measurement of pavement disasters based on Convolutional Networks. China J Highway Transp 31(1):1–10 (in Chinese)
Shu JX, Zhang JL, Wu JT (2017) Research on identification of slope disasters along highways based on deep convolution neural network. Highway Transp Appl Technol 154:70–74 (in Chinese)
Sun Q, Shi QM (2020) Study on the risk zoning of urban earthquake disaster based on GIS: Take Zibo City as an example. Earthquake Res Sichuan 2:19–24 (in Chinese)
Sun DL, Xu JF, Wen HJ, Wang DZ (2021) Assessment of landslide susceptibility mapping based on Bayesian hyperparameter optimization: A comparison between Logistic regression and random forest. Engineering Geology 281:105972
Sun DL, Shi SX, Wen HJ, Xu JH, Zhou XZ, Wu JP (2021) A hybrid optimization method of factor screening predicated on GeoDetector and Random Forest for Landslide Susceptibility Mapping. Geomorphology 379:107623
Vild A, Teixeira S, Kühn K, Cuniberti G, Sencadas V (2016) Orthogonal experimental design of titanium dioxide-Poly(methyl methacrylate) electrospun nanocomposite membranes for photocatalytic applications. J Environ Chem Eng 4(3):3151–3158
Wang Y, Duan HX, Hong HY (2019) A comparative study of composite kernels for landslide susceptibility mapping: A case study in Yongxin County, China. CATENA 183:104217

Wen Q, Xia LG, Li LL, Wu W (2013) Automatically samples selection in disaster emergency oriented landcover classification. Geom Inf Sci Wuhan Univ 38(7):799–804 ((in Chinese))

Wu XL, Yang JY, Niu RQ (2020) A landslide susceptibility assessment method using SMOTE and convolutional neural network. Geom Inf Sci Wuhan Univ 45(8):1223–1232 ((in Chinese))

Xie J, Hu K, Li GF, Guo Y (2021) CNN-based driving maneuver classification using multi-sliding window fusion. Expert Syst Appl 169:114442

Xiong Y, Pan YJ, Wu L, Liu BH (2021) Effective weight-reduction- and crashworthiness-analysis of a vehicle’s battery-pack system via orthogonal experimental design and response surface methodology. Eng Failure Anal 128:105635

Yang JT, Song C, Yang Y, Xu CD, Guo F, Xie L (2019) New method for landslide susceptibility mapping supported by spatial logistic regression and GeoDetector: A case study of Duwen Highway Basin, Sichuan Province, China. Geomorphology 324:62–71

Yi YN, Zhang ZJ, Zhang WC, Jia HH, Zhang JQ (2020) Landslide susceptibility mapping using multiscale sampling strategy and convolutional neural network: A case study in Jiuzhaigou region. CATENA 195:104851

Yin C (2020) Hazard assessment and regionalization of highway flood disasters in China. Nat Hazards 100:535–550

Yin C, Zhang JL (2018) Hazard regionalization of debris-flow disasters along highways in China. Nat Hazards 91:129–147

Yin C, Li HR, Che F, Li Y, Hu ZN, Liu D (2020) Susceptibility mapping and zoning of highway landslide disasters in China. PLoS ONE 15(9):e0235780

Zeng LC, Sun B, Zhu DQ (2021) Underwater target detection based on Faster R-CNN and adversarial occlusion network. Eng Appl Artif Intell 100:104190

Zhang GL, Wang M, Liu K (2019) Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. Int J Disaster Risk Sci 10(3):386–403

Zhang SW, Wang Z, Wang ZL (2020a) Method for image segmentation of cucumber disease leaves based on multi-scale fusion Convolutional Neural Networks. Trans Chinese Soc Agric Eng 36(16):149–157 ((in Chinese))

Zhang MK, Xu L, Xiong J, Zhang XD (2020) Correlation filter via random-projection based CNNs features combination for visual tracking. J Visual Commun Image Represent 77:103082

Zhang HP, Dong ZR, Sun MY, Gu HZ, Wang ZM (2021) TP-CNN: A Detection Method for atrial fibrillation based on transposed projection signals with compressed sensed ECG. Comput Methods Prog Biomed 210:106358

Zhang YF, Zhao ZD, Deng YJ, Zhang XH, Zhang Y (2021) Human identification driven by deep CNN and transfer learning based on multiview feature representations of ECG. Biomed Signal Process Control 68:102689

Zhang KK, Wu QF, Chen YP (2021) Detecting soybean leaf disease from synthetic image using multi-feature fusion faster R-CNN. Comput Electron Agric 183:106064

Zhao Y, Cheng J, Zhang P, Peng X (2020) Ecg classification using deep cnn improved by wavelet transform. Comput Mater Continua 64(3):1615–1628

Zhou SB, Tan B (2020) Electrocardiogram soft computing using hybrid deep learning CNN-ELM. Appl Soft Comput 86:105778

Zhou C, Yin KL, Cao Y, Ahmed B (2016) Application of time series analysis and PSO-SVM model in predicting the Bazimzen landslide in the Three Gorges Reservoir, China. Eng Geol 204:108–120

Zhu HH (2013) Key algorithms on computer-aided electro-cardiogram analysis and development of remote multi-signs monitoring system. (Doctor Thesis) Suzhou Institute of Nano-tech and Nano-bionics, Chinese Academy of Sciences, Suzhou, Jiangsu, China

Zhu T, Zhou J, Wang H (2017) Localization and characterization of the Zhangdian-Renhe fault zone in Zibo city, Shandong province, China, using electrical resistivity tomography (ERT). J Appl Geophys 136:343–352

Zhu AX, Miao YM, Yang L, Bai SB, Liu JZ, Hong HY (2018) Comparison of the presence-only method and presence-absence method in landslide susceptibility mapping. CATENA 171:222–233

Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.