A Research on the Methods for Prediction of the Slope Stability of Open-pit Mine

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***Abstract*—In order to improve the slope stability of open-pit mine, this paper proposed four prediction methods BP (Back Propagation)Neural Network, Naive Bayes Classifier, Decision Tree and Support Vector Machine for predicting the classification of slope stability of open-pit mine.Firstly, the sample data of slope stability in open-pit mine are preprocessed, and the new sample data are obtained after data standardization, discretization and attribute reduction. Then, the corresponding prediction model is established by selecting different methods. All the four methods have been successfully applied to the prediction of 8 groups of samples to be tested. In order to determine the optimal method, the detailed accuracy and node error rate are compared to analyze the prediction results. The research shows that the BP neural network has high reliability and good practicability in the evaluation of the slope stability of open-pit mine.**

Keywords—slope stability, back propagation, naive bayes classifier, support vector machine, decision tree, prediction

I. INTRODUCTION

There are two kinds of mining methods for various mineral resources in China: open-pit mining and underground mining. Because of the large production scale and high mining efficiency, open-pit mining is generally adopted in the mining areas with open-pit mining conditions because of its large production scale and high mining efficiency. The boundary of each open-pit is composed of steep slopes of different forms, the slope address conditions are very complex, slope stability has been one of the major public relations issues in the mining industry, and has been widely concerned by the relevant scholars at home and abroad [1-5]. In literature [6], fuzzy neural network is used to evaluate slope stability, in literature [7] grey relational analysis and analytic hierarchy process are applied to slope stability, in literature [8] support vector machine is used. In reference [9], the Bayes discriminant analysis method of slope stability prediction is adopted. Each literature is evaluated by a single method, which can not be used to predict the slope stability in an all-round way

Although the above literature on open-pit slope stability research and discussion, and achieved a lot of results, but the research method is relatively simple, select a small number of indicators and samples, can not be a comprehensive evaluation of slope stability. Therefore, in this paper, six indexes which affect the slope stability of open-pit are selected, and BP neural network, Naive Bayes classifier, decision tree and support vector machine are used to find an optimal rule which can determine the attribution of new samples. So it can effectively judge the stability of the slope in the open-pit area.

II. SELECTION OF INDEXES OF MINE SLOPE STABILITY

There are many factors affecting the stability of mine slope, many of which are fuzzy and uncertain. According to the combination of literature [12-14], the evaluation indexes of mine slope stability are as follows:

Slope rock mass. It mainly refers to the important factors affecting the stability of mine slopes. Slope rock mass density per cubic meter of mass.

Cohesion. It is the attraction between adjacent parts of the same substance. From another perspective, the cohesion is the shear strength of the failure surface without any normal stress. The cohesion values obtained both contain stable true cohesion and unstable cohesion.

The angle of internal friction. One of the shear strength indicators of soil or rock reflects the magnitude of internal friction between particles within the soil or rock. The greater the internal friction angle, the higher the intensity.

Angle of pit slope. It determines the slope angle is the angle between the line from the top line of the topmost step to the bottom line of the bottom step and the horizontal line on the profile of the vertical slope. The smaller the slope angle, the greater the stripping ratio.

The height of the slope. It is related to the slope of the slope.Grade of side slope refers to the ratio of the height and width of the slope.

The pore-pressure ratio. It mainly refers to the ratio of the pore-pressure at one point in the site soil to the pressure of the upper earth cover. Pore-pressure means the pressure caused by the pore water and gas in the soil due to the load change, or the pressure transmitted through the pore water in the soil or the rock.

III. INTRODUCTION OF ALGORITHM

A. Back Propagation Neural Network

The most commonly used neural network is Back Propagation Neural Network(BPNN), which corrects the weight by repeatedly testing the training samples in order to the weight value is best stabilized at the minimum value. The relationship between the input layer to the hidden layer and the hidden layer to the output layer is as follows:

$$hidden[j] = f\left(\sum_{i=1}^{n} w_{ij}a_i - \theta_j\right) \quad (1)$$

$$out[i] = f\left(\sum_{i=1}^{n} w_{ji}b_j - r_i\right) \quad (2)$$

In the formula, a_i is the i -th point input; b_j is the j -th hidden layer node output; w_{ij} is the weight of the input layer to the hidden layer; w_{ij} is the weight of the hidden layer to the input layer; r_i is the weight from hidden layer to the output layer. θ is the threshold of the hidden layer.

B. Naive Bayes Classifier

The Naive Bayes classifier(NBC) is a simple and effective classifier which has been used successfully in practice[15,16]. The formula of naive Bias classifier is as follows,

$$C(X) = \arg\max_{C_i \in C} P(C_i)\prod_{k=1}^{n} P(x_k | C_i) \quad (3)$$

Where x_k is the number k attribute value of X.P (C_i) and $P(X_K|C_i)$ can be figured out by calculating the simultaneous frequency of different classes and attributes in the training sample. $P(C_i)$=S_i/S and S_i stand for the number of occurrences of C_i in the training sample. S stands for the total number of sample in the training sample.

C. Decision Tree

Decision Tree (DT) is an algorithm that is easy to use and operate for analyzing data. This algorithm is based on the Aokum razor theory and expound the concept of an information entropy.

$$Entropy(S) = -\sum_{i=1}^{m} p_i \log_2 p_i \quad (4)$$

Where S is the training set P_i (i = 1,2, .., m) is the frequency of the category attribute with the category label in all samples.

D. Support Vector Machine

Support vector machine(SVM) is a kind of algorithm to improve the generalization ability of learning machine by using the principle of minimizing the risk and confidence range. It has the advantages of strong global optimization ability and good generalization performance, which makes SVM widely used and has become the focus of many scholars.

According to the Kuhn-Tucker condition, the necessary and sufficient condition of the optimal hyper plane is that the classification hyperplane can satisfy the following relations:

$$\alpha_i^0\{[(x_i \cdot \omega_0) - b_0]y_i - 1\} = 0, \quad i = 1, 2, \ldots, l \quad (5)$$

Where ω is the weight matrix of classification, b is threshold of classification. a_i is lagrange multiplier factor. y_i represents a class that can be classified.

IV. MODEL BUILDING

A. Sample collection

Based on the literature mentioned and the grade evaluation system of mine slope stability[17], 30 representative training samples were selected. Mine slope stability is divided into 2 grades, which are stable (I)and destroy (II). The lope rock mass, cohesion, the angle of internal friction, angle of pit slope, the height of the slope, the pore-pressure ratio, mine slope stability are marked as X1、X2、X3、X4、X5、X6、R respectively.Shown as Table I.

B. Data preprocessing

As the original data have different engineering units, the indicators may differ by several orders of magnitude, so if use the original data directly to predict it will possibly cause the loss of information and the instability of numerical calculation. Therefore, we need to process the data to improve the prediction accuracy of the model. The steps are as fol

Step1: Standardization

Due to the selection of the indexes of water enrichment from coal seam roof have different dimensional and dimensional units which will affect the data analysis results.

So that we need data standardization. The data in Table I are standardized according to the following formula.

$$w_{ij} = \frac{s_{ij} - \min(s_j)}{\max(s_j) - \min(s_j)} \quad (6)$$

In the formula,s_{ij} is the sample before standardization. ω_{ij} is the sample after standardization.min (s_j) is the minimum in the original sample; max (s_j) is the maximum in the original sample.

TABLE I. SAMPLES OF SLOPE STABILITY

No.	***X1*** /(kn/m3)	***X2*** /(c/kPa)	***X3*** /(°)	***X4*** /(°)	***X5*** /(H/m)	***X6***/(ru/kPa)	***stability***
1	21.43	0	20	20	61	0.5	II
2	19.06	11.71	28	35	21	0.11	II
3	18.84	14.36	25	20	30.5	0.45	II
4	14	11.97	26	30	88	0.45	II
5	18	24	30.15	45	20	0.12	II
6	23	0	20	20	100	0.3	II
7	22.4	10	35	45	10	0.4	II
8	20	20	36	45	50	0.5	II
9	27	40	35	43	420	0.25	II
10	27.3	26	39	50	92	0.25	II
11	27	32	33	42	301	0.25	I
12	31.3	68	37	49	200	0.25	I
13	31.3	68	37	46	366	0.25	I
14	31.3	68	37	47	305	0.25	I
15	20.41	24.9	13	22	10.67	0.38	I
16	18.84	15.32	30	25	10.67	0.25	I
17	22.4	100	45	45	15	0.3	I
18	24	0	40	33	8	0.35	I
19	27.3	16.8	31	50	90.5	0.25	I
20	27.3	10	39	41	511	0.15	I
21	21.51	6.94	30	31	76.81	0.38	?
22	20.41	33.52	11	16	45.7	0.2	?
23	18.84	0	20	20	7.62	0.45	?
24	27.3	10	39	40	470	0.25	?
25	25	46	35	47	443	0.25	?
26	20	0	20	20	8	0.25	?
27	27	50	40	42	407	0.25	?
28	27	35	35	42	359	0.25	?
29	27	37.5	33	37.8	320	0.25	?
30	27	32	31	42	289	0.25	?

Step2: Discretization

Discretization can effectively overcome the hidden defects in the data and reduce the influence of extreme values and outliers and then make the results more stable. Entropy based method is one of the most efficient discretization methods. Specific formulas are as follows:

$$e_i = -\sum_{j=1}^{k} p_{ij} \log_2 p_{ij} \quad (7)$$

Where k is the number of different class labels; $p_{ij}=m_{ij}/m_i$ is the probability of class j in the i-th interval,m_i is the number of the median of the i-th partition, and m_{ij} is the number of values of class j in interval i.

Step3: Attribute Reduction

Attribute reduction can effectively eliminate the redundancy of data and reduce the training time and then improve the prediction accuracy. After discretization, the data is to be attribute reduction. We found that the data of the third group and the fourth group are repeat, the seventh group and the eighth group are repeat, the twelfth group and the fourteenth group are repeat, so we delete the third group, theseventh group and twelfth group data. In remaining 27 groups of data, the first 17 groups of data are training samples and other 10 groups are the sample to be tested.:

V. ESTABLISH MODEL

According to the selection of slope stability indexes, six indexes are selected as input vectors of the classification model (slope rock mass, cohesion, angle of internal friction, slope angle of foundation pit, slope height, pore pressure ratio). At the same time, the slope stability of open-pit is classified as stability and failure, and then it is regarded as the output category attribute of classification model. The relationship among the six indexes is shown in figure 1.

In figure 1, each plot represents the correlation between six indices and the slope stability of an open-pit respectively, and the seventh chart represents the comprehensive correlation between the indicators. According to the change of the red and blue cylinders, the correlation between the indexes and the slope stability of the open-pit mine is judged. The red columns of the first, third and fourth charts become longer gradually, indicating that the three indexes are positively related to the slope stability of the open-pit mine. The red columns of the second and the fifth plots become shorter gradually, which shows that the two indexes have negative correlation with the slope stability of open-pit. The change of red cylinder in the sixth chart is irregular, which indicates that this index is not related to the slope stability of open-pit mine.

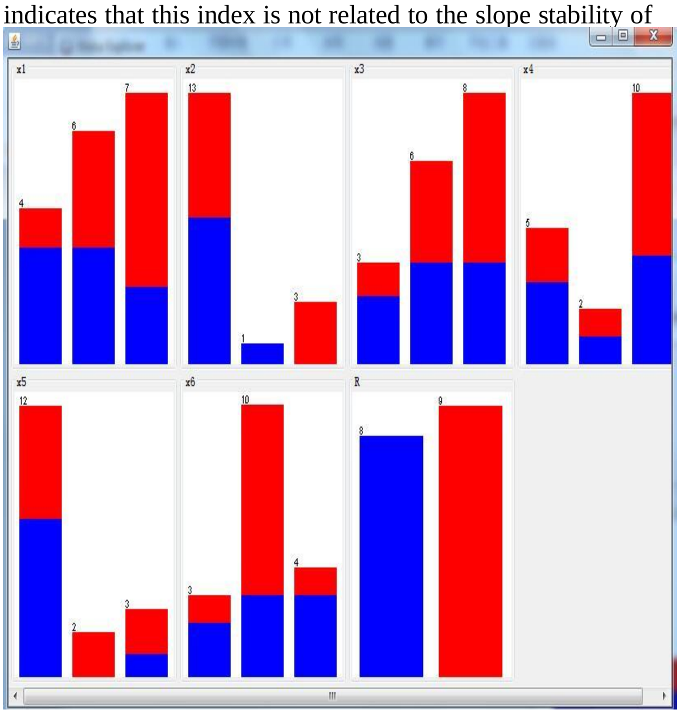

Fig.1. The relationship between the indicators

The BPNN model, NBC model, DT model and SVM model were established based on Weka platform. Then 17 training sample attributes are reduced and imported into weka. Select the test mode for the Supplied test set with high accuracy in the test options column and select Set to import 10 sets of samples to be tested..

VI. RESULT ANALYSIS

A. *Design of measurement scheme*

The accuracy rate (AR) of NBC, BPNN, DT, and SVM are 90%, 80%, 70%, and 70% respectively.The accuracy of the four algorithms are more than 70% which are ideal result. However, the accuracy of BPNN and NBC are 90%, and the prediction results also have some contingency and error so it is hardly to judge which method is better. Therefore, it is necessary to conduct further comparative analysis from the two aspects of precision and node error rate.

B. *Detailed accuracy*

It is clearly shown in Table Ⅲ that:

a) In TP Rate, NBC>BPNN>DT=SVM;

b) In FP Rate, DT>SVM>BPNN>NBC;

c) In Precision, NBC>BPNN>DT>SVM;

d) In Recall NBC>BPNN>DT=SVM;

e) In F-Measure, NBC>BPNN>DT>SVM;

f) Iin ROC Area, NBC>BPNN>DT>SVM.

We can see from the detailed aspect of accuracy, NBC is better than DT, BPNN, and SVM.

C. *Node error rate*

From the output of the four algorithms in the classify we can get the modeling time. The modeling time of BPNN, NBC, DT, and SVM are 0.09s, 0.03s, 0.16s and0.12s respectively. We combined the node error rate with modeling time of the four algorithms and comparatively analyze the node error rate .Table Ⅳ shows that:

a) In Mean absolute error, SVM>DT>NBC>BPNN;

b) In Root means quared error DT>SVM>BPNN> NBC;

c) In Relative absolute error,DT>SVM>BPNN>NBC

d) In Root relative squared error, DT>SVM>BPNN> NBC.

It can be seen from the comparison that the higher DT node error rate is not suitable for slope stability prediction. The error rate of BPNN and NBC is almost the same in value. In modeling time-consuming, BPNN is 0.09s larger than NBC 0.03s. It can be said that NBC is slightly better than BPNN in controlling node error rate. It can be concluded that NBC is better than BPNN in controlling the error rate of nodes, and BPNN is better than SVM and DT.

TABLE II. PREDICTION RESULTS OF THE FOUR ALGORITHMS

Test sample	***X1***	***X2***	***X3***	***X4***	***X5***	***X6***	*Actual results*	*BPNN*	*NBC*	*DT*	*SVM*
21	21.51	6.94	30	31	76.81	0.38	II	II	II	II	II
22	20.41	33.52	11	16	45.7	0.2	II	II	II	I	I
23	18.84	0	20	20	7.62	0.45	II	II	II	II	II
24	27.3	10	39	40	470	0.25	I	I	I	I	I
25	25	46	35	47	443	0.25	I	I	I	I	I
26	20	0	20	20	8	0.25	I	II	II	II	II
27	27	50	40	42	407	0.25	I	I	I	I	I
28	27	35	35	42	359	0.25	I	I	I	I	I
29	27	37.5	33	37.8	320	0.25	I	I	I	I	I
30	27	32	31	42	289	0.25	I	II	I	II	II

TABLE III. DETAILED ACCURACY

Detailed accuracy	***BPNN***	***NBC***	***DT***	SVM
TP Rate	0.8	0.9	0.7	0.7
FP Rate	0.086	0.043	0.193	0.125
Precision	0.88	0.925	0.733	0.49
Recall	0.8	0.9	0.7	0.7
F-Measure	0.808	0.903	0.71	0.576
ROC Area	0.762	0.905	0.619	0.5

TABLE IV. COMPARISON OF NODE ERROR RATE

node error	***BPNN***	***NBC***	***DT***	SVM
Mean absolute error	20.65%	22.18%	35%	37.87%
Root mean squared error	34.45%	33.57%	52.44%	47.68%
Relative absolute error	42.19%	40.32%	71.5%	67.16%
Root relative squared error	70.69%	68.49%	93.06%	92.29%

VII. CONCLUSIONS

(1)We selected 6 influence factors of the slope stability of open-pit mine such as the lope rock mass, cohesion, the angle of internal friction, angle of pit slope, the height of the slope, the pore-pressure ratio. Through sample collection and data preprocessing, the slope stability of open-pit mine model was established.

(2)Based on Weka, the four selected algorithms have all predicted successfully the 10 groups of sample upon the slope stability of open-pit mine in which the accuracy rate of NBC90%>BPNN80%>DT70%=SVM70%.

(3)It can be seen from the following four aspects: the accuracy of prediction, the accuracy of detail, the error node rate and the modeling time of NBC is 90%. The precision and the node error rate of NBC are obviously better than the other three models, and the modeling time is 0.03s. Therefore, NBC on the study of slope stability of open-pit mine have better effect so it is feasible to predict the slope stability of open-pit mine.

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