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Classification and Prediction of Rock Burst Based on BP Neural Network

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ABSTRACT

According to the characteristics of rock burst with fewer sample example data, factors influencing rock burst and the correlation between these factors are analyzed. By using BP Neural Network and other related theory and method of nonlinear discipline, prediction of rock burst hazard under small sample data is realized. Rock burst prediction model based on the BP Neural Network is established and verified from detailed accuracy and confusion matrix. Predicted results of eight groups and the actual situation is entirely consistent with accurate rate of 100%. This not only has a certain research value, but also provides a new approach for the prediction of rock burst hazard.

KEYWORDS: BP Neural Network, Rock Burst, Correlation, Classification Model

INTRODUCTION

The Introduction of Rock Burst

Rock burst, a mining dynamical disaster, is referred to a sudden, violent and sharp release of resilience accumulating on the inside of rock mass under some conditions causing failure accidents underground face in the process of mining and driving. All countries in the world have occurred rock burst phenomena in various degrees in mining engineering. In general, the occurrence of rock burst is correlated with two conditions, natural geological such as mining depth, faults, folds, coal seam thickness and dip angle, etc and production and technological conditions which is human factors and can be improved and controlled.

Comprehensively considering the impact in the various degrees on the above factors and the ease to measure, eight sample attributes initially defined, they are mining depth, roof lithologic character, complexity of structure, coal seam dip angle, coal seam thickness, mining method, pillar and mining technology.

The Introduction of BP Neural Network

BP neural network algorithm is Delta learning rule, the algorithm is based on the minimizing quadratic function, and its essence is to convert sample data input and output into a nonlinear optimization problem and the weight will change along the direction of negative gradient of the error function utilizing the steepest descent method.

The topological structure of BP neural network model consists of input layer 、hidden layer and output layer.

BP neural network can learn and store a large amount of mapping relationship of input-output model, and need not mathematics describing of mapping relationship in advance. An activation function called S-type function is commonly used:

Input:

$$net = x_1 w_1 + x_2 w_2 + x_3 w_3 + \cdots + x_n w_n$$

Output:

$$y = f\left(net\right) = \frac{1}{1 + \mathrm{e}^{-net}}$$

The structure of BP neural network consists of input layer with n neurons, hidden layer with p neurons and output layer with q neurons.

The global error is :

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}\left(d_o(k) - y_o(k)\right)^2$$

Among them, d_0 is expected output vectors, y_0 is output vectors of output layer[1-10].

ROCK BURST SAMPLE DATA PRETREATMENT

Data Pretreatment

The paper collects 23 groups of sample data associated with the rock burst, the first 17 groups being the training sample, and the rest ones being samples to be tested.

In the table below: mining depth(/m) is represented by a; roof lithologic character (sandstone or mudstone) is represented by b; complexity of structure (simple, medium or complex) is represented by c; coal seam dip angle($/^0$) is represented by d; coal seam thickness

(/m) is represented by e; mining method (Long-wall or Short-wall) is represented by f; pillar (YES or NO) is represented by g; mining technology (Fully Mechanized OR Blasting Mining) is represented by h; The degree of risk (weak, medium or strong) is represented by i. As is shown in Table 1:

Table 1: Sample data

NO	a	b	c	d	e	f	g	h	i
1	-540	sandstone	simple	10	3.1	Long-wall	NO	Fully Mechanized	weak
2	-560	sandstone	simple	13	2.6	Long-wall	NO	Fully Mechanized	weak
3	-549	sandstone	medium	11	2.7	Short-wall	NO	Fully Mechanized	weak
4	-556	sandstone	simple	11	2.3	Long-wall	NO	Fully Mechanized	weak
5	-563	mudstone	simple	9	2.2	Short-wall	NO	Fully Mechanized	weak
6	-602	sandstone	medium	12	2.6	Long-wall	YES	Fully Mechanized	weak
7	-573	mudstone	simple	11	2.2	Short-wall	NO	Fully Mechanized	medium
8	-522	sandstone	medium	9	2.1	Long-wall	NO	Fully Mechanized	medium
9	-660	mudstone	medium	16	3.2	Long-wall	NO	Fully Mechanized	medium
10	-609	mudstone	complex	16	2.9	Long-wall	YES	Blasting Mining	medium
11	-629	mudstone	medium	18	3.1	Short-wall	YES	Blasting Mining	medium
12	-642	mudstone	medium	17	3	Long-wall	YES	Fully Mechanized	medium
13	-702	sandstone	medium	19	3.1	Short-wall	NO	Fully Mechanized	strong
14	-674	sandstone	complex	18	3.2	Short-wall	YES	Blasting Mining	strong
15	-739	mudstone	complex	17	2.8	Short-wall	NO	Blasting Mining	strong
16	-690	sandstone	complex	19	3.5	Short-wall	YES	Blasting Mining	strong
17	-725	sandstone	complex	16	3.0	Short-wall	YES	Blasting Mining	strong
18	-622	mudstone	medium	15	2.8	Short-wall	YES	Blasting Mining	?
19	-732	sandstone	complex	16	3.1	Short-wall	YES	Blasting Mining	?
20	-654	mudstone	complex	18	3	Long-wall	NO	Fully Mechanized	?
21	-579	sandstone	simple	10	2	Short-wall	NO	Fully Mechanized	?
22	-590	sandstone	medium	12	2.5	Long-wall	YES	Fully Mechanized	?
23	-698	sandstone	complex	20	3.2	Short-wall	NO	Blasting Mining	?

Due to the fact that the original sample data involves different units, the numerical value of each variant may differ by several orders of magnitude. If the original data is calculated directly, certain information may be lost, which may give rise to the instability of numerical calculation as well as prolongation in model training. Consequently, it is essential to normalize the original sample data, so as to enhance the prediction accuracy and calculation stability of the model. And the normalized formula is as follows:

$$s_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

The original data should be pretreated in the process of data mining based on rough set theory. Besides, providing that the range of some condition attribute or decision attribute is successive, the original data needs a discrete process before being used. Moreover, despite that the data is a discrete one, sometimes, it is also necessary to combine the discrete value so as to get one at a more abstract level.

After attribute reduction based on rough set theory, it is found that the 8 attributes are all indispensable, so all the attribute are retained, and the nucleus of the attribute set should be{a, b, c, d, e, f, g, h}.

The relationship between the eight influencing factors is as shown in Figure 2.

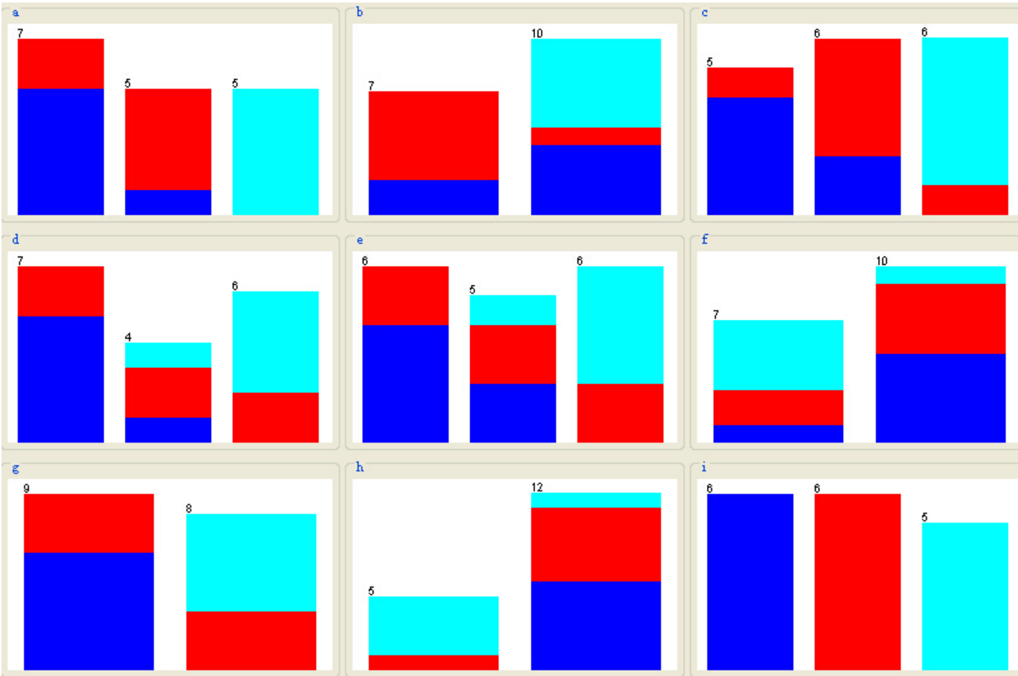


Figure 2: Visualize All

Table 2: Pearson correlation

		a	b	c	d	e	f	g	h	i
a	Correlation	1	0.086	.729**	.860**	.716**	.426**	0.392	.677**	.875**
	Sig.(two-tailed)		.684	0.000	0.000	0.000	0.034	0.053	0.000	0.000
b	Correlation	0.086	1	0.031	0.171	0.022	0.053	0.007	0.068	0.000
	Sig.(two-tailed)	0.684		0.882	0.413	0.916	0.8	0.975	0.747	1
c	Correlation	.729**	0.031	1	.705**	.624**	0.211	.446*	.680**	.739**
	Sig.(two-tailed)	0.000	0.882		0.000	0.001	0.312	0.025	0.000	0.000
d	Correlation	.860**	0.171	.705**	1	.849**	0.262	.416**	.658**	.806**
	Sig.(two-tailed)	0.000	0.413	0.000		0.000	0.205	0.038	0.000	0.000
e	Correlation	.716**	0.022	.624**	.849**	1	0.129	.442*	.585*	.651**
	Sig.(two-tailed)	0.000	0.916	0.001	0.000		0.539	0.027	0.002	0.000
f	Correlation	.426*	0.053	0.211	0.262	0.129	1	0.045	.458*	.400*
	Sig.(two-tailed)	0.034	0.800	0.312	0.205	0.539		0.830	0.021	0.047
g	Correlation	0.392	0.007	.446*	.416*	.442*	0.045	1	.592**	.403*
	Sig.(two-tailed)	0.053	0.975	0.025	0.038	0.027	0.830		0.002	0.046
h	Correlation	.677**	0.068	.680**	.658**	.585**	.458**	.592**	1	.714**
	Sig.(two-tailed)	0.000	0.747	0.000	0.000	0.002	0.021	0.002		0.000
i	Correlation	.875	0	.739**	.806**	.651**	.400**	.403**	.714**	1
	Sig.(two-tailed)	0.000	1.000	0.000	0.000	0.000	0.047	0.046	0.000	

**. $p<0.01$

*. $P<0.05$

Pearson Correlation

We carried on the Pearson correlation of the major factors of the risk degree of Rock Burst in SPSS software, and the results were as shown in Table 2.

The Pearson correlation of the major factors of the risk degree of rock burst were analyzed, and there were mining depth, coal seam dip angle, complexity of structure, mining technology, coal seam thickness, pillar, mining method and roof lithologic character from big to small.

CLASSIFICATION MODEL OF ROCK BURST

On account of that mining depth, roof lithologic character, complexity of structure,coal seam dip angle, coal seam thickness, mining method, pillar and mining technology, these eight factors exert a most tremendous impact on rock burst, the index data of these eight factors are chosen as the input vector of the classifier model. Here, grade of The degree of risk from strong (represented by 3), medium (represented by 2), to weak(represented by 1) serve as the classification attribute of the classification model.

Select 10-fold cross-validation as the test mode in the weka platform, to test the accuracy of classification algorithm.

Final training results are as follows:

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 16 94.1176 %
Incorrectly Classified Instances 1 5.8824 %
Kappa statistic 0.9115
Mean absolute error 0.0541
Root mean squared error 0.1416
Relative absolute error 12.1991 %
Root relative squared error 30.099 %
Total Number of Instances 17

(1) As Detailed Accuracy by Class shown in Table 4:

Table 4: The Detailed Accuracy of BP Neural Network

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0.091	0.857	1	0.923	0.992	1
	0.833	0	1	0.833	0.909	0.992	2
	1	0	1	1	1	1	3
Weighted Avg.	0.941	0.032	0.95	0.941	0.941	0.995	

(2) As Confusion Matrix shown below:

=== Confusion Matrix ===
a b c <-- classified as
6 0 0 | a = 1
1 5 0 | b = 2
0 0 5 | c = 3

The diagonal value of Confusion Matrix is rather high, which reveals the classifier model produces satisfactory results. In particular, predictions of training in category 1(weak) and category 3(strong) are all correct, while in category 2 (medium), there is only one error.

Manifestations in Visualize Classifier Errors are shown in Figure 5:

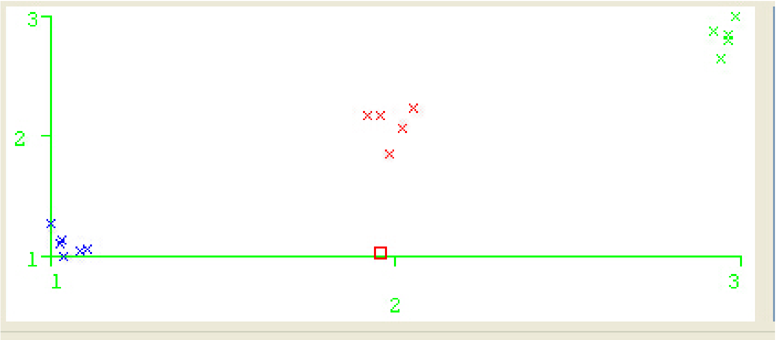


Figure 5: Visualize Classifier Errors

As Visualize Classifier Margin Curve shown in Figure 6:

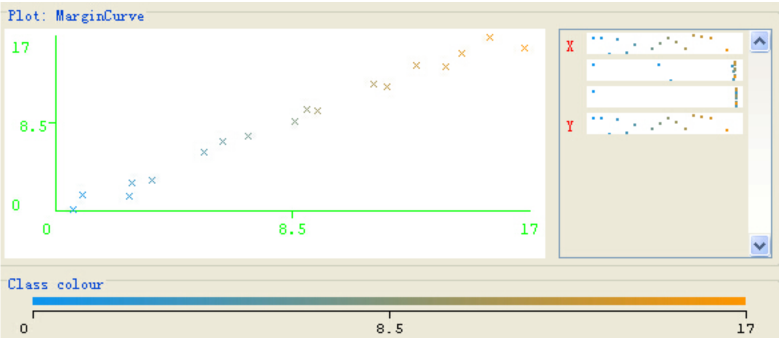


Figure 6: Visualize Classifier Margin Curve

As Visualize Classifier Cost Curve shown in Figure 7:

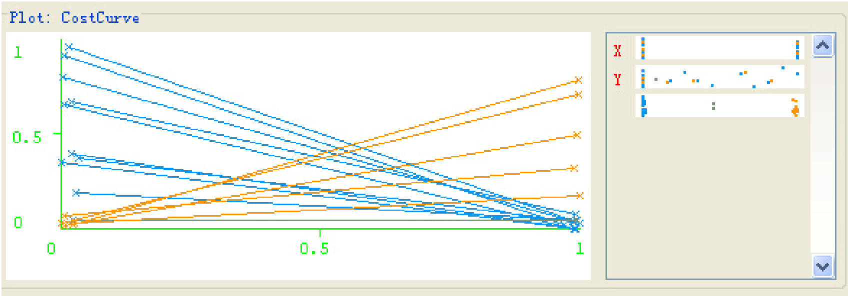


Figure 7: Visualize Classifier Cost Curve

In conclusion, it is found that the training effect of establishing models on the basis of BP Neural Network is the best.

Classification and Prediction of Rock Burst

Assuming that the classification of the eight groups of samples to be tested belongs to 1,(i.e. the degree of risk is weak), which can be completed through UltraEdit. And edit code as shown below:

@relation '????-weka.filters.unsupervised.attribute.Discretize-B3-M-1.0-R1,4,5'
@attribute a {'\'(-inf-0.333333]\'','\'(0.333333-0.666667]\'','\'(0.666667-inf)\''}
@attribute b {0,1}
@attribute c {0,0.5,1}
@attribute d {'\'(-inf-0.333333]\'','\'(0.333333-0.666667]\'','\'(0.666667-inf)\''}
@attribute e {'\'(-inf-0.333333]\'','\'(0.333333-0.666667]\'','\'(0.666667-inf)\''}
@attribute f {0,1}
@attribute g {0,1}
@attribute h {0,1}
@attribute i {1,2,3}
@data
'\'(0.333333-0.666667]\'',0,0.5,'\'(0.333333-0.666667]\'','\'(0.333333-0.666667]\'',0,1,0,1
'\'(0.666667-inf)\'',1,1,'\'(0.333333-0.666667]\'','\'(0.666667-inf)\'',0,1,0,1
'\'(0.333333-0.666667]\'',0,1,'\'(0.666667-inf)\'','\'(0.666667-inf)\'',1,0,1,1
'\'(-inf-0.333333]\'',1,0,'\'(-inf-0.333333]\'','\'(-inf-0.333333]\'',0,0,1,1
'\'(-inf-0.333333]\'',1,0.5,'\'(-inf-0.333333]\'','\'(-inf-0.333333]\'',1,1,1,1
'\'(0.666667-inf)\'',1,1,'\'(0.666667-inf)\'','\'(0.666667-inf)\'',0,0,0,1

As we all know, The path of BP Neural Network in weka is: Classifier-Function-MultilayerPerceptron. Introduce the trained model into Weka, and select “MultilayerPerceptron” among “Classifier” to introduce into the eight groups of samples to be tested, as shown in Figure 8:

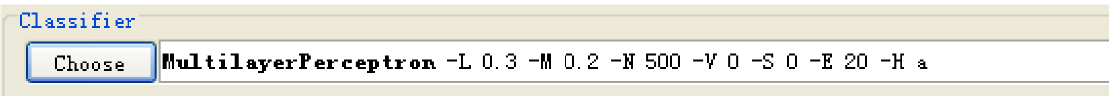
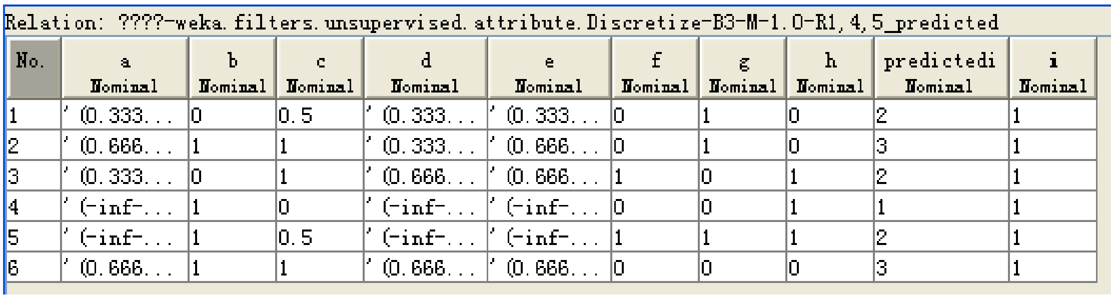


Figure 8: classifier chosen

and select “supplied test set” among “test options” to introduce into the eight groups of samples to be tested, and click on “start”, and then click on model selection “visualize classifier errors” on the right side of window “result list”, and to save it the prediction results can be obtained. As is shown in Figure 9:


Relation: ????-weka.filters.unsupervised.attribute.Discretize-B3-M-1.0-R1,4,5_predicted

No.	a Nominal	b Nominal	c Nominal	d Nominal	e Nominal	f Nominal	g Nominal	h Nominal	predictedi Nominal	i Nominal
1	'(0.333...	0	0.5	'(0.333...	'(0.333...	0	1	0	2	1
2	'(0.666...	1	1	'(0.333...	'(0.666...	0	1	0	3	1
3	'(0.333...	0	1	'(0.666...	'(0.666...	1	0	1	2	1
4	'(-inf-...	1	0	'(-inf-...	'(-inf-...	0	0	1	1	1
5	'(-inf-...	1	0.5	'(-inf-...	'(-inf-...	1	1	1	2	1
6	'(0.666...	1	1	'(0.666...	'(0.666...	0	0	0	3	1

Figure 9: the results by weka

According to Figure 9, it is clearly concluded that the predicted results of eight groups of samples are{2,3,2,1,2,3}, that is, the degrees of risk of eight groups of samples are {medium, strong, medium, weak, medium, strong }

Among the samples to be tested, the all eight groups of samples are all correct, which are manifested in the following table 10.

Table 10: comparison of prediction result and actual result

NO	a	b	c	d	e	f	g	h	Predicted	Actual	Result
18	-622	mudstone	medium	15	2.8	Short-wall	YES	Blasting Mining	medium	medium	True
19	-732	sandstone	complex	16	3.1	Short-wall	YES	Blasting Mining	strong	strong	True
20	-654	mudstone	complex	18	3	Long-wall	NO	Fully Mechanized	medium	medium	True
21	-579	sandstone	simple	10	2	Short-wall	NO	Fully Mechanized	weak	weak	True
22	-590	sandstone	medium	12	2.5	Long-wall	YES	Fully Mechanized	medium	medium	True
23	-698	sandstone	complex	20	3.2	Short-wall	NO	Blasting Mining	strong	strong	True

From Table 10, it can be concluded that in the prediction for degrees of risk, the eight groups of samples under test of BP Neural Network are identical with actual results, and the accuracy is 100%.

CONCLUSION

(1) By analyzing factors involving the risk degree of rock burst, this paper concludes the eight major factors. The pearson correlation of the major factors of the risk degree of rock burst were analyzed, and there were mining depth, coal seam dip angle, complexity of structure, mining technology, coal seam thickness, pillar, mining method and roof lithologic character from big to small.

(2) The prediction model of rock burst based on BP Neural Network was built. Test the models from two aspects, including detailed accuracy by clas and confusion matrix , and the test results were this model based on BP Neural Network was best.

(3) Finally, use the established models to predict for the eight groups of samples under test and the results are identical with the actual results, and the accuracy is 100%.

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