Prediction of Coal Mine Pressure Hazard Based on Logistic Regression and Adagrad Algorithm—A Case Study of C Coal Mine

Bobin Zhu 1,2, Yongkui Shi 1,2,*, Jian Hao 1,2,* and Guanqun Fu 1,2

Abstract: Effectively avoiding coal mine safety accidents has always been an important issue in the process of coal mining. In order to predict mine pressure hazard and reduce the occurrence of mine safety accidents, this paper innovatively combines logistic regression and mine pressure hazard prediction to establish a mine pressure hazard prediction model. By standardizing the data, the model improves the reliability of the mine pressure data and reduces the interference of the prediction effect of random errors. Based on the batch gradient descent algorithm and the Adagrad optimization algorithm, the prediction model is solved innovatively, which greatly improves the calculation speed and prediction accuracy of the model. Accuracy rate, precision rate, recall rate, and F1-score were selected as the evaluation indices to evaluate the prediction effect of the Adagrad optimization algorithm to solve the logistic regression model for mine pressure hazard. Compared with the existing classification algorithms, such as SVM and decision tree, the Adagrad optimization algorithm has the highest four indices when solving the logistic regression prediction model, and it takes the least time to predict. The results show that the model can efficiently predict mine pressure hazard. Finally, C Coal Mine was selected as the example for analysis. The prediction function was added to the mine pressure monitoring interface design. The practical application effect is similar to the theoretical verification. The establishment of this model provides a reliable guarantee for the secure and efficient production of coal mines and provides helpful research for the prediction of mine pressure.

Keywords: mine pressure hazard prediction; logistic regression; Adagrad gradient algorithm

1. Introduction

China is rich in mineral resources; 193 kinds of minerals have been discovered in the country. China’s confirmed coal reserves rank third in the world and have always been the main energy source in the country. China also has the world’s fifth-largest iron ore reserves, and it is an important supplier of iron mineral resources in the world [1,2]. When an ore body is mined, the original stress of the rock mass is destroyed and redistributed. At the same time, the surrounding rock is deformed, thus producing ore pressure on the working face, roadway, and surrounding rock. In the process of increasing the depth and intensity of coal mining, more dangerous mining pressure phenomena appear, such as the “crushing” of the coal wall and support, as well as surface collapse, which restricts the safe and efficient production of mines [3,4]. In recent years, the Shen dong method of “double-lane” mining has been adopted in the Meng shan area. Although the output efficiency has increased, hazards such as rock burst occur often [5]. The effective way to predict and forecast mine pressure under the existing conditions is to establish a mine pressure prediction model by mastering the roof pressure mechanism and the change law of support.
load. In this process, researchers need to explore the relationship between rock movement and support load [6,7]. ZHANG Yong-gang [8] studied the causes of dynamic mine disasters in the Hegang area to analyze the close relationship between mine earthquakes and gas overflow. ZHAO Bo used the mine field development mode of the Dachang Coal Mine as the research object and proposed measures to prevent accidents according to the actual mine conditions [9].

HE Chuan [10] used the APH-SA model to determine the evaluation indicator parameters and established the hazard evaluation system of rock burst in working faces. Fan Zhan-wen [11] analyzed the advance abutment pressure of coal wall and traditional mine pressure observation through the microseismic monitoring method. LIU Shi-tao et al. [12] used one-way ANOVA to obtain the initial and periodic pressure steps, which were basically consistent with the theoretical calculation. LIU Cheng et al. [13] used similar simulation research to establish a similar model for a comprehensive analysis of mine pressure. XIN Xian-yao et al. [14] introduced the technology of microseismic monitoring based on the analysis of multi-source data, such as support pressure, and studied the characteristics of various mine pressure behavior anomalies in working face. MA Zi-min et al. [15] studied the abnormal occurrence mechanism of mine pressure and roof control technology in fully mechanized caving stope through theoretical analysis and field measurement. XU Gang et al. [16] proposed a method for calculating the evolution of rock pressure in large-thickness roofs of fully mechanized caving faces and analyzed the evolution law of roof pressure in fully mechanized caving stope. YANG Jun-zhe et al. [17] studied the law of mine pressure behavior in a working face with an 8.8 m support and super mining height via means of large data analysis of mine pressure. LI Jian-wei et al. [18] combined theoretical analysis, numerical simulation, and field measurement to analyze the influence of factors such as the as buried depth of the shallow coal seam on the mine pressure behavior of the working face. JU Jin-feng et al. [19] summarized the law of mine pressure behavior in different mining stages and analyzed the differences in mine pressure behavior in fully mechanized mining faces with different mining heights. The above research adopted the traditional methods of evaluation analysis, numerical simulation, and field measurement to analyze the rules and characteristics of the occurrence of mine pressure. These articles provide theoretical guidance for the research of this paper. However, most of these studies were carried out after mine pressure appeared, and the aim of early prediction is not achieved.

Now, more researchers are using data-driven methods and machine learning techniques to predict mine pressure in advance. JI Wen-li et al. [20] established a pressure prediction model of MBCT-SR-RF based on random forest and showed that the MBCT-SR-RF prediction model had higher prediction accuracy than BP neural network and SVM. LIU Yi-xin [21] established a prediction model of mine pressure behavior in the working face based on machine learning through similar simulation experiments. WANG Zhi-kui [22] conducted a regional analysis and prediction on the pressure law of the working face roof based on the big data of the working resistance of the working face support. GONG Shi-xin et al. [23] proposed a prediction method of mine pressure in a fully mechanized mining face based on a manifold regularization domain adaptive function link prediction error integration algorithm. CHENG Hai-xing et al. [24] established a prediction model of mine pressure data based on a back-propagation neural network. YIN Xi-wen et al. [25] constructed a two-period dynamic analysis and prediction model of mine pressure via means of field measurement, data mining, and theoretical analysis. CHANG Feng [26] established a prediction model of working face roof mine pressure based on the optimized GA-BP neural network. The training results showed that the prediction effect of the optimized GA-BP neural network model was better than that of the BP neural network.

The above studies achieved significant results in the prediction of mine pressure numerical value and mine pressure behavior based on machine learning methods, which provide valuable research experience for the establishment of a mine pressure hazard prediction model in this paper. However, they mostly used regression algorithms and will
eventually obtain continuous values, not a category. Managers often need to quickly and accurately predict whether the mine pressure data are abnormal or dangerous. When this occurs, a classification algorithm will play an indispensable role.

The research purpose of this paper is to predict whether danger exists in coal mine pressure, help managers predict and judge the danger caused by mine pressure exceeding the threshold, and make appropriate decisions in due time. In order to manage users more conveniently, the output results only need to be the presence of danger and the absence of danger, so as to provide a decision-making basis for managers. It is clear that this problem is a binary classification problem.

CHEN Jie et al. [27] analyzed the differences between traditional prediction and machine learning early warning and listed evaluation indicators for evaluating rock burst, but they did not put forward specific solutions for a certain problem. MOU Liang [28] used the Gaojiapu Coal Mine as the research object and proposed a rock burst prediction method based on the deviation value of mine earthquake precursor characteristics and the dynamic change rate as the index. This study only predicted the impact of one working face in a single mining area. The limitations of the study are extensive. JIA Bao-xin et al. [29] put forward “global-region-local” multi-parameter comprehensive index rock burst monitoring technology for the Huo tai Mine. This technology can improve accuracy through the real-time monitoring of stratified and complementary regions. However, research has focused more on making predictions from different ranges to improve accuracy. WU Jian-bo et al. [30] established a logistic regression early warning model composed of comprehensive indicators to classify the occurrence of rock burst and verified the model based on the field-measured data of the Qianqiu Coal Mine. However, there were less data used in this study, the data mining depth was not deep enough, and the logistic regression algorithm was not really applied to the mine as a practical function.

This paper applied logistic regression to the prediction of mine pressure hazard for the first time in a real sense, analyzed the relationship between the influencing factors of mine pressure and mine pressure hazard, selected evaluation indicators to establish a mine pressure hazard prediction model supported by a large amount of data, adopted the Adagrad optimization algorithm to solve the model, and put forward a set of mine pressure prediction methods. At the same time, the logistic regression model was applied to the downhole as a practical system interface, which can be used for managers’ reference.

This prediction model can predict the emergence of danger in time, effectively reduce the occurrence of safety accidents, provide a powerful tool for mine managers to make decisions in advance, and provide a reliable guarantee for the safe and efficient production of coal mines.

2. Method Introduction and Data Processing

2.1. Method Introduction

Logistic regression is an analytical method that estimates the probability of an event based on a dataset of independent variables. The model can explore the influencing factors of certain disasters and quantitatively predict the probability of the disaster based on the hazard factors [31]. This method can obtain the coupling weights of various disaster monitoring indicators and present the prediction results of disaster occurrence in the form of event occurrence probability [32,33].

The Adagrad algorithm can adaptively adjust the learning rate of each dimension to deal with problems such as quadratic optimization [34]. It adaptively adjusts the learning rate according to the training degree. When the loss value is closer to the minimum value, the learning rate is smaller, which can prevent the loss function from approaching the minimum value due to a too-large learning rate or slow training convergence due to a too-small learning rate [35].

Because the sensors in C Coal Mine in the underground working face are subject to more interference, the data recorded by the mine pressure monitoring management
information system are abnormal. It is necessary to preprocess the acquired data to reduce the interference of abnormal data for prediction.

2.2. Denoising Processing

The obtained data were denoised to reduce the interference of the original data on the prediction. The process included the following:

a. Outlier processing: Due to the interference of the sensors in the underground working face, some data in the sample data clearly deviate from the rest. In this paper, the $3\sigma$ principle is used to identify outliers in the sample data; that is, the data other than the three standard deviations in the sample data can be regarded as wrong and thus be removed.

b. Missing value processing: Due to power outages, coal mining operation stoppage, etc., sensors and mine pressure monitoring systems shut down, resulting in data not being collected. This situation is often solved by using averages, medians to fill in or delete those data, etc. In this paper, the method of deleting missing data is adopted to reduce the impact of missing values on the prediction results.

c. Repeat value processing: Due to system reasons, a piece of data appears many times. It is necessary to delete the remaining duplicate pieces of data and retain only one of each datum.

d. Convert qualitative variables to numerical variables: The form of hydraulic support in the sample data of the mine pressure is a categorical variable, and the values of this variable are ["support-type", "shield-type", "support-shield-type"]; they cannot be directly used for logistic regression prediction so it is necessary to convert them to numeric-type variables. In this paper, the value of "support-type" is converted to a value of 0, the value of "shield-type" is converted to a value of 1, and the value of "support-shield-type" is converted to a value of 2. These values are all discrete values because they are class variables converted to numerical variables. In the subsequent calculation process, since these values also exist in the calculation, the remaining continuous values are approximated as discrete values.

2.3. Standardized Processing

The Sigmoid function is used as the activation function of the logistic regression model. If the distribution range of the sample data is very wide, the model can easily directly fall into the saturation area, resulting in the disappearance of the gradient. Hence, it is necessary to standardize the data in advance. The processing method often uses Z-score standardization and min–max standardization.

2.3.1. Z-Score Standardization

Z-score standardization can convert dimensional data to dimensionless data. The calculation formulas of this method are shown in Formulas (1) and (2).

$$
\sigma = \sqrt{\frac{1}{m} \sum_{j=1}^{m} (x_j - \mu)^2} \tag{1}
$$

$$
x'_j = \frac{x_j - \mu}{\sigma} \tag{2}
$$

In these formulas, $\sigma$ represents the standard deviation of the sample data, $\mu$ represents the average value of the sample data, $x_j$ for $j = 1, 2, \ldots, m$ represents the j-th sample data, $x'_j$ represents the new data of the j-th sample data after normalization, $j = 1, 2, \ldots, m$, and $m$ represents the amount of sample data.
2.3.2. Min–Max Standardization

The purpose of deviation standardization is to make the value range of the new data [0,1]. The calculation formula of this method is shown in Equation (3).

\[ x'_j = \frac{x_j - \min}{\max - \min} \]  

(3)

In the formula, \( x_j \) for \( j = 1, 2, \ldots, m \) represents the j-th sample data, \( x'_j \) represents the new data of the j-th sample data after normalization, \( j = 1, 2, \ldots, m \), \( m \) represents the amount of sample data, \( \min \) represents the minimum value in the sample data, and \( \max \) represents the maximum value in the sample data.

3. Model Building and Algorithm Design

3.1. Problem Formulation

This paper selects the ore pressure data of C Coal Mine as the research dataset and uses the logistic regression method to predict the mine pressure hazard. The prediction model is shown in Figure 1.

![Figure 1](image-url)  

Figure 1. The mine pressure hazard prediction model.

The purpose of this paper is to predict whether there is danger in the mine pressure, help managers predict and judge whether the danger is caused by mine pressure exceeding the threshold value, and make appropriate decisions in time. In order to manage users more conveniently, in terms of the result orientation, the output results only need to be the presence of danger and the absence of danger, so as to provide decision-making basis for managers. It is clear that the problem is a binary classification problem. Therefore, the mine pressure hazard is divided into “existence danger” and “non-existence danger”. Let \( y \) represent whether the mine pressure is dangerous; then, \( y = 0 \) means that the mine pressure does not exceed the standard and there is no danger, and \( y = 1 \) means that the mine pressure exceeds the standard and there is danger. There are many factors that affect mine pressure hazard, and together they form the evaluation indicator system that affects the mine pressure hazard. Let the evaluation indicator system \( X = [x_1, x_2, \ldots, x_i] \); \( x_i \) for \( i = 1, 2, 5 \ldots n \) represent the i-th evaluation indicator selected in the preprocessed data. The logistic regression prediction model is used to study the degree of influence of each evaluation indicator on the mine pressure hazard and the prediction results. The input of the prediction model is the evaluation indicator system \( X \), that is, the preprocessed mine pressure data, and the output is the prediction result \( y \), that is, whether the mine pressure is dangerous. Finally, the logistic regression prediction model driven by the sample data of the mine pressure is established.
3.2. Model Establishment

Through the evaluation indicator system $X = [x_1x_2x_3 \ldots x_i]$ that affects the mine pressure hazard, the linear regression function that affects the mine pressure hazard can be obtained as shown in Formula (4), which is the input of the logistic regression model.

$$z = W^TX + b = \omega_1x_1 + \omega_2x_2 + \ldots + \omega_nx_n + b$$  \hspace{1cm} (4)

In the formula, $x_i$, for $i = 1, 2, 3 \ldots n$, represents the $i$-th evaluation indicator; $\omega_i$, for $i = 1, 2, 3 \ldots n$, represents the weight of the $i$-th evaluation indicator; and $i = 1, 2, \ldots, n$, where $n$ represents the number of extracted evaluation indicators. $b$ represents the partial regression coefficient. Since the output result of the linear regression is continuous in the real-number field, but the result of the mine pressure hazard is “danger” or “no danger”, which is not a continuous value, it is necessary to introduce the Sigmoid function as the activation function. The Sigmoid function is shown in Formula (5).

$$h(z) = \frac{1}{1 + \exp(-z)}$$  \hspace{1cm} (5)

The Sigmoid function is an S-shaped curve, which can map any real number to a value between 0 and 1, but it does not take 0 and 1.

In this activation function, when $z$ approaches positive infinity, the value of $h(z)$ approaches 1; when $z$ approaches negative infinity, $h(z)$ approaches 0. The value range of the independent variable is any real number, and the function value range is $[0,1]$. Through the Sigmoid function, any input is mapped to the $[0,1]$ interval so as to obtain a predicted value in the linear regression $z$, and then the value is mapped to the Sigmoid function, thus completing the transformation from the value to the probability of occurrence of mine pressure hazard. The derived prediction model of mine pressure hazard based on logistic regression is shown in Formula (6).

$$h_\omega(x) = \frac{1}{1 + \exp(-\omega_1x_1 - \omega_2x_2 - \ldots - \omega_nx_n - b)}$$  \hspace{1cm} (6)

In general, we consider that when any input is mapped to the interval $[0,1]$ using the Sigmoid function, and the result $h_\omega(x) \geq 0.5$, the prediction $y = 1$, indicating that there is a danger that the value of mine pressure exceeds the standard. When $h_\omega(x) \leq 0.5$, the prediction $y = 0$, indicating that there is no danger that the value of mine pressure exceeds the standard. By using the conversion of the Sigmoid function, whether the mine pressure value is dangerous is converted into two interval ranges. The conversion value, which can be used to calculate and compare the mine pressure hazard, is obtained.

3.3. Model Solution

In logistic regression, the sample set of the training model consists of $m$ groups of labeled data:

$$\{ (X^{(1)}, Y^{(1)}), (X^{(2)}, Y^{(2)}), \ldots, (X^{(m)}, Y^{(m)}) \}$$  \hspace{1cm} (7)

$X^{(i)}$ represents the evaluation indicator system, its dimension is $n$, and the value of $n$ is the number of selected evaluation indicators. $Y^{(i)}$ represents the output results of whether the mine pressure is dangerous. Bringing each group of sample data into Formula (6), the probability of occurrence of mine pressure hazard predicted by this group of data can be obtained, as shown in Formula (8).

$$h_\omega(x^{(i)}) = \frac{1}{1 + \exp[-(\omega_1x_1^{(i)} + \omega_2x_2^{(i)} + \ldots + \omega_nx_n^{(i)} + b)]}$$  \hspace{1cm} (8)
In the formula, \( i = 1, 2, \ldots, n \), and \( n \) represents the number of selected evaluation indicators; \( j = 1, 2, \ldots, m \), and \( m \) represents the number of samples, that is, the amount of obtained mine pressure sample data.

Suppose that the probability that the mine pressure is dangerous is \( h_\omega(x) \), that is, the probability that \( y = 1 \). This is shown in Formula (9).

\[
p(y = 1|x; \omega) = h_\omega(x) \tag{9}\]

The probability that the mine pressure is not dangerous, that is, the probability of \( y = 0 \), is shown in Formula (10).

\[
p(y = 0|x; \omega) = 1 - h_\omega(x) \tag{10}\]

For the convenience of calculation, the above assumption functions are integrated to obtain Formula (11).

\[
p(y|x; \omega) = [h_\omega(x)]^y \cdot [1 - h_\omega(x)]^{1-y} \tag{11}\]

Finally, the maximum likelihood function is solved; that is, the greater the probability of all sample data finally being obtained, the better. For the convenience of calculation, the logarithm of the above likelihood function is taken. Taking the logarithm does not affect the monotonicity of the original function; rather, it enlarges the difference between the function values, so that the categories of each sample can be better distinguished. The result of taking the logarithm is shown in Formula (13).

\[
l(\omega) = \log L(\omega) = \sum_{j=1}^{m} \left[ y^{(j)} \cdot \log h_\omega(x_j) + (1 - y^{(j)}) \cdot \log (1 - h_\omega(x_j)) \right] \tag{13}\]

After taking the logarithm, the new function obtained is an upward convex function, which can be solved with a gradient boosting algorithm to obtain the maximum likelihood function value. Alternatively, we can multiply the above function by \(-1\) to make it a minimum negative log-likelihood function, which is a downward convex function, for which the new function can be solved with a gradient descent algorithm. The loss function is obtained by taking the average of \( m \) samples and the minimum negative log-likelihood function. The loss function is shown in Formula (14).

\[
J(\omega) = -\frac{1}{m} l(\omega) = -\frac{1}{m} \sum_{j=1}^{m} \left[ y^{(j)} \cdot \log h_\omega(x_j) + (1 - y^{(j)}) \cdot \log (1 - h_\omega(x_j)) \right] \tag{14}\]

The traditional solution method uses the batch gradient descent algorithm to solve the parameter values of the equations. The update formula of \( \omega \) in the batch gradient descent algorithm is shown in Formula (15).

\[
\omega_i := \omega_i - \alpha \frac{\partial}{\partial \omega_i} J(\omega_i) \tag{15}\]

In the formula, \( := \) represents the variable value update symbol, and the purpose is to continuously change the influence weight of the corresponding indicator on the mine pressure hazard according to the gradient of the mine pressure hazard evaluation indicator in each iteration and finally find the optimal weight \( \omega \) of each evaluation indicator.
\[
\frac{\partial}{\partial \omega_i} J(\omega_i) \]
represents the partial derivative of the loss function \( J(\omega_i) \) with respect to \( \omega_i \), and the derivation process is as follows:

\[
\frac{\partial}{\partial \omega_i} J(\omega_i) = -\frac{1}{m} \sum_{j=1}^{m} \left[ y^{(j)} \cdot \frac{1}{h_{\omega}(x^{(j)})} \cdot \frac{\partial h_{\omega}(x^{(j)})}{\partial \omega_i} - \left( 1 - y^{(j)} \right) \cdot \frac{1}{1 - h_{\omega}(x^{(j)})} \cdot \frac{\partial h_{\omega}(x^{(j)})}{\partial \omega_i} \right]
\]

\[
= -\frac{1}{m} \sum_{j=1}^{m} \left[ \left( y^{(j)} - \left( 1 - y^{(j)} \right) \cdot h_{\omega}(x^{(j)}) \right) \cdot \frac{\partial h_{\omega}(x^{(j)})}{\partial \omega_i} \right]
\]

\[
= -\frac{1}{m} \sum_{j=1}^{m} \left[ \left( y^{(j)} - h_{\omega}(x^{(j)}) \right) \cdot \frac{\partial h_{\omega}(x^{(j)})}{\partial \omega_i} \right]
\]

The update formula for \( \omega \) in the batch gradient descent algorithm is shown in Formula (17).

\[
\omega_i := \omega_i - \alpha \cdot \frac{1}{m} \sum_{j=1}^{m} \left[ h_{\omega}(x^{(j)}) - y^{(j)} \right] x_i^{(j)}
\]

In the formula, \( i = 1, 2, \ldots, n \), and \( n \) represents the number of selected evaluation indicators; \( \alpha \) represents the learning rate. Finally, the obtained \( \omega_i \) is brought into Formula (6), and the quantitative expression between the mine pressure hazard and each evaluation indicator can be obtained.

In order to improve the accuracy, computational speed, and robustness of the logistic regression prediction model, the Adagrad gradient algorithm is used to solve the model in this paper. The core idea of the Adagrad gradient algorithm is that if the gradient of a parameter is always very small, its corresponding learning rate will become smaller to prevent oscillation. If the gradient of a parameter is always very large, then the learning rate of the parameter becomes larger, allowing it to be updated more quickly. The update formula for \( \omega \) in the Adagrad gradient algorithm is shown in Formula (18).

\[
\omega_{t+1,i} := \omega_{t,i} - \frac{\alpha}{\sqrt{G_{t,i} + \varepsilon}} g_{t,i}
\]

In the formula, \( t \) represents the number of rounds for calculating the gradient, \( \alpha \) represents the learning rate, \( G_{t,i} \) represents the quadratic sum of the gradients from the first round to the \( t \)-th round, \( \varepsilon \) represents the smoothing term, which is used to avoid the case where the denominator is 0 and is usually taken as \( 10^{-10} \), and \( g_{t,i} \) for \( i = 1,2,3, \ldots i \), represents the gradient of the \( i \)-th evaluation indicator calculated in the \( t \)-th round.

3.4. Prediction Algorithm Design

According to the analysis of the above model establishment and solution, the mine pressure hazard prediction algorithm is designed, and the design process of the algorithm is shown in Figure 2.

The design process of the algorithm mainly includes the following steps:

Step 1. Obtain the original mine pressure monitoring data in the mine pressure monitoring management information system of C Coal Mine.

Step 2. Preprocess original data to obtain the sample dataset, including denoising processing and standardized processing, to eliminate the interference of abnormal data and dimensions on the prediction results.

Step 3. Initialize the weights of all evaluation indicators as decimals between 0 and 1.
Step 4. Substitute the initialized weights and the sample dataset into Formula (6) to calculate the predicted values of this iteration.

Step 5. Calculate the gradient of this iteration according to Formula (16).

Step 6. Update the weights of all evaluation indicators using the Adagrad gradient algorithm according to Formula (18).

Step 7. Determine whether the number of iterations reaches the initial setting. If it does not reach the initial setting, go back to step 4 for the next iteration; if it reaches the initial setting, output the current weights.

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Figure 2. Design process of prediction algorithm.

The prediction algorithm is implemented according to the design process, and the pseudo code is shown in Algorithm 1.

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**Algorithm 1**: Pseudo code for solving prediction model of mine pressure hazard. The solution of logistic regression

```python
1: Input: Features = \{F_1, F_2, \ldots, F_m\}, Labels = \{l_1, l_2, \ldots, l_m\}, LearnRate
2: Output: W = \{\omega_0, \omega_1, \omega_2, \ldots, \omega_n\}
3: Step1: Load Data and assign them to Features and Labels
4: for i in range m do //m is the number of samples
5: for j in range n do //n is the number of Features
6: F_i = \{f_1, f_2, \ldots, f_j\} ← feature_pushback(F_i)
7: end for
8: l_i ← label_pushback(l_i)
9: end for
10: Step2: Standardize the loaded data
11: for i in range n do
12: \mu ← average(F_i)
13: \sigma ← standard_deviation(F_i)
14: for j in range m do
15: f_i_j ← (f_j - \mu) / \sigma
16: end for
17: end for
18: Step3: Initialize W
19: for i in range n do
20: \omega_i ← random_number(0,1) //Initialize each \omega to a decimal between 0 and 1
21: end for
22: Step4: Train model
23: while Stopping criterion not met do
24: for i in range m do
25: \omega ← \omega - \nabla_w L(h(Features; \omega), \text{Labels}) / m //Compute gradient by the Sigmoid function and loss function
26: end for
27: \tau ← r + \epsilon + \omega^2 (\text{square element-wise}) //Accumulate gradient, and \epsilon is smooth index
28: \omega ← \omega - \frac{LearnRate}{\sqrt{\tau}} \odot \omega (\text{element-wise}) //Update \omega
29: end while
30: Return W
```
4. Experiments

4.1. Data Preparation

The data of the mine pressure monitoring management information system of C Coal Mine are obtained and preprocessed as a sample dataset. The dataset has a total of 1436 sets of data and a total of 25 data indicators. The coal mine has a total of five working faces, and the dataset example is shown in Table 1. We used Z-score standardization to eliminate the impact of different dimensions on the prediction results. The measured value was not processed. A measured value of 0 indicates that the mine pressure value does not exceed the standard and there is no danger. A measured value of 1 indicates that the mine pressure value exceeds the standard and there is danger.

<table>
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<th>Dip Angle of Coal Seam (Degrees)</th>
<th>Form of Hydraulic Support</th>
<th>Support Resistance (Mpa)</th>
<th>Microseismic Energy ((10^5 \text{ J}))</th>
<th>Borehole Stress (Mpa)</th>
<th>Initial Pressure Step of Old Roof (m)</th>
<th>Periodic Pressure Step of Old Roof (m)</th>
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<td>35</td>
<td>8</td>
<td>2</td>
<td>30</td>
<td>17.84</td>
<td>15.86</td>
<td>50</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
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</tr>
<tr>
<td>23203</td>
<td>4.8</td>
<td>1</td>
<td>1</td>
<td>39</td>
<td>17.07</td>
<td>15.76</td>
<td>100</td>
<td>100</td>
<td>1</td>
</tr>
<tr>
<td>23203</td>
<td>4.8</td>
<td>1</td>
<td>1</td>
<td>31</td>
<td>17.7</td>
<td>15.04</td>
<td>100</td>
<td>100</td>
<td>0</td>
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<td>...</td>
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<td>...</td>
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<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>23301</td>
<td>35</td>
<td>8</td>
<td>2</td>
<td>13</td>
<td>18.51</td>
<td>15.58</td>
<td>72</td>
<td>42</td>
<td>0</td>
</tr>
<tr>
<td>23301</td>
<td>35</td>
<td>8</td>
<td>2</td>
<td>6</td>
<td>4.55</td>
<td>15.19</td>
<td>72</td>
<td>42</td>
<td>0</td>
</tr>
</tbody>
</table>

Among the influencing factors, eight of the influencing factors shown in Table 1 were selected as the evaluation index system \(X\) [29,32] in the sample dataset. The evaluation indicators are detailed as follows [36]:

1. Coal seam thickness: When the thickness of the coal seam is large, the stress balance in the pressure rise zone is broken and the supporting pressure of the coal wall is greatly reduced on the original basis.
2. Coal seam dip angle: This factor has a great influence on the ore pressure appearance of the coal mining face. With the increase in the coal seam dip angle, the pressure of the overlying strata on the layer decreases and the tangential slip force along the layer increases. The falling gangue in the goaf may not be retained in situ and it is likely to slip along the floor, thus changing the movement law of the overlying strata. Due to the slip of the falling gangue in the goaf, the upper part of the goaf is empty and the lower part is empty, which leads to the unbalanced stress of the working face support.
3. Support form: The support in the roadway can be roughly divided into support-type, cover-type, and support-cover-type. Different forms of support have different effects on roof pressure.
4. Support resistance: The support resistance has an important influence on the mine pressure. If the support resistance is insufficient, it may cause spalling in the working face, roof fall, step sinking, and a reduction in the mining efficiency.
5. Microseismic energy: Microseismic energy has a good early warning effect on the periodic weighting of the working face. When the microseismic energy is greater than a certain value, it can be determined that the roof of the working face may be in a state of weighting and roof management needs to be carried out in time.
(6) Drilling stress: The promotion of the working surface causes a disturbance in the stress of the coal seam, and it can easily produce a large number of microfracture structures in the coal seam. The potential hazard of coal and gas outburst is further increased under the dual coupling of high gas pressure and coal body damage. The location of the borehole stress bulge should eliminate the hazard of coal and gas outburst.

(7) The first weighting interval of the main roof: The first collapse of the immediate roof is backward, and the working face continues to advance. The main roof can be regarded as a plate structure. With the continuous collapse of the direct roof, the main roof suspension span gradually increases until the limit span is reached. When the main roof breaks, it collapses.

(8) The periodic weighting spacing of the main roof: The main roof falls behind for the first time. As the coal mining face continues to advance, the main roof strata above the working face are exposed. Then, the collapse phenomenon of the main roof appears again and again, and the periodic mine pressure appears in the working face.

4.2. Assessment Indicators

Accuracy, precision, recall, and F1-score were selected as the criteria for assessing the logistic prediction model. The calculation formulas are shown in Formulas (19)–(22).

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{19}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{20}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{21}
\]

\[
\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{22}
\]

In these formulas, TP indicates the number of times a danger is present and predicted, FN represents the number of times there is danger but it is not predicted, TN indicates the number of times a danger is not present and is not predicted, and FP represents the number of times there is no danger but danger is predicted. The meaning of accuracy is that the number of correct predictions of mine pressure hazard accounts for the total number of validation samples, which can be understood as the overall accuracy of the prediction model. The meaning of the precision is that the number of correct predictions of mine pressure as dangerous accounts for the number predicted to be dangerous, which can be understood as the percentage of correct predictions of danger in the data. The meaning of the recall is that the number of predictions of danger in the mine pressure accounts for the actual number of dangerous instances, which can be understood as the percentage of the actual dangerous data that are correctly predicted. F1-score is an index used to comprehensively assess the performance of the classification model on the presence and absence of mine pressure hazard, and it is the harmonic average of the accuracy rate and the recall rate. It combines the performance of both to measure whether the mine pressure hazard prediction model can maintain a good balance between the accuracy and recall rates. If the F1-score of the model is high, the prediction performance of the model is good.

A low accuracy indicates that there are many pieces of non-dangerous data predicted to be dangerous, requiring mine managers to waste resources to find the problems, or even stopping mining operations, resulting in the disruption of normal production. Low recall indicates that there are many pieces of dangerous data not correctly predicted, and safety problems may occur, causing equipment damage and casualties, affecting safe and efficient production. A low F1-score indicates that the prediction performance of the established mine pressure hazard prediction model is weak, and its ability to predict mine pressure hazard is low.
4.3. Model Validation

The sample data of mine pressure in Table 1 are used as the fitted data of the solution model, the Adagrad optimization algorithm is used to iteratively solve the logistic regression prediction model established above, and the weight of each evaluation index is obtained so as to determine the importance of each index. In logistic regression, evaluation indicators and results are mapped. A large absolute value of the coefficient of an evaluation index indicates that this feature has great influence on the classification result. In the evaluation index system of this paper, the absolute value of the index coefficient corresponds to the importance of the index. A large absolute value of the coefficient of this evaluation index is large, indicating that the index has a high degree of importance in regression prediction and has a great impact on the classification result of whether there is danger in mine pressure. The calculated results are shown in Table 2.

Table 2. Evaluation index weight calculation results.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.3712</td>
<td>0.398</td>
<td>0.047</td>
<td>−5.8</td>
<td>−6.78</td>
<td>−0.648</td>
<td>−1.61</td>
<td>2.315</td>
</tr>
</tbody>
</table>

The quantitative expression between the mine pressure hazard and each indicator is obtained as shown in Formula (23).

\[
h_\omega(x) = [1 + \exp(-8.386 - 0.3712x_1 - 0.398x_2 - 0.047x_3 + 5.8x_4 + 6.786x_5 + 0.648x_6 + 1.61x_7 - 2.315x_8)]^{-1}
\] (23)

In the formula, \(x_1\) represents the coal seam thickness, \(x_2\) represents the dip angle of the coal seam, \(x_3\) represents the form of hydraulic support, \(x_4\) represents the support resistance, \(x_5\) represents the microseismic energy, \(x_6\) represents the borehole stress, \(x_7\) represents the initial pressure step of the old roof, and \(x_8\) represents the periodic pressure step of the old roof. The predicted value interval obtained using Formula (23) is \([0, 1]\). When its value is greater than 0.5, it is considered that the mine pressure value exceeds the standard and there is danger.

There are five working faces in C Coal Mine. In this study, 50 pieces of ore pressure monitoring data were selected from each working face to verify the regression model after fitting. We compared the predicted results with the actual situation, as shown in Figure 3.

In the figures, the black square represents the measured value, and its value is 0 or 1. A value of 0 indicates that the mine pressure value does not exceed the standard and there is no danger; a value of 1 indicates that the mine pressure value exceeds the standard and there is danger. The red circle represents the predicted value, which is calculated using the mine pressure hazard prediction model. The value interval is \([0, 1]\). A predicted value greater than 0.5 indicates that the mine pressure is dangerous, and a predicted value less than 0.5 indicates that the mine pressure is not dangerous. The predicted and measured values of the five working surfaces were compared and analyzed statistically. The predication results are shown in Table 3.
There are five working faces in C Coal Mine. In this study, 50 pieces of ore pressure monitoring data were selected from each working face to verify the regression model after fitting. We compared the predicted results with the actual situation, as shown in Figure 3.

(a) 

(b) 

(c) 

Figure 3. Cont.
Figure 3. (a) Working face 1 comparison of predicted and measured values of the prediction model. (b) Working face 2 comparison of predicted and measured values of the prediction model. (c) Working face 3 comparison of predicted and measured values of the prediction model. (d) Working face 4 comparison of predicted and measured values of the prediction model. (e) Working face 5 comparison of predicted and measured values of the prediction model.

Table 3. Prediction results of the model.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Danger</th>
<th>No Danger</th>
<th>Danger and Predicted (TP)</th>
<th>Dangerous but Not Predicted (FN)</th>
<th>No Danger and Not Predicted (TN)</th>
<th>No Danger but Predicted (FP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working face 1</td>
<td>12</td>
<td>38</td>
<td>12</td>
<td>0</td>
<td>36</td>
<td>2</td>
</tr>
<tr>
<td>Working face 2</td>
<td>8</td>
<td>42</td>
<td>7</td>
<td>1</td>
<td>41</td>
<td>1</td>
</tr>
<tr>
<td>Working face 3</td>
<td>11</td>
<td>39</td>
<td>10</td>
<td>1</td>
<td>38</td>
<td>1</td>
</tr>
<tr>
<td>Working face 4</td>
<td>11</td>
<td>39</td>
<td>10</td>
<td>1</td>
<td>37</td>
<td>2</td>
</tr>
<tr>
<td>Working face 5</td>
<td>10</td>
<td>40</td>
<td>9</td>
<td>1</td>
<td>40</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>52</td>
<td>198</td>
<td>48</td>
<td>4</td>
<td>192</td>
<td>6</td>
</tr>
</tbody>
</table>

According to Table 3 and Formulas (19)–(22), the accuracy, precision, recall, and F1-score of the total mine pressure hazard prediction model based on logistic regression are 96%, 88.89%, 92.31%, and 0.91, respectively. The results of the four comprehensive
evaluations are relatively high, which preliminarily confirms the feasibility of logistic regression for the mine pressure prediction model.

4.4. Experimental Analysis
4.4.1. Data Credibility Analysis

Cronbach’s alpha was used to analyze the credibility of the sample data before and after preprocessing, and the calculation formula is shown in Formula (24).

\[ \alpha = \frac{n}{n-1} \left( 1 - \frac{\sum S_i^2}{S^2} \right) \]  

(24)

In the formula, \( n \) represents the number of selected evaluation indicators affecting the mine pressure hazard, \( S_i^2 \) represents the variance in the \( i \)-th evaluation indicator in all samples, and \( S^2 \) represents the variance in the sum of all evaluation indicators in all samples.

Considering the influence of the data obtained through different preprocessing methods on the prediction model, eight different data preprocessing methods were designed, and the Cronbach’s alphas of the processed data were calculated, respectively, to compare and analyze the credibility of the data. The comparison of the pretreatment methods is shown in Table 4.

<table>
<thead>
<tr>
<th>Method</th>
<th>Outlier Processing</th>
<th>Missing Value Processing</th>
<th>Standardized Processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Non-processed</td>
<td>Fill the median</td>
<td>Min–max standardization</td>
</tr>
<tr>
<td>2</td>
<td>Non-processed</td>
<td>Fill the median</td>
<td>Z-score standardization</td>
</tr>
<tr>
<td>3</td>
<td>Non-processed</td>
<td>Delete missing values</td>
<td>Min–max standardization</td>
</tr>
<tr>
<td>4</td>
<td>Non-processed</td>
<td>Delete missing values</td>
<td>Z-score standardization</td>
</tr>
<tr>
<td>5</td>
<td>3σ principle to remove outliers</td>
<td>Fill the median</td>
<td>Min–max standardization</td>
</tr>
<tr>
<td>6</td>
<td>3σ principle to remove outliers</td>
<td>Fill the median</td>
<td>Z-score standardization</td>
</tr>
<tr>
<td>7</td>
<td>3σ principle to remove outliers</td>
<td>Delete missing values</td>
<td>Min–max standardization</td>
</tr>
<tr>
<td>8</td>
<td>3σ principle to remove outliers</td>
<td>Delete missing values</td>
<td>Z-score standardization</td>
</tr>
</tbody>
</table>

The Cronbach’s alphas of the sample data obtained with the eight different preprocessing methods were calculated using Formula (24), and the results are shown in Figure 4.

Figure 4. Cronbach’s alphas of the different data preprocessing methods.
It can be seen from Figure 5 that the outlier processing of the first four groups of data adopts the method of non-processing, the Cronbach’s alphas of the obtained data are all less than 0.6, and the credibility of the data is very poor. The Cronbach’s alpha of the data obtained by deleting missing values is larger than that obtained by filling the median. The Cronbach’s alpha of the data obtained by standardizing the data using Z-score standardization is larger than that of min–max standardization.

![Figure 5](image.png)

**Figure 5.** The influence of data obtained using different preprocessing methods on the prediction results.

In this paper, the $3\sigma$ principle, deleting missing values, and Z-score standardization are used to preprocess the data. The data obtained through this preprocessing method have the highest Cronbach’s alpha, greater than 0.9. It can be seen that the sample data obtained using this method have the highest credibility.

4.4.2. Experimental Design

Experiment 1:

Experimental objective: Verify the influence of eight different data preprocessing methods on the prediction model.

Experimental process: The data processed with these eight different data preprocessing methods were fitted and solved, respectively, for the logistic regression model of mining pressure hazard, and the accuracy, recall, and F1-scores of the predicted results were calculated, respectively.

Experiment 2:

Experimental objective: Verify the influence of the selected number of rating indicators on the prediction model.

Experimental process: Select 1, 2, 3 . . . 12 evaluation indicators to resume logistic regression prediction models, which were solved using the data processed using the optimal preprocessing method in Experiment 1. The accuracy rate, recall rate, and F1-score of each prediction result were also calculated.
Experiment 3:

Experimental objective: Verify the prediction effect of the logistic regression model solved using the Adagrad optimization algorithm.

Experimental process: Logistic regression model, support vector machine (SVM), decision tree, and naive Bayes were selected as comparison models, and the accuracy, recall, F1-score, and prediction time of each model were calculated, respectively.

4.4.3. Experimental Comparative Analysis

The results of Experiment 1 are shown in Figure 5. In this paper, the $3\sigma$ principle, deleting missing values, and Z-score standardization are used to preprocess the data. Compared with other preprocessing methods, the data obtained through this method can improve the accuracy, precision, recall, and F1-score of model prediction results up to 88%, 66.67%, 68.3%, and 67.46%.

The results of Experiment 2 are shown in Figure 6. When the number of evaluation indicators is selected from one to three, the accuracy of the model prediction results does not reach 50%, indicating that the model established by selecting too few evaluation indicators cannot accurately predict the mine pressure hazard. As the number of evaluation indicators increases, the accuracy of the model prediction results increases, and when the number of evaluation indicators reaches eight, the accuracy, precision, recall, and F1-score of the model prediction results reach the maximum value. After the number of evaluation indicators exceeds eight, the accuracy of the model prediction results decreases as the number of evaluation indicators increases.

![Figure 6. The influence of the number of evaluation indicators selected on the prediction results.](image)

In this paper, eight evaluation indicators were selected to establish the prediction model of mine pressure hazard, and the accuracy, precision, recall, and F1-score of the model reached the maximum value, meaning the model can correctly predict the mine pressure hazard.

The results of Experiment 3 are shown in Table 5. It can be concluded from the table that the logistic regression model is significantly better than the other models for classifying
and predicting the mine pressure hazard. Additionally, the logistic regression model solved using the Adagrad gradient algorithm showed the highest increase in accuracy, precision, recall, and F1-score of 17.5%, 54.74%, 66.64%, and 50% compared with other models, while the model took the shortest time to make predictions. Therefore, the logistic regression prediction model solved using the Adagrad gradient algorithm can be used as an effective method to predict mine pressure hazard.

<table>
<thead>
<tr>
<th>Prediction Model</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Time Spent on Prediction (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic (via Adagrad gradient algorithm)</td>
<td>94%</td>
<td>83.33%</td>
<td>90.9%</td>
<td>0.87</td>
<td>112,375</td>
</tr>
<tr>
<td>Logistic (via batch gradient descent algorithm)</td>
<td>86%</td>
<td>66.67%</td>
<td>72.73%</td>
<td>0.7</td>
<td>356,178</td>
</tr>
<tr>
<td>SVM</td>
<td>82%</td>
<td>56.25%</td>
<td>81.82%</td>
<td>0.67</td>
<td>182,741</td>
</tr>
<tr>
<td>Decision tree</td>
<td>84%</td>
<td>66.67%</td>
<td>54.55%</td>
<td>0.6</td>
<td>219,746</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>80%</td>
<td>53.85%</td>
<td>63.64%</td>
<td>0.58</td>
<td>276,193</td>
</tr>
</tbody>
</table>

The algorithms mentioned above are briefly introduced below [37].

1. Support vector machine (SVM) is a binary classification model, and its learning strategy is to maximize the interval. It can deal with nonlinear classification tasks. At present, it is only suitable for tasks with small batch samples. When the number of samples is large, the calculation complexity is high.

2. Decision tree is a recursive process from root to leaf; it can be used for both classification and regression tasks. Its core problem is how to select the appropriate properties to split the sample at each step. However, it can easily overfit when using too-complex data.

3. The naive Bayes classifier is a supervised learning algorithm, which originates from classical mathematics theory. It needs to estimate few parameters and has a stable classification efficiency. It is suitable for incremental training, and its speed is fast, but can easily have poor classification effect, and it is more sensitive to the expression form of input data.

In comparison with these other models, the accuracy rate, precision rate, recall rate, and F1-score of the prediction results of the logistic regression model solved using the Adagrad optimization algorithm increased by 17.5%, 54.74%, 66.64%, and 50% at the highest, and the prediction time of this model was the shortest. Therefore, the prediction method using the Adagrad optimization algorithm to solve the logistic regression model can be used as an effective mine pressure hazard prediction method.

4.5. Practical Application

After the logistic regression prediction model is established, the mine pressure data are preprocessed, the Adagrad optimization algorithm is used to solve the prediction model, and the mine pressure data actually recorded by the C Coal Mine pressure monitoring management information system are used to verify the fitted prediction model. At the same time, by comparing the four evaluation indices with the existing classification algorithms, it can be concluded that the improved algorithm in this paper is the best of the four indices, and the prediction takes the least time. This proves that the improved algorithm can be effectively applied to the actual mine pressure warning scenario. After proving this, the mine pressure hazard prediction function is added to the mine pressure monitoring management information system of C Coal Mine in a practical application. This function is based on the logistic regression prediction method, and the mine pressure hazard warning interface is designed to display the warning results. The specific display of the interface is shown in Figures 7 and 8. The interface displays the number and position of each hydraulic
support and the ore pressure data and time read by the sensor in real time. When the sensor records the new ore pressure data into the database, the interface immediately predicts the incoming data.

**Figure 7.** Mine pressure hazard warning interface.

**Figure 8.** Warning interface in the presence of hazard data.

In the prediction process, if $y = 0$ is calculated from the measured data, the early warning result in the system returns to 0. The information of the hydraulic support on the interface is displayed as white, indicating that the mine pressure value in the mining operation area is safe and there is no danger, as shown in Figure 7. In this case, the mining face can work normally. If $y = 1$ is obtained from the measured data through calculation, the warning result returns to 1 and the hydraulic support on the interface becomes an eye-catching red color, as shown in Figure 8. The red data send a warning signal to mine managers. Since the location coordinates of the hydraulic support are also included in the early warning interface, it is more convenient for managers to trace the source to find the mine location where the hydraulic support is located. According to the data corresponding to the hydraulic support, the manager can analyze and judge the situation and make correct production decisions in time, which can effectively avoid possible dangers.
early warning interface, it is more convenient for managers to trace the source to find the mine location where the hydraulic support is located. According to the data corresponding to the hydraulic support, the manager can analyze and judge the situation and make correct production decisions in time, which can effectively avoid possible dangers.

After the mine pressure hazard prediction function was implemented in C Coal Mine, the actual results of the prediction function were continuously recorded within six weeks. The results are shown in Figure 9.

![Graphs showing predicted results for different weeks.](image1)

**Figure 9.** (a) Predicted results for week 1. (b) Predicted results for week 2. (c) Predicted results for week 3. (d) Predicted results for week 4. (e) Predicted results for week 5. (f) Predicted results for week 6.

The results shown in Figure 9 show that within 6 weeks of using the mine pressure hazard prediction function in C Coal Mine, 20 pieces of data were selected at random time points in advance each week, and the prediction results of each datum were recorded. The prediction results were compared with the actual and statistically analyzed data to obtain
Table 6. During the six weeks when the mine pressure hazard prediction function was used in C Coal Mine, 20 corresponding pieces of evaluation index data were selected at random time points each week in advance, and the prediction results of each piece of data were recorded.

Table 6. Statistics of prediction results.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Danger</th>
<th>No Danger</th>
<th>Danger and Predicted (TP)</th>
<th>Dangerous but Not Predicted (FN)</th>
<th>No Danger and Not Predicted (TN)</th>
<th>No Danger but Predicted (FP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 1</td>
<td>5</td>
<td>15</td>
<td>5</td>
<td>0</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Week 2</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td>Week 3</td>
<td>4</td>
<td>16</td>
<td>3</td>
<td>1</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>Week 4</td>
<td>6</td>
<td>14</td>
<td>5</td>
<td>1</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>Week 5</td>
<td>5</td>
<td>15</td>
<td>5</td>
<td>0</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Week 6</td>
<td>1</td>
<td>19</td>
<td>1</td>
<td>0</td>
<td>18</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>21</td>
<td>99</td>
<td>19</td>
<td>2</td>
<td>95</td>
<td>4</td>
</tr>
</tbody>
</table>

According to Table 6 and Formulas (19)–(22), the accuracy rate, precision rate, recall rate, and F1-score of the prediction function are 95%, 82.61%, 90.48%, and 0.86. The prediction results of the mine pressure hazard prediction function are similar to the actual comparison results. Among them, 19 of the 21 pieces of dangerous data were accurately predicted, with an accuracy of 90.4%. The prediction function effectively reduces the possibility of accidents caused by the occurrence of mine pressure danger. In the case test, it helped the mine manager of C Coal Mine locate the danger location and analyze the reason according to the predicted danger warning and make the right decision in time. The results of the comparison of the examples prove the feasibility of applying the logistic regression prediction model calculated using the Adagrad optimization algorithm for the actual mine pressure hazard prediction.

5. Discussion

Mine pressure changes during mining due to geological disturbance, often causing hidden danger. If workers are not made aware of these dangers in time, mine pressure accidents can very easily occur. To solve this problem, this paper combines logistic regression and mine pressure hazard prediction, calculates the evaluation index, and establishes a new mine pressure hazard prediction model based on logistic regression. The prediction model is simulated and compared using the Adagrad optimization algorithm and then applied to C Coal Mine for practical example verification. The main results are as follows:

1. The data obtained using the 3σ principle to remove outliers, delete missing values, and 0-mean normalized preprocessing have the best reliability among the data of the different studied preprocessing methods. The four evaluation indices of model prediction results were higher for the predicted model than those of the other pretreatment methods.

2. In this paper, the Adagrad optimization algorithm based on the batch gradient descent algorithm is used to solve the logistic regression model. The coefficients of eight evaluation indices in the regression model were obtained via iteration. The data were fed into a regression model with determined coefficients, and the predictions were calculated. Comparing the predicted results with the actual hazard results, the accuracy rate, precision rate, recall rate, and F1-score were 96%, 88.89%, 92.31%, and 0.91, respectively. Through the comparison of the results, the model proved to be effective in the simulation process and can be used for the actual prediction test in the actual production process.

3. By comparing the Adagrad optimization algorithm with SVM and decision tree classification algorithms, the accuracy rate, precision rate, recall rate, and F1-score of
the results are up to 17.5%, 54.74%, 66.64%, and 50%, and the prediction time is the lowest. The calculation reliability of the Adagrad algorithm is proven.

4. The results obtained with the mine pressure hazard prediction function in the final example are similar to those produced in practice. Of the 21 pieces of dangerous data, 19 were accurately predicted, with an accuracy of 90.4%.

6. Conclusions

The research results of this paper confirm the feasibility of applying the proposed new mine pressure hazard prediction model based on logistic regression into actual mine pressure hazard prediction. This prediction model realizes a more efficient and accurate prediction of mine pressure hazard and can effectively provide theoretical and tool support for mine managers to predict mine pressure hazard and make appropriate decisions in time. However, there are different grades and categories of mine pressure hazards, and the mine conditions of coal mines and metal mines are different. Therefore, in the future, the multi-classification prediction of mine pressure hazard and the characteristics of metal ore will be thoroughly studied to further realize the intelligent decision making of the prediction function. After the system predicts the level and type of mine pressure danger, the induced causes are intelligently analyzed and corresponding solutions are formulated to guide production.

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References


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