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Method for intelligently identifying underground safety accidents based on fully connected neural network

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***Abstract*—Coal mine production is generally a multi-step and multi-step process of underground mining. The geology and mining conditions are complex, and there are many uneasy factors. They are often affected by gas, water and fire, carbon monoxide, ventilation, temperature, and roofs. Therefore, only by putting coal mine safety first in the work can keep the safety of underground workers and the normal progress of coal mine production work be ensured. Nowadays, predicting the cause of the alarm is the primary task of coal production. Moreover, many coal mining industries still remain at the manual recording stage for the cause of the alarm. Most of them rely on staff to manually record underground and then enter the system for storage. This makes it impossible to obtain timely feedback processing and statistics on hidden dangers. Moreover, underground work also includes a lot of sensor alarms caused by normal work, such as blasting, calibration and maintenance of circuits and other reasons, so it also caused a waste of time. Not only that, in the history of coal mining, it has been found that most of the casualties were caused by the ”three violations”. In short, it was man-made. In order to avoid these errors and reduce the phenomenon of ”three violations”, it is necessary to strengthen the protection of the mining personnel. Compliance inspections and one's own safety awareness can fundamentally reduce the occurrence of casualties.**

***Keywords*—DNN,underground safety accident,CO,intelligent identification,sensor alarm.**

I. Introduction

'Detection and Early Warning of Gas Outliers Based on Correlation Analysis' published by Liao Yinglei published in July 2020: In order to achieve hierarchical early warning of gas dangers, based on the analysis of the correlation between abnormal data, a weight-based Value-optimized Apriori association rules (Gas early warning modcl of Weight Optimization Apriori, WO-Apriori) gas danger early warning model. First, the gas concentration detected by the aforementioned algorithm and related abnormal monitoring data are binarized to construct a learning set of association rules. Secondly, calculate the support degree of the learning set and find the association rules generated in the high-frequency and high-frequency items. Finally, according to the association rules, a hierarchical early warning mechanism is designed [1] to determine the validity of abnormal data and achieve hierarchical early warning of hidden dangers of gas accidents. Although the prior art can provide graded early warning of gas danger, it does not reflect the cause of the accident corresponding to the graded gas warning.

Aiming at the existing technical problems, a method for intelligently identifying and predicting downhole safety accidents based on CO monitoring data is proposed. This method is based on the neural network model to effectively identify carbon monoxide detection data in coal mines [2], and input the carbon monoxide detection data into the trained neural network model to obtain the cause of the accident behind the detection data in real time. Some technicians do not need to use manual statistics or data entry to achieve objective statistics on the causes of accidents behind carbon monoxide data exceeding the standard, which greatly improves the efficiency of intelligent identification. Even if there are errors, the staff only need to partially modify the data.

II. Theoretical basis of fully connected neural network

Fully connected neural network is the simplest neural network, it has the most network parameters and the largest amount of calculation. The fully connected neural network model is a multi-layer perceptron. The principle of the perceptron is to find the most reasonable and robust hyperplane between categories. The most representative of the perceptron is the SVM support vector machine algorithm. Neural network draws on perceptron and bionics at the same time. Generally speaking, the animal nerve will send each neuron after receiving a signal. After receiving the input, each neuron will judge by animal, activate and generate the output signal and then aggregate to realize the identification and classification of the information source.

A. Fully connected neural network

The structure of DNN is not fixed. A general neural network includes an input layer, a hidden layer and an output layer. A DNN structure has only one input layer and one output layer. The input layer and the output layer are all hidden layers [3]. Each layer of neural network has several neurons. The neurons between the layers are connected to each other, the neurons in the layer are not connected to each other, and the neurons in the next layer are connected to all the neurons in the previous layer.

A neural network with more hidden layers (>2) is called a deep neural network (the number of layers in a DNN does not include the input layer). The expressive power of a deep neural network is stronger than that of a shallow network. A neural network with only one hidden layer It can fit any function, but it requires many, many neurons.

B. Backpropagation and gradient descent

The backpropagation algorithm is suitable for a learning algorithm of multilayer neural network, which is based on the gradient descent method. The input and output relationship of the backpropagation algorithm network is essentially a mapping relationship: a BP neural network with n inputs and m outputs [4] completes the function of moving from n-dimensional Euclidean space to a finite field in m-dimensional Euclidean space Continuous mapping, this mapping is highly non-linear.

Gradient descent is a kind of iterative method that can be used to solve least squares problems (both linear and nonlinear). When solving the model parameters of machine learning algorithms, that is, unconstrained optimization problems, Gradient Descent is one of the most commonly used methods, and another commonly used method is the least squares method. When solving the minimum value of the loss function, the gradient descent method can be used to solve it step by step to obtain the minimized loss function and model parameter values. Conversely, if we need to solve the maximum value of the loss function, then we need to use the gradient ascent method to iterate. In machine learning, two gradient descent methods have been developed based on the basic gradient descent method, namely stochastic gradient descent method [5] and batch gradient descent method.

III. INTELLIGENT RECOGNITION METHOD OF CO SENSOR ALARM

A. Data set division and preprocessing

The carbon monoxide data is divided into a training set and a test set. The training set and the test set respectively include multiple sets of data set of carbon monoxide data is $x = (x_1 , x_2 ... x_n)$, and each set of alarm reasons is $o = (o_1 , o_2 ... o_p)$. In the implementation of the method, 200 sets of carbon monoxide sensors are selected Analyze the data at the time of alarm, the first 180 sets of data are used as the training set, and the last 20 sets of data are used as the test set;

Use Min-Max standardization to map all carbon monoxide data to [0,1]:

$$z_i = \frac{x_i - \min\limits_{1 \le j \le n}\{x_j\}}{\max\limits_{1 \le j \le n}\{x_j\} - \min\limits_{1 \le j \le n}\{x_j\}} \tag{1}$$

This technical feature is used to eliminate the dimensional influence between the data and conduct a comprehensive comparison evaluation, which makes the neural network more efficient and predictive, and requires standardized processing of the original data;

Anti-normalization processing:

$$x_i = z_i(\max_{1 \le j \le n}\{x_j\} - \min_{1 \le j \le n}\{x_j\}) + \min_{1 \le j \le n}\{x_j\} \tag{2}$$

In formulas (1) and (2), z_i is the preprocessed data, $\min\limits_{1 \le j \le n}\{x_j\}$ and $\max\limits_{1 \le j \le n}\{x_j\}$ is the minimum and maximum values of each group of carbon monoxide data.

B. Model architecture

Including input layer, hidden layer and output layer. The number of neurons in the input layer is n, the number of hidden layers is 10, and the numbers of neurons are respectively s_1 , s_2 , s_3 ... s_{10}.

The number of neurons in the output layer is p, as shown in Fig.1:

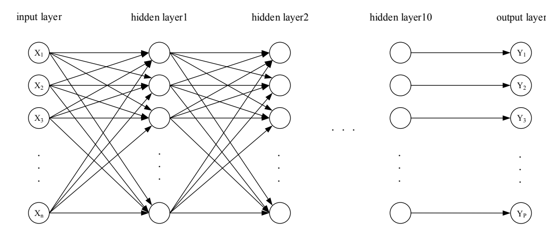

Fig. 1. neural network structure.

It also includes the activation function: Sigmoid function. The Sigmoid function is the most widely used activation function. It is a smooth function that is convenient for derivation and is similar to the integral form of the normal distribution function. The derivative calculation is relatively simple and satisfies the fully connected The need for frequent derivation of network. and the ability to compress data, to ensure that there is no problem with the data amplitude, the value range is (0,1), and a real number is mapped to the interval of (0,1), which is suitable for binary classification problems. To meet the needs of this article, the Sigmoid function is defined as:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

In formula (3), the x is the input value of the neuron.

A neural network includes an input layer, a hidden layer, and an output layer; a neural layer is composed of multiple neurons, and each neuron is composed of weights, thresholds, and activation functions. Therefore, building a neural network requires multiple weights [6], thresholds And activation function.

When constructing a fully connected neural network, you need to define weights and biases, since there will be multiple weight values in a neural layer, these weight values are basically similar in characteristics, so a variable is used to store all weight values of this neural layer. The initial value is generally a random variable, and each neuron has only one bias, and its initial value is usually a decimal number that is not 0, such as 0.1.

C. Model training and testing

The training set is used to train the fully connected neural network model.

Solution from input layer to hidden layer:

$$y_i = f(\sum_{j=1}^{n} w_{ij} z_j + b_i) \tag{4}$$

In formula (4), y_i is the result of the hidden layer solution; w_{ij} represents the weight between the j-th neuron in the previous layer and the i-th neuron in the current layer, where the neural network is a group of neural networks composed of layers Each neuron is a mathematical operation. It accepts the input multiplied by its weight, and then passes the sum to the weight between other neurons through the activation function. The initial value of the weight is arbitrarily selected, and then according to Backpropagation updates the weights; z_j represents the output value of the j-th neuron in the previous layer; b_i represents the bias term of the i-th neuron in the hidden layer, and the initial value of the bias term is arbitrarily selected, The initial value is usually a decimal not equal to 0, and then the bias term is updated according to gradient descent [7].

Solution from hidden layer to output layer:

$$o_i = f(\sum_{j=1}^{n} w_{ij} y_j + b_i) \tag{5}$$

In formula (5), o_i is the result of the output layer solution; w_{ij} represents the weight between the j-th neuron in the previous layer and the i-th neuron in the current layer; y_j represents the output of the j-th neuron in the previous layer Value; b_i represents the bias of the i-th neuron in the output layer.

The loss function used is:

$$MSE = \sum_{i=1}^{p} \psi_i (o_i^{'} - o_i)^2 \tag{6}$$

In formula (6), p is the number of carbon monoxide sensor alarm reasons, that is, the number of neurons in the output layer; ψ_i is the proportion of the i-th alarm reason in all training sets, and $o_i^{'}$ is the i-th nerve in the output layer The model output value of the element, o_i is the result of the output layer solution.

The method for adjusting the weight and bias term is:

$$\Delta w = -\alpha \frac{\delta MES}{\delta w} \tag{7}$$

$$\Delta b = -\alpha \frac{\delta MES}{\delta b} \tag{8}$$

In formulas (7) and (8), Δw is the adjustment of the weight, Δb is the adjustment of the bias term, and α is the learning rate, which represents the step factor for searching in the gradient direction. Is a value between to (0,1]; w represents the weight between the neurons in the previous layer and the neurons in the current layer; b represents the bias term of the neurons in the current layer.

The weight relationship before and after adjustment is as follows:

$$w(k+1) = w(k) + \Delta w(k) \tag{9}$$

The relationship of the offset items before and after adjustment is:

$$b(k+1) = b(k) + \Delta b(k) \tag{10}$$

$w(k)$ and $b(k)$ respectively represent the weight and bias terms after the kth adjustment.

The global mean square error is:

$$MSE_{oas} = \frac{1}{m} \sum_{k=1}^{m} \sum_{i=1}^{p} \psi_i (o(k)_i^{`} - o(k)_i)^2 \tag{11}$$

In formula (11), m is the number of groups in the training set, p is the number of carbon monoxide sensor alarm reasons, that is, the number of neurons in the output layer, ψ_i is the proportion of the i-th alarm reason in all training sets, $o(k)_i^{'}$ represents the model output value of the i-th neuron in the output layer of the k-th training set, and $o(k)_i$ represents the true value of the i-th neuron in the output layer of the k-th training set;

By continuously adjusting the weights and bias terms to make the global mean square error less than the acceptable value, the training ends, and finally the fully connected neural network model after training is obtained. The acceptable value is the artificially set mean square error value , Can be adjusted according to specific application scenarios, such as 0.000001.

Use the test set to test the trained fully connected neural network model:

Until the corresponding alarm reason data obtained by testing the carbon monoxide sensor data according to the fully connected neural network model is the same as the true value.

Input the carbon monoxide sensor data to be identified, and output the corresponding alarm reason data.

IV. Beneficial technical effects of the present invention

1. The current deep learning method recognizes fewer reasons for sensor alarms. The method presents an efficient sensor alarm reason analysis process, which utilizes cheap computing resources and reduces a large amount of labor costs. The method can quickly know whether the sensor alarm is caused by normal operation, such as various reasons such as blasting, calibration and maintenance of the circuit, so as to obtain timely feedback processing and statistics of hidden dangers. And then realize the overall management of coal mine production work by the managers of coal mine enterprises. A fully connected neural network is used to extract the characteristics of a certain alarm reason data input to each sensor, and then use gradient descent to optimize the weight parameters, identify and classify the input data, and use the error back propagation method to train the model.

2. Compared with the artificial statistical method, the fully connected neural network can predict sensor alarms and identify more than 20 sensor alarm causes with higher accuracy.

Its prediction accuracy is high, it can prevent problems before they happen, and its characteristics such as a wide variety of recognition, high reliability, rapidness and ease of use can play an important role in future coal production work. Achieve more accurate analysis and prediction of alarm causes, and no error or omission of alarm causes due to the size of the data volume. Through this patent, it can be predicted whether the sensor will alarm, if the alarm is caused by which reason, it is helpful for the staff to quickly solve the problem, and enables timely feedback processing and statistics of hidden dangers. This is of great significance to coal mine production during actual use.

3. The pmethod can analyze the causes of sensor alarms in a timely manner, allowing relevant supervisors to quickly analyze the causes of sensor alarms required, which is beneficial to strengthen the compliance inspection of staff, reduce the occurrence of ”three violations”, and is effective Reduce the occurrence of casualties. It is conducive to realizing the overall management of coal mine production by the managers of coal mine enterprises, strengthening the safety self-inspection of national supervisors, and reducing the occurrence of casualties.

4. The method reduces subjective differences, and does not cause differences in sensor alarm reasons due to the subjective judgment of the staff. This patent can predict in advance whether the carbon monoxide sensor will give an alarm. If it does, it can also determine the cause. This can not only prevent troubles before they happen, but also make it possible to deal with hidden dangers in time, and it can also quickly know whether it is caused by normal operation. The alarm caused by the sensor can provide timely feedback processing and statistics, which greatly saves time and reduces coal mine disasters.

V. Conclusion

At present, deep learning methods identify the causes of sensor alarms. This article presents an efficient analysis process of sensor alarms, which utilizes cheap computing resources and reduces a lot of labor costs. It can quickly know whether the sensor alarm is caused by normal operation, such as blasting, calibration, and circuit maintenance, etc., so that hidden dangers can be timely processed and counted. And then realize the overall management of coal mine production work by the managers of coal mine enterprises. Through the fully connected neural network, the characteristics of a certain alarm cause data of each sensor are extracted, and then the gradient descent is used to optimize the weight parameters, the input data is recognized and classified, and the error back propagation method is used to train the model [8]. Coal production during use is of great significance.

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