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Research Article

A Support Vector Machine Based Prediction on Sensitivity to Coal Ash Blast for Different Degrees of Deterioration

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Coal ash blast is a potential hazard that causes serious disasters in coal mines. In explosion control, research work on coal ash sensitivity prediction is of practical importance to improve accuracy, reduce blindness of explosion protection measures, and strengthen targets. The potential and destructive characteristics of coal ash blast vary greatly from coal to coal, especially in coal mines with complex and changing environments, where the characteristics of coal ash blast show great variability under the influence of various factors. In addition, due to the lack of systematic and comprehensive understanding of the occurrence mechanism of coal ash blast, it is necessary to conduct systematic research on the occurrence mechanism of coal ash blast. Current coal ash blast sensitivity summarizes and concludes prediction methods to create reliable predictions for coal ash blast. A new general learning method, support vector machine (SVM), has been developed, which provides a unified framework for solving limited sample training problems and can better solve small sample training problems. With the purpose of determining the coal mine problem and coal ash sensitivity prediction sensitivity indicators and thresholds, the SVM method is used to set the sensitivity function of each prediction indicator, and the sensitivity of each prediction indicator for the proposed study mine is expressed quantitatively. The experimental results show that the prediction accuracy of SVM for positive and negative categories is 15.6% higher than that of BP neural network and 35.1% higher than that of Apriori algorithm. Therefore, the prediction effectiveness of the SVM algorithm is proved. Therefore, it is practical to adopt SVM method for prediction on sensitivity to coal ash blast and apply the latest statistical learning theory SVM to predict the risk of coal ash.

1. Introduction

Coal ash accidents are mainly coal and coal ash protrusion, coal ash blast, and coal ash asphyxiation injuries [1]. When such events occur, they not only cause significant losses to local mines and affect the normal process of coal production but also often cause incalculable economic and psychological damage to the employees of the enterprise, miners, and their families [2]. The frequency and intensity of coal mine accidents are alarming, and the level of safety management is still far from that of developed countries, especially because of insufficient safety investment [3]. It causes extremely bad social impacts and huge economic losses [4]. Coal ash itself is a hazard that not only has the potential to cause secondary or chain explosions but also can easily explode together with flammable and explosive gases [5]. This will further increase the potential and fatal hazards of coal ash blast accidents [6]. Therefore, there is a very complex nonlinear relationship between the degree of coal ash blast and the gas product, and the state of coal ash blast can be determined by monitoring.

Prediction on sensitivity to coal ash blast is the first link in the comprehensive measures of gas disaster prevention and control, and it is also a decisive link to ensure safe and efficient production in hazardous coal seams [7]. The degree of blast damage varies from large to small, and the intensity of the explosion varies [8]. This is related to the dust content and particle size of the coal ash involved in the explosion and the quality of the coal in that mine [9]. All current monitoring systems for coal ash focus on coal ash monitoring, which truly records data and provides, but does not provide, early warning of coal ash concentration exceedances [10]. As a result, much historical data from coal ash concentrations are not reasonably available [11]. Data-driven machine learning is an important aspect of modern intelligence technology, which begins with the study of finding patterns in observed data samples and using these patterns to predict future or unobservable data [12].

The SVM method is a specialized method to achieve the structural risk minimization criterion, which has the advantages of global optimality, simple structure, and high generalization ability, and has been widely studied in recent years [13]. At present, the fugacity of coal ash is controlled by local structures because the cause of explosion is unknown. Therefore, coal mines with different geological units currently exist in different regions or within the same region [14]. The traditional statistical study is an asymptotic theory in which the number of samples is infinite, but in practical problems, the number of samples is limited [15]. Therefore, some theoretically good learning methods may perform poorly in practical applications. Therefore, the SVM method can be used to conduct prediction studies of coal ash blast coal ash to determine the risk level of exploding coal ash and take action to prevent the disaster.

The innovations of this paper are.

(1) Basic research on domestic and international coal mine disasters and comprehensive research on the causal mechanisms and epidemiological evolution of major coal mine disasters using support vector mechanics in the context of continuous improvement. The construction of coal mine energy and momentum conservation prediction on sensitivity to coal ash blast model

(2) Study the explosion characteristics of coal ash with different degrees of denaturation and establish the relationship between coal quality index and coal ash blast characteristics according to the influence of coal quality on coal ash blast characteristics

(3) Applying SVM theory, an SVM identification system for coal mine sensitivity prediction is established for online prediction of whether coal ash will explode

The research framework of this paper consists of five parts, which are structured in detail as follows.

The first part of the paper introduces the background and significance of the study and describes the main tasks of the paper. The second part introduces the prediction on sensitivity to coal ash blast and related works related to the support vector mechanics technique. The third part summarizes the relationship between coal quality index and coal ash blast characteristics, establishes the SVM-based prediction on sensitivity to coal ash blast model, and gives a more comprehensive understanding of the idea of sensitivity prediction. The fourth part is the core of the paper, from the analysis of the construction of the sample data in SVM and the analysis of the learning training of SVM, to complete the description of the application of SVM in the prediction on sensitivity to coal ash blast. The last part of the paper is the summary of the work.

2. Related Work

2.1. Prediction on Sensitivity to Coal Ash Blast. Coal ash blast not only wastes resources but also burns equipment, affects production, and causes gas and coal ash blast, resulting in casualties. In recent years, the state has actively promoted coal ash prevention and control, established a coal ash prevention and control work system, increased investment in technological innovation in coal mine safety, and organized scientific and technological work. And despite the consistent results of national-focused coal ash remediation actions, coal mine accidents still pose a major threat to coal safety production in China. Therefore, coal ash accidents in mines are the great enemy of coal mine production and such accidents must be eliminated.

Shi et al. proposed that one of the important means to prevent dust explosion and reduce the risk of explosion is to master the explosive thermodynamic parameters and explosion mechanism model of such dust through theoretical analysis or experimental studies of explosion strength, maximum explosion pressure, and explosion [16]. Li et al. used fuzzy mathematical comprehensive evaluation technique to analyze and improve the coal ash blast criterion, and then the coal ash blast was analyzed and improved [17]. Szkudlarek and Janas studied the pressure and flame propagation velocity during detonation against an obstacle and found that the addition of an obstacle could increase the instantaneous velocity of the flame in front of the obstacle by up to 24 times compared to the unobstructed flame velocity [18]. The mechanism of explosion-induced coal ash blast was investigated experimentally and numerically by Ban et al. The rise of deposited coal ash due to external forces was simulated [19]. Tan et al. coal ash studied the effect of obstacles on flame propagation patterns in explosions and found that the flame propagation velocity increased significantly with the increase in the number of obstacles [20].

According to China's current coal ash control capability and technical level, it should realize modern management, manage coal ash in mines by scientific methods, and make scientific prediction of coal ash disaster in mines, so as to grasp the dynamics of coal ash in mines, correctly identify coal ash blast or not, and propose anti-disaster countermeasures in time.

2.2. Support Vector Machine Technology. Although SVMs have been proposed for many years, they have matured to develop very rapidly and have been evaluated more widely, especially in applied research. SVM-based prediction on sensitivity to coal ash blast can provide dynamic information on environmental safety parameters for production managers and business units at all levels. The comparative analysis of the measured parameters provides data for disaster and accident prevention. Therefore, it will be of great practical importance for accident prevention and mine production if continuous and accurate advance prediction of coal ash can be made by using SVM.

Sumaya et al. applied the classification method of SVM to prediction on sensitivity to coal ash blast and showed by the results that the SVM-based prediction on sensitivity to coal ash blast method has high accuracy and the method is scientifically feasible and has wide application prospects [21]. Liu et al. proposed a chunking algorithm to solve the large training sample SVM problem, and the chunking algorithm is efficient when the number of support vectors is much smaller than the number of training samples, but the algorithm is still complex when the number of support vectors is large [22]. Luo et al. mathematically calculated the deformability of the coal seam, the kinetic energy of the surrounding rock, the expansion effect of the explosion sensitivity, and the work required to cause coal ash based on laboratory simulations. However, it is not yet possible to explain the asymptotic damage process and damage conditions of coal-bearing explosions [23]. Harris and Sapko proposed a training algorithm for SVM called sequence minimization, which is a special case of decomposition methods [24]. Qian et al. argued that fuzzy mathematical theory is an important tool for representing and dealing with imprecise data and conditions of fuzzy information. Incremental training consists of SVM and new samples, and all unsupported vectors are discarded [25].

SVM is the most successful implementation of statistical learning theory to date and is still under development. Therefore, the use of SVM to establish a sound and reasonable index system for coal ash prediction and to improve the accuracy of coal ash blast prediction is an urgent problem for mines to solve.

3. SVM-Based Prediction on Sensitivity to Coal Ash Blast with Different Deterioration Degree

3.1. Relationship between Coal Quality Index and Coal Ash Blast Characteristics. Coal ash blast intensity characteristics mainly include flame, pressure, temperature, and impact airflow properties [26]. Since coal ash blast intensity characteristics are influenced by different factors, in many cases, changes in certain factors can greatly affect the blast intensity and even change the nature of the blast [27]. In a discrete time signal, if two very close samples have different algebraic signs, they are called over-zero:

$$Z_n = \sum |\mathrm{sgn}\,[x(m)] - \mathrm{sgn}\,[x(m-1)]|\, w(n-m), \tag{1}$$

sgn []—take symbols
m—window starting point
w(n)—window function
Get the corresponding decision function, namely, SVM:

$$f(x) = \mathrm{sgn}\left[\sum_{i=1}^{s} y_i \alpha_i^{\,*} K(x_i \cdot x) + b^*\right]. \tag{2}$$

Define the risk of each time window as the standard deviation of logarithmic rate of return, namely:

$$\mathrm{S} = \sqrt{\frac{1}{n\text{-}1}\sum_{j=1}^{n}\left(Z_{j\Delta t} - \bar{Z}\right)^2}, \tag{3}$$

$$\bar{\mathrm{Z}} = \frac{1}{n}\sum_{j=1}^{n} Z_{j\Delta t}. \tag{4}$$

By solving the control equations of discrete phase and continuous phase alternately, the bi-directional coupling calculation of discrete phase and continuous phase is realized until both converge, as shown in Figure 1.

First of all, the pressure characteristics of coal ash blast are an important parameter to characterize the strength of coal ash blast [28]. The rheological properties of coal are prediction on sensitivity to coal ash blast that occur on the physical basis of the time lag, and its substance is just one of the three main factors in the occurrence of the explosion of the nature of coal. And some sampling algorithm is used to select the most favorable samples in the training sample set for the classifier performance, label its class, and add it to the initial training sample set and retrain the classifier. In this case, the computational complexity of the classifier is:

$$O\left(N_{sv}{}^2 + LN_{sv}{}^2 + dLN_{sv}\right), \tag{5}$$

L—scale of training sample set
d_i—enter the dimension of the sample
N_{sv}—number of support vectors

The minimum empirical risk is found in each subset, and then the subset that minimizes the sum of the minimum empirical risk and the confidence range is selected. However, this is more time-consuming, especially infeasible when the number of subsets is large or even infinite [29]. Therefore, for linearly divisible problems, we should choose a hyperplane that can completely and correctly partition the training set, which may lead to the nonexistence of a hyperplane for linearly indivisible problems. The location of the source of the explosion can be determined by technical means, and time sensors that can accurately measure the movement time of the object as well as flame sensors can be installed in the explosive section to obtain data on the farthest distance and propagation time of the flame propagation, which can be used for explosion energy estimation.

Secondly, due to the complex and variable environmental conditions and many influencing factors in underground coal mine operations, the variability of coal ash blast flame characteristics in its generation and propagation process is great under the interference of different factors. According to the law of mass conservation, the unidirectional flow of coal ash in nonhomogeneous coal seam has:

$$\frac{\partial P}{\partial t} + \frac{\partial q}{\partial x} = 0. \tag{6}$$

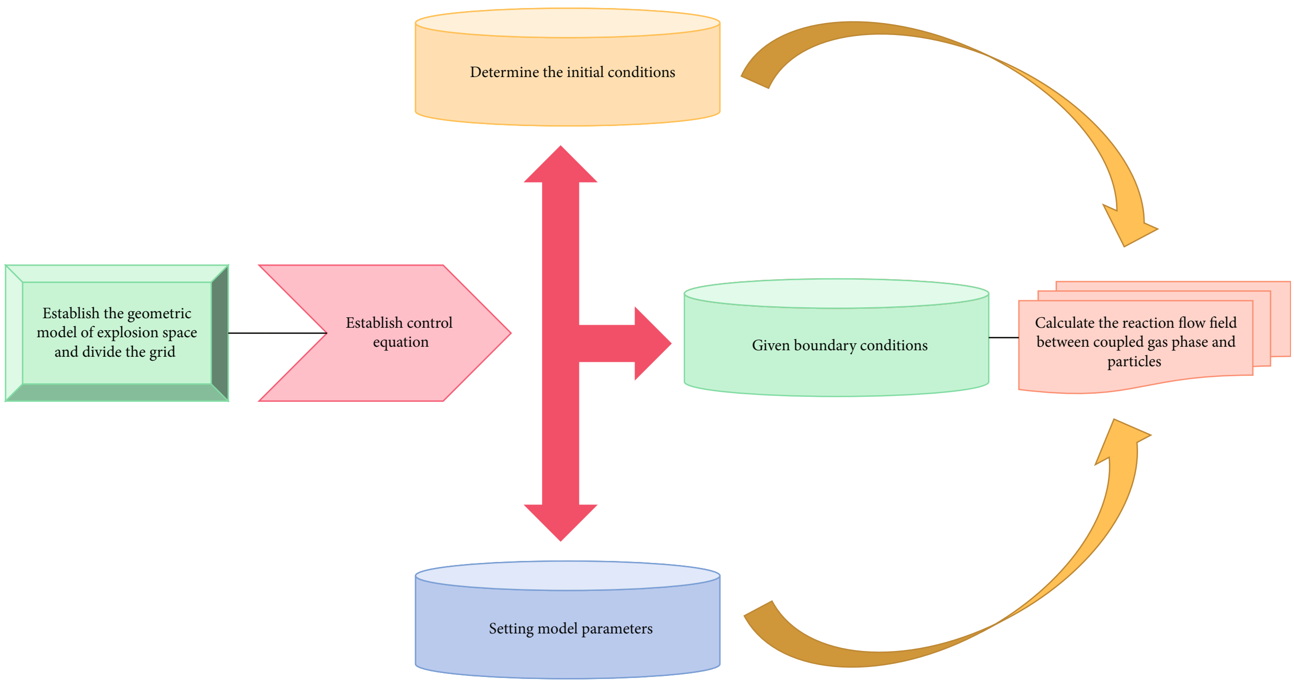

Figure 1: Coal ash blast simulation calculation flow.

So the coal ash emission calculation formula:

$$q = -\lambda \frac{\partial P'}{dx}, \tag{7}$$

P'—coal ash pressure

The explosion destabilization theory considering time effects illustrates that destabilization damage of the system can occur only when creep causes the system to become unstable under certain stresses and pore coal ash pressure, i.e., explosion occurs. The training is performed using samples to determine the specific parameters of the SVM classification identifier. The SVM prediction system is shown in Figure 2.

Design a certain structure of the function set so that each subset can obtain the minimum empirical risk, and then only need to choose the appropriate subset so that the confidence range is minimum, then the subset so that the function of the minimum empirical risk is the optimal function. Due to the complex and changing environmental conditions of underground coal mine operations and the influence of many factors, so in the interference of different factors, coal ash blast flame characteristics in its generation and propagation process are of great variability. As long as the explosion trace identification is to determine the farthest distance of the flame propagation, you can deduce the explosion experience time, and then substituted into the energy prediction model can also be derived from the results.

Finally, in the maximum pressure of coal ash blast in the near spherical space, the maximum pressure rise rate and the characteristics of the flame peak in the horizontal pipe space are combined with the complex and variable characteristics of the influence of coal ash blast. In full use of the experimental device on the basis of short experimental cycle and easy to repeat the advantages of the analysis of different test parameters on the impact of explosion strength characteristics. The occurrence of explosive hazards is extremely irregular, the system in which they are located is a constantly changing system, a variety of mechanical effects with the geological body is formed by these effects, and most are in a complex nonlinear state. In order to ensure safety, the emphasis is on predicting nonexplosive to complete accuracy, so the critical value of the explosion is set relatively low, the result of many nonexplosive hazard sites. Due to the need to use a uniform critical value, it is considered to be an explosion hazard, and explosion-proof measures must be taken. At the same time, make the calculation process greatly simplified, eliminating the previous complex partial differential equation of the arithmetic process and reducing the high requirements for mastery of mathematical theory in the model solution.

3.2. Establishment of Prediction on Sensitivity to Coal Ash Blast Model Based on SVM. Prediction on sensitivity to coal ash blast not only can guide the scientific application of explosion-proof measures and reduce the amount of explosion-proof measure works but also ensure the personal safety of coal seam operators due to the uninterrupted inspection of the explosion hazard at the working face [30]. Therefore, the establishment of SVM-based prediction on sensitivity to coal ash blast model is particularly important.

First, the blast moment and stress drop are measured by the microburst monitoring system for the original data, after the software preprocessing and saved. Each day can be measured in multiple sets of blast moment and stress drop

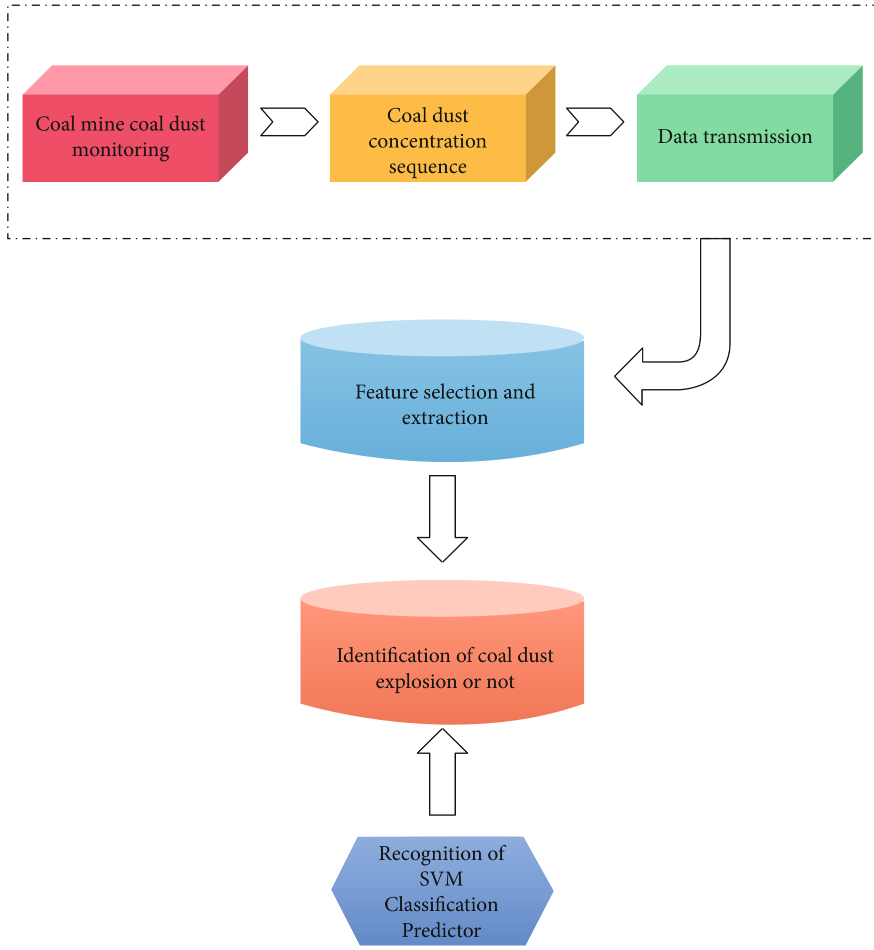

Figure 2: SVM prediction system.

values, by taking the average value of a value as a representative of the day. The SVM algorithm is shown in Figure 3.

Once the parameters are determined, they are not modified in subsequent SVM constructions. The simplest method of parameter selection is to define a training set, a confirmation set, and a test set. Then, several different sets of parameters are selected, and the support vector values are introduced from the training data in the training set, and the set of parameters that minimizes the data errors in the confirmation set is selected as the model parameters. For this purpose, pre-weighting is performed in preprocessing. For all functions in the indicator function set, the probability between the empirical risk and the actual risk satisfies:

$$R(w) \leq \operatorname{Re} mp(w) + \sqrt{\frac{h \ln (2l/h + 1) - \ln h/4}{l}}, \tag{8}$$

h—dimension of function set

n—sample number

Coal ash desorption in coal mines is a long process, while the explosion process is a fast-moving process. Small explosions last only a few seconds, and large explosions last only a few tens of seconds, and the time for coal ash desorption during the explosion may be only milliseconds, relying on the energy of the coal ash desorbed during this time to throw the coal ash mass from its original location into the roadway space. The prediction objective is based on the purpose of this paper, i.e., to predict the propensity of coal ash blast, and the parameter that can quantitatively assess the propensity of coal ash blast, i.e., the cumulative energy release rate, is chosen as the target vector. By using the squared term as the optimization index, only the equation is constrained, so that the initial problem is no longer a quadratic programming solution, and can be expressed as:

$$\min \frac{1}{2}\|w\|^2 + \frac{1}{2} r \sum_{i=1}^{l} \xi_i^{\,2}, \tag{9}$$

r—error penalty component

Secondly, the corresponding SVM program was prepared, and the corresponding prediction model of coal dust explosion propensity was established, using a large number of example data as training samples and prediction samples. Then, an error rate was obtained for each test set, and finally

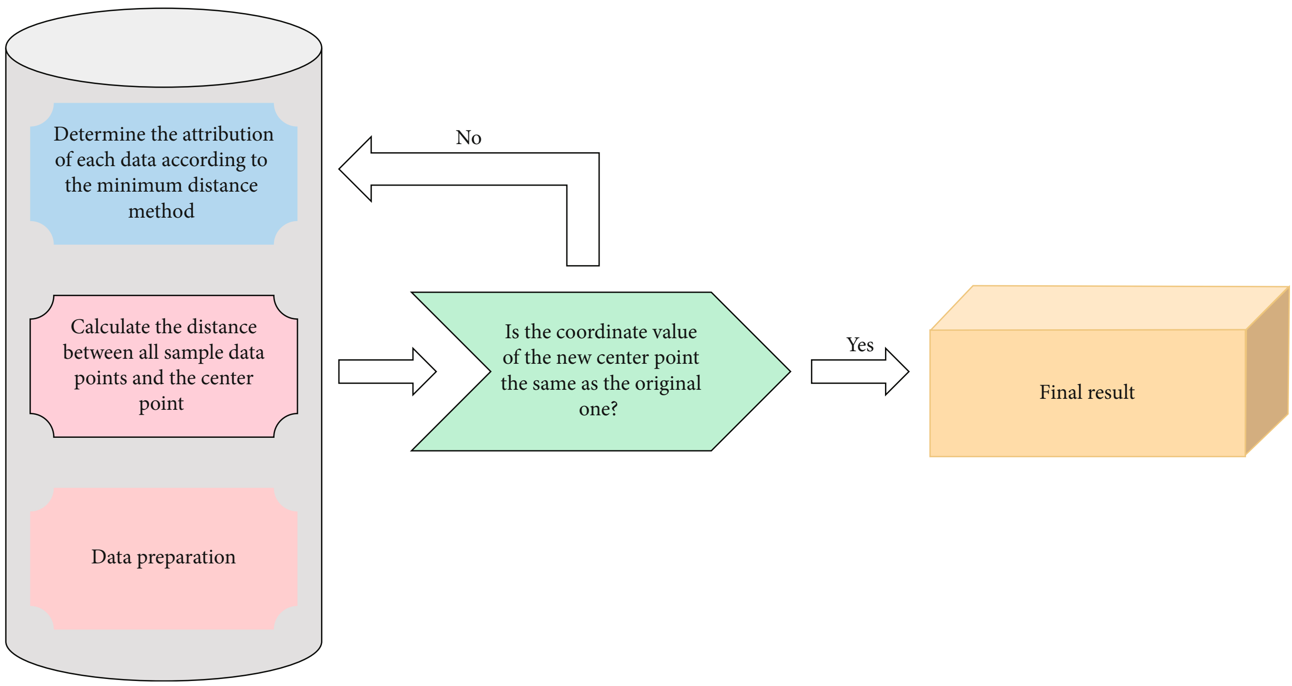

Figure 3: SVM algorithm.

the average of all error rates was taken as the final error rate. The ground stress and coal ash pressure values within the unloading zone are both greatly reduced from their original values; the ground stress within the concentrated stress zone is higher than the original value, and the coal seam permeability is sharply reduced to prevent the discharge of coal ash, so the high coal ash pressure gradient and gas pressure values are maintained. The rock structure, when receiving external stresses, causes different dynamic phenomena and elastic waves in the coal mine due to inelastic deformation and structural nonstability. In the absence of any information at all, this discretized probability distribution should satisfy the following "maximum entropy" problem:

$$\max H(\lambda) = -\sum_{i=1}^{m} \lambda_i \ln \lambda_i, \tag{10}$$

$H(\lambda)$_Shannon entropy

Since the shape and frequency spectrum of the stress waves emitted from the coal mine at different deformation stages are different, and the generation of coal ash blast requires a certain amount of energy, there will be a period of energy accumulation before the occurrence of coal ash blast, i.e., a period of smoothness. Then, we estimate the upper limit of the error rate by using the result obtained, and then adjust the parameters of the kernel function by using the gradient descent method for the upper limit of the error rate, and repeat the above steps until we get the minimum upper limit of the error rate. The method of converting analog signals to digital signals is based on regularization theory. The regularization problem can be obtained in the following form:

$$\min \frac{1}{l} \sum_{i=1}^{l} V\left(y_i, f(x_i) + \lambda \|f\|_K^2\right), \tag{11}$$

λ_regularization factor

$\|f\|_K^2$_reproducing kernel Hilbert space

V_loss function

Finally, we train the classifier with the normalized training data to obtain the diagnostic model and then use the model to test on the test set. The maximum and minimum values of the parameters to be selected are set, and the jump step is also set for each parameter. Then, the parameters are combined by the jump step separately, and finally the combination with the highest accuracy is found by validation. In particular, as the mining depth increases, the coal ash pressure and ground stress increase, and the corresponding gas internal energy and deformation potential of coal seam also grow. It causes more and more coal ash containing coal rock explosion induced disasters; prediction on sensitivity to coal ash blast and prevention work are more and more difficult. Thus, for linear systems, when the estimated model order is the same as the actual model order, the accuracy of identification is high, and vice versa, the accuracy of identification is reduced. For the nonlinear system, the accuracy of identification is related to the complexity of the kernel function, and the accuracy decreases with the increase of the complexity of the kernel function.

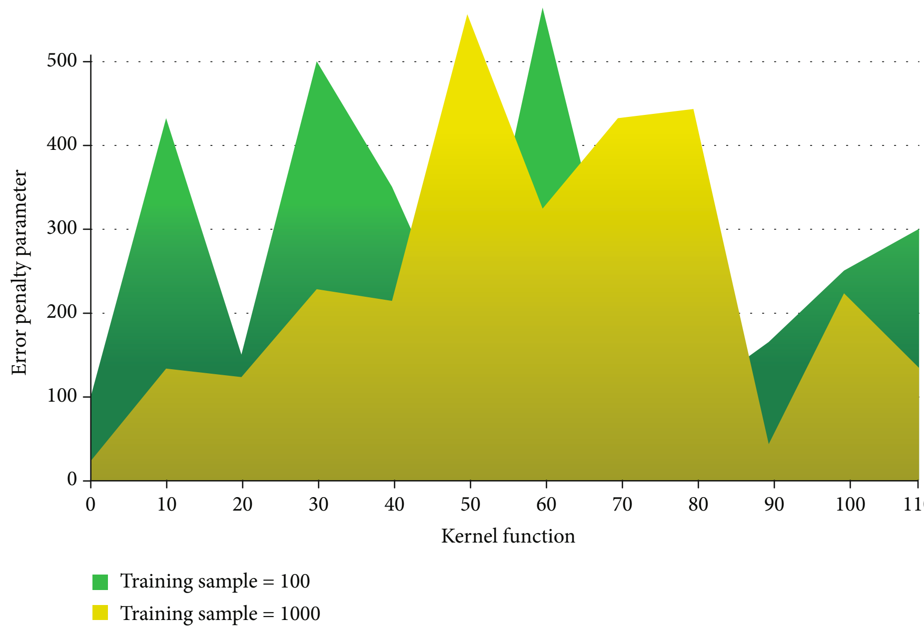

Figure 4: Changes of SVM performance with kernel parameters.

4. Application Analysis of SVM in Prediction on Sensitivity to Coal Ash Blast

4.1. Construction and Analysis of Sample Data in SVM. Different SVM models are handled in different ways. The sample data regulate the maximum step size of the flight direction of the global optimal particle and the individual best particle, respectively; if it is too large, it will lead to a sudden flight towards or over the target region; if it is too small, the particles are likely to be far away from the target region. If it is possible to predict continuously whether an explosion occurs in a coal mine or not based on the sample data of previous explosion events in that mine, this is the research of this chapter.

First, the factors affecting the predicted values are grouped into three main indicators: effective base concentration, sulfation, and factor. For a given sample point that cannot be separated or approximated by a hyperplane, a transformation can be used to map it to a space of higher dimensionality in order to improve the classification accuracy. In the following, a prediction on sensitivity to coal ash blast with 100 training samples and 1000 test samples is used in a one-to-many training mode to find the variation of the performance of Gaussian kernel SVM with kernel parameters and error penalty parameters. The results are shown in Figures 4 and 5.

Fault is also an important factor affecting the explosion, especially near the inverse fault. This is due to the strong extrusion of the reverse fault, fault near the structure of coal is generally very developed, and this strong structural damage to the coal permeability is very poor, often become an important barrier to prevent the transport of coal ash. Different degrees of coal ash volatile fraction of different degrees of metamorphosis, the material composition of the coal quality between the large differences, different degrees of coal ash reaction reducing agent content has a large difference, resulting in a large difference in the maximum pressure of the explosion. And coal ash concentration is low, coal ash particles are less, the particle spacing is relatively large, the particles absorb heat transfer, and reaction time will increase, resulting in the total duration of combustion also increased.

Secondly, in order to eliminate the influence of each factor due to different magnitudes and units, the input and output parameters of the samples are normalized separately. A part of the samples is selected to form the working sample set for training, the nonsupport vectors are removed, and the training results are used to test the remaining samples. The samples that do not meet the training results are generally those that violate the conditions or some of them are combined with the support vectors of this result into a new working sample set and then retrained. Assuming that all categories contain the same number of samples, the core of the algorithm complexity is still the solution of the constraint extreme value problem. The performance comparison of different multi-classification prediction methods is shown in Table 1.

However, in the geological structure complex area or the tunnel will be through the section, this cycle is often broken, resulting in the superposition of the coal body stress in front of the workings. The coal ash concentration where the maximum value of coal ash blast pressure and the minimum value of burning duration are located is different for different degrees of metamorphism. Therefore, coal samples should be taken downhole and adsorption experiments should be carried out in the laboratory to determine coal ash basic parameters such as coal to coal ash adsorption constants, moisture, and ash content at constant temperature. The coal seam coal ash content is then calculated from the measured original coal ash pressure of the coal seam.

Figure 5: Changes of SVM performance with error penalty parameters.

Table 1: Performance comparison of different multi-classification forecasting methods.

Multiple classification method	One-to-one	One-to-many	Global optimization
Error rate	34.3	39.1	44.6
Total number of support vectors	32	44	36
Training time	65	78	93
Average sum function budget times	17	23	41

Finally, by mapping the data into the feature space and trying to describe the data in the feature space with a hypersphere, the majority of the data is to be included in this hypersphere. The size of the working sample set is fixed within the tolerable limit of the algorithm speed, and the iterative process only swaps some of the worst-case samples from the remaining samples with the samples in the working sample set in equal amounts. Even if the number of mathematical models and algorithms studied in support vector data mining exceeds the size of the working sample set, the size of the working sample set is not changed, and only a part of the support vector is optimized. With the increase of coal seam burial depth, the thickness of overburden rock on coal seam gradually increases, and the ground stress increases accordingly; with the increase of coal seam burial depth, the permeability of coal seam and surrounding rock will decrease, and the distance of coal ash transport to the surface increases, which is favorable to the coal ash fugacity. Close to the optimal concentration of coal ash blast, the maximum explosion pressure is also larger, indicating that the coal ash close to the optimal coal ash blast concentration has a higher risk, in the actual production of coal ash concentration should be strictly controlled.

4.2. Analysis of Learning and Training Based on SVM. The learning training of SVM adopts training sample sequence input method instead of batch input method, which has the advantages of generating fewer SVMs and strong generalization performance. The increase in stress causes the electron clouds between molecules to overlap, the mobility of electrons between molecules increases, and the electron conductivity increases. Therefore, it is not possible to say qualitatively whether the electrical conductivity of coal increases or decreases when it is subjected to stress, but it is necessary to conduct specific experimental analysis for specific coal samples.

First, the samples are sequentially fed into the SVM algorithm in a sequential manner, and a forecast model containing a support vector is obtained after training. In the optimization problem description, different penalty coefficients are applied to each sampling point data to obtain more accurate classification. The plot of the simple step response SVM algorithm using simulation, compared with the Apriori algorithm, is shown in Figure 6.

While the optimization variables of the fixed working sample set method contain only working samples, the objective function contains the whole training sample set, i.e., the multipliers of the samples outside the working sample set are fixed as the results of the previous iteration. Instead of being set to two as in the block algorithm, the fixed working sample set method also involves a problem of determining the change-out samples. With the increase of ignition energy,

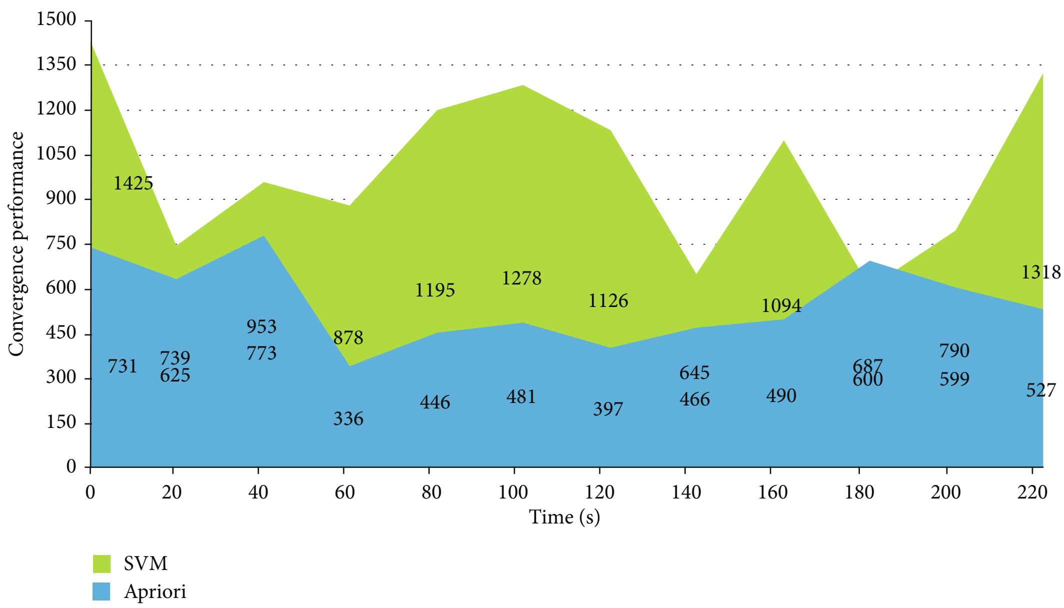

Figure 6: Convergence comparison.

Table 2: Prediction accuracy of three algorithms.

		SVM	BP neural network	Apriori
Positive category	Test data	76.5%	56.7%	49.5%
	Training data	98.5%	66.1%	34.6%
Negative category	Test data	87.1%	78.3%	63.1%
	Training data	93.4%	94.6%	87.1%

the maximum pressure of different degrees of deterioration coal ash blast is generally on the rise and the overall duration of combustion is on the decline. Since each coal ash particle is subjected to different magnitude and direction of force, these particles are in a chaotic turbulent state after mixing with the gas. The prediction accuracies of the three algorithms for each category are shown in Table 2.

From Table 2, the prediction accuracy of SVM on positive and negative categories improved by 15.6% over BP neural network and 35.1% over Apriori algorithm. Thus, the predictive effectiveness of the SVM algorithm was proved.

Secondly, the data input is limited by the moving window method, i.e., the size of the training samples. The nearest data are taken as the training set in turn. In the sample space or feature space, the optimal hyperplane is constructed to maximize the distance between the hyperplane and the different classes of the sample set, so as to achieve the maximum generalization ability. Since there are only two variables, and one can be expressed in terms of the other by applying the equation constraint, the optimal solution of the subproblem at each step of the iterative process can be found directly by analytical methods. After the coal ash particles are lifted up, coupled with the sweeping of the shock wave, the internal energy of the coal ash particles increases, the temperature rises, and some combustible gases are decomposed by heat, which are ignited and oxidized resulting in the ignition of the coal ash cloud to participate in the explosion. Since the number of training samples and test samples are small, the test error can be regarded as a reflection of the true generalization ability of the SVM. Figures 7 and 8 show the training error and test error of the SVM with the kernel and penalty parameters, respectively.

With the increase of ignition energy, the ambient temperature and volatile precipitation are increased, the effective ignition volume is increased, and the turbulence induced by high ignition energy can enhance the combustion efficiency. The air volume required at the coal mining face and the rated air volume of the local ventilation fan. The so-called optimal ventilation refers to seeking the minimum ventilation of the mine while ensuring that the coal ash concentration and coal ash concentration in each working face and return airway are not exceeded, forming an optimization problem with the goal of minimizing the total ventilation.

Finally, several free parameters in the model, including the bandwidth of the Gaussian basis kernel function, the regularization factor that balances the complexity and accuracy of the model, and the effect of the magnitude of the error coefficient on the generalization ability and complexity of the model prediction referring to the number of generated SVMs, are to be examined. In this way, a judgment function can be established, and for new sample points, if the function is calculated to be positive, it is a normal sample; otherwise, it is a singular point. There are differences in the content of volatile matter precipitated from coal ash with different degrees of deterioration at the same ignition energy, resulting in different corresponding maximum explosion pressures and burning durations. When a new individual sample appears, how it relates to the original sample set or

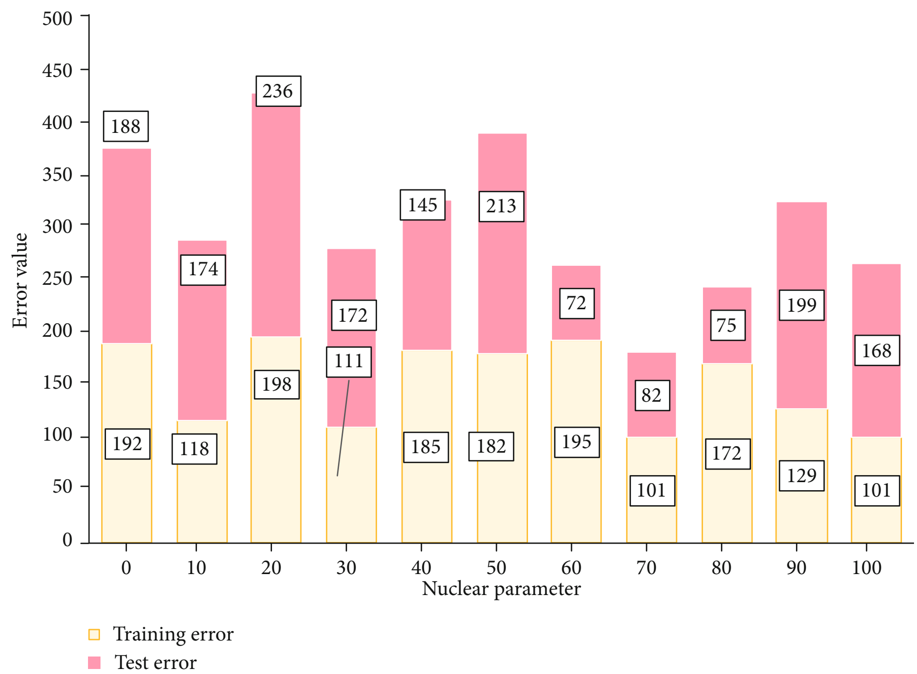

Figure 7: Training error and testing error of SVM under different kernel parameters.

	0	10	20	30	40	50	60	70	80	90	100
Training error	391	315	768	335	778	388	308	1276	580	389	1241
Test error	270	1134	213	786	1300	889	1200	800	436	1350	1200

Figure 8: Training error and testing error of SVM under different penalty parameters.

its subset, or to the training results of the original sample set, e.g., what effect its addition has on the support vector set of the original sample set, how to quickly determine the contribution of bamboo to the new classifier function, etc.

5. Conclusions

The continuous development of communication technology, automation technology, and artificial intelligence technology has led to great progress in the research of coal ash blast sensitivity prediction technology. Coal ash blast is a major hidden danger for coal mine safety in China, and the prediction and prevention of explosion accidents in mines play a very important role in ensuring the safety of mines. Sensitivity forecasting is the core technology of coal mine excavation and mining, and the reliability of its sensitivity forecasting is related to the economic benefits of coal mines and the lives and health of workers. For this reason, carrying out coal ash blast sensitivity forecasting and establishing a reasonable coal ash blast sensitivity forecasting system can effectively carry out coal ash blast disaster prevention and control and reduce disaster losses. SVM regression is a new theory and method, which has many issues worth further research in both training algorithms and practical applications. Due to its unparalleled advantages in many traditional machine learning algorithms, it has become a popular research direction in the world at present and has been successfully applied in many aspects. SVM is used for natural fire prediction of coal seams, and the rationality and scientific validity of the method are verified through experiments. According to the prediction of different metamorphic degree coal ash blast sensitivity of SVM, a stable and high safety factor anti-seismic equipment can be designed according to the special situation of the mine, so as to reduce the danger caused by explosion.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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