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A Coal Gangue Identification Method Based on HOG Combined with LBP Features and Improved Support Vector Machine

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Abstract: Identification of coal and gangue is one of the important problems in the coal industry. To improve the accuracy of coal gangue identification in the coal mining process, a coal gangue identification method based on histogram of oriented gradient (HOG) combined with local binary pattern (LBP) features and improved support vector machine (SVM) was proposed. First, according to the actual underground working environment of the mine, a machine vision platform for coal gangue identification was built and the coal gangue image acquisition experiment was carried out. Then, the images of coal and gangue were denoised by median filtering, and the coal and gangue features were extracted by using the HOG combined with LBP feature extraction algorithm, and these features were normalized and principal component analysis (PCA) reduced dimension to remove the correlation and redundancy between the features. Finally, SVM, SVM optimized by genetic algorithm (GA-SVM), SVM optimized by particle swarm optimization (PSO-SVM) algorithm, and SVM optimized by grey wolf optimization (GWO-SVM) algorithm were used as classifiers for identification and classification, respectively. The experimental results show that the GWO-SVM classification model has the highest accuracy, and the average classification accuracies were 96.49% and 94.82% of the training set and test set, respectively, which shows that grey wolf algorithm to optimize support vector machine has a good effect on classification of coal gangue images, which proves the feasibility and accuracy of the proposed method.

Keywords: coal gangue identification; feature extraction; grey wolf optimization; support vector machine

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1. Introduction

Coal is one of the important energy sources for human survival and has played an essential role in global economic development. China is also the world's largest coal producer and consumer, and China's energy consumption structure will continue to be dominated by coal for a long time to come [1,2]. In 2021, China's energy consumption structure is shown in Figure 1, of which coal energy consumption accounted for 56%. Additionally, in the process of energy structure transformation, coal should play a leading role. However, gangue is a kind of solid waste with low carbon content emitted in the process of coal mining. Its main chemical components are SiO_2 and Al_2O_3 [3,4]. Raw coal mixed with gangue will not only reduce the quality of coal but also seriously pollute the atmospheric environment when burned. Therefore, coal gangue identification and separation is a vital part of the coal production process. In China, the coal industry will enter a stage of high-quality development, and the Chinese government is actively promoting efficient, clean, and green coal mining [5–8].

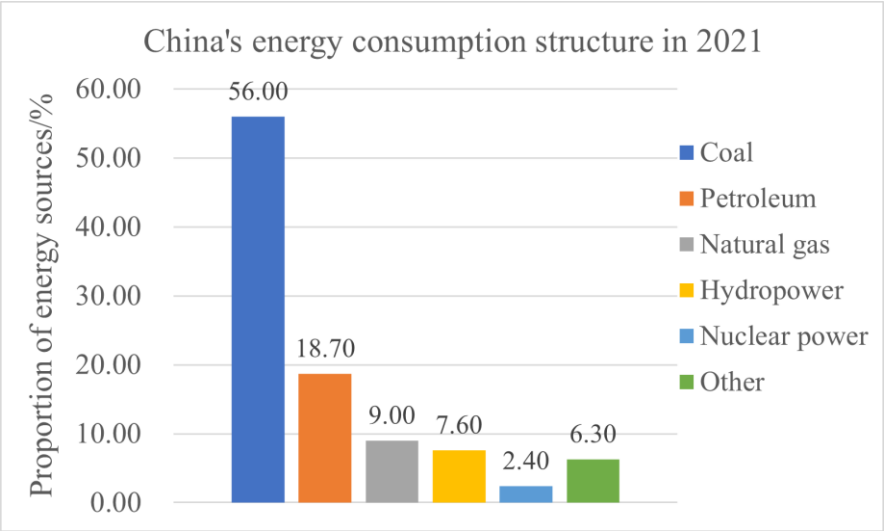


Figure 1. Diagram of China's energy consumption structure in 2021.

There are many ways to identify coal and gangue. Traditional manual identification work is intense, and coal gangue sorting efficiency is low [9]. Mechanical vibration identification is mainly through coal and coal gangue particles and metal plate collision vibration signal recognition, but this method will reduce the quality of coal [10,11]. Xing et al. [12] proposed a coal and gangue identification method based on the intensity image of lidar and DenseNet. 3D laser scanning combined with dynamic weighing is an identification method based on the density difference between coal and gangue [13], but these methods have large measurement error. Hu et al. [14,15] used multispectral, thermal imaging, and infrared spectroscopy methods to identify coal and gangue [16–19], but these methods are easily affected by ambient temperature and light and are only suitable for a laboratory environment and are difficult to promote and apply in actual coal gangue sorting. High-energy rays (such as X-rays, γ rays) [20,21] have high costs for coal and gangue identification and are radiation hazards to the human body. Therefore, compared with the above methods, machine vision technology has the advantages of environmental protection, no harm, low cost, and real-time acquisition of images.

In recent years, machine vision and image processing technologies have been widely used in various fields, such as defect detection [22], medical diagnosis [23], etc. In the field of coal, Huang et al. [24] proposed a binocular machine vision and particle queuing method for online detection of coal content in gangue. Chaves et al. [25] used machine vision techniques for automatic characterization of coke during pulverized coal combustion. Image processing of coal and gangue mainly focuses on feature extraction [26], machine learning [27,28], and deep learning [29,30], etc. Li et al. [31] proposed a coal gangue detection and recognition algorithm based on deformable convolution YOLOv3 (DCN-YOLOv3). This algorithm effectively detects and recognizes coal gangue, improves the accuracy and efficiency of detecting and recognizing small-size coal and gangue, and improves environmental robustness. Although the classification accuracy of deep learning is high, unfortunately, deep learning requires a large amount of image data when building the model, the network model is complicated, and the processing time is long. In image recognition based on machine learning, the most commonly used are back propagation (BP) neural network and support vector machine (SVM). BP neural network has the disadvantages of slow convergence speed and falling into local extremum [32]. However, support vector machine has good generalization performance and takes into account the advantages of training error minimization and test error minimization. Support vector machine is a machine learning model for binary classification, which is especially suitable for classification of small samples and high-dimensional features [33]. In view of the above problems, inspired by the good optimization ability of the wolf pack intelligent optimiza-

tion algorithm and the classification performance of SVM, this paper applies the grey wolf optimization (GWO) algorithm to optimize SVM parameters [34] and proposes a method for coal gangue identification based on GWO-SVM. This method is different from any previous method of coal gangue identification. First, we acquired a coal gangue image by machine vision technology and denoised it by median filtering. Then, we extracted coal gangue features using a histogram of oriented gradient (HOG) combined with local binary pattern (LBP) feature extraction algorithm. As far as we know, this is the first study of coal gangue image feature extraction. In addition, we also used the principal component analysis (PCA) method for feature dimension reduction to remove the correlation and redundancy between features. Finally, we used support vector machine as the classification model and, respectively, used genetic algorithm (GA), particle swarm optimization (PSO), and grey wolf optimization (GWO) algorithms for optimization and comparison. The experimental results show that the classification accuracy of the GWO-SVM model is the highest, which proves that the GWO algorithm can improve the accuracy and generalization ability of the model.

The rest of this paper is organized as follows. Section 2 introduces the design of the coal gangue image acquisition test platform. Section 3 introduces image processing of coal gangue. Section 4 introduces feature extraction of the coal gangue image and proposes a new feature extraction method for HOG combined with LBP features. Section 5 introduces SVM classification, focusing on grey wolf optimization algorithm to optimize SVM. Section 6 introduces the comparative simulation experiments of SVM, GA-SVM, PSO-SVM, and GWO-SVM models to prove the feasibility and accuracy of the proposed method. Conclusions and future work are summarized in Section 7.

2. Design of Image Acquisition Experimental Platform

The experimental samples of coal and gangue were selected from the coal mine in Panji District, Huainan, Anhui Province, China. The particle size of coal and gangue was distributed in 40–100 mm. Among them, the surface of the sample coal was black and shiny, with a few cracks and soft texture, while the surface of gangue was black–gray, dull and rough, and hard in texture. To realize acquisition of coal and gangue images, we imitate the actual working environment of the underground to build a machine vision experimental platform in the laboratory, as shown in Figure 2, and the platform consists of a conveyor belt, charge coupled device (CCD) industrial camera, USB3.0 data cable, double LED light as a light source, and computer. CCD industrial camera is the core equipment of the image acquisition device; selection of the camera determines the resolution and image quality of the acquired images. The camera model used in this experiment is Hikvision MV-CA050-11UC 5-million-pixel color camera, which supports manual adjustment of gain and exposure time, the resolution is 2448 × 2048, and frame rate is 35 fps. Using USB 3.0 data interface communication and connection to the computer, the camera can collect images of coal and gangue in real time. The light intensity during the experiment is 2000 Lux, and the speed of the conveyor belt is 0.2 m/s.

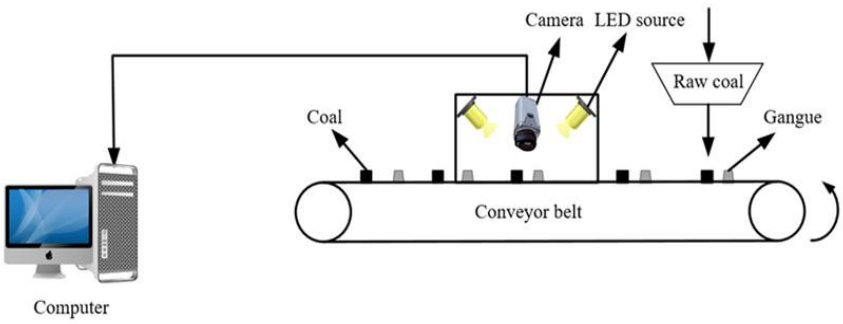
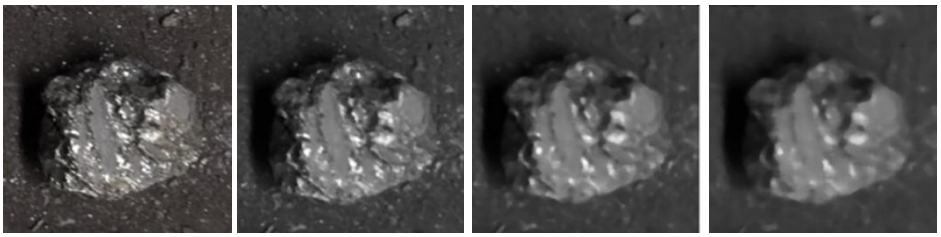


Figure 2. Coal gangue identification machine vision experimental platform.

3. Image Processing

In this experiment, a total of 300 coal and gangue samples were selected for image acquisition. To save storage space and improve the training speed of subsequent classification models, each image is cropped and the original image is uniformly captured into an image with a size of 200 × 200 pixels. The environment of the actual coal gangue sorting site is harsh, which leads to environmental interference, such as dust and light in the process of image collection, which makes the collected coal gangue images contain noise and become fuzzy and unclear. To ensure clarity and identification accuracy of the image, it is necessary to process the original image. In this paper, the median filter is used for denoising processing, which can ensure the quality of the original image without distortion, but the filtering effect is very dependent on the size of the filtering window. To find the best filter window, 3 × 3, 5 × 5, and 7 × 7 three window sizes are selected, and image comparison before and after filtering is shown in Figure 3.



(**a**) (**b**) (**c**) (**d**)

Figure 3. The effect of the three filtering methods. (**a**) Original image; (**b**) 3 × 3 filtering; (**c**) 5 × 5 filtering; (**d**) 7 × 7 filtering.

As can be seen from Figure 3, the larger the filter window size, the blurrier the edge of the image; if it is too small, the denoising effect will be poor. When the window size is 5 × 5, the image will be clearest. Therefore, this paper chooses a 5 × 5 filtering window size.

4. Future Extraction

4.1. Histogram of Oriented Gradient

In the process of coal and gangue identification based on machine vision and image processing technology, feature extraction of images is crucial, which directly affects the accuracy of coal and gangue identification. The feature of histogram of oriented gradient is a description operator used to detect objects in computer vision and image processing [35]. It composes features by calculating and counting the gradient direction histogram of local areas of the image. HOG feature extraction combined with SVM classifier has been widely used in image identification [36]. The basic steps of HOG feature extraction are as follows:

Step 1: Image graying. The color information in the image does not play much of a role, so the original image is converted to gray-scale image.

Step 2: Image normalization. The Gamma correction method is used to normalize and compress the input image, which aims to adjust the contrast of the image, reduce the influence of local shadow and lighting changes of the image, and suppress the interference of noise. The gamma compression expression is:

$$I(x,y) = I(x,y)^{Gamma} \tag{1}$$

where $I(x, y)$ is the input image, and *Gamma* takes 1/2.

Step 3: Calculate the gradient size and direction for each pixel. The calculation formula is:

$$|\nabla I(x,y)| = \sqrt{(G_x(x,y))^2 + (G_y(x,y))^2} \tag{2}$$

$$\theta(x,y) = arctan\frac{G_y(x,y)}{G_x(x,y)} \tag{3}$$

where $Gx(x, y)$ and $Gy(x, y)$ are gradients in the x and y directions, respectively, and $\theta(x, y)$ represents the gradient direction of the image at coordinates (x, y).

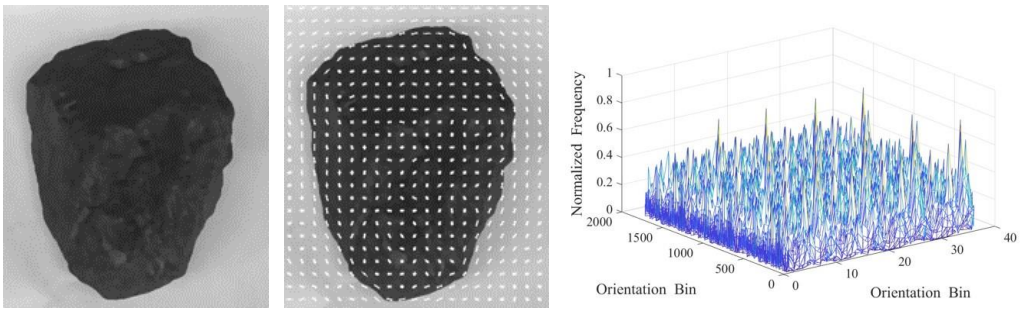
Step 4: Divide the image into square cells. Calculate the histogram of gradient direction for each square cell. The gradient direction is divided into K bars in the [0,π] interval, and bin_K is used to represent the K-th gradient direction; if the gradient direction of a pixel in the square cell is bin_K, the corresponding column value of the gradient direction is added to the gradient value of the pixel. In this paper, K takes 9; that is, the gradient direction is between 0° and 180°, and every 20° is divided into one direction to obtain 9 gradient directions.

Step 5: Calculate the HOG feature vector in one block by forming adjacent elements into blocks. The gradient direction histogram of each square cell in the block is converted into a single-dimensional vector, that is, a vector composed of the number of gradients corresponding to the direction, and all the square cell vectors are connected in series to form the HOG eigenvector of the block.

Step 6: HOG feature vector normalization. The purpose of normalization is to reduce the effect of feature vectors from lighting, shadows, and edge changes.

Step 7: The final HOG feature vector of the image is obtained. The feature vectors of all blocks of the sample are combined to obtain the final HOG feature vector of the original image.

A schematic diagram of HOG features and histograms in a coal image is shown in Figure 4. The pixels in the image can be used to train machine learning algorithms by using this HOG feature representation and can improve the learning efficiency of the algorithm, which is the beauty of gradient direction histograms, and it is also an advantage of the method proposed in this paper.



(**a**) (**b**) (**c**)

Figure 4. HOG feature visualization of coal. (**a**) Original image; (**b**) HOG feature diagram; (**c**) HOG feature histogram.

4.2. Local Binary Pattern

4.2.1. Basic LBP Operator

LBP is a kind of operator, which is used to describe the local texture feature of an image [37]. It has strong classification ability, high computational efficiency, and invariability to monotonous grayscale change. This operator was originally proposed by Ajala et al. in 1994 [38], and the original LBP operator is calculated as shown in Figure 5, and the calculation formula is:

$$LBP(x_C, y_C) = \sum_{P=0}^{P-1} 2^P \cdot s \cdot (g_p - g_C) \tag{4}$$

$$s(x) = \begin{cases} 1 & if \geq 0 \\ 0 & else \end{cases} \tag{5}$$

where (x_c, y_c) is the coordinates of the central pixel, p is the p-th pixel of the neighborhood, g_p is the gray value of the neighborhood pixel, g_c is the gray value of the central pixel, and $s(x)$ is the symbol function.

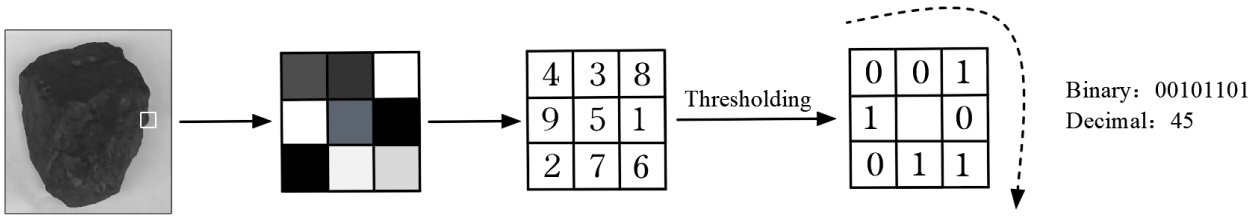


Figure 5. Schematic diagram of the basic LBP operator.

The implementation process of the original LBP feature extraction algorithm is as follows:

Step 1: Divide the detection window into 3 × 3 small cells.

Step 2: For the gray value of the pixel in each cell, the gray value of the adjacent 8 pixels is compared with the gray value of the central pixel, and, if the gray value of the pixel is greater than the central threshold, it is recorded as 1; otherwise, it is denoted as 0.

Step 3: Read the thresholded binary number clockwise from the upper left corner of the region, and then convert the binary number to a decimal number as the LBP feature value of the image.

4.2.2. Improved LBP Operator

The original LBP operator can only cover a fixed range of regions, which obviously cannot meet the requirements of rotational invariance and grayscale invariance. To adapt to the texture features of different scales, the original LBP operator is improved. The original 3 × 3 neighborhood is extended to any neighborhood, and the original square neighborhood is replaced by a circular neighborhood. The improved LBP operator has obvious symmetry, as shown in Figure 6. The improved LBP operator is represented by $LBP_{P,R}$; that is, in the circular neighborhood with radius R, there are P pixels compared with the central pixel threshold point, and, finally, its minimum value is the LBP value of the neighborhood.

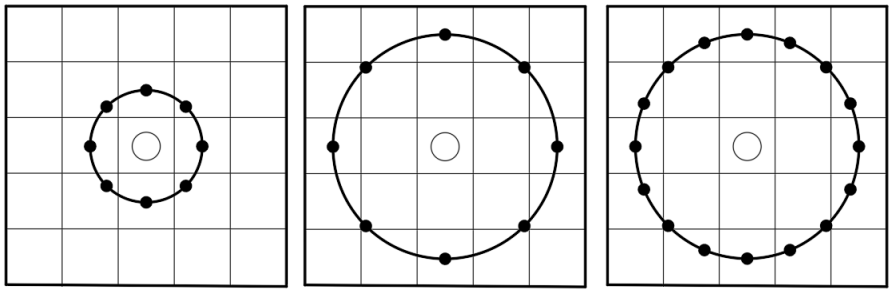


Figure 6. LBP operator for circular domain. (**a**) $LBP_{8,1}$; (**b**) $LBP_{8,2}$; (**c**) $LBP_{16,2}$.

For a given center point (x_c, y_c), its neighborhood pixel position is (x_p, y_p), $p \in P$, and the sampled pixel point (x_p, y_p) can be calculated as follows:

$$\begin{cases} x_p = x_c + Rcos(\frac{2\pi p}{P}) \\ y_p = y_c - Rsin(\frac{2\pi p}{P}) \end{cases} \quad (6)$$

In the formula, R is the neighborhood radius, p represents the p-th pixel point, and P is the total number of neighborhood pixels, $p \in P$.

4.3. HOG Combined with LBP Features

The image of coal gangue not only has contour information but also contains texture information. HOG features can represent the contour information of the coal gangue image, LBP features include a local texture feature that can only reflect the local texture information in the image. To comprehensively and better reflect the feature information of coal gangue

images, this paper proposes a feature extraction method combining HOG and LBP, which is also an innovation point of this paper. There are many different ways of feature fusion, such as weighted fusion, parallel fusion, and serial fusion. According to the feature types of HOG and LBP, this paper chooses the serial fusion mode. The schematic diagram of the serial fusion of HOG and LBP features of coal gangue is shown in Figure 7. This method can maximize retention of the contour and texture information of the coal gangue image, ensuring that the feature information is not distorted and the identification accuracy is high.

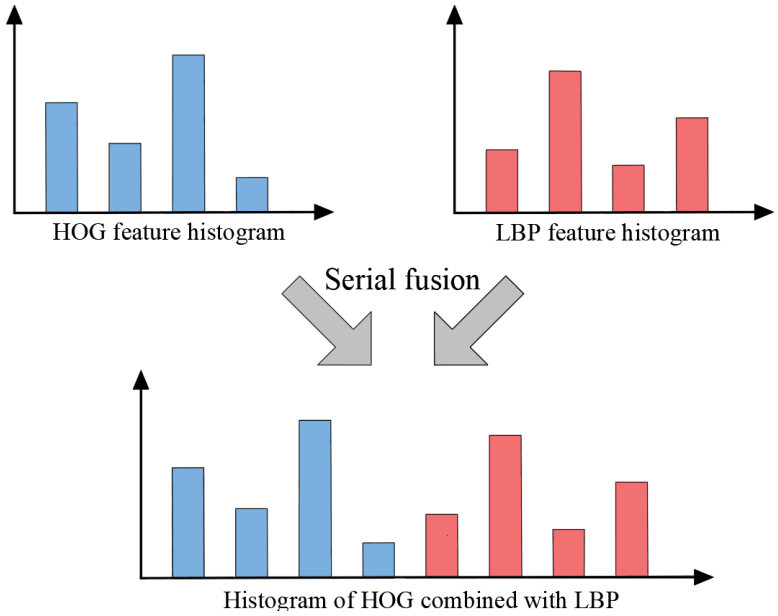


Figure 7. Serial fusion diagram of HOG and LBP features.

To eliminate the dimensional influence between different features, make each feature data in the same order of magnitude, we also need to normalize these features before building a classification model. In this paper, normalized to 0~1 interval, and then the principal component analysis (PCA) method is used to reduce the dimension of the feature vector to remove the correlation and redundancy between the components. The calculation formula of the cumulative contribution rate in PCA is shown in Equation (7):

$$R = \sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{p} \lambda_i \tag{7}$$

where we set R to 85%, because p principal components can be obtained in the PCA method. If the cumulative contribution rate of the first k principal components reaches 85%, it indicates that the k principal components basically contain all the information contained in all feature vectors, so as to achieve the purpose of feature dimension reduction.

5. Support Vector Machine Classification

5.1. Basic Principles of Support Vector Machine

Support vector machine [39] is a binary machine learning model, which is essentially a classification method to quantify the difference between two types of data. In recent years, it has been widely used in practical engineering, which proves that SVM is a classification model with strong generalization ability [40] since some features of the actual coal and gangue samples are linearly inseparable. Therefore, for the problem of linear indivisibility, the support vector machine can map the sample data from the original two-dimensional space to a high-dimensional feature space through the kernel function, making the sample linearly divisible in this feature space, as shown in Figure 8.

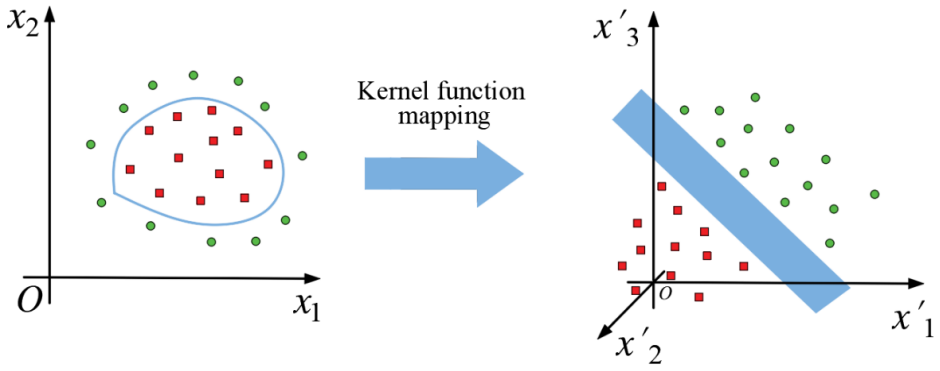


Figure 8. Schematic diagram of SVM dataset dimensioning.

Suppose a given sample dataset $D = \{(x_1, y_1), (x_2, y_2),..., (x_n, y_n)\}$, where $x_i \in R_n$, $y_i \in \{-1, +1\}$, $(i = 1,2,..., n)$. Considering linear inseparable data, SVM takes sample classification as the starting point to find an optimal classification hyperplane by introducing penalty factors and relaxation variables to obtain the following inequality constraint minimization problem:

$$\begin{cases} \min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \\ \text{s.t.} \begin{cases} y_i(\omega^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2, \cdots n \end{cases} \end{cases} \tag{8}$$

where ω is the weight vector, C is the penalty factor, which is the positive parameter set manually to balance the importance of the penalty term, ξ_i is the relaxation variable, and b is the classification threshold. Obviously, this is a convex quadratic programming problem, so there is a unique minimal solution; the Lagrangian function of Equation (9) can be obtained by the Lagrangian multiplier method:

$$L(\omega, b, \alpha, \xi, \beta) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\alpha_i[y_i(\omega^T x_i + b) - (1 - \xi_i)] - \sum_{i=1}^{n}\beta_i\xi_i \tag{9}$$

where $\alpha_i \geq 0$, $\beta_i \geq 0$, α_i, and β_i are Lagrange multipliers. Let the partial derivatives of $L(\omega, b, \alpha, \xi_i, \beta)$ to ω, b, and ξ_i be 0, respectively:

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum_{i=1}^{n}\alpha_i y_i x_i \\ \frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n}\alpha_i y_i = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \Rightarrow \alpha_i + \beta_i = C \end{cases} \tag{10}$$

by introducing the kernel function $K(x_i, x_j)$, according to the KKT condition and solving the dual problem, a new objective function is obtained:

$$\begin{cases} \max \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \\ \text{s.t.} \begin{cases} \sum_{i=1}^{n}\alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C, i = 1, 2, \cdots, n \end{cases} \end{cases} \tag{11}$$

selection of kernel functions is critical, and, if the kernel function selection is not appropriate, it means that the sample is mapped to an inappropriate high-dimensional feature space, potentially leading to poor generalization of the classification. To better realize the feature transformation of sample data, this paper chooses Gaussian radial basis function (RBF) as

the kernel function, which is a kind of radially symmetric scalar function. The expression of the kernel function is:

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2g^2}) \tag{12}$$

where g is the parameter of the kernel function. Therefore, the decision function of the support vector machine can be expressed as:

$$f(x) = sgn(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x_j) + b) \tag{13}$$

Determination of parameter g and penalty factor C in the kernel function has a great influence on the performance of the support vector machine model. To find optimal parameters C and g, intelligent optimization algorithms are often required to improve the optimization.

5.2. Genetic Algorithm Optimizes Support Vector Machine

GA is an adaptive global optimization search algorithm [41] that simulates the process of heredity and evolution in the natural environment. Genetic algorithms have the characteristics of operating the coding of parameters, needing no derivation and additional information, non-certainty, and adaptability of optimization rules. The basic processes of genetic algorithm optimization support vector machines are as follows:

Step 1: Parametric initialization of genetic algorithms. Setting the population size *Np*, crossover probability *Pc*, mutation probability *Pm*, and genetic maximum evolution algebra *G*.

Step 2: Chromosome encoding. Generating initial population by binary encoding.

Step 3: Individual evaluations. Calculating the fitness of each individual in the population.

Step 4: Genetic operation. Using the Selection, Crossover, and Variation operators to process the current population to determine whether to terminate the condition and, if satisfied, output the optimal individual to obtain optimal parameters C and g input into the SVM model. Otherwise, return to Step 3.

5.3. Particle Swarm Optimization Algorithm Optimizes Support Vector Machine

PSO is a swarm intelligence optimization algorithm based on parallel global search of birds swarm [42], which finds the optimal solution through cooperation and information sharing among individuals in the group. PSO has the advantages of fewer adjustment parameters and fast convergence speed and can be optimized in high-dimensional space. The basic process of particle swarm optimization support vector machine is as follows:

Step 1: Randomly initializing subgroups, including group size N, position of each particle, and velocity.

Step 2: Determining the fitness function according to the SVM decision function.

Step 3: Calculating and evaluating the fitness value of each particle.

Step 4: Searching for the global optimal parameters and iteratively updating the position and velocity of the particles. Determine whether the termination condition is met. If yes, optimal parameters C and g are output and input into the SVM model for training classification. Otherwise, Step 3 is returned.

5.4. Grey Wolf Optimization Algorithm Optimizes Support Vector Machine

GWO is a swarm intelligence optimization algorithm proposed by Australian scholars Mirjalili et al. in 2014 [43]. The algorithm is inspired by grey wolf predation prey activities and developed an optimized search method, which has the advantages of strong convergence performance and few parameters. In recent years, it has been widely studied by scholars and has been successfully applied to parameter optimization, fault diagnosis, image classification, and other fields [44,45]. GWO algorithm imitates the leadership level and hunting mechanism of the grey wolf in nature [46]. It consists of four kinds of grey

wolves, Alpha (α), Beta (β), Delta (δ), and Omega (ω), which are used to simulate the various classes of grey wolves. The hierarchy of grey wolves is shown in Figure 9.

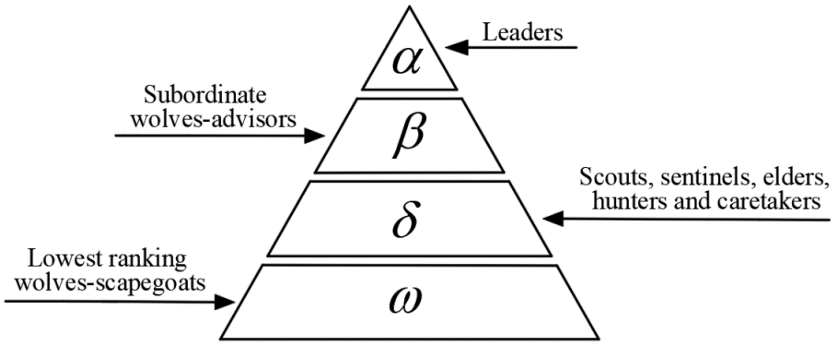


Figure 9. The grey wolf hierarchy.

The grey wolf hunting process is divided into three stages: tracking prey, encircling prey, and attacking prey. During hunting, grey wolves round up their prey, defined as follows:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{14}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{15}$$

where $\vec{D}$ is the current distance between the grey wolf and the prey, $\vec{A}$ and $\vec{C}$ is the coefficient vector, t is the current iteration number, $\vec{X}$ is the position vector of the grey wolf, and $\vec{X}_p$ is the position vector of the prey. The formula for calculating $\vec{A}$ and $\vec{C}$ is as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{16}$$

$$\vec{C} = 2\vec{r_2} \tag{17}$$

where a is the convergence factor, which decreases linearly from 2 to 0 during the iteration, the value of a can be obtained by the Equation (18), and the modulus of r_1 and r_2 takes a random number between [0, 1].

$$a = 2 - 2\left(\frac{t}{t_{max}}\right) \tag{18}$$

where t_{max} is the maximum number of iterations. The hunting process is usually led by α wolves, β wolves, and δ wolves will guide the wolves to surround the prey. However, in the search space, we do not know the best position of the prey; therefore, we assume that α wolves, β wolves, and δ wolves have a better understanding of the location of prey. The change in the location of the wolf pack round-up prey is formulated as follows:

$$\begin{cases} \vec{D_\alpha} = \left| \vec{C_1} \times \vec{X_\alpha}(t) - \vec{X}(t) \right| \\ \vec{D_\beta} = \left| \vec{C_2} \times \vec{X_\beta}(t) - \vec{X}(t) \right| \\ \vec{D_\delta} = \left| \vec{C_3} \times \vec{X_\delta}(t) - \vec{X}(t) \right| \end{cases} \tag{19}$$

$$\begin{cases} \vec{X_1} = \vec{X_\alpha} - \vec{A_1} \times \vec{D_\alpha} \\ \vec{X_2} = \vec{X_\beta} - \vec{A_2} \times \vec{D_\beta} \\ \vec{X_3} = \vec{X_\delta} - \vec{A_3} \times \vec{D_\delta} \end{cases} \tag{20}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{21}$$

where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ represent the current position vectors of α, β, and δ wolves, respectively. $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ are the distances between α, β, and δ wolves and prey, respectively. The position of ω wolves is constantly adjusted to be closer to the prey under the guidance of α, β, and δ wolves. $\vec{X}(t+1)$ represents the final position of ω wolves. The position update of gray wolves around prey is shown in Figure 10.

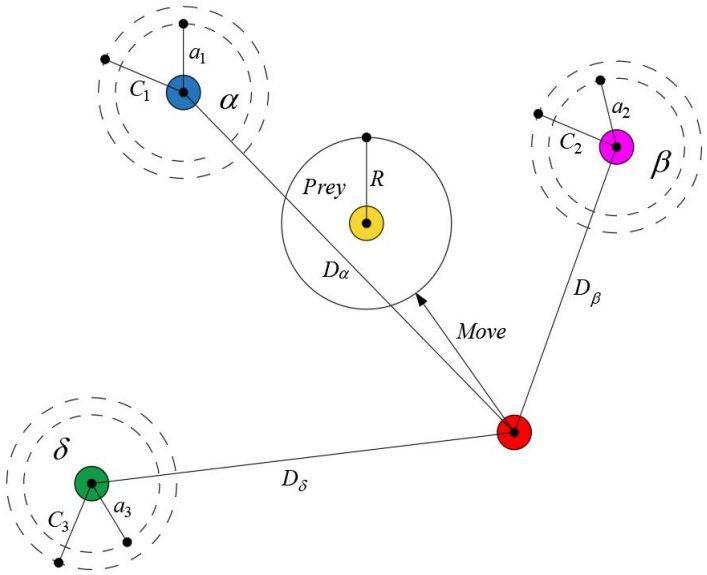


Figure 10. Grey wolf position update in GWO algorithm. Blue circle: α wolves; purple circle: β wolves; green circle: δ wolves; red circle: ω wolves or any other hunters; yellow circle: position of the prey.

Based on the advantages of GWO algorithm, such as simplicity and less parameter setting, the method proposed in this paper is to optimize the parameters of SVM by GWO algorithm, obtain the best penalty factor C and kernel function parameter g of SVM through iterative optimization, and improve the training speed, generalization ability, and classification accuracy of the model. Finally, the flow chart of the GWO-SVM model proposed in this paper is shown in Figure 11.

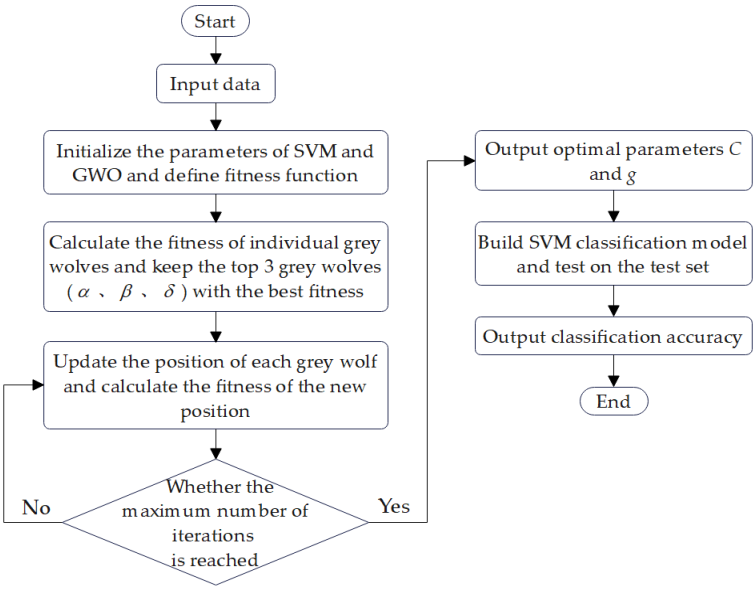


Figure 11. Flow chart of GWO-SVM model.

6. Experimental Validation

6.1. Preparation of Dataset

To verify the feasibility of the proposed method of coal gangue identification based on GWO-SVM, we acquired 300 images of coal and gangue as sample datasets through the coal gangue identification machine vision experimental platform constructed in Section 2. The method of random sampling was used to divide the dataset, and the training set and the test set were divided in a ratio of 7:3. Among them, 210 are used as training sets, the remaining 90 are used as test sets, and the two datasets are independent of each other without crossover.

6.2. Model Parameter Setting

To prove that the proposed method has good performance, we use SVM, GA-SVM, PSO-SVM, and GWO-SVM classification models to test, respectively. The parameter settings of these algorithm models are shown in Table 1. The experiment was run on a computer with Chinese Lenovo CPU(AMD Ryzen7 5800H with Radeon Graphics 3.20 GHz) Microsoft's Windows11 (64bit) and simulated on MATLAB R2022a software from MathWorks USA.

After setting the parameters of the model, according to the method proposed in Section 4.3, the histograms of the extracted HOG and LBP features are fused in series and then the feature data are normalized to the normalized interval of [0, 1], and, after normalization, feature dimensionality reduction is processed by the PCA. Finally, the datasets after normalized and PCA dimensionality reduction are input into the established SVM, GA-SVM, PSO-SVM, and GWO-SVM classification models, respectively. To better obtain the classification accuracy of the proposed model and compare the classification accuracy and performance stability of these four classification models, optimization simulation experiments were run 30 times.

Table 1. Parameter settings of different models.

Number	Model	Parameter Setting
1	SVM	The training function libsvmtrain is called here to train the SVM model, and the test set is tested and verified by the libsvmpredict function to obtain the identification classification accuracy. The experiment was run on MATLAB R2022a software.
2	GA-SVM	Genetic algorithm is used to optimize the support vector machine. The genetic algorithm is called MATLAB R2022a toolbox. The population size Np is 100, the cross-probability Pc is 0.7, the probability of variation Pm is 0.005, and the genetic maximum evolutionary algebra G is 200.
3	PSO-SVM	Particle swarm optimization is used to optimize the support vector machine. The experiment has the following related settings by calling the toolbox of "PSOt" in MATLAB: the number of particles N = 20, learning factor c1 and c2 are 1.5, the inertia weight w is 0.8, and the maximum number of iterations G is 200.
4	GWO-SVM	GWO algorithm was used to optimize the penalty factor C and kernel parameter g of SVM, where the population size of grey wolf M is 20 and the maximum number of iterations $t_{\max}$ is 200.

6.3. Experimental Results and Analysis

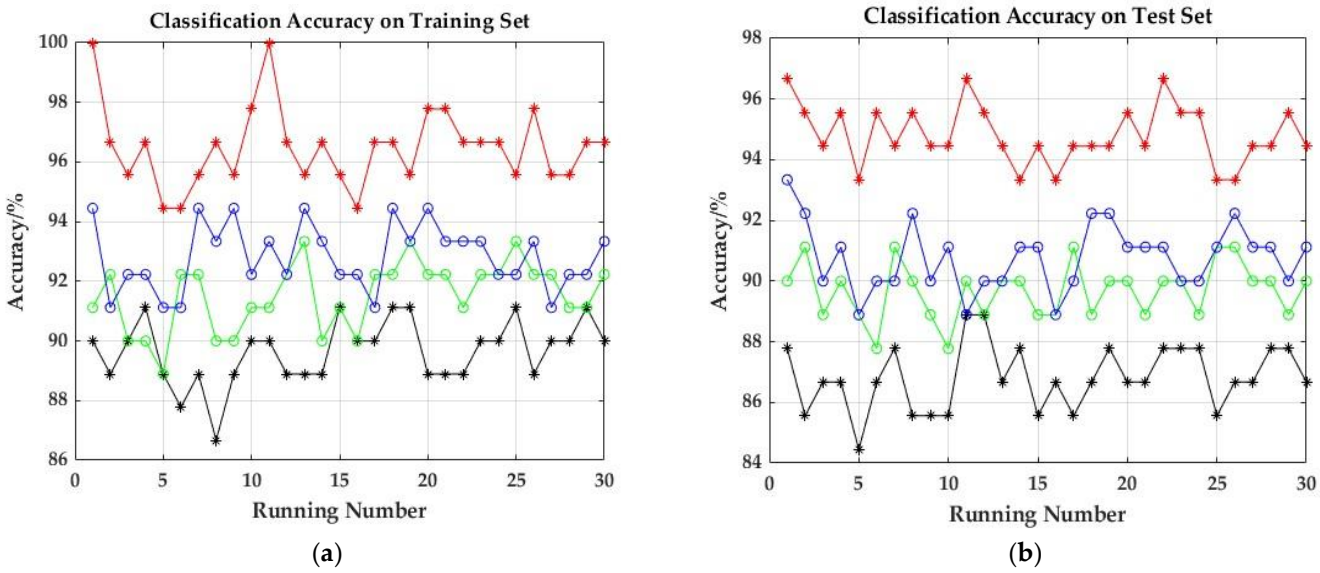
Table 2 shows the classification accuracy and average accuracy of different classification methods on the training set and test set in the 30 experiments. Figure 12a,b shows the classification accuracy of the four classification models SVM, GA-SVM, PSO-SVM, and GWO-SVM on the training and test sets based on the data in Table 2, respectively. From the figure, we can clearly find that, whether in the training set or the test set, the accuracy of the GWO-SVM classification model is the highest, and its classification accuracy on the training set and the test set can reach 100% and 96.67%, followed by the PSO-SVM model; the original SVM has the lowest classification accuracy. In addition, as can also be seen from Table 2 and Figure 12, the method proposed (HOG combined LBP features and GWO-SVM) of all the methods in this paper has the highest average accuracy on the

training set and test set, which indicates that the support vector machine optimized by grey wolf algorithm has the best classification effect in coal gangue image recognition applications. According to Section 5, the principle of optimizing support vector machine by these three intelligent optimization algorithms is to optimize SVM parameters C and g through iterative updating. However, their classification effect is very different. Grey wolf algorithm has the best optimization effect, which is because the GWO algorithm has fewer parameter settings, better robustness, and higher accuracy.

Table 2. Classification accuracy of different methods.

Number	Classification Accuracy on Training Set				Classification Accuracy on Test Set			
	SVM	**GA-SVM**	**PSOSVM**	**GWO-SVM**	**SVM**	**GA-SVM**	**PSO-SVM**	**GWO-SVM**
1	90.00%	91.12%	94.45%	100.00%	87.78%	90.00%	93.34%	96.67%
2	88.89%	92.23%	91.12%	96.67%	85.56%	91.12%	92.23%	95.56%
3	90.00%	90.00%	92.23%	95.56%	86.67%	88.89%	90.00%	94.45%
4	91.12%	90.00%	92.23%	96.67%	86.67%	90.00%	91.12%	95.56%
5	88.89%	88.89%	91.12%	94.45%	84.45%	88.89%	88.89%	93.34%
6	87.78%	92.23%	91.12%	94.45%	86.67%	87.78%	90.00%	95.56%
7	88.89%	92.23%	94.45%	95.56%	87.78%	91.12%	90.00%	94.45%
8	86.67%	90.00%	93.34%	96.67%	85.56%	90.00%	92.23%	95.56%
9	88.89%	90.00%	94.45%	95.56%	85.56%	88.89%	90.00%	94.45%
10	90.00%	91.12%	92.23%	97.78%	85.56%	87.78%	91.12%	94.45%
11	90.00%	91.12%	93.34%	100.00%	88.89%	90.00%	88.89%	96.67%
12	88.89%	92.23%	92.23%	96.67%	88.89%	88.89%	90.00%	95.56%
13	88.89%	93.34%	94.45%	95.56%	86.67%	90.00%	90.00%	94.45%
14	88.89%	90.00%	93.34%	96.67%	87.78%	90.00%	91.12%	93.34%
15	91.12%	91.12%	92.23%	95.56%	85.56%	88.89%	91.12%	94.45%
16	90.00%	90.00%	92.23%	94.45%	86.67%	88.89%	88.89%	93.34%
17	90.00%	92.23%	91.12%	96.67%	85.56%	91.12%	90.00%	94.45%
18	91.12%	92.23%	94.45%	96.67%	86.67%	88.89%	92.23%	94.45%
19	91.12%	93.34%	93.34%	95.56%	87.78%	90.00%	92.23%	94.45%
20	88.89%	92.23%	94.45%	97.78%	86.67%	90.00%	91.12%	95.56%
21	88.89%	92.23%	93.34%	97.78%	86.67%	88.89%	91.12%	94.45%
22	88.89%	91.12%	93.34%	96.67%	87.78%	90.00%	91.12%	96.67%
23	90.00%	92.23%	93.34%	96.67%	87.78%	90.00%	90.00%	95.56%
24	90.00%	92.23%	92.23%	96.67%	87.78%	88.89%	90.00%	95.56%
25	91.12%	93.34%	92.23%	95.56%	85.56%	91.12%	91.12%	93.34%
26	88.89%	92.23%	93.34%	97.78%	86.67%	91.12%	92.23%	93.34%
27	90.00%	92.23%	91.12%	95.56%	86.67%	90.00%	91.12%	94.45%
28	90.00%	91.12%	92.23%	95.56%	87.78%	90.00%	91.12%	94.45%
29	91.12%	91.12%	92.23%	96.67%	87.78%	88.89%	90.00%	95.56%
30	90.00%	92.23%	93.34%	96.67%	86.67%	90.00%	91.12%	94.45%
Average accuracy	89.63%	91.52%	92.82%	96.49%	86.82%	89.67%	90.78%	94.82%

Figure 13 is a columnar diagram of the dataset classification accuracy comparison. As can be seen from the figure, the proposed method has higher classification accuracy on the training set and test set than other classification models, and the GWO-SVM method has an average accuracy of 96.49% and 94.82% on the training set and test set, respectively. That is, the GWO-SVM model is best classified under the condition of same training sample. In fact, compared with other intelligent optimization algorithms, the grey wolf algorithm can accurately find the best penalty factor C and kernel function parameter g of SVM, which can improve the classification accuracy of the model, which is also the feasibility and superiority of the method proposed in this paper.



(**a**) (**b**)

Figure 12. (**a**) Classification accuracy on the training set; (**b**) classification accuracy on the test set. Red *: GWO-SVM; blue circles: PSO-SVM; green circles: GA-SVM; black *: SVM.

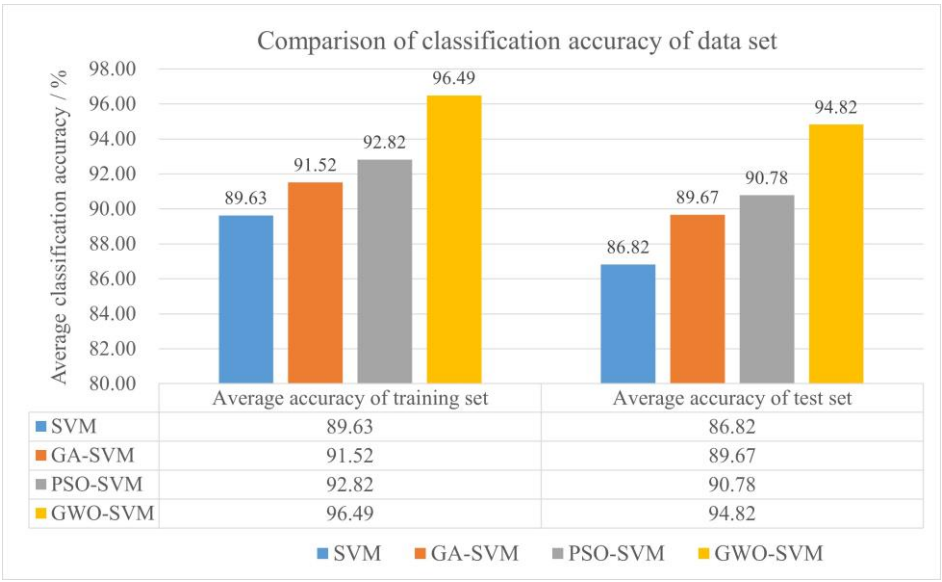


Figure 13. Comparison of classification accuracy of data set.

7. Conclusions and Future Work

To improve the accuracy of coal gangue image identification, a coal gangue identification method based on HOG combining LBP features and improved support vector machine was proposed in this paper. To verify its feasibility, first, we built a machine vision experimental platform for coal gangue recognition by imitating the actual underground environment and acquired 300 coal gangue images as sample image datasets. Median filtering denoising was performed on the images of coal and gangue, HOG and LBP features of the images were extracted, and we combined the two feature histograms in series. To eliminate the dimensional influence between different features, we normalized the feature data to the [0, 1] interval and carried out PCA down-dimensional processing to remove correlation and redundancy between the features. Finally, 30 identification and classification experiments were conducted with SVM, GA-SVM, PSO-SVM, and GWO-SVM, respectively. The experimental results show that the average classification accuracy of the GWO-SVM model on the training set and test set is 96.49% and 94.82%, respectively, and its classification

effect is better than that of SVM. Both the GA-SVM and PSO-SVM models are good, which proves the efficiency and accuracy of the proposed method in this paper.

However, our current work still has some shortcomings, such as the small number of samples, and the algorithm is prone to fall into the local optimal solution. In addition, grey wolf optimization algorithm is still a heuristic optimization technique, and the optimal solution generated is only close to the original optimal solution, not the optimal solution of the problem. Therefore, in future work, we will further expand the image dataset of coal gangue samples, continue to optimize classification performance, and carry out in-depth research on coal gangue identification by different feature selection methods and optimization algorithms so as to further improve the accuracy of coal gangue identification.

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