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A sorting method for coal and gangue based on surface grayness and glossiness

Introduction

Coal is the "raw stone of industry" in China's industrial sector and still assumes the primary energy mission under the "double carbon" target (Hu et al. 2022). Gangue is a kind of rock that accompanies the coal seam in the process of coal formation and is produced in the coal mining process (Cheng et al. 2023). The high gangue content not only increases the transportation cost but gangue combustion generated by SO_2, H_2S, NO_x, and other gases also reduced reduce the air quality of the surrounding environment while causing acid rain

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and other natural disasters (Jia et al. 2022). Therefore, to protect the natural environment and improve coal quality, there is an urgent need to include a pre-treatment step of coal gangue sorting in the mining process. The current sorting method used in China's coal mines is mainly manual (Pu et al. 2019). However, manual sorting is intensive, and the sorting efficiency is low. In recent years, the wet sorting method, as a representative of mechanical sorting, has been widely used in coal production lines (Zou et al. 2020). However, the process requires more expensive machinery and equipment, and the wet sorting method needs to consider the factors of adequate water supply in the region. Additionally, the emissions can also pollute the surrounding environment with the rise of photoelectric technology, the X-ray transmission method, three-dimensional laser scanners, infrared thermal imaging, and other photoelectric technology based on the rapid development of coal gangue sorting research. Among the current study, the X-ray transmission method for gangue sorting technology is more mature (Osipov et al. 2020; Kayalvizhi et al. 2022). The use of dual-energy rays for gangue sorting is a method that effectively improves the efficiency of gangue sorting. However, X-ray radiation is intense and seriously endangers human health. The use of laser 3D scanners and dynamic weighing is an emerging method that sorts coal and gangue by obtaining information on their density. Wang et al. (Wang et al. 2017) used this method in the laboratory to achieve the separation of coal gangue, but the separation rate of this method could be higher. Infrared thermal imaging, as a unique imaging method in the coal gangue identification operation, has the advantage of high identification efficiency. Alfarzaeai et al. (Alfarzaeai et al. 2020) found that the identification rate of coal gangue using infrared thermography reached 98.75%. However, before identifying the gangue, it needs to use the heat source to heat the ore for some time, so the method is challenging to achieve in actual operation. In recent years, learning models and image-processing techniques have developed rapidly and play an essential role in medicine, new energy, and automotive traffic (Doan and Carpenter 2019; Fan et al. 2022). This technique has become a new channel for efficiently identifying coal and gangue. In the coalfield, Huang et al. (Huang et al. 2022) proposed a binocular machine vision and particle queuing method to detect coal content in the gangue online. Lei et thetOv3-A model was the best for coal and gangue classification by comparing the recognition accuracy and recognition time of multiple deep learning models. These studies have demonstrated the feasibility of image-processing techniques and learning models in coal gangue identification operations. Furthermore, the method can achieve higher recognition rates with its in-depth analysis.

Classification models based on statistical theory have recently been developed and machine learning and deep learning have been widely used in the coal industry (Gao et al. 2020; Lin et al. 2022). Unfortunately, the deep learning model needs image data to support it. The deep learning model is complex and has a long classification time, which is unsuitable for efficient sorting, although the sorting accuracy is high. By contrast, using machine learning models to identify coal gangue has the advantages of a high recognition rate and a relatively simple model suitable for coal gangue operations. Research on classification using machine learning models has been gradually enriched, facilitating the development of the technical aspects of coal gangue identification. Among these, support vector machine (SVM) has been widely used in coal gangue sorting – this is a classification model that can handle small samples and nonlinear problems (Shen et al. 2017). Among the studies of SVM for coal gangue sorting, Wang et al. (Wang et al. 2021) used grayscale first-order moments and grayscale co-occurrence matrix in images as feature information. They used SVM for classification, which achieved a classification rate of 95%. However, the tremendous computational effort and feature dimensionality of the grayscale co-occurrence matrix lead to the common generalization and complicated steps of such methods. The recognition rate can be further improved by optimizing the SVM model. The Gaussian kernel parameters and penalty factors are essential for efficient SVM models. Using intelligent optimization algorithms to optimize the search for the best parameters in the solution space can improve the recognition rate of SVM models. Therefore, the intelligent optimization algorithm combined with a support vector machine can further optimize the recognition model and improve the convergence and binning rate of the model. According to previous studies, intelligent optimization algorithms such as particle swarm algorithm (Shi et al. 2017; Subasi 2013) (PSO) and genetic algorithm (Yin and Ren 2021) (GA) have been used in the identification model of coal gangue sorting, and the recognition effect has been further improved. However, the convergence speed of PSO and GA algorithms could be faster, and the randomness of the search for the optimal solution is strong, leading to a low probability of obtaining the optimal solution. By contrast, the Grey Wolf algorithm (GWO) has the advantages of merit-seeking solid ability and fast convergence speed to meet the production requirements. The GWO combined with the SVM model can be applied to the coal gangue identification operation.

Given the abovementioned shortcomings in the recognition process, this paper proposes a comprehensive sorting method based on coal and gangue's surface gloss and greyness values. This method uses an industrial CCD camera to acquire sample color images of coal and gangue and images under light source irradiation. It adopts the pre-processing approach of median filtering with a 3×3 convolution kernel for deblurring and denoising. The features of coal and gangue images are then extracted by image processing techniques such as image segmentation, Retinex enhancement, and OTSU maximum threshold segmentation. In addition, this paper uses a decision tree model to evaluate the feature importance of the extracted greyscale feature vectors from which the features that contribute most to the classification accuracy of the gangue are selected as the feature vectors of the greyscale information, simplifying the model. Secondly, this paper fuses the extracted greyscale and glossiness features into a comprehensive discriminant value based on the entropy weight method. The comprehensive discriminant value was used as the input to the classification model. The recognition accuracy and training time of GA-SVM, PSO-SVM and GWO-SVM were investigated under the condition that the same dataset was used as the input of the classification algorithm. It was found that GWO-SVM has good performance in recognition accuracy and finding time, which provides a basis for the GWO-SVM classification model to identify coal and gangue effectively. Finally, the single feature vector and the combined discriminant values were input into the trained GWO-SVM, and by comparing the binning rate, it was found that the method presented in this paper can effectively improve the recognition rate of coal and gangue, which should be a guide for practical application.

1. Image acquisition and image pre-processing

1.1. Experimental platform for image acquisition

The samples of coal and gangue selected for this test were all from the Pansan mining area in Huainan, Anhui Province. The crusher crushed the coal and gangue in the samples, and the diameter particles were distributed between 40 and 100 mm. The experimental platform for image acquisition was built to acquire images of coal and gangue samples, as shown in Figure 1. The image acquisition experimental platform mainly comprised a feeding table, a light source, a mask, a conveyor belt and an industrial CCD camera. The camera uses USB 3.0 as the data interface to connect with the computer to achieve the real-time acquisition of coal gangue samples. The sample images collected in this test include color images of coal and gangue and images of coal and gangue under the light source's illumination; the latter is called illumination images of coal and gangue in this paper. In acquiring illumination images, a light source of 2500 lex was selected to irradiate the ore

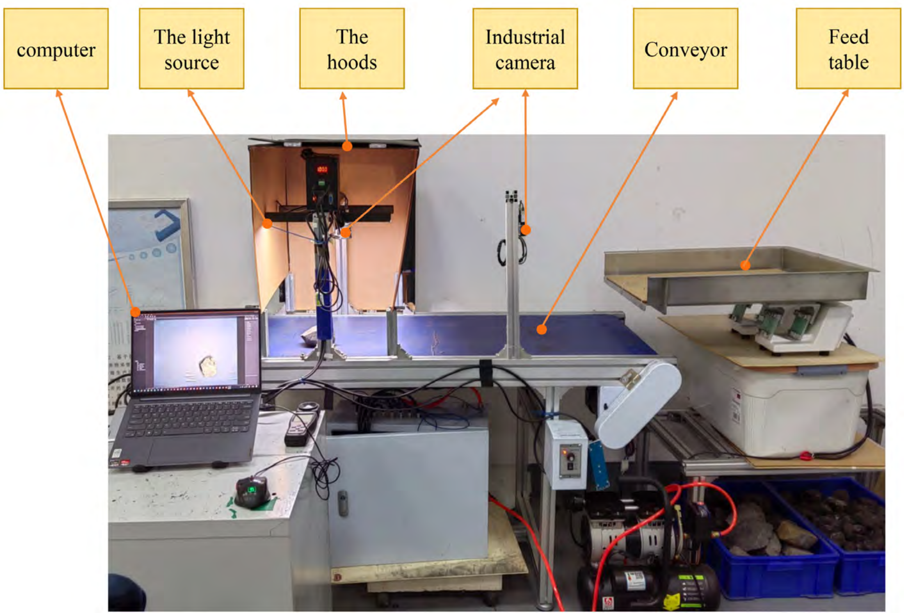

Fig. 1. Pictures of the test bench
Source: own study

Rys. 1. Stanowisko badawcze

samples. Using a hood device, external light sources avoided interfering with the illumination image-acquisition process. The coal and gangue samples pass through two CCD cameras at a speed of 0.1m/s by the action of a conveyor belt. The cameras transfer the captured images to a computer via a USB data cable and categorize them for subsequent processing.

1.2. Image pre-processing

In the coal and gangue production environment, the air contains a large amount of dust, resulting in the CCD camera acquisition of coal and gangue images being disturbed by the external environment, the image captured in the presence of noise. To simulate the photos of coal and gangue taken under actual sorting conditions while making the filtering results, more intuitive, pepper noise replaced the images of contaminated samples from the virtual environment. The mean, Gaussian, and median filters pre-process the degraded sample images. To ensure a minor distortion before and after image preprocessing, the size of the filter convolution kernel should be selected appropriately during preprocessing. In this paper, three pre-processing methods of conventional 3×3, 5×5, and 7×7 convolution kernels are used to pre-process the contaminated images, and the pre-processing results are shown in Figure 2.

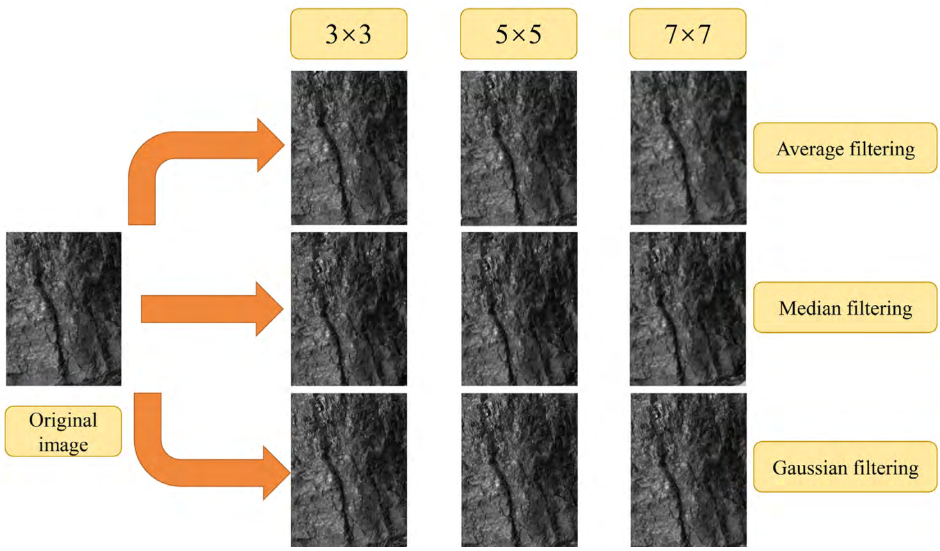

Fig. 2. Processing results of different image pre-processing methods
Source: own study

Rys. 2. Wyniki przetwarzania różnych metod wstępnego przekształcania obrazu

By comparing the preprocessing results, median and mean filtering is more effective than Gaussian filtering, and the pepper noise in the image is somewhat suppressed. To objectively evaluate the preprocessing effect of each method under different size convolution kernels, the mean square error (MSE) of the image is used in this paper to evaluate the denoising effect between other image processing methods. The performance of the filtering algorithm can be evaluated by calculating the mean value of the sum of squares of the corresponding pixel points between the reconstructed image and the original image, the mean square error of the image. The smaller the mean square error value, the more similar the image; the smaller the distortion of the image, the better the pre-processing effect of the algorithm, and the expression of the root mean square value is as follows.

$$MSE = \frac{1}{M \cdot N} \sum_{\mathrm{i}=1}^{M} \sum_{j=1}^{N} [f(i,j) - g(i,j)]^2 \tag{1}$$

The size of the original image is $M \times N$; $f(i,j)$ denotes the grey value of the coordinate in the original image, which means the grey matter of the coordinate (i,j) in the denoised image; $g(i,j)$ is the image after pre-processing. Twenty images of coal and gangue were randomly selected. The coal and gangue pictures were preprocessed using median, Gaussian, and mean filtering under different convolution kernels. The mean of the root mean square values of all images before and after preprocessing were calculated and plotted as histograms, and the results are shown in Figure 3.

Figure 3 shows that the images of coal and gangue with Gaussian filtering have more significant distortion than the other two filtering methods. Among the three filtering methods, median filtering has the best effect, and the distortion of the obtained image is more minor.

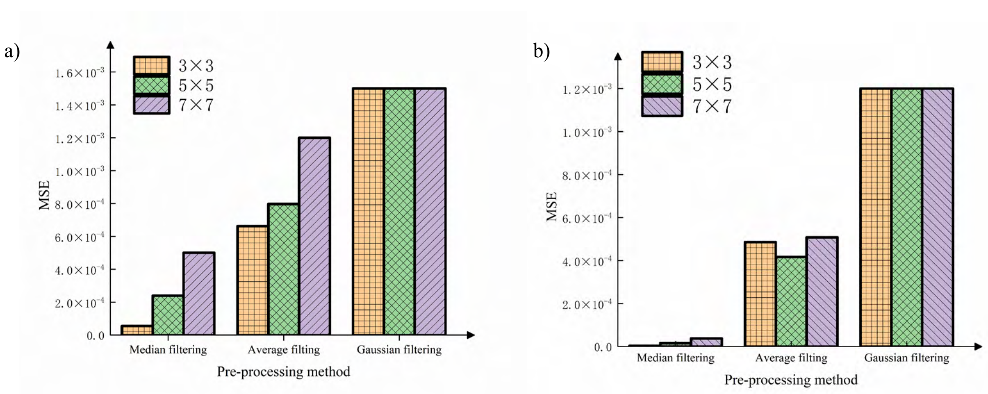

Fig. 3. Comparison of filtering results of different filtering methods
a) Coal image filtering root mean square value, b) Root mean square value of gangue image filtering
Source: own study

Rys. 3. Porównanie wyników filtrowania różnymi metodami filtrowania
a) Średnia kwadratowa filtrowania obrazu węgla, b) Średnia kwadratowa wartości filtrowania obrazu skały płonnej

In the same case of median filtering, the filtering effect of 3×3 convolutional kernels is obvious due to other sizes of convolutional kernels, which can effectively reduce the problem of image blur caused by convolutional kernels being too large, so the median filtering of coal and gangue noise image preprocessing using 3×3 convolutional kernel template is better.

2. Feature extraction of coal and gangue

The surface characteristics of an object contain properties such as texture, surface roughness, color and surface gloss. Objects can be effectively distinguished according to their respective surface properties. Coal and gangue are different ores, and their surface characteristics differ significantly. The vast majority of the surface color of coal differs from gangue, so the two can be distinguished according to the grayscale value of the sample image. At the same time, under a light environment, the surface gloss of coal is more evident than that of gangue. Based on the above two surface differences, the method presented in this paper sorts coal and gangue by extracting the grayscale and glossy features of coal and gangue sample images as feature vectors.

2.1. Grayscale statistical feature selection

The grayscale statistical features of an image are generally used to describe the grayscale distribution characteristics of a grayscale image. In the grayscale feature information, to describe a particular part of a sample in a grayscale image, the mean value of grayscale, the variance of grayscale, the image entropy value, and the grayscale value corresponding to the maximum frequency are usually selected to describe the features of the image. The average grey level of the image is a description of the brightness level of the image, which can be used to describe the difference between the surface color of coal and gangue. The grey variance of the image is a statistical measure of the distribution of the grey level of the image, which measures the dispersion of the distribution of the grey level of the image, there are differences in the surface colour and texture of coal and gangue, so the distribution of the grey level of the two is also different. The image entropy is a description of the size of the information in the digital image, which is used to measure the complexity and randomness of the image. The maximum frequency grey level is the plurality of the grey level in an image, which reflects the overall brightness distribution characteristics of the image. There is an overlap of the grey value range of both in the grayscale image, and it isn't easy to distinguish the samples of coal and gangue efficiently with single grey-scale information. To improve the recognition rate of the method in this paper, the feature metric that contributes most to the classification accuracy in the grey-scale features should be selected as the feature vector. Eighty-color images of coal and gangue were chosen randomly. After pre-processing, the grayscale feature information of the sample images was extracted and the obtained ranges of each feature parameter are shown in Table 1.

Table 1. Sample image grayscale parameter values

Tabela 1. Przykładowe wartości parametrów skali szarości obrazu

Category	Grayscale average	Grayscale variance	Image Entropy	Maximum frequency grayscale
Coal	0.0378~0.119	0.0670~0.124	2.30~4.91	0.047~0.184
Gangue	0.6070~0.205	0.0788~0.191	2.28~5.42	0.094~0.302

Source: own study.

Feature importance is assessed by counting the degree to which different features contribute to the model's accuracy when building a prediction model. The feature selection model requires a metric for each feature so that the importance of the feature can be ranked using that metric. A decision tree model is a machine learning model in which, at each node of the decision tree, the algorithm evaluates different features and calculates metrics such as purity or Gini index for each group in order to measure the contribution value to the prediction result. Therefore, the higher the index of the node corresponding to the feature, the higher the importance of the quality for the classification result, so this paper uses the decision tree model for the feature selection of the four features in Table 1. The specific implementation method is as follows: select the selection of eighty photos of coal and gangue and the extraction of the feature information in each image in Table 1, the extracted feature information and coal gangue category information is then placed into the decision tree

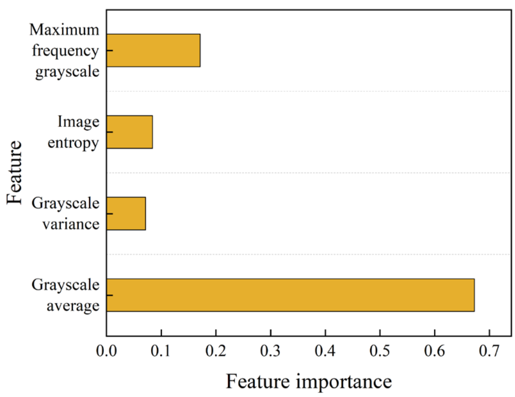

Fig. 4. Feature importance results
Source: own study

Rys. 4. Wyniki ważności cech

model while adjusting the maximum depth of the decision tree to prevent overfitting of the model. The obtained feature importance map is shown in Figure 4.

Figure 4 shows that the feature corresponding to the first-order moment of greyscale has the highest importance in this decision tree model. Therefore, in the case where this feature alone is used to sort coal and gangue, it can differentiate coal and gangue to the greatest extent. Thus, this paper selects the grayscale first-order moment as the feature vector of grayscale information.

2.2. Glossiness feature extraction

2.2.1. Image enhancement based on Retinex Theory

When light acts on the surface of an object, the light is reflected and refracted by the object's surface. Reflected light on the surface of smooth things mainly includes specular reflected light and diffuse reflected light, and the two exist and act together (Atkinson and Hancock 2006; Zhang et al. 2018). When specular reflection presents an imaginary image on the surface of the object. When the reflected light source is vital, the reflective area on the surface of the object forms a highlight area on the surface of the object (Miyazakiet al. 2003, 2004) hindering the human eye's observation of the thing itself. According to relevant studies, the microscopic fraction of coal contains a large number of specular components (Congo et al. 2003), which under the action of the incident light, have the effect of specular reflection, forming a high-bright area on the surface of the object and appearing as an observable white "spot" on the image. In contrast to gangue, which has a generally flat surface, the surface of coal illuminated by an external light source has a substantial specular reflection effect, so the nature of surface gloss can be applied to distinguish between the two ores. According to the above analysis, the glossiness of an object is a reflection of the reflected light information on the object's surface, which is the light component of the image and the brightness information of the image. In the image captured by the CCD camera, the "white spot" in the high brightness area is represented by the pixel value of the more considerable gray value in the image brightness component; the more pixels corresponding to the high gray area in the image brightness component, the more brightness information is contained and the stronger the surface gloss of the sample. However, the coal and gangue surface is black and dark grey. The incident light absorption ability is relatively strong, resulting in the coal and gangue surface part of the specular reflection area reflected light being relatively weak; part of the image brightness information is not easy to observe and extract, so you need to enhance the image of the light component properly.

Image enhancement uses Retinex theory which is based on the illumination-reflection model of an image and which considers that an image consists of the illumination field of a light source (illumination function) and the reflected field of reflected light from an object (reflection function) with the illumination function is generally changing slowly and the reflection function mainly reflects the essential details of the image. The illumination function is in the low-frequency region of the image spectrum. The reflection function is in the high-frequency area of the image spectrum; thus, using the Fourier transform, it can achieve the purpose of separating the illumination function and the reflection function of the image, and the expression of the illumination-reflection model is as follows.

$$f(x,y) = i(x,y) \cdot r(x,y) \tag{2}$$

$i(x,y)$ is the image's illumination function; $r(x,y)$ represents the image's reflection function; $f(x,y)$ is the image function. Different Retinex algorithms have different methods for estimating the illumination component and have other effects on image enhancement. The center-surround Retinex enhancement algorithm used in this paper estimates the illumination component of the image by a Gaussian function, which is calculated as.

$$i(x,y) = h(x,y) \cdot f(x,y) \tag{3}$$

The "·" denotes the convolution operation, $h(x,y)$ is a two-dimensional Gaussian function with the following expression.

$$h(x,y) = Ke^{\frac{-(x^2+y^2)}{\sigma^2}} \tag{4}$$

K and σ are both coefficients of the function K is the normalization factor; σ it is the standard deviation, representing the Gaussian surround function scale constant and determining the range of action of the convolution kernel. To compare the processing effects of different center-surround Retinex algorithms on coal and gangue sample images, SSR (single-scale retinex), MSR (multi-scale Retinex), and MSRCR (multi-scale Retinex with color restoration) of the center-surround Retinex method are selected to process the sample images in this paper. The enhancement results are shown in Figure 5.

Fig. 5. Comparison of processing results of three Retinex algorithms
Source: own study

Rys. 5. Porównanie wyników przetwarzania trzech algorytmów Retinex

According to Figure 5, the contrast of the coal and gangue sample images enhanced by MSR and MSRCR is slight, resulting in poor visualization of the images, inconspicuous luminance information, and not easy extract. Compared with the other two algorithms, the enhanced image of the SSR algorithm shows more luminance information and high contrast of the image, which is convenient for extracting and observing illumination information. To further verify the generalizability of the SSR algorithm, twenty randomly selected images from the coal and gangue sample images were experimented with three different Retinex algorithms. By capturing the root mean square value as an objective evaluation of the image illumination enhancement algorithm index, the root-mean-square value of an image is a metric for assessing the brightness of an image, reflecting the average level of brightness of the image, and can be used to compare the magnitude of brightness between different images. The larger the root-mean-square value, the richer the brightness information of the image. The root mean square value of the enhanced sample images is plotted using the form of a line graph. Figure 6 shows the root mean square value of the image enhancement under different Retinex enhancement algorithms. The root mean square value of the image enhanced by the SSR algorithm is much greater than when using the the other two algorithms. It shows that the image brightness information is richer after the SSR algorithm enhancement, so the SSR enhancement algorithm is chosen for the gangue image processing.

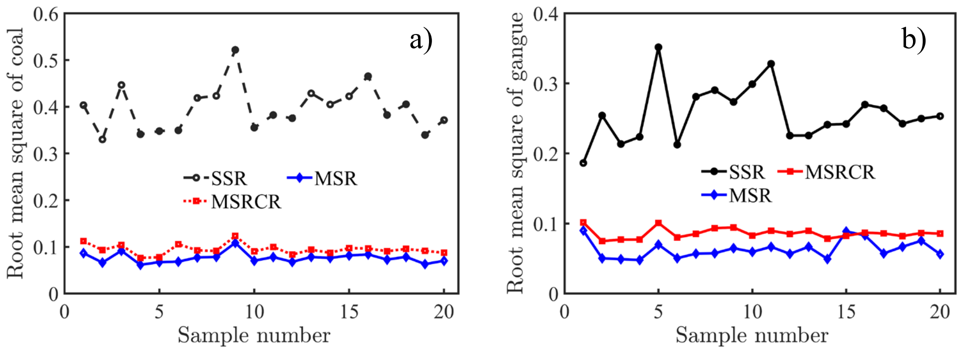

Fig. 6. Image standard deviation values
a) Root mean square values of coal-enhanced images, b)Root mean square value of gangue enhanced image
Source: own study

Rys. 6. Wartości odchylenia standardowego obrazu
a) Średnia wartość kwadratowa obrazów wzmocnionych węglem,
b) Średnia wartość kwadratowa obrazu wzmocnionego skałą płonną

2.2.2. Extraction of HSV color space and luminance information

RGB color space is a color standard in the industry, and a variety of colors are obtained by superimposing the R (red), G (green), and B (blue) channels on each other. RGB's color standard encompasses almost all of colors that humans can perceive and is one of the most widely used color systems. However, the hue and luminance information cannot be effectively distinguished in the RGB space, making it difficult to extract the luminance information of the image in the RGB model. By contrast, HSV color space consists of hue, saturation, and luminance, and the three components are independent of each other, which makes it simple and feasible to separate the luminance components of an image. In the coal and gangue image illumination component image, the number of pixel points in the high grey area reflects the intensity of coal and gangue surface gloss.

To objectively select the threshold value to distinguish between high and low grey regions of the image, the maximum between-class variance method (OTSU) is chosen to segment the image. The OTSU method is a method that uses the between-class and within-class variance to measure and select the threshold that minimizes the within-class variance or maximizes the between-class variance as the best threshold from the perspective of the image grayscale histogram. The method can apply one threshold to segment the image and multiple points to partition the grayscale values of the image into different intervals so that each interval has minimal within-class variance, the most considerable between-class variance, or the smallest ratio of within-class to between-class variance. The most significant advantage of using the OTSU method is obtaining multi-level image thresholds objectively through statistical mathematics. This paper adopts the multi-level threshold segmentation method of the OTSU method because the "spot" formed by the reflected light from the coal surface in the image belongs to the pixel point corresponding to the high grey area, so the most significant threshold value in the multi-level threshold is used as the image segmentation threshold. After the experiment, and after enhancing and extracting the luminance information of the image by the HSV model, the OTSU method is used to segment the image. The segmentation results obtained are shown in Figure 7.

Comparing the threshold segmentation plot and the thermal density plot of the pixel point distribution in Figure 8, we know that the coal image gradually decreases the luminance information retained in the image as the image threshold level increases. The 2-level threshold segmentation contains more redundant luminance information than the original image. By contrast, the 4-level threshold segmentation has a loss of luminance information compared with the original image, and the 3-level threshold segmentation retains most of the luminance information of the image. The segmentation effect is better compared with the 2-level and 4-level threshold segmentation. In the multi-level threshold segmentation of the gangue image, the impact of 4-level threshold segmentation can retain the initial brightness information of the picture to the greatest extent compared with other levels. After several experiments, it was found that using a 3-level segmentation threshold to segment coal image and a 4-level segmentation threshold to segment gangue image can retain the adequate brightness information of the image to the greatest extent, so the 3-level threshold of coal image and 4-level threshold of the gangue image have been selected and segmented by the OTSU method.

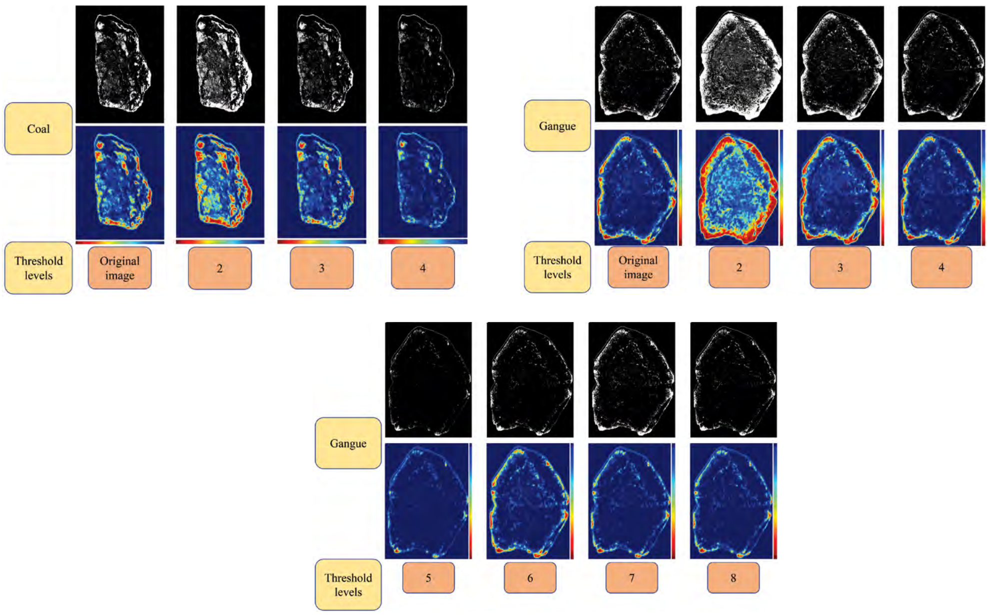

Fig. 7. Threshold segmentation map of coal and gangue images
Source: own study

Ryc. 7. Mapa segmentacji progowej obrazów węgla i skały płonnej

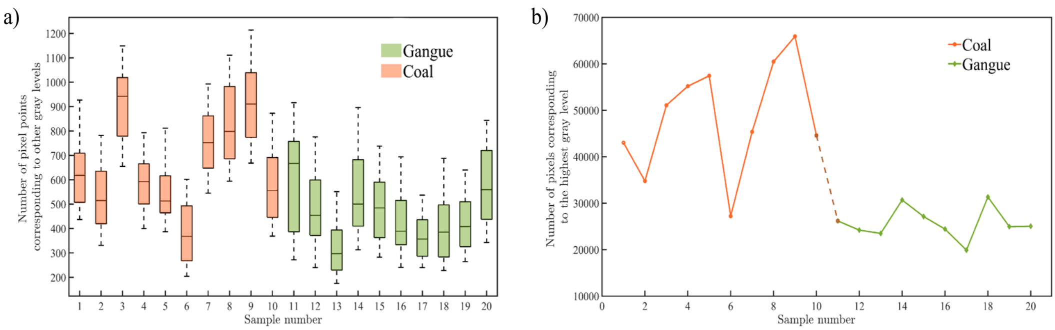

Fig. 8. Pixel distribution of sample images
a) Other gray levels corresponding to the distribution of pixel point values,
b) Number of pixels corresponding to the highest grey level
Source: own study

Rys. 8. Rozkład pikseli przykładowych obrazów
a) Inne poziomy szarości odpowiadające rozkładowi wartości punktowych pikseli,
b) Liczba pikseli odpowiadająca najwyższemu poziomowi szarości

The number of pixel points corresponding to high gray levels in the segmented region is the target of feature extraction. Ten images of coal and gangue were selected after segmentation to study the distribution of pixel points corresponding to each gray level in the segmented region. The distribution of the number of pixels corresponding to the grey level in the luminance information of coal and gangue images was described as a fold line. By contrast, the number of pixel points corresponding to other grey values was described using a box line diagram, and the visualization results are shown in Figure 8.

From the box plots, it can be observed that there is a small difference between the upper edge, the lower edge and the median of the pixel point distribution of the coal and gangue images at the other gray levels, indicating that there is an approximate distribution of the number of pixel points between the two at different gray levels. The difference is that there is a significant difference between the number of pixels corresponding to the highest gray level of the coal and gangue images, with most of the coal having a much larger number of pixels than the gangue. This phenomenon shows that the difference between coal and gangue luminance information is mainly reflected in the number of pixels corresponding to the highest level of gray value. The number of pixels corresponding to the highest gray level is used as a glossy feature of coal and gangue to simplify the extracted feature information and distinguish coal and gangue more effectively. So the number of pixels corresponding to the highest pixel level in the image luminance component is extracted as the binned glossiness feature vector.

2.3. Feature Fusion

Through the discussion in Section 2, the number of pixel points corresponding to the highest pixel level in the grayscale first-order moments and image brightness components of the sample images are extracted as the feature vectors for coal and gangue sorting, which can achieve the requirement of distinguishing coal and gangue. In this paper, 128 pieces of coal and gangue were selected, the images were acquired using the test bench and the coal and gangue were pre-processed and feature extracted using the method described above, forming a data set of 256 × 2 feature matrix, some of the feature extraction results are shown in Table 2.

When establishing a more perfect coal gangue identification system relying on single-feature information it is difficult to reflect the rationality of the identification system, so it is necessary to combine the extracted two features of coal and gangue for a comprehensive evaluation in order to achieve the purpose of establishing a perfect structure and reasonable method for the evaluation system. The entropy weight method is a method to assign weights to multiple pieces of evaluation information objectively. In the process of using it, the entropy weight of each index is calculated and corrected using information entropy according to the dispersion of feature vector data so that objective weights can be obtained.

Table 2. Partial target feature extraction results

Tabela 2. Wyniki częściowej ekstrakcji cech docelowych

Category	Number	Feature Name	
		grayscale average	number of pixels at the highest grey level
Coal	1	0.0704	51,072
	2	0.0378	57,327
	3	0.1004	59,383
	4	0.0561	48,154
	5	0.0605	63,343
Gangue	1	0.1755	29,644
	2	0.1609	24,591
	3	0.1205	19,517
	4	0.1238	25,731
	5	0.1167	32,501

Source: own study.

Compared with the hierarchical analysis method, the weights calculated by the entropy weighting method are more accurate. The entropy weighting method can correct the consequences, so the obtained weighting values have higher adaptability. In this paper, we first normalize the extracted feature vectors, then calculate the weight values of the normalized vectors and finally use the weight values combined with the normalized vectors to obtain the integrated discriminant values. The schematic diagram of feature fusion is shown in Figure 9.

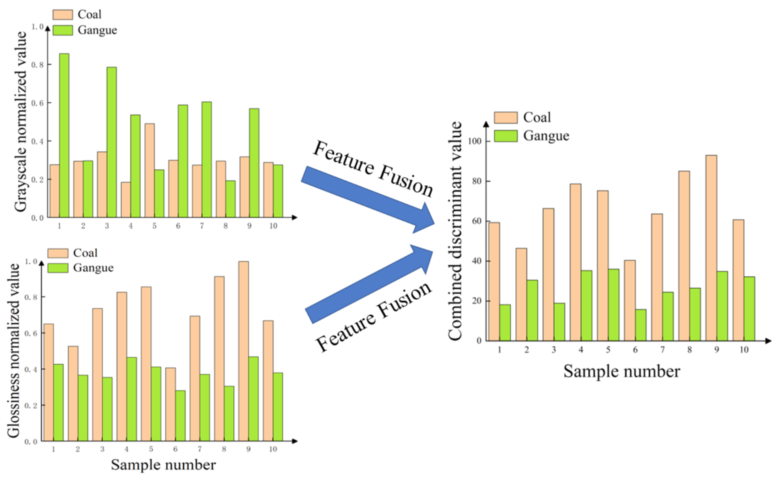

Fig. 9. Feature tandem fusion
Source: own study

Rys. 9. Charakterystyka fuzji tandemowej

Through observation and analysis, we know that the grayscale and glossiness features extracted from the samples have individual sample values that produce overlap before feature fusion. A single feature vector must reach the objective identification standard if it is used to identify coal gangue. After the feature fusion using the entropy power method, the values in the coal and gangue feature vectors are clearly distinguished. The total discriminant value obtained by feature fusion using the entropy power method can be used as the feature vector for gangue identification.

3. Classification model and parameter optimization

3.1. Support Vector Machine

The coal and gangue classification problem is a small sample, nonlinear classification problem. The support vector machine is a two-class classifier with a maximum interval defined on Hilbert space, which can reduce the difficulties of the problem of solving convex quadratic programming. It provides a more accurate and robust approach to solving non-linear problems than other classification algorithms (Bharat et al. 2017). However, the sample feature space is related to the support vector machine's performance, and the kernel function's choice determines whether the samples are mapped into a suitable feature space.

Table 3. Common kernel functions

Tabela 3. Typowe funkcje jądra

Name	Expression	Parameters
Linear Kernel	$\kappa(x_i, x_j) = x_i^T x_j$	–
Polynomial Kernel	$\kappa(x_i, x_j) = \left(x_i^T x_j\right)^d$	$d \geq 1$
Gaussian Kernel	$\kappa(x_i, x_j) = \exp\left(-\frac{\lVert x_i - x_j \rVert^2}{2\sigma^2}\right)$	$\sigma > 0$
Laplace Nucleus	$\kappa(x_i, x_j) = \exp\left(-\frac{\lVert x_i - x_j \rVert}{\sigma}\right)$	$\sigma > 0$
Sigmoid Nucleus	$\kappa(x_i, x_j) = \tanh\left(\beta x_i \; x_j + \theta\right)$	$\beta > 0, \theta > 0$

Source: organized by the author.

Therefore, the choice of kernel function and the choice of kernel function parameters affect the efficiency of coal and gangue identification; among the support vector machines, the commonly used kernel functions are shown in Table 3.

In general, linear kernels are mainly used for linearly differentiable problems. Although polynomial kernels can map a low-dimensional input space to a high-dimensional feature space, polynomial kernels are more suitable for orthogonal normalized data (Singla et al. 2019). The Gaussian kernel function has better performance in handling both large and small sample data. Compared with the polynomial kernel, the Gaussian kernel requires fewer parameters to be set in the process of operation, which is convenient for the subsequent parameter optimization work. Therefore, the Gaussian kernel support vector machine model is chosen as the model for coal gangue sorting in this paper, and the expressions for the support vector machine classification hyperplane discriminant function and the Gaussian kernel function are as follows:

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha *_i y_i K(x_i, x_j) + b * \right) \tag{5}$$

$$K(x_i, x_j) = \exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2} \right) \tag{6}$$

The symbol "*sign*" indicates the sign function, $a*_i$, $b*_i$ and y_i are the parameters of the hyperplane, $K(x_i,x_j)$ is the positive definite kernel function, and σ is the Gaussian kernel parameter.

3.2. Parameter optimization algorithm

SVM has good results in solving small sample nonlinear data sets. After choosing the Gaussian kernel function, the generalization ability of SVM is closely related to the Gaussian kernel parameters in the kernel function. The larger σ is, the better the training effect, and the more reduced is the generalization ability of the model. Additionally, the selection of the parameter penalty factor C also affects the generalization ability of the model. To improve the model's performance further, this paper needs to select the best Gaussian kernel parameter σ and penalty factor C by an optimization algorithm to build a robust generalization model.

There are many kinds of intelligent optimization algorithms, among which the algorithms with better performance in finding the best and faster convergence include the particle swarm algorithm, genetic algorithm and grey wolf algorithm. A genetic algorithm is an intelligent optimization algorithm based on Darwin's theory of biological evolution. The algorithm first encodes the sample data and uses physical operations such as selection, crossover and variation to generate the optimal solution through continuous iterations (Bharat et al. 2022). However, encoding data in the computational process reduces the algorithm's efficiency. Compared with the particle swarm algorithm, the genetic algorithm performs poorly in finding the best solution and does not converge quickly. The particle swarm algorithm originated from a study of bird predation behavior (Wang et al. 2022) and is based on finding the hyperparameters of the SVM by initializing the particle swarm. The principle of the particle swarm algorithm is simple, easy to implement, and fast to converge, and can effectively find the hyperparameters in the feasible solution space. However, the input parameters of the particle swarm algorithm are significant. The values of learning factors a and b inside the algorithm affect the convergence speed and the optimization capability of the particle swarm algorithm, so to bring out the best performance of the algorithm, it is often necessary to optimize the parameters of the particle swarm algorithm with other optimization algorithms, which leads to the whole process being too complicated.

The grey wolf algorithm was proposed in 2014 by Mirjalili et al. (Mirjalili et al. 2014). The algorithm has a strong convergence performance with a simple structure, few parameters to be adjusted, and is easy to implement. There also exists a convergence factor that can be adaptively adjusted and an information feedback mechanism that can achieve a balance between the local search for excellence and global tracking, so it has good performance regarding solution accuracy and convergence speed for the problem. The algorithmic idea of the grey wolf algorithm is to use the hierarchy of grey wolves and the characteristics of grey wolves hunting collectively to initialize the wolf pack in the algorithmic solution space and, through the iterative method, make the wolf pack constantly update its position under the command of the head wolf, to achieve the purpose of gradually approaching, encircling, approaching and attacking the prey (optimal solution). To facilitate the calculation, the grey wolf algorithm divides the four hierarchies of wolves into α, β, δ, ω. The order of these four hierarchies is shown in the Figure 10.

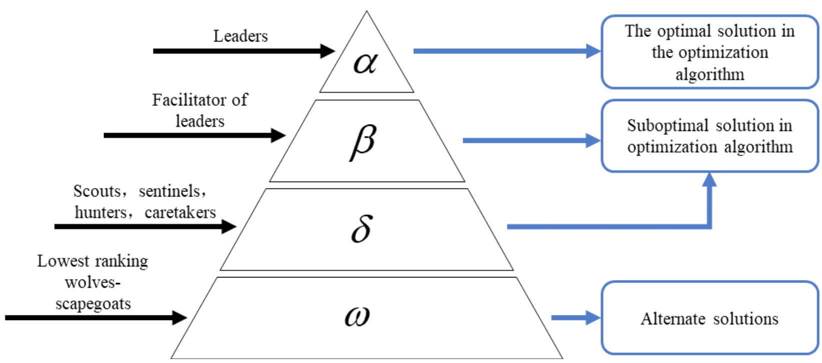

Fig. 10. Grey wolf algorithm wolf pack level diagram
Source: Cheng et al. 2023

Rys. 10. Algorytm wilka szarego, diagram poziomu stada wilków

The grey wolf algorithm divides the hunting behavior into three steps: approaching the prey, chasing and surrounding the prey, and attacking the target. The optimal solution X_p position is unknown in the solution space. The model of GWO assumes that the wolf α, β, δ within the wolf pack, as the optimal wolf pack, knows the potential location of the prey better than a wolf ω and can judge the location of the target by the location of the first three while forcing the latter to update the location according to the optimal grey wolf individual in order to achieve the purpose of approaching and surrounding the prey. When the grey wolf finds the prey, the β, δ wolf starts to surround the prey under the leadership of the wolf; other individual grey wolves gradually approach the location of the prey under the guidance of the optimal wolf group. The mathematical model of individual grey wolves chasing the prey is expressed as follows.

$$\begin{cases} \vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t)\right| \\ \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta(t) - \vec{X}(t)\right| \\ \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)\right| \end{cases} \tag{7}$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \tag{8}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{\quad} \tag{9}$$

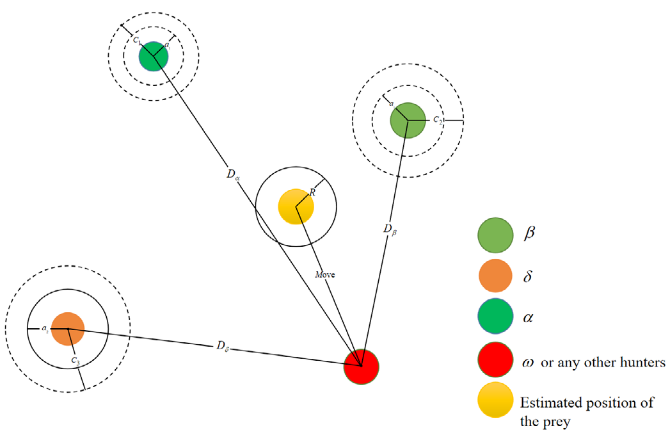

Fig. 11. Schematic diagram of grey wolf hunting
Source: Cheng et al. 2023

Rys. 11. Schematyczny diagram polowania na wilka szarego

$\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$ represents the distance between α, β, δ and other individuals, $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ represents the current position of α, β, δ, $\vec{C}_1, \vec{C}_2, \vec{C}_3$ is a random vector and $\vec{x}$ is the current position of the grey wolf. The mechanism of updating the prey position within the wolf pack is shown in Figure 11 . Based on the characteristics and advantages of the grey wolf algorithm, this paper finds the optimal penalty factor *C* and Gaussian kernel parameter of the support vector machine in the solution space by GWO to improve the recognition rate, generalization ability, and recognition efficiency of the model. The flow of SVM optimization using GWO is shown in Figure 12.

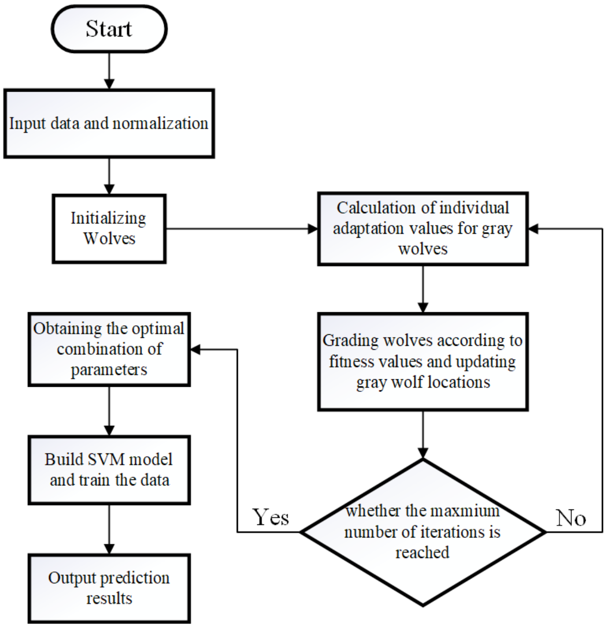

Fig. 12. GWO-SVM algorithm flow chart
Source: own study

Rys. 12. Schemat blokowy algorytmu GWO-SVM

4. Experimental analysis

To verify that the GWO-SVM model performs well in coal gangue identification operations, two classification models, PSO-SVM and GA-SVM, are selected for comparison with the model in this paper. Set the parameters of the classification model as shown in Table 3.

The integrated discriminant values obtained in Chapter 2 were randomly divided at a ratio of 5:3, with 160 items of data as the training set and the remaining 96 items of data as the test set. Coal and gangue were given labels to facilitate identification and classification.

Table 3. Algorithm parameter setting table

Tabela 3. Tabela ustawień parametrów algorytmu

Algorithm name	Population size	Number of iterations	*c*	*g*	*v*
PSO-SVM	30	300	0.1~100	0.01~1000	5
GA-SVM	30	300	0.1~100	0.01~1000	5
GWO-SVM	20	300	0.1~100	0.01~1000	5

Source: own study.

Subsequently, the aligned dataset was randomly divided into five equal parts using the 5-fold cross-validation method, and the dataset was trained. In the feasible solution space, the intelligent optimization algorithm is susceptible to interference from local optimal points, resulting in a stochastic nature of the optimization search. The PSO-SVM, GA-SVM, and GWO-SVM classification models were used to train the data set for each cross-validation thirty times to verify the algorithm's performance. During the experiment, the time and recognition accuracy of each training were recorded, and the statistical results were plotted as line graphs for trend analysis, of which one cross-validation training result is shown in Figure 13.

The box plot shows that the training time of GWO-SVM is less than that of the other algorithms, and the upper edge of its training time is much smaller than that of GA-SVM. Meanwhile, the training time of GWO-SVM is mainly distributed below 1.5 s, and the distribution is compact, indicating that GWO-SVM has higher stability and faster convergence performance compared with the other two algorithms. Regarding recognition rate, the plurality of the correct recognition rate of GWO-SVM was 96% in thirty binning experiments.

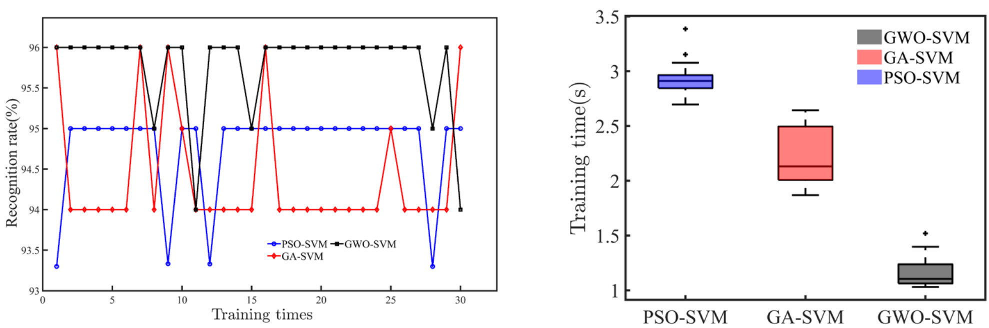

Fig. 13. Algorithm classification results
a) Model classification rate, b) Model classification time
Source: own study

Rys. 13. Wyniki klasyfikacji algorytmów
a) Szybkość klasyfikacji modelu, b) Czas klasyfikacji modelu

By comparison, the plurality of the correct recognition rate of GA-SVM and PSO-SVM was 94% and 95%. Thus, GWO-SVM has a clear advantage in coal gangue identification and proves that the GWO algorithm finds the optimal solution in the feasible domain easier than the other two algorithms. At the same time, PSO-SVM and GA-SVM are prone to fall into the trap of locally optimal solutions in the possible domain leading to a lower recognition rate. Although the initialized population size in the PSO and GA algorithms can be changed to improve the algorithm's ability to find the global optimal point, the rise in the initialized population size tends to increase the algorithm's training time and reduce the model's recognition efficiency. By contrast, in this experiment, GWO-SVM achieved a higher recognition rate using less population size search, proving that the GWO-SVM model performs well and is suitable for coal gangue recognition work.

In accordance with the results discussed above, the trained GWO-SVM classification model was used to perform recognition tests on coal and gangue samples. A new sample of forty-eight pieces each of coal and gangue was selected, and the above experimental procedure was repeated. The extracted grayscale features, glossy features, and integrated discriminant values were used as the input vectors of the GWO-SVM model for thirty classification experiments, and the average recognition rate of the experiments was taken. The results are shown in the following table.

Table 4. Test classification results

Tabela 4. Wyniki klasyfikacji testów

Name	Numerical value
Grayscale features	86.17%
Glossiness characteristics	91.20%
Combined discriminant value	98.14%

Source: own study.

The validation results show that compared with a single feature and PSO-SVM and GA-SVM-based models, the classification rate in the experiments using this method reaches 98.14%, which is a better recognition rate. For the classification of small sample sets, the GWO-SVM algorithm has excellent merit-seeking ability and convergence of the algorithm, and the classification ability is solid and stable. Therefore, in actual engineering practice, the stability of gangue classification can be guaranteed after adjusting the relevant parameters according to the method of this paper.

Conclusion

1. Combined with the different physical properties of coal and gangue surfaces, this paper uses information on the grayscale and gloss of coal and gangue surfaces to sort them out. For the grayscale features, the mean grayscale value of the image is selected as the feature vector for the grayscale information by using the decision tree model-based feature importance assessment. In terms of glossy features, the Retinex algorithm with OTSU segmentation was used to process the image to facilitate the extraction of luminance information and the idea of using the number of pixels under the highest gray level in the luminance component of the image as a feature vector of glossy information was proposed. Furthermore, the entropy weighting method was used to assign weights to the grayscale and glossiness feature information, coupling the two groups of feature information into a combined discriminant value. Compared to other single-feature classification models, using the combined discriminant values improves the correct recognition rate of the model, allowing the model to handle more complex problems and improving the robustness of the model.
2. Regarding model selection, a support vector machine model suitable for small sample classification was used to improve the classification rate of samples. Based on the original support vector machine model, it was optimized using the grey wolf algorithm and compared with the GA-SVM and PSO-SVM classification models. It was found that the experimental classification accuracy of GWO-SVM reached 98.14%, which was higher than that of GA-SVM and PSO-SVM. The classification time was also significantly shortened compared with GA-SVM and PSO-SVM, which improved the robustness of the classification model. The classification time was also significantly reduced compared with GA-SVM and PSO-SVM, which improved the robustness and stability of the classification model and simultaneously achieved the purpose of improving the efficiency and accuracy of coal gangue sorting.
3. The method in this paper only verifies the reliability of coal and gangue sorting in the case of a small sample set, and the data set of coal and gangue should be expanded in subsequent studies to enhance the generalizability of the method. This paper is also a study of a single coal type only, which has limitations in practical sorting. The coal quality of the world is complex and diverse. In subsequent studies, coal samples from different mines should be collected extensively to further expand the method's universality.

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A SORTING METHOD FOR COAL AND GANGUE BASED ON SURFACE GRAYNESS AND GLOSSINESS

Keywords

glossiness, gangue recognition, image recognition, supervised classification, grey wolf algorithm, support vector machine

Abstract

Sorting coal and gangue is important in raw coal production; accurately identifying coal and gangue is a prerequisite for effectively separating coal and gangue. The method of extracting coal and gangue using image grayscale information can effectively identify coal and gangue, but the recognition rate of the sorting process based on image grayscale information needs to substantially higher than that which is needed to meet production requirements. A sorting method of coal and gangue using object surface grayscale-gloss characteristics is proposed to improve the recognition rate of coal and gangue. Using different comparative experiments, bituminous coal from the Huainan area was used as the experimental object. It was found that the number of pixel points corresponding to the highest level grey value of the grayscale moment and illumination component of the coal and gangue images were combined into a total discriminant value and used as input for the best classification of coal and gangue using the GWO-SVM classification model. The recognition rate could reach up to 98.14%. This method sorts coal and gangue by combining surface greyness and glossiness features,

optimizes the traditional greyness-based recognition method, improves the recognition rate, makes the model generalizable, enriches the research on coal and gangue recognition, and has theoretical and practical significance in enterprise production operations.

METODA SORTOWANIA WĘGLA I SKAŁY PŁONNEJ NA PODSTAWIE SZAROŚCI I POŁYSKU POWIERZCHNI

Słowa kluczowe

połysk, rozpoznawanie skały płonnej, rozpoznawanie obrazu, klasyfikacja nadzorowana, algorytm szarych wilków, maszyna wektorów nośnych

Streszczenie

Sortowanie węgla i skały płonnej jest ważne w produkcji węgla surowego; dokładna identyfikacja węgla i skały płonnej jest warunkiem wstępnym skutecznego oddzielenia tych surowców. Metoda rozdzielenia węgla i skały płonnej przy użyciu informacji w skali szarości obrazu może skutecznie identyfikować węgiel i skałę płonną, ale stopień rozpoznawania procesu sortowania w oparciu o te informacje być znacznie wyższy niż wymagany do spełnienia wymagań produkcyjnych. W artykule zaproponowano metodę sortowania węgla i skały płonnej wykorzystującą charakterystykę połysku i skali szarości powierzchni obiektu w celu poprawy szybkości rozpoznawania węgla i skały płonnej. W badaniach wykorzystano próbki węgla kamiennego z obszaru Huainan. Stwierdzono, że liczbę punktów pikseli odpowiadającą najwyższemu poziomowi szarości momentu w skali szarości i składowej oświetlenia obrazów węgla i skały płonnej połączono w całkowitą wartość dyskryminującą i wykorzystano jako dane wejściowe dla najlepszej klasyfikacji węgla i skały płonnej przy użyciu modelu klasyfikacji GWO-SVM. Wskaźnik rozpoznawalności może osiągnąć nawet 98,14%. Ta metoda sortowania węgla i skały płonnej poprzez połączenie cech szarości i połysku powierzchni, optymalizuje tradycyjną metodę rozpoznawania w oparciu o szarość, poprawia współczynnik rozpoznawania, umożliwia uogólnienie modelu, wzbogaca badania nad rozpoznawaniem węgla i skały płonnej, ma znaczenie teoretyczne i praktyczne w operacjach produkcyjnych przedsiębiorstwa.