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Multispectral Imaging: A New Solution for Identification of Coal and Gangue

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ABSTRACT Accurate identification of coal and gangue is an important prerequisite for the effective separation of coal and gangue. The application of imaging technology combined with image processing steps (like enhancement, feature extraction, etc.) and classifier is used to identify coal and gangue, which effectively avoids the shortcomings of traditional methods (radiation, pollution, etc.). However, ordinary image detection is greatly influenced by environmental factors such as light, dust and so on. Multispectral imaging technology, as a new generation of optical non-destructive testing technology, is less affected by illumination, so we propose a new solution for the recognition of coal and gangue by using multispectral imaging. Firstly, we respectively tested the classification performance of different image feature extraction methods under GS-SVM, GA-SVM, and PSO-SVM classifiers, and selected the best feature extraction method is LBP. And then, we compared the classification effects under different wavelengths and found that the ninth wavelength works best. That is, the difference in imaging between coal and gangue at 773.776 nm is greatest. Finally, the performance of the proposed model for the identification of coal and gangue was carried out. And the highest classification accuracy can be obtained by using GS-SVM as the classifier, at which point, $C = 8$, $g = 0.17678$. The results show that multispectral imaging technology can be used for the identification of coal and gangue, and the prediction accuracy of the model combined with LBP feature extraction and GS-SVM can reach 96.25% (77/80). The conclusions could provide reference evidence for the intelligent dry selection in coal preparation plants and underground coal mine.

INDEX TERMS Coal-gangue identification, multispectral imaging, feature extraction, support vector machine.

I. INTRODUCTION

Coal, known as ''industrial grain'', is one of the main energy sources used by humans since the eighteenth century. According to the BP World Energy Statistical Yearbook, the global coal market has recovered slightly in 2017, reflecting the fact that coal still plays an important role in primary energy. In the process of coal mining, it is usually accompanied by the companion of coal, namely gangue [1], [2]. Gangue is the rock with combustible materials in coal seam or around coal seam, which has lower carbon content and is harder than coal. From the appearance, gangue is usually gray, cyan, grayish black and black ash. In terms of material composition, gangue is mainly composed of SiO_2 and Al_2O_3 [3], which not only contains high sulfur content but also contains a large number of heavy metals (such as arsenic, cadmium, chromium, copper, and mercury). In view of the low heat value of the gangue, when coal is mixed with gangue, it will affect the calorific value of the coal and reduce the utilization rate of coal. What's worse, the combustion process can cause serious pollution to the environment [4]. Therefore, the separation of gangue from coal is a vital treatment step before the use of coal. The separation of coal and gangue has a very important prerequisite, that is, the precise classification of coal and gangue [5].

In the technology of coal (gangue) separation [6], in addition to manual selection of gangue, the automatic gangue separation technology can be divided into wet separation and dry

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selection according to whether water resources are utilized. In recent years, the research and application of dry selection have been developing rapidly, including dual-energy gamma-ray detection [7], X-ray detection [8], laser detection [9], image detection [10] and so on. Ray detection techniques (like gamma-ray and X-ray) are easy to achieve integration, but there is radiation in the process of use, so radiation isolation is required. At the same time, the continuous development of technologies such as image processing and pattern recognition [11] has led to the development of gangue separation by using image recognition technology. In image detection, the industrial camera is used to collect images of coal and gangue on the conveyor belt. Then, with the help of digital image processing methods (such as noise reduction [12], image enhancement [13], feature extraction [14], and so on), and finally the identification of coal and gangue are carried out on the computer by using pattern recognition. Image detection is considered to be a promising method for the separation of coal and gangue, but there are also some problems with this method, which are greatly influenced by environmental factors such as light, dust and so on.

Spectral imaging technology [15], which emerged in the 1980s, is a new generation of optical non-destructive testing technology, which involves many disciplines such as optics, electronics and information science and many other disciplines. Multispectral imaging [16] (MSI) effectively avoids the narrowband range and susceptibility to interference in traditional RGB images by collecting images of several different spectral regions. At the same time, compared with hyperspectral imaging [17] (HSI), MSI has the following advantages: firstly, the spectral band output is less and the real-time information collection is good; secondly, the amount of data is small, which is easy to transmit, store and process; thirdly, the cost of design and manufacture is lower. Taking these advantages into account, combined with the development of image processing, pattern recognition, deep learning, and other technologies, MSI has been successfully applied in agriculture, food industry, biomedical and many other fields. Ghooshkhaneh *et al*. [18] used the MSI technology to identify whether the citrus were rotten or not. The recognition rates of decay citruses and healthy citruses were 98.6% and 100.0%, respectively, which indicated that MSI technology could be used to detect the fruit rot caused by penicillin. In order to meet the requirements of non-destructive testing of beef, Yu *et al*. [19] used the MSI system to collect the multispectral information of frozen beef, extracted the region of interest (ROI), and combined principal component analysis (PCA) with support vector machine (SVM) to quickly, non-destructively and accurately detect different frozen beef. Carano *et al*. [20] proposed MSI to describe the temporal evolution characteristics of cerebral ischemia, and qualitative analysis of acute and subacute ischemic diseases can be achieved by the K-means classification and fuzzy C means classification.

With those in mind, the aim of this paper is to explore whether multispectral imaging technology is suitable for the identification of coal and gangue. Firstly, the experimental setup and materials are introduced. The common image feature extraction methods and SVM classifiers are described next. Then, we analyze the classification performance under combination strategies of different feature extraction methods and classifiers and determine the best feature extraction method, classifier, and wavelength through the accuracy of the test set and training set. After that, the performance of the proposed method for the identification of coal and gangue is carried out. Finally, the paper concludes with a summary of this study.

II. MATERIALS AND METHODS

A. INSTRUMENTATION

A schematic diagram of the experimental setup used for the classification of coal and gangue is set out in Fig. 1(a), it mainly consists of an auto-scan light, an MSI system, and a computer. The light source is a halogen light source (LS-LHA, Sumita Optical Glass, Inc., Saitama, Japan) commonly used in optical inspection and its power is set to 150 W. The composition of the MSI system is shown in Fig. 1(b), which is mainly composed of a filter device, a fixed focal length lens, and a spectral camera. The filter device consists of a 975 nm shortpass filter (Edmund Optics, Barrington, United States) and a 675 nm longpass filter (Edmund Optics, Barrington, United States), which limits the spectral range of the acquisition to between 675 and 975 nm. The lens is a 16 mm VIS-NIR fixed focal length lens, which is very suitable for machine vision applications in NIR or VIS-NIR bands and meets the requirements of factory automation and inspection applications for working distance and resolution. The camera is a xiSpec series of array spectral camera (MQ022HG-IM-SM5X5-NIR, XIMEA GmbH, Munster, Germany), equipped with a CMOS imager (CMV 2000, Interuniversity Microelectronics Centre, Leuven, The Kingdom of Belgium), which enables 25 wavelengths of imaging. With the help of the USB 3.0 interface, HSImager software (V2.6.4) can easily and rapidly acquire multispectral (hyperspectral) raw data.

When collecting multispectral data of coal and gangue, the focal length of the fixed focal length lens is set at 2.8 mm. The exposure time is set to 70.01 ms by the HSImager software and the experimental data are saved by the software. By the way, the parameters of the MSI system are kept unchanged during the measurement, which ensures that the data is more reliable.

B. MATERIALS AND SAMPLES

Considering that Huainan is an important coal producing area in China, coal and gangue in the Huainan mining area were selected as the research object of this experiment. The experimental materials were collected in the Huainan mining area of Anhui Province on March 16, 2019. We selected 200 pieces of coal and gangue with similar size to obtain multispectral images, respectively. All samples were tested

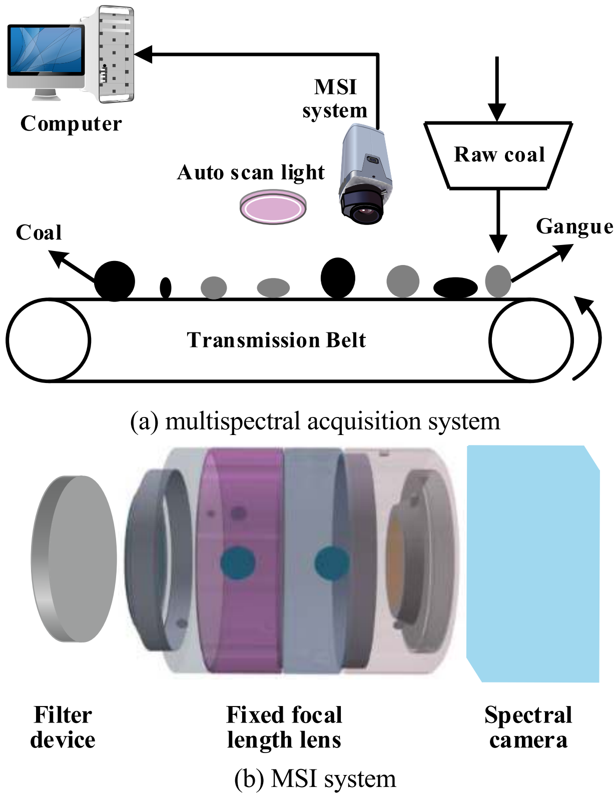

FIGURE 1. Schematic diagram of the experimental setup.

under the same conditions to ensure that the experimental data were more realistic and reliable. 160 multispectral images for coal and gangue were randomly selected and a total of 320 multispectral images were used as the training set. The remaining 40 multispectral images for coal and gangue and a total of 80 multispectral images were used as the test set.

C. IMAGE FEATURE EXTRACTION METHODS

1) HISTOGRAM OF ORIENTED GRADIENT

Histogram of oriented gradient [21] (HOG) is a feature descriptor used for object detection in computer vision and image processing. This feature was originally proposed by Dalal and Triggs [22] for pedestrian detection, which maintains good invariance to the small geometric deformations and local contrast changes of the image. Therefore, the HOG feature combined with the SVM classifier has been widely used in image recognition. The implementation process of the HOG feature extraction algorithm is as follows:

(1) Grayscale;

(2) Standardizing (normalizing) the color space of the input image using the Gamma correction method;

(3) Calculate the gradient (including size and direction) of each pixel of the image;

(4) Divide the image into small cells (such as, 6*6/cell);

(5) Count the gradient histogram of each cell (the number of different gradients), that is, form the descriptor for each cell;

(6) Each cell is composed of a block (for example, 3*3 cell/block), and the feature descriptors of all the cells in one block are connected in series to obtain the HOG feature descriptor of the block;

(7) By concatenating the descriptors of all the blocks in the image, we can get the HOG feature descriptor of the image.

2) LOCAL BINARY PATTERN

Local binary pattern [23] (LBP) is an operator used to describe the local texture features of an image and it has significant advantages such as rotation invariance and gray invariance. It was first proposed by Ojala *et al.* [24] in 1994 for texture feature extraction. The implementation process of the LBP feature extraction algorithm is as follows:

(1) Divide the detection window into small areas of 16×16;

(2) For one pixel in each cell, compare the grayscale value of the adjacent 8 pixels to the central pixel value, and the position of the pixel is marked 1, otherwise 0;

(3) The histogram of each cell is calculated, that is, the frequency at which each number appears, and then the histogram is normalized;

(4) The statistical histogram of each cell is connected into a feature vector, i.e. the LBP texture feature vector of the entire image.

3) HAAR

Haar feature [25] is a weak feature based on the grayscale images. This feature is used to express the image intensity of a rectangular area near a certain position of the image and calculate the difference in intensity. The rectangular block shown in Fig. 2 represents three common Haar features. The size of these block features is not fixed, but the shape and size of gray and white squares are always the same.

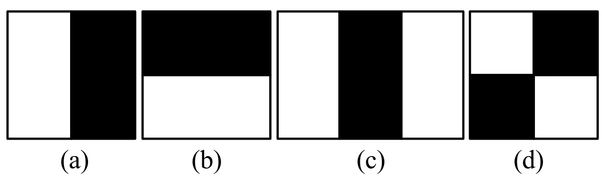

FIGURE 2. Different Haar features.

Wherein, the double rectangular features (also known as edge features) represented by Figs. 2(a) and (b) are used to calculate the intensity difference between two horizontal (or vertical) rectangular blocks. The three rectangular features (also known as linear features) shown in Fig. 2(c) are used to calculate the difference in intensity between the two sides and the center. The four rectangular features (also known as diagonal features) shown in Fig. 2(d) are used to calculate the difference in intensity between the two diagonal pairs. If the difference is detected to be greater than the threshold, it is determined to be a feature.

D. SVM CLASSIFIER

1) SVM

SVM (Support Vector Machine) [26], [27] is a supervised learning model with associated learning algorithms that analyzes data used for classification and regression analysis. An SVM constructs a hyperplane or a set of hyperplanes in a high or infinite-dimensional space, which can be used for classification, regression, and so on.

Suppose m samples constitute sample sets: $\boldsymbol{A} = [\boldsymbol{A}_1, \boldsymbol{A}_2, \boldsymbol{A}_3, \ldots, \boldsymbol{A}_j, \ldots, \boldsymbol{A}_m]^T$, where sample $\boldsymbol{A}_j = [x_{j_1}, x_{j_2}, x_{j_3}, \ldots, x_{j_n}, y_j] (j = 1, 2, 3, \ldots, m)$ consists of n sample feature data x_{j_n} and one sample label y_j. The SVM takes the sample classification as the starting point and finds an optimal classification hyperplane, so as to construct the decision function $f(x)$ to classify the samples as much as possible.

$$
\begin{aligned}
&min\frac{1}{2}\left\|\omega\right\|^2 + C\sum\nolimits_{i=1}^{n}\varepsilon_i \\
&\text{s.t.} y_i\left(\omega x_i + b\right) \geq 1 - \varepsilon_i, \quad i = 1, 2, \ldots, n, \qquad (1)
\end{aligned}
$$

where ω is weight vector, C is penalty parameter, ε_i is relaxation variable, and b is the classification threshold.

By introducing Lagrange function and solving the dual problem, and a new objective function is obtained.

$$
\begin{aligned}
&max\ w\left(\alpha\right) = \sum\nolimits_{i=1}^{n}\alpha_i - \frac{1}{2}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{n}\alpha_i\alpha_j y_i y_j K\left(x_i, x_j\right) \\
&\text{s.t.}\sum\nolimits_{i=1}^{n} y_i\alpha_i\alpha_j = 0, \quad C \geq \alpha_i \geq 0,\ i = 1, 2, \ldots, n, \qquad (2)
\end{aligned}
$$

where α is the Lagrange multiplier and K is the kernel function. We consider radial basis function(RBF) as the kernel function, and $K\left(x_i, x_j\right) = \exp\{-g\left|x_i - x_j\right|^2\}$, g is the parameter of the kernel function. SVM decision function can be represented as

$$
f\left(x\right) = sgn(\sum\nolimits_{i=1}^{n}\alpha_i y_i K\left(x_i, x_j\right) + b). \qquad (3)
$$

The determination of the parameter g in the kernel function and the penalty factor C have a great influence on the performance of the support vector machine model. In order to find the optimal parameters C and g, grid search (GS), genetic algorithm (GA), particle swarm optimization (PSO), etc. are usually selected to optimize the parameters.

2) GS-SVM

In the grid search method [28], all possible parameters are counted and grouped. The grouping is based on the network determined by the step size. Then, the possible optimal parameters in each network are calculated, and whether the observed results are optimal or not, that is, the optimal parameters found. The basic process for the SVM parameter optimization of the grid search method is as follows:

(1) Initialize the search range and step size of C and g in the grid search. Here, the search range of parameter C and g is set to $[2^{-8}, 2^8]$ and the search step of C and g is set to 0.5;

(2) The current C and g are used to train and test the data to obtain the prediction accuracy;

(3) Repeat Step (2) until all parameters in the grid are searched;

(4) Draw the 3D contour map of prediction accuracy and select the best C and g.

3) GA-SVM

GA [29] is a computational model that simulates the natural evolution of Darwin's biological evolution theory and the biological evolution process of genetic mechanism. It is a method to search for optimal solution by simulating natural evolutionary processes. The basic process for the SVM parameter optimization of the GA method is as follows:

(1) Initialization for the parameters of GA. Construct a certain number of initial populations, determine the maximum genetic algebra, the maximum number of populations generated, crossover probability and the probability of variation;

(2) Coding. The range of the penalty factor C and the parameter g is set to [0, 100] and [0, 1000], respectively. It is binary coded to construct the initial population;

(3) Calculate the fitness function (the accuracy of cross-validation), and calculate the fitness value of each individual;

(4) Selection operation. The next-generation population is obtained by using cross-crossing and mutant genetic operators to process the current generation population, and Determine whether the termination condition has been met. If the condition is met, go to the next step to decode the optimal parameters$C$ and g, the resulting parameters are entered into the SVM model, and the mean square error (MSE) of the SVM model is tested with the test set data. Otherwise, return to Step (3) to continue;

(5) Selection operation. Using roulette operators to ensure the high-quality individuals are selected;

(6) Cross operation. Cross-combinations of genes between paternal individuals;

(7) Mutation operation. Individual variation is randomly selected based on the rate of variation to ensure the formation of new offspring, and Step (3) is continued.

4) PSO-SVM

PSO [30] is a kind of population-based parallel global search strategy, which finds the optimal solution through the collaboration and information sharing among individuals in the group. The advantages of the algorithm are that the adjustment parameters are few, the convergence speed is fast, the application range is wide, and it can be optimized in the high-dimensional space. The basic process for the SVM parameter optimization of the PSO method is as follows:

(1) In the D-dimensional parameter space, m particles are randomly initialized to determine their position and velocity (the SVM parameters are determined), and a certain input sample is selected to establish the SVM model;

(2) Determine the function value based on the SVM classification decision function;

(3) The calculation and evaluation of particle fitness values are carried out;

(4) Find the global optimal parameter. If the termination condition is not met, the speed and position of the particles are updated by iterative search, and then go to Step (2);

(5) If the termination condition is satisfied, the optimal parameters are obtained, and the SVM is retrained as the final classifier for recognition and classification.

III. RESULTS AND DISCUSSION

A. MULTISPECTRAL IMAGES OF SAMPLES

The multispectral images for coal and gangue are collected by the experimental setup, and the multispectral data for each sample contains single channel images with 25 wavelengths (409×216 per wavelength). The 25 wavelengths are 891.324, 900.953, 882.983, 872.871, 959.369, 798.282, 811.391, 786.994, 773.776, 682.921, 748.688, 762.053, 736.254, 722.264, 697.419, 932.076, 939.082, 924.726, 914.684, 954.412, 851.482, 863.274, 841.439, 829.877, and 946.453 nm, respectively. The single-channel images under some wavelengths of coal and gangue are presented in Fig. 3.

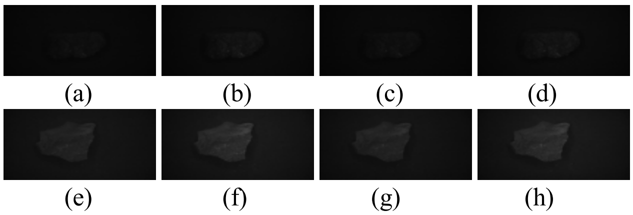

FIGURE 3. Single-channel images under some wavelengths. (a) Image of coal at 882.983 nm. (b) Image of coal at 773.776 nm. (c) Image of coal at 697.419 nm. (d) Image of coal at 851.482 nm. (e) Image of gangue at 882.983 nm. (f) Image of gangue at 773.776 nm. (g) Image of gangue at 697.419 nm. (h) Image of gangue at 851.482 nm.

From the figures, we can see that the image of the same coal (or gangue) has some differences in different wavelengths, and the differences between the images of coal and gangue in different wavelengths are also different. We can not visually distinguish which multispectral image at the wavelength is the most suitable for the recognition of coal and gangue. Hence, it is necessary to classify and identify with the help of image processing and pattern recognition methods and find out the most suitable wavelength for the classification of coal and gangue.

B. CLASSIFICATION MODEL FOR COAL AND GANGUE

In order to find the best wavelength for the identification of coal and gangue using multispectral data, we analyze the recognition performance of different feature extraction methods under the GS-SVM, GA-SVM, and PSO-SVM classification models. We build the recognition model of coal and gangue according to the steps shown in Fig.4.

Firstly, we extract the HOG, LBP, and Haar features of the images at all the 25 wavelengths. Then, we normalize these features (normalize to 0 to 1 interval) and process them with PCA (set the cumulative contribution rate to 95%). Finally, the data after normalization and PCA dimensionality reduction are input to three SVM classifiers (GS-SVM,

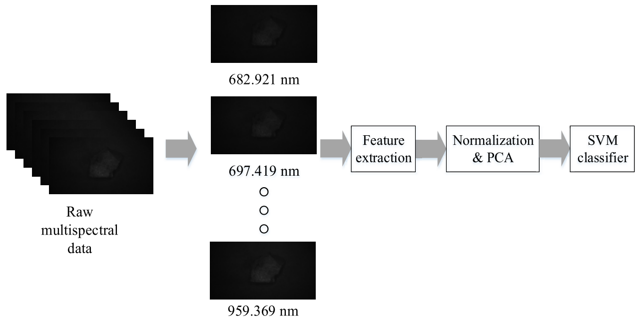

FIGURE 4. Construction of the SVM identification model of coal and gangue.

GA-SVM, and PSO-SVM) to construct the identification model of coal and gangue. Typical SVM identification models of coal and gangue were initially developed on MATLAB R2018b. The models were built on a desktop computer with the Intel CPU (Core i7-9700K 3.60GHz) and 16 GB RAM (DDR4 3000MHz) in a Windows 10 environment.

1) CASSIFICATION MODEL BASED ON GS-SVM

According to the above modeling ideas, the best C and g are searched by the grid search method, and the GS-SVM model suitable for the recognition of coal and gangue is established by using single-channel graphs with all the 25 wavelengths. Subsequently, the recognition performance of the model is validated by the test set, and the results are compared in Fig. 4. Based on Fig. 5, it is obvious that when the same image feature extraction method is used, there are certain differences in recognition rates under different wavelengths. That is to say, the difference degree of coal and gangue images in different wavelengths is different. When using GS-SVM as the classifier, the recognition rate of test set under HOG feature is between 56.25% and 77.5%, the recognition rate of test set under LBP feature is between 78.75% and 96.25%, and the recognition rate of the test set under Haar feature is between 62.5% and 93.75%. That is when using GS-SVM as a classifier, the LBP feature of the image can achieve the best classification effect, while the HOG feature is the

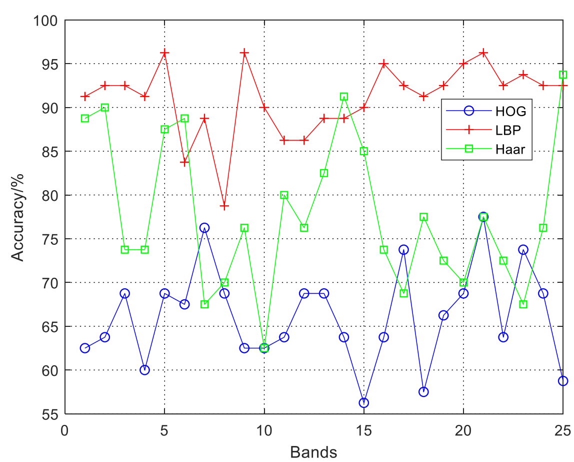

FIGURE 5. Test accuracy of the GS-SVM model under different features.

worst. At the same time, we find that the images in the 5th (959.369 nm), 9th (773.776 nm) and 21st (851.482 nm) wavelengths have good performance for the classification of coal and gangue.

2) CLASSIFICATION MODEL BASED ON GA-SVM

The test accuracy of the GA-SVM model for the recognition of coal and gangue under different features is compared in Fig. 6. When using GA-SVM as the classifier, the recognition rate of test set under HOG feature is between 50.0% and 83.75%, the recognition rate of test set under LBP feature is between 78.75% and 96.25%, and the recognition rate of the test set under Haar feature is between 50.0% and 98.75%. Although better recognition accuracy can be obtained by using Haar features under some specific wavelengths, LBP features have better classification performance in general. In addition, a more stable classification effect can be obtained by using the LBP features. We also find that the images of the 9th (773.776 nm) and 21st (851.482 nm) wavelengths have good performance for the classification of coal and gangue.

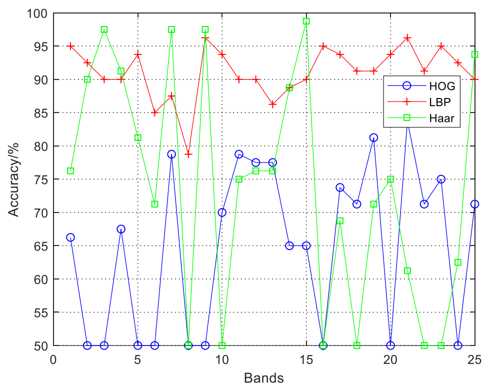

FIGURE 6. Test accuracy of the GA-SVM model under different features.

3) CLASSIFICATION MODEL BASED ON PSO-SVM

The test accuracy of the PSO-SVM model for the recognition of coal and gangue under different features is compared in Fig. 7. When using PSO-SVM as the classifier, the recognition rate of test set under HOG feature is between 50.0% and 82.5%, the recognition rate of the test set under LBP feature is between 78.75% and 97.5%, and the recognition rate of the test set under Haar feature is between 50.0% and 93.75%. At the same time, with the help of HOG and Haar features for the classification of coal and gangue, the recognition rate fluctuates greatly. That is to say, when PSO-SVM is used as the classifier, better and more stable classification results can be achieved with the help of LBP features of the image. We also find that the images in the 5th (959.369 nm), 9th (773.776 nm), 16th (932.076 nm), 21st (851.482 nm), and 23rd (841.439 nm) wavelengths have good performance for the classification of coal and gangue.

4) COMPARISON OF DIFFERENT CLASSIFICATION MODELS

From the results in Sections III.B 1) to 3), we can see that the use of LBP features for the classification of coal and gangue

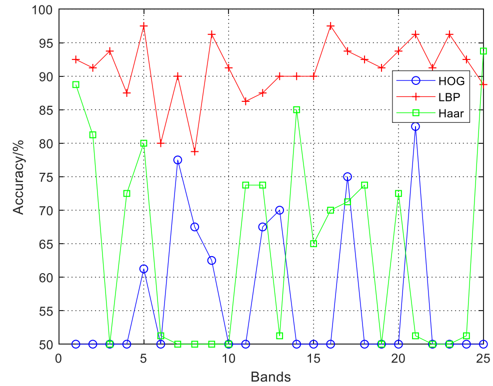

FIGURE 7. Test accuracy of the PSO-SVM model under different features.

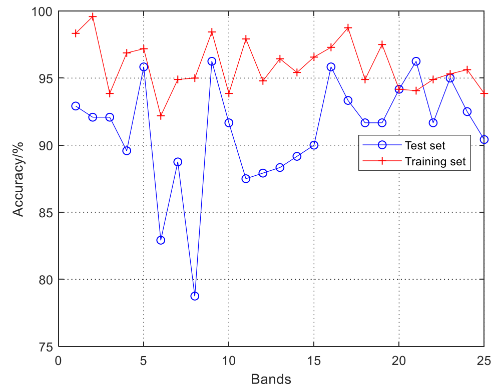

FIGURE 8. Average classification accuracy under LBP features.

can achieve better recognition rate. Therefore, we decide to use the LBP of the coal and gangue images for the construction of the classification model. We calculate the classification accuracy of the three SVM classification models for the test set and the training set under the LBP features, as shown in Fig. 8. First of all, we observe the average recognition rate of the test set. We can find that using the multispectral images of the 5th, 9th, 16th and 21st wavelengths for the classification, coal and gangue can obtain better classification results, and the classification accuracy is 95.83%, 96.25%, 95.83%, and 96.25%, respectively. Then, when we compare the average recognition rate of the training set under the four wavelengths, and we find that the highest recognition rate, 98.44%, is obtained by using the 9th wavelength.

Based on the above analysis, we select the multispectral image of the 9th wavelength to construct the recognition model of coal and gangue. To build the best classification model for coal and gangue, we carry out the following steps. First, we extract the LBP features of the multispectral image at the ninth wavelength, and the obtained LBP feature has a dimension of 59. The LBP features of a coal and gangue sample are randomly selected for display, as shown in Fig. 9. It can be seen that the LBP features of multispectral images of coal and gangue are somewhat different, with some differences being small.

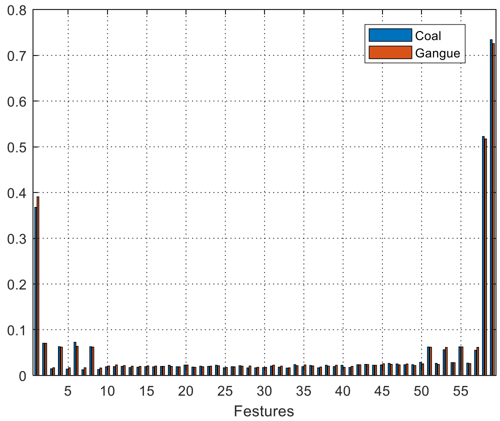

FIGURE 9. LBP features of coal and gangue.

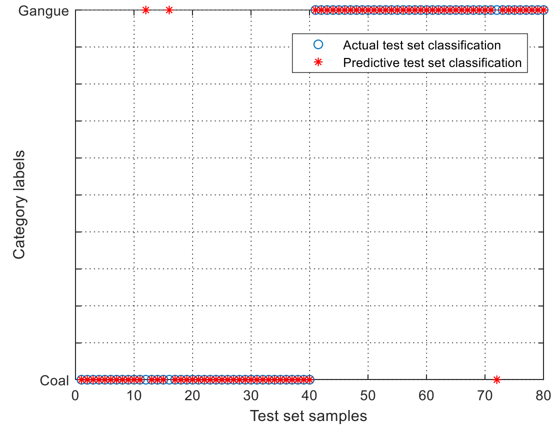

FIGURE 10. Actual classification and predictive classification of the test set.

TABLE 1. Results of the three SVM classifiers.

	best C	best g	Training accuracy	Test accuracy
GS-SVM	**8**	**0.17678**	**99.375%**	**96.25%**
GA-SVM	61.376	0.040531	97.5%	**96.25%**
PSO-SVM	13.11	0.11256	98.4375%	**96.25%**

Next, we normalize the LBP features to the [0,1] interval, and then PCA processing is carried out. Setting the cumulative contribution rate of 95%, 26 principal components can be obtained. Finally, the 26 principal components are fed into the SVM classifiers with three optimization strategies, and the results are compared in Table 1. Through Table 1, we can see that the test set accuracy of the three SVM classifiers is 96.25%, but the highest accuracy of the training set can be obtained by using GS-SVM as the classifier, at which point, the model parameters of the SVM are $C = 8$, $g = 0.17678$.

C. PERFORMANCE OF THE PROPOSED MODEL

Fig. 10 provides the classification effect of the trained GS-SVM classification model for the test set samples. We can find that only 3 of the 80 test set samples are classified incorrectly, which indicates that the constructed GS-SVM model can identify coal and gangue very well. In other words, we first use the multispectral imaging system to obtain multispectral data of coal and gangue. After LBP feature extraction, normalization, and PCA dimensionality reduction, the GS-SVM classification model can be used to achieve the accurate identification of coal and gangue.

IV. CONCLUSION

In this paper, we have proposed a new solution for the classification of coal and gangue from multispectral images. To verify its feasibility, we first collected the multispectral data of coal and gangue, then used the feature extraction algorithms (HOG, LBP, and Haar) and the SVM classifier (GS-SVM, GA-SVM, and PSO-SVM) to construct and analyze the model. The results show that 1) multispectral imaging technology can be used for the identification of coal and gangue; 2) better results can be achieved by using LBP features of multispectral images for the classification of coal and gangue; 3) the multispectral image of coal and gangue at ninth wavelength can achieve the best classification effect, that is, the difference in imaging between coal and gangue at 773.776 nm is greatest; 4) the highest test accuracy (96.25%) and training accuracy (99.375%) can be obtained by using GS-SVM as the classifier, at which point, $C = 8$, $g = 0.17678$. The new method for the identification of coal and gangue proposed in this paper can provide reference evidence for intelligent dry selection in coal preparation plants and underground coal mine.

Despite the achievement of some research results, there are some limitations in this study. The present investigation considers the classification of coal and gangue under the strategy combine feature extraction with a classifier. However, different feature extraction methods and classifiers will have a certain impact on the results, and it is not easy to choose the appropriate feature extraction method and a classifier. Therefore, in future work, it will be necessary to study the deep learning algorithms for the identification model. In this way, we can eliminate the feature extraction, dimension reduction, and other processing steps.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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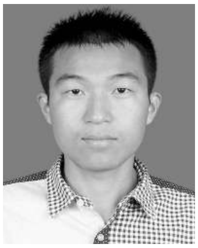

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