Competitive Voting-based Multi-class Prediction for Ore Selection

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***Abstract*— Sensor-based intelligent sorting technology is a mineral separation technology with the merits of high-efficiency, energy-saving and water-saving. However, the prediction accuracy of conventional machine learning methods is unstable in multi-class selection of ores. The purpose of this study is to propose a competitive voting method to improve the multi-class prediction accuracy of ores in machine vision-based sorting system by combining the classification advantages of various machine learning methods. The operations of image segmentation, feature extraction and feature selection are presented to obtain the multi-class datasets. Three ones of traditional machine learning models with higher classification accuracies are used to establish competitive voting classification models. A case study using the image data of a gas coal shows the merits of the proposed approach. Results derived using this competitive voting approach reveal that it outperforms pre-existing approaches.**

I. Introduction

In mining industry, close to 50% of the total electricity consumption is dedicated to crushing and milling activities. Therefore, it is vital to reduce ore processing quantity and gangue quantity for energy saving production. Ore sorting has been done by hand for centuries by identifying mineralization on the surface of individual stones. However, modern technology affords the opportunity to accurately and automatically identify the quality of ore in spectral ranges invisible to the naked eye. Sensor-based sorting technology came into being and it played a vital role on gangue sorting and multi-class sorting due to the advantages of energy-saving, water-saving and high-efficiency.

Sensor-based ore sorting technology is mainly consisted of the transmission unit, detection unit and separation unit. The detection unit is key section to guarantee the separation accuracy. The advanced sensors in mineral engineering within the past decades have achieved great developments, including machine vision [1-4], X-ray transmission (XRT) [5, 6], laser-induced breakdown spectroscopy (LIBS) [7], X-ray fluorescence (XRF) [8, 9], radiometric sorting [10], hyperspectral analysis [11, 12] and near-infrared (NIR) sensing [13, 14]. Each detection sensor has its own merit in ore sorting, but machine vision is the one with higher cost performance and good identification accuracy at present stage, which enable it to have a wilder application market.

In machine vision-based sorting technology, the main steps include image preprocessing [15,16], feature extraction and selection [17, 18], and ore classification model [19]. Each of these links will have an impact on ore identification. In related works of classification model, two classification issues, such as ore and gangue, or two products of different grades are the main research focus, and the vast majority of them have good prediction effect. With the decrease of ore quantity and quality, the research demand of ore multi-classification is increasing. However, the multi-class prediction accuracy of ores changes a lot with the difference of ore composition and different classification methods. Patel et al. attempted to develop an online vision-based technology for four-class prediction of iron ores by SVM, K-nearest neighbour, classification discriminant, Naïve Bayes, classification tree and probabilistic neural network, and the results indicated that the SVM classification model performs better than the other classification methods [3]. Furthermore, Patel et al. designed and developed two types of SVM-based machine vision system (classification and regression), and the prediction accuracies of five-class dry and wet iron ore sample images were up to 97% and 93%, respectively [1]. Fu and Aldrich compared the random forest model and convolutional neural network to select three gold ores with different grades and the classification accuracies of test dataset were 35% and 53.2%, respectively [20]. Zhang et al proposed a four-class prediction method of coarse coal by use of kernel methods and machine vision and the classification accuracy of SVM is up to 84.67% [21]. Ebrahimi et al. proposed a novel way which combines the artificial neural networks and analytic hierarchy process (AHP) approaches to detect sixteen types of ores. The final results show that the proposed method is up to 77.21%, 10% higher than the other image processing techniques for ores type detection [22].

The above classification methods are mainly based on machine learning models such as support vector machines, decision trees, neural networks and clustering. They can achieve decent multi-classification effect under different conditions. Therefore, a method that combines the classification advantages of above models might work better in ore sorting system, and it can ensure that the ore classification accuracy will not fluctuate greatly under the current environment.

The scope of this paper is to propose and investigate a competitive-voting classification model based on several common machine learning methods for ore sorting online. The subsequent sections are structured as follows. The research problem of this study is stated in Section 2. Subsequently, the methodology is proposed in Section 3, including the process of image segmentation, feature extraction, feature selection, and competitive-voting classification method. Then a case study with which aims at the multi-products classification of gas coal is revealed in

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Section 4. Finally, the findings and further works are concluded in Section 5.

II. Problem Statement

The practical problem in this paper is multi-class prediction in online ore sorting based on machine vision. Intelligent mineral sorting technology has attracted much attention in recent years due to its application advantages [16,19]. The schematic map of online ore sorting system is shown in Figure 1. The main principle is to separate multiple products by the high-pressure injection after identifying them by sensors. Therefore, the classification accuracy of multi-products is the key problem to be solved. In this paper, the image segmentation, feature extraction and classification recognition are carried out by the processor after the multi-product mineral image is acquired by the machine vision sensor.

Figure 1. Sketch map of online ore sorting system

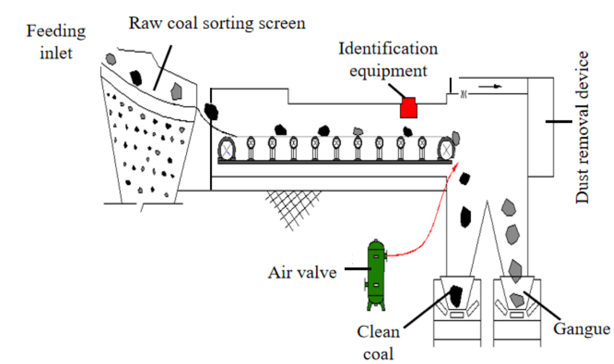
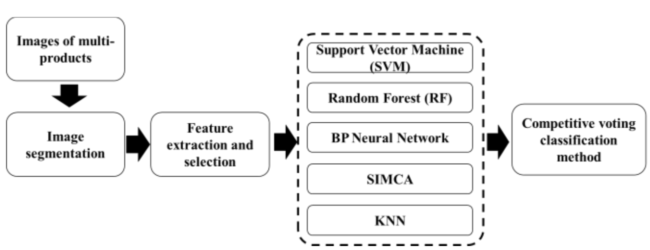


Figure 2. The method flow chart of this paper



Although a variety of classification models have been used for ore classification research and application, such as Support Vector Machine, BP, Random Forest, KNN, etc., and achieved good results, there is still space to improve the classification accuracy. In this paper, we try to establish a joint classifier by a competitive voting method to further improve the classification effect of ore images on the basis of the common classification models.

Based on the ore image acquisition of multi-class ores, image segmentation algorithm is used to identify and separate the target region and background region for feature extraction and selection. The optimal feature dataset obtained by PSO is taken as the input of five common classifiers. Finally, the competitive voting classification method is proposed based on the accuracies of above common classifiers. The method flow chart of this paper is shown in Figure 2

III. Methodology

A. Image segmentation

Image preprocessing is an essential step in quantifying the surface characteristics of ore particles. There are many factors affecting the quantification of surface features, such as adhesion problems and the particles on the edge of the image. This paper presents an improved algorithm called "Finite Erosion and Exact dilation (FEED)" to segment overlapped particles, and a particle-on-edge region segmentation (PERS) algorithm to ensure that all particles are detected. It could preferably avoid the over-segmentation and under-segmentation of particle regions and achieve the full analysis of target regions. The steps are as follows:

(1) Color threshold segmentation algorithm. Setting an appropriate pixel threshold to separate the target region from the background area;

(2) Binarization processing. Converting original RGB color image into binary image, and adopting area threshold and hole filling algorithm to remove noise and fine particles smaller than area threshold and fill the holes in the target area;

(3) Edge particle removal algorithm. Incomplete coal particles at the top and bottom edges of the coal particle image will adversely affect the surface feature quantification of the target area, so the pixel index and associated region marking algorithm are used to remove them;

(4) Finite erosion. Firstly, an initial area threshold (R) was set corresponding to the minimum particle size. The value of R also can be adjusted in a small range according to the segmentation effect. Based on the binary image, all target regions were eroded sequentially by 10*10 pixel structural elements. The target regions whose area was less than R were retained, and the corresponding frequency of erosion operations were recorded until the end. The purpose of the limited erosion operation is to break the contiguous part of the overlapping particles without losing any coal particle region.

(5) Exact dilation. We marked the regions after finite erosion and then dilated precisely according to the recorded frequency of erosion operations on each target region, to ensure that the sizes of the particle regions were restored and the overlapping regions were effectively separated, which is the pseudo-color map of coal images after exact dilation, and the marked target regions are displayed in different colors. According to the location map, each coal particle region in the original image was intercepted by using the method of the minimum bounding rectangle, and the background color was set as black, which was retained for the feature extraction.

(6) Segmentation of particle-on-edge regions. To segment the edge particles of the two adjacent frames, we cut half of each image near the edge and spliced them together, and then applied the background removing and binarization operations. Only the particle regions on the centerline were reserved for further treatments of finite erosion and exact dilation.

By the above operations, it is feasible to obtain the segmentation regions of all particles and make it possible to get the image information of each particle for online detection.

B. Feature extraction and selection

RGB color model exhibits non-uniformity in the description of texture features and also includes all colors that human vision can perceive. In contrast, HSV color model can describe the saturation, chrominance and brightness of an image, express image color and intensity information independently and display surface texture from different dimensions. Therefore, surface color features of ores are extracted through RGB color components, and texture features are extracted through HSV color components.

The low-order statistical characteristics of color components have been proved to represent the vast majority of color information. Therefore, we extract the features of first-order moment (mean), second-order moment (standard deviation), third-order moment (skewness), and fourth-order moment (kurtosis) of each color component.

The Gray Level Co-occurrence Matrix (GLCM) and Wave Textural features (WTF) that have proved the effectiveness and usefulness were selected to quantify the difference. We extracted the mean, skewness, and kurtosis of the approximate coefficient matrix and tri-directional coefficient matrixes of wave decomposition, and the contrast and correlation features of GLCM in H, S, and V components, respectively. All the color and texture features should be normalized.

Additionally, all above features are filtered by combining Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) classifier. PSO is an effective global optimization algorithm, which guides optimization search through swarm intelligence. Compared with traditional evolutionary algorithms, PSO retains population-based global search strategy, but adopts more simple speed-displacement model and avoids complex genetic operations.

According to PSO-specific memory, the current search condition can be dynamically tracked to adjust the search strategy. What matters most is that the optimal solution can be found in few iterations due to the dual advantages of "self-learning" and "learning from others". The iteration is set to 500. PSO adopts fitness function to measure the goodness of the solution. In this paper, the reciprocal of the accuracy rate of the SVM test set data is selected as the fitness function. Individuals with smaller fitness value are closer to the optimal solution.

C. Competitive-voting classification method

Each pattern recognition algorithm has its own advantages for specific classification issues, but there are problems such as poor generalization ability and low precision when dealing with classification with diverse target types [1, 3]. Therefore, we establish a competitive-voting classification model based on multiple pattern recognition algorithms.

In this study, five commonly used supervised pattern recognition algorithms are selected, including Support Vector Machine (SVM), Random Forest, BP Neural Network, SIMCA, and an unsupervised pattern recognition algorithm KNN. SIMCA is a mathematical model that constructs a principal component regression model for each class, and classifies the samples on this basis. The above classification models are typical supervised pattern recognition algorithms except KNN. Two-thirds of each product dataset are taken as training set and one-third of dataset is selected as test set for modeling testing. Each classifier was repeatedly operated ten times.

In order to complement the advantages of the classifiers and further improve the classification accuracy when faced with different ore types, the classifier with the top three classification accuracy are selected and combined to develop a competitive-voting classification strategy. For the same ore particle, suppose the prediction results of top three classifiers are H_1, H_2 and H_3 respectively, then there are three cases in total.

(1) When H_1=H_2=H_3, the common result of the three is taken as the final classification result;

(2) When H_1=H_2≠H_3, H_1≠H_2=H_3 and H_1=H_3≠H_2, the common result of the two methods is taken as the final classification result;

(3) When H_1≠H_2≠H_3, the prediction result with the highest classification accuracy is taken as the final classification result.

For further evaluating the effect of the competitive-voting classification method, its classification misjudgment rate for each class is analyzed. The calculation formula is shown as follows:

$$F_i = 1 - T_i \tag{1}$$

$$F_{i\to j} = N_{F_{i\to j}} / N_{F_i} \cdot 100\% \tag{2}$$

Where, i, j represents class, and $i \neq j$; Fi is the classification misjudgment rate of the i-th class, Ti is the classification accuracy of the i-th class; $F_{i\to j}$ means the misjudgment rate in classifying i-th class to j-th class, $N_{F_{i\to j}}$is the number of i-th class classified into j-th class, N_{F_i} is the total number of misjudged i-th class.

IV. CASE STUDY

This case study was conducted based on the multi-class gas coal images collected from an ore sorting system. The aim is to verify the classification performance of five common machine learning models and the proposed competitive voting method based on the operations of image segmentation, feature extraction and selection.

A. Data acquisition

About 100kg gas coal of 6~25mm was separated into four products by the floating and sinking test. Four density fractions are <1.4g/cm³, 1.4~1.6g/cm³, 1.6~1.8g/cm³ and >1.8g/cm³, respectively. The ash and macerals of coal samples at each density level were measured, as shown in Table I. It was worth noting that maceral was associated with the surface appearance of coal at each density level. Therefore, this paper sets three classification criteria according to the ash content and use of gas coal, as shown in Table II.

Each coal image acquired by the ore sorting system was processed using the FEED image segmentation algorithm, as shown in Figure 3 and Figure 4. Based on the single coal particle image, pseudo color image representation and histogram were adopted to analyze the pixel distribution characteristics of ore particle images, as shown in Figure 5.

The difference exists in pixel distribution of multi-products will be observed and it is helpful to select the appropriate color features. In this case study, the pixel value distributions of RGB component images are basically the same through comparing the pseudo color maps and histograms of coals at four density fractions. Therefore, only the mean, skewness and kurtosis of V component were extracted as the color features. Through quantization of above coal particle surface features, three color features and twenty-four texture features are extracted as the feature inputs of the pattern recognition, as shown in Figure 6.

TABLE I. Ash Content And Macerals of Coal Samples At Each Density Fraction

		<1.4 g/cm³	1.4~1.6 g/cm³	1.6~1.8 g/cm³	>1.8 g/cm³
Ash content (%)		6.38	15.67	30.89	73.35
Productivity (%)		33.32	14.36	20.35	31.97
Organic content (%)	Vitrinite	69.2	64.0	52.6	12.6
	Exinite	16.4	19.8	22.8	5.6
	Inertinite	12.4	10.5	11.9	4.1
	Aggregate	98.0	94.3	87.3	22.3
Inorganic content (%)		2.0	5.7	12.7	77.7
Aggregate (%)		100	100	100	100

TABLE II. CLASSIFICATION CRITERIA

Classification criterion		Application
Four products	Class1 (<1.4g/cm³)	It belongs to low ash coal, which can be used for gasification or coking.
	Class2 (1.4~1.6g/cm³)	It belongs to medium ash coal, which can be used as power coal and coking coal.
	Class3 (1.6~1.8g/cm³)	It belongs to height ash coal, which can be used as power coal and blended coal for coking as well as re-sorted.
	Class4 (>1.8g/cm³)	It belongs to ultra-high ash coal,which can be used as building materials.
Three products	Class1 (<1.6g/cm³)	It belongs to low ash coal, which can be used for gasification or coking.
	Class2 (1.6~1.8g/cm³)	It belongs to height ash coal, which can be used as power coal and blended coal for coking as well as re-sorted.
	Class3 (>1.8g/cm³)	It belongs to ultra-high ash coal，which can be used as building materials.
Two products	Class1 (<1.8g/cm³)	The product enters the resorting process after pre-discharging gangue.
	Class2 (>1.8g/cm³)	It belongs to ultra-high ash coal，which can be used as building materials.

The feature parameters are filtered using PSO-SVM algorithm, and the selected features under different classification criteria are shown in Table III. The variation trend of the optimal individual fitness function and evolutionary algebra under each classification standard is shown in Figure 7.

B. *Comparison of classification effects*

The optimized features were taken as the input of five classification models (SVM, RF, BP, KNN and SIMCA), the classification results under each classification criterion are shown in Table IV. The above classification results indicate that SVM and random forest have ideal classification effect among "four products" classification, and the classification accuracy is about 90%, which has especially good classification effect for Class1 and Class4. It is worth noting that SIMCA has the highest classification accuracy (73.53%) for Class 2, which is better than that of other classification models.

Figure 3. Effect diagram of dynamic coal image segmentation algorithm, (a) original coal image acquired; (b) the image after background removal; (c) the image after binarization; (d) the image after particle-on-edge regions removal; (e) the image after finite erosion; (f) the pseudo-color map of coal images after exact dilation

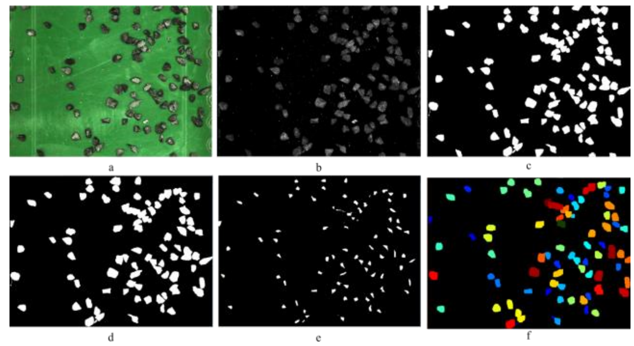


Figure 4. The segmentation of particle-on-edge regions

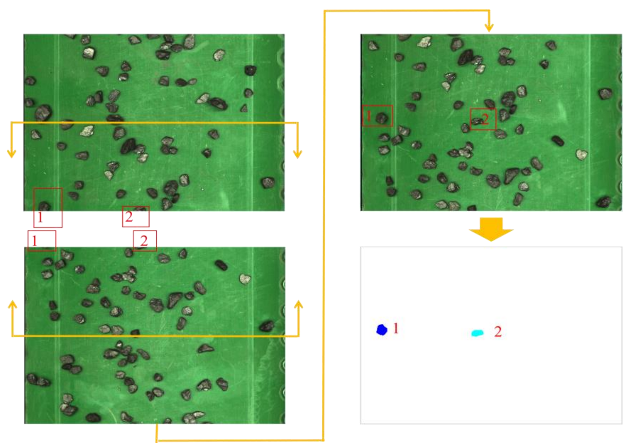


Figure 5. Pseudo-color image and histogram of coal particle: (a)Original ore image acquired; (b) Pseudo-color graph of R, G and B components；(c) Histogram of R components of each density level

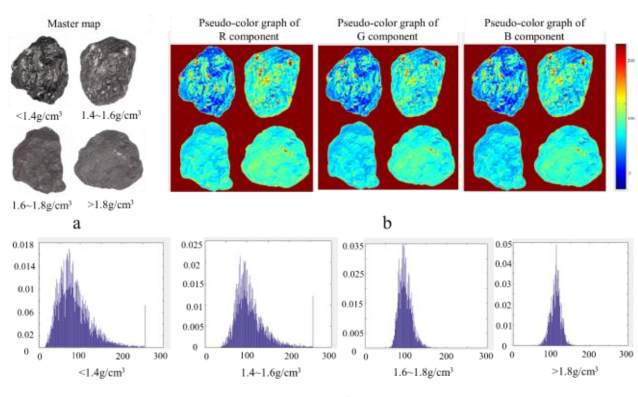


Figure 6. Twenty-seven color and texture features

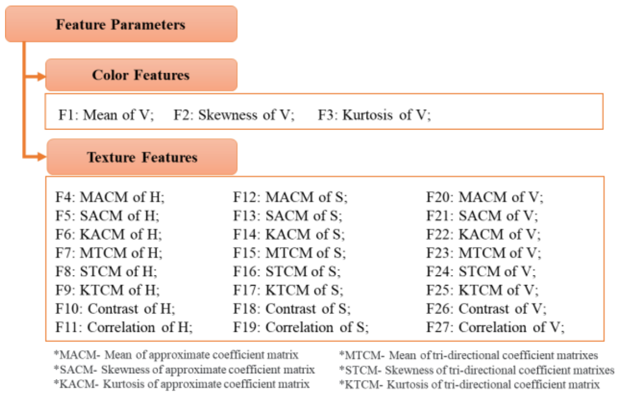
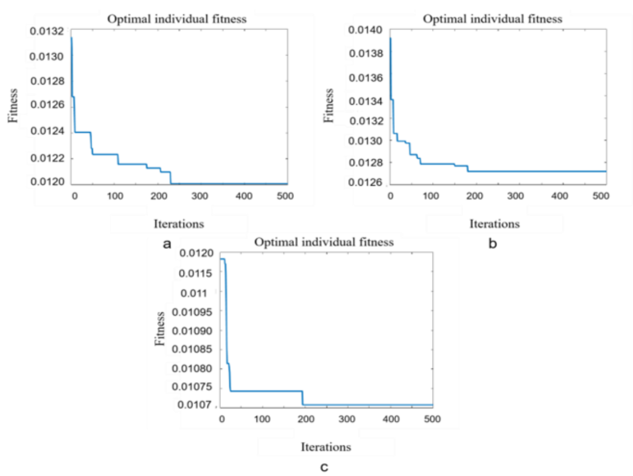


TABLE III. SELECTED FEATURES BY PSO-SVM

Classification criterion	Features
Four products	F1、F2、F3、F4、F5、F6、F9、F10、F11、F12、F13、F17、F19、F26、F27
Three products	F1、F2、F3、F4、F5、F6、F7、F9、F10、F11、F12、F14、F17、F18、F19、F26、F27
Two products	F1、F2、F5、F6、F7、F8、F9、F10、F11、F12、F15、F17、F19、F26

Figure 7. The relationship between optimal individual fitness function and iterations: (a) Four products; (b) Three products; (c)Two products



The classification accuracy of SVM and random forest ranks the top two in “three products” classification, showing significant advantages in Class1 and Class3 classification. SIMCA has a far higher classification effect on Class2 than other classification models.

The classification accuracy of each model in "two products" is high due to that it is easy to identify coal from waste rock by surface characteristics.

The classification effect shows that SVM and random forest classifications are more accurate and stable, while SIMCA has a better recognition effect for intermediate products. Additionally, the fewer the products there are, the higher the classification accuracy is.

Moreover, non-adjacent products have fine classification effect, for instance, Class1 and Class4 in the “four products” classification, Class1 and Class3 in the “three products” classification. When the products with density level<1.4g/cm^3 and 1.4~1.6g/cm^3 are combined into one class (1.6~1.8g/cm^3), the classification accuracy is greatly improved, which is mainly due to that adjacent products have similar coal composition, resulting in a misjudgment rate.

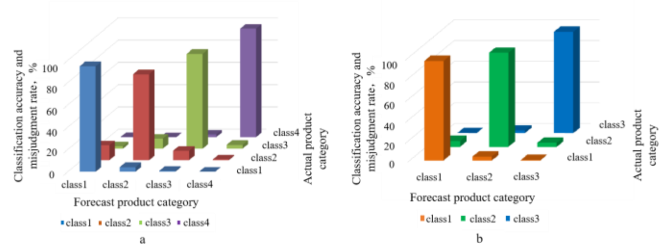
Based on the above analysis and combining classification accuracy of each model, SVM, random forest and SIMCA were selected to develop a competitive voting classification model (C-Voting). The competitive voting classification effect is shown in Table IV. The “four products” total classification accuracy rate is 2.15% higher than that of SVM, the “three products” total classification accuracy rate is 6.38% higher than that of SVM, and the “two products” total classification accuracy rate is 0.52% higher than that of SVM. In addition, classification accuracy of each product has been improved. In particular, Class2 classification accuracy in "four products" is 4% higher than that of SIMCA, and Class2 classification accuracy in "three products" is higher than that of SIMCA by nearly 6%.

The results indicated that the competitive voting method can effectively compensate the prediction error of single classification model, and ensure that the classification accuracy is improved, and not affected by different classification models.

TABLE IV. PREDICTION RESULTS AND RUNNING TIME OF MULTIPLE PRODUCT CLASSIFICATION

Classification criterion		Classification accuracy (%) and running time (s)					
		SVM	RF	BP	KNN	SIMCA	C-Voting
Four products	Class1	*93.83*	93.09	86.98	85.99	79.01	94.80
	Class2	43.73	40.00	45.69	23.33	*73.53*	77.25
	Class3	*86.02*	82.51	56.11	69.19	77.16	85.17
	Class4	*96.79*	95.06	85.02	86.01	90.81	97.31
	Sum	*90.35*	88.58	77.62	79.10	81.60	*92.50*
	Time	0.89	2.56	0.83	0.58	0.01	3.80
Three products	Class1	91.68	*91.71*	88.72	83.58	77.33	95.68
	Class2	83.36	70.80	54.64	43.65	*84.17*	90.43
	Class3	*98.56*	97.63	95.96	89.84	97.97	97.45
	Sum	*88.66*	87.87	84.73	78.15	85.10	*95.04*
	Time	0.67	2.07	0.67	0.43	0.01	3.17
Two products	Class1	98.93	98.20	97.83	92.92	98.09	99.30
	Class2	96.09	94.44	96.00	86.45	96.02	96.31
	Sum	*97.95*	96.90	97.20	90.69	97.38	*98.47*
	Time	0.63	1.88	0.41	0.18	0.01	2.22

Figure 8. Classification accuracy and misjudgment rate of "C-Voting": (a) Four products; (b) Three products



The classification accuracy and misjudgment rates of "four products" and "three products" are shown in Figure 8. The results show that adjacent products have significantly higher misjudgment rate than products at both ends. Combining micro-coal components of each product, the closer the product's micro-coal component is, the more similar the surface color, luster and texture is, the more difficult it is to distinguish machine vision means, and the higher the misjudgment rate is.

Additionally, we conducted a runtime comparative analysis of each classification model, shown in Table IV. SIMCA model has the fastest operation speed, while C-Voting model has the slowest operation speed, which is about 5 times that of SVM operation speed. Considering timeliness of online classification model, optimal classification model should be selected combining classification accuracy and runtime in industrial applications. For example, SVM model is able to use for "two products" classification because the C-Voting model classification accuracy is not improved much, while C-Voting model can be chosen for "three products" and "four products".

V. Conclusion

In this paper, the focus is to propose a competitive voting method for multi-class prediction of ore selection given an example of gas coal in the machine vision-based ore sorting system. This approach is based on the commonly used machine learning methods and combines their predict advantages. The validity of the proposed competition voting classification method is verified through comprehensive evaluation. Experimental results indicated the competitive voting method can obtain better prediction effect in multi-class problem than single classification model, but the prediction time is relatively longer. In practice, a more suitable classification model should be selected according to the prediction accuracy and prediction time.

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