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Multiclass Classification of Coal Gangue Under Different Light Sources and Illumination Intensities

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Abstract

As a solid mixture discharged during coal production, coal gangue possesses comprehensive utilization potential. Efficient sorting and pre-enrichment of its classification are crucial for green mining practices. This study categorizes coal gangue into four types—residual coal (RC), gray gangue (GG), red gangue (RG), and white gangue (WG)—based on their apparent color and utilization properties. The research systematically analyzed how different light sources and illumination intensities affect the visual characteristics of these gangue types. The results indicate that white light sources most accurately reproduce the real coloration and texture features of coal gangue, with optimal textural clarity achieved at moderate illumination levels. Different colored light sources selectively enhance spectral reflectance, and red light significantly improves RG recognition. Support vector machine (SVM)-based classification experiments demonstrate that white light sources achieve optimal performance under moderate illumination (23,000 Lux) with Macro-F1 = 0.90, representing a 15.38% improvement over other conditions. These findings reveal that reasonable matching of light source and illumination intensity can substantially enhance the accuracy of the visual recognition of coal gangue, providing valuable optimization guidance for future precise classification applications.

Keywords: illuminance; light source; texture feature; color feature; SVM; coal gangue

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1. Introduction

Coal gangue is the main solid waste generated during coal mining and washing, and its annual emissions are huge, posing significant environmental challenges [1,2]. From the perspective of ore resources, this waste contains nonmetallic minerals (e.g., kaolinite, quartz) and residual carbon components, which are potential secondary resources [3–5]. Through comprehensive classification of coal gangue, its negative environmental impacts can be mitigated while efficient resource utilization is achieved [6].

Current classification methods for coal gangue primarily include gravity separation, flotation, and color sorting. Gravity separation utilizes density differences to separate coal gangue particles, requiring high-precision sorting with dedicated media recovery systems [7,8]. Flotation separates fine particles based on surface hydrophobicity variations, but this method involves high reagent costs and risks secondary pollution [9–11]. While

γ-ray, X-ray, and hyperspectral techniques offer high accuracy, they come with expensive equipment and radiation safety concerns [12–14]. In contrast, machine-vision-based sorting technology identifies coal gangue by color variations, yet struggles to distinguish particles with similar colors effectively [15,16].

The core of visual sorting systems lies in image acquisition quality, where light source spectrum and illumination intensity are key parameters determining feature contrast [17,18]. Regarding light source coloration, a combination of red (R), green (G), and blue (B) LED lights provides rich spectral information, which helps to distinguish minerals with different colors and compositions [19–21]. Meanwhile, the control of illumination is also very important [22–24], that is, appropriate illumination enhances the contrast and clarity of the image, while excessive or insufficient illumination can compromise the image quality.

Image feature extraction serves as a pivotal step in visual sorting technique. Classical methods include gray level covariance matrix (GLCM) texture features, local binary pattern (LBP) features, color moment features, etc. [25,26]. These features can describe the texture, shape, and color information of gangue from multiple perspectives. Recent advancements in deep learning have introduced innovative approaches to image feature extraction. However, the training of deep learning models requires substantial data and computational power resources [27–29].

Most of the current research classifies coal gangue as a single mineral category without detailed classification. In our preliminary study [30], we conducted multiclass classification according to appearance characteristics, chemical composition, physical composition, and application properties and explored the feasibility of pre-classification using image recognition methods to solve the comprehensive utilization of coal gangue. However, the mechanisms influencing surface reflection characteristics under different colored light sources and illumination intensities remain unclear. This study further investigated the influence of light source parameters on coal gangue's reflective properties and quantified the correlation between light source types, illuminance levels, and multiclass classification performance. The main contributions of this work are as follows:

(1) The superiority of a white light source was demonstrated in enhancing the distinguishability of color and texture features through its full-spectrum reflection.
(2) Optimal texture feature extraction was identified under moderate illumination, where maximum macro-classification accuracy was attained.
(3) A multi-feature fusion framework combining a white light source and medium illumination is suggested to balance classification efficiency and accuracy.

2. Experiment/Methodology

2.1. Coal Gangue Preparation

The raw ore samples in this study were collected from comprehensive coal gangue at a coal preparation plant in the Jungar area of Inner Mongolia, China, which can be classified into residual coal (RC), gray gangue (GG), red gangue (RG), and white gangue (WG) according to the apparent color and comprehensive utilization attributes. The previous work [30] provided mineralogical and chemical characterization of the same coal gangue samples.

- RC exhibited high organic matter content, as evidenced by its significant Loss on Ignition (LOI ≈ 56%) and low density (−1.7 g/cm^3), making it suitable for coal-fired power generation.
- GG was primarily composed of kaolinite, confirmed by XRD analysis, and was rich in SiO_2 (64.44%) and Al_2O_3 (31.41%), identifying it as an important nonmetallic mineral resource.

- RG appeared light brown due to the presence of iron and titanium elements within a hard kaolinite matrix, supported by chemical assays that showed elevated Fe_2O_3 and TiO_2. After removal of these chromatic substances, it yielded high-whiteness kaolin.
- WG was predominantly composed of quartz particles, as confirmed by XRD, with SiO_2 content up to 83.80%. Its high structural stability made it widely useful in construction and glass production.

2.2. Image Acquisition and Pre-Processing

Different types of coal gangue were placed in a studio with a white background, as shown in Figure 1. An industrial camera (HIKVISION MV-CU060, Hangzhou, China) with a lens (HIKVISION ZX-SF2514, Hangzhou, China) and a ring light source (LOMOSEN-ZX-LA15000, Shenzhen, China; for specifications, see Table 1) was positioned approximately 20 cm directly above the ore. The experimental illumination levels were set to 7000, 15,000, 23,000, 31,000, and 39,000 Lux, measured with an illuminance meter (TASI TA631A, Suzhou, China) on a white background panel. A total of 400 original images (2448 × 2048 pixels) were processed to extract non-overlapping sub-images (300 × 200 pixels) focused exclusively on sample regions. Using Python 3.7.16 with Pillow 9.3.0 and NumPy 1.21.5, each image was converted to RGBA format, and the alpha channel was binarized to separate sample from background. An integral image was computed to efficiently evaluate opaque pixel density. Candidate sub-images were generated systematically and ranked by both opacity density and centrality. Non-overlapping regions were selected to ensure independence. This process produced 18,000 high-quality sub-images, eliminating edges and background interference to form a clean dataset for analysis. Figure 2 displays the local feature maps of various coal gangue types under different illumination conditions.

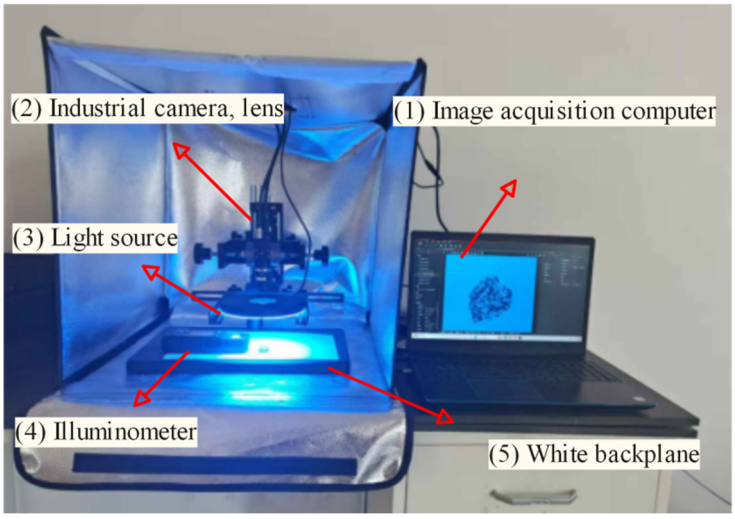


Figure 1. Image acquisition device for coal gangue illumination with different light sources.

Table 1. Parameter table of ring light source.

Vendor	LOMOSEN, Shenzhen, China
Model	ZX-LA15000-color source
ZX-LA15000-W	6500–7500 K (color temperature)
ZX-LA15000-R	630–640 nm (wavelength)

Table 1. *Cont.*

ZX-LA15000-G	520–530 nm (wavelength)
ZX-LA15000-B	465–470 nm (wavelength)
Diameter	Inner diameter 50 mm and outer diameter 150 mm
Angle	0° vertical illumination
Light intensity controller	ZX-LLPAC2408-4

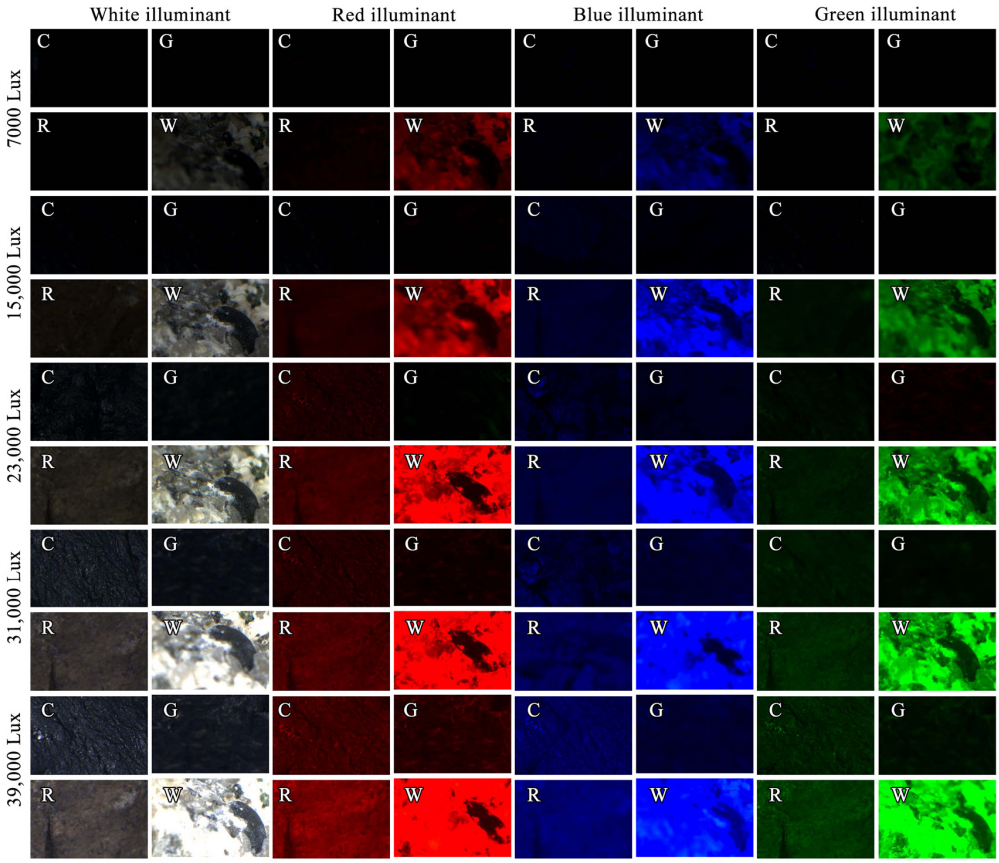


Figure 2. Local sub-images of comprehensive coal gangue under illuminance with different light sources (C—residual coal; G—gray gangue; R—red gangue; W—white gangue).

As shown in Figure 2, the surface color characteristics of various types of gangue under the white light source are closest to the real values, which is mainly due to the white light being able to uniformly reflect all wavelengths. Other lighting sources selectively enhance specific spectral reflections: red light intensifies red fluorescence while suppressing green and blue reflections, resulting in an overall reddish appearance. At low illumination levels, dark mineral residues, GG, and RG show indistinguishable coloration and texture patterns, appearing uniformly black. As illumination increases, dark ore textures gradually become discernible. WG displays optimal texture clarity at medium illumination (23,000 Lux), but excessive exposure causes partial texture and edge features to fade. Notably, color differentiation among various ores becomes apparent with increasing illumination under white light.

2.3. Image Feature Extraction

Image feature extraction is the basis of image analysis, recognition, classification, and other tasks. The local views of various types of gangue images in the aforemen-

tioned database were subjected to feature extraction, specifically including color and texture features.

Regarding the color features, the color moments can effectively represent the concentration trend and dispersion degree of the image color. In this study, images were converted into RGB color space and HSV color space, and numerical moments were calculated for each color channel in each color space, including first-order moment (mean), second-order moment (variance), and third-order moment (skewness).

Four features from the grayscale co-occurrence matrix (GLCM), namely contrast (Con), correlation (Cor), homogeneity (Hom), and ASM, were selected to comprehensively describe the texture features of coal gangue images. To enhance computational efficiency, the original image was first converted into a grayscale version with a reduced grayscale level of 16. Subsequently, the means and variances of the four spatial orientations were calculated separately to obtain eight texture feature parameters.

2.4. Coal Gangue Classification

The ultimate goal of gangue classification is to accurately map the extracted image features to different classes. Support vector machine (SVM) is a commonly used classification algorithm. It can achieve gangue classification by finding the optimal hyperplane, demonstrating good generalization ability and high classification accuracy.

3. Results and Discussion

3.1. Analysis of Color Characteristics

Figure 3 shows the box statistics of color characteristics of different coal gangue types under different colored light sources. The results reveal distinct variations in color channel metrics (mean, variance, and skewness) across coal gangue mineral images under different lighting conditions. RC exhibited lower RGB mean values across all illumination sources, while WG demonstrated higher RGB mean values. These differences stem from the reflective properties of mineral surfaces, with light source color directly influencing surface color perception. The red channel's mean value (r_mean) became more pronounced under red lighting. GG exhibited similar coloration to RC, making them difficult to distinguish. Considering these findings in combination with Figure 2 and statistical analysis of RGB channel variance and skewness, it is evident that WG displayed more prominent highlights and color dispersion, exhibiting richer details and variations compared to other gangue samples. RC, GG, and RG showed overall dimmer tones with more shadows and more uniform color distribution. These variations were further amplified by corresponding channel characteristics under specific colored light sources.

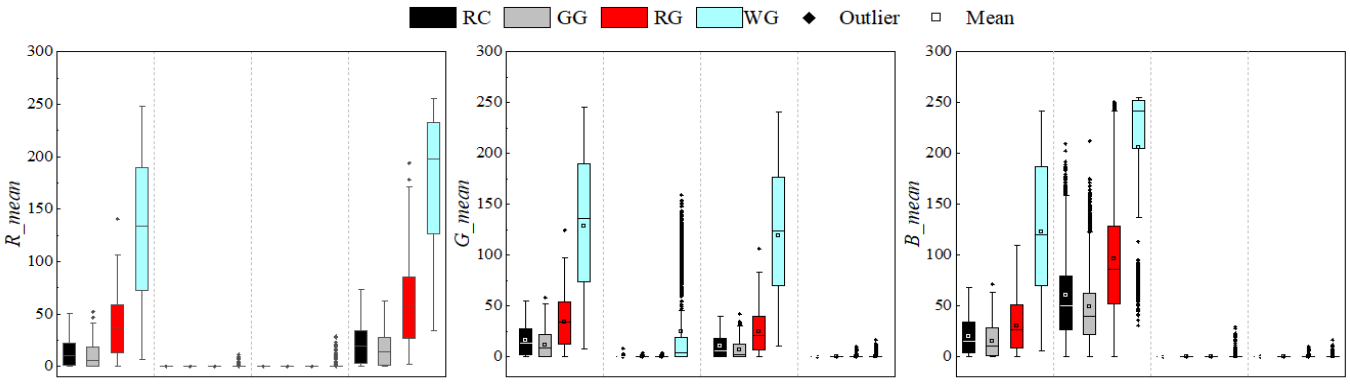


Figure 3. *Cont.*

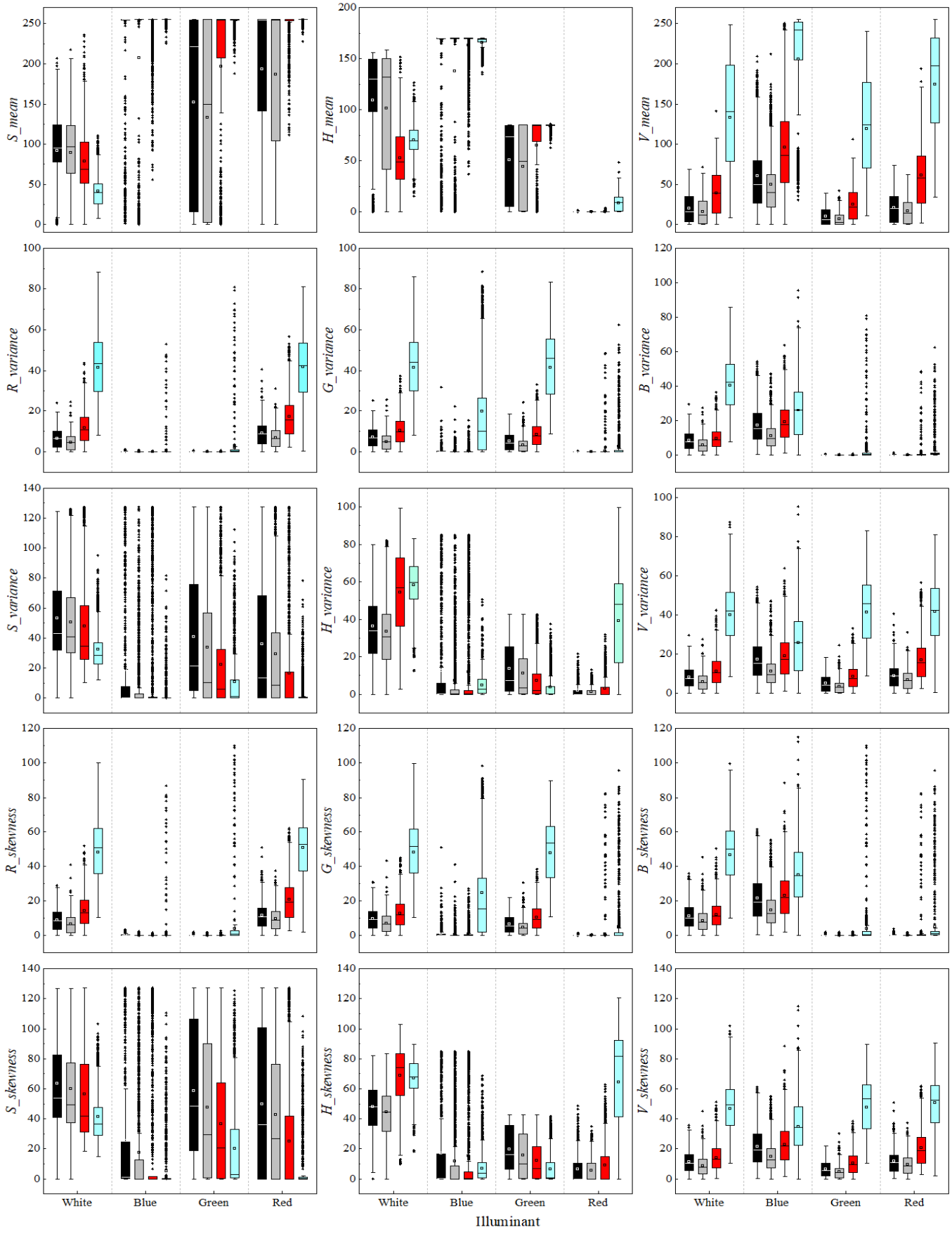


Figure 3. Statistical diagram of color characteristics of different types of coal gangue under different light sources.

As illumination intensity increased, the mean values of various color channels (e.g., *r_mean*, *g_mean*, *b_mean*) for different types of coal gangue showed an overall increasing trend. Figure 4 illustrates the color characteristics changes of different coal gangues under red light sources with varying intensities. WG exhibited the most significant color enhancement, while dark-colored RC and GG showed relatively minor variations. Under high-intensity red lighting, RG demonstrated greater differentiation compared to RG and GG. In terms of variance and skewness, the color distribution across channels remained concentrated with low variance and skewness at lower illumination levels. With increasing illumination intensity, the color distribution became more dispersed, accompanied by increased variance and skewness, showing rising trends in RG, GG, and RC. Combined with the results in Figure 2, the corresponding coal gangue exhibited more detailed textures under high illumination. Conversely, WG first increased then decreased in detail, with its surface being overwhelmed by the light source's coloration under excessively high brightness, resulting in loss of substantial color texture features.

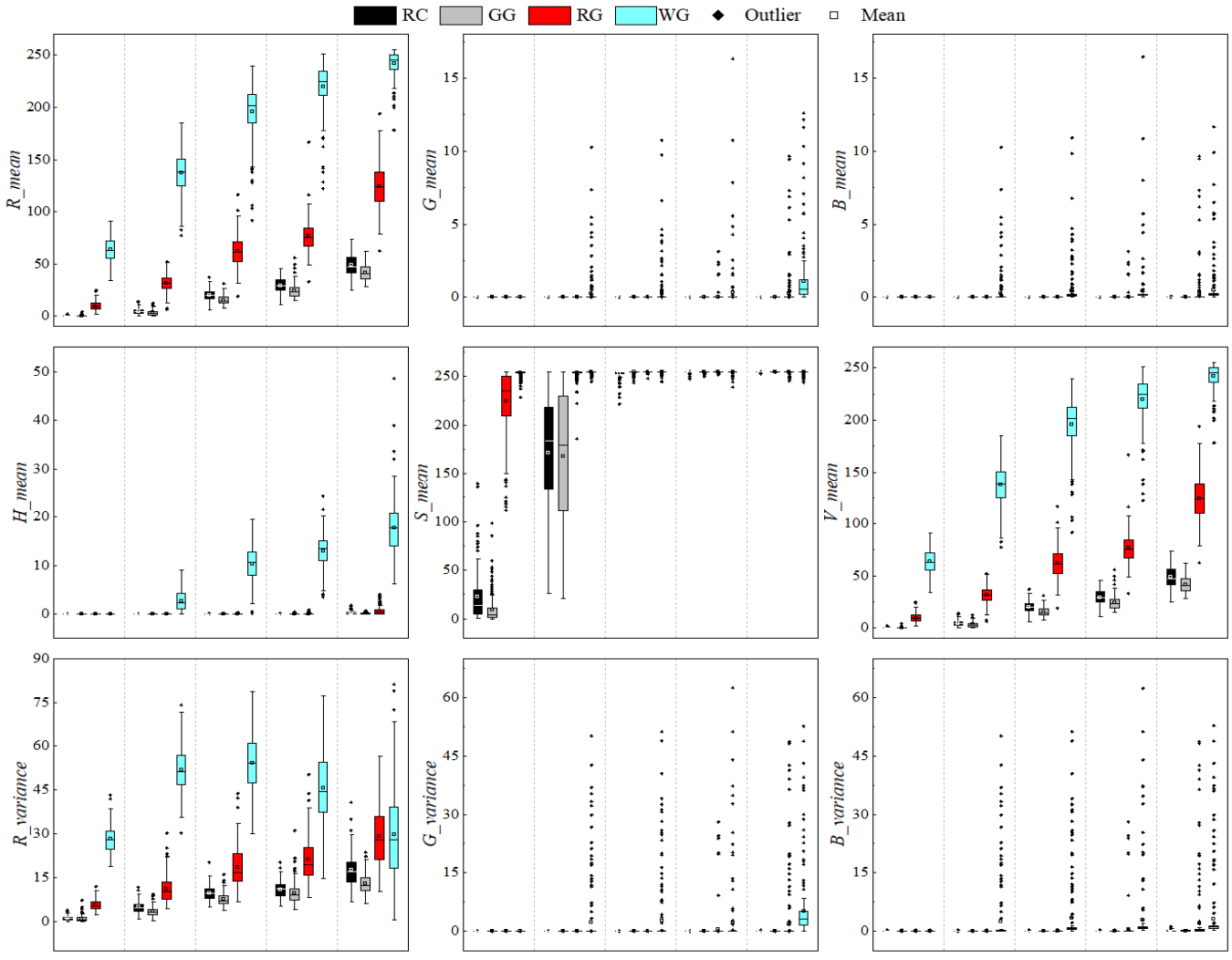


Figure 4. *Cont.*

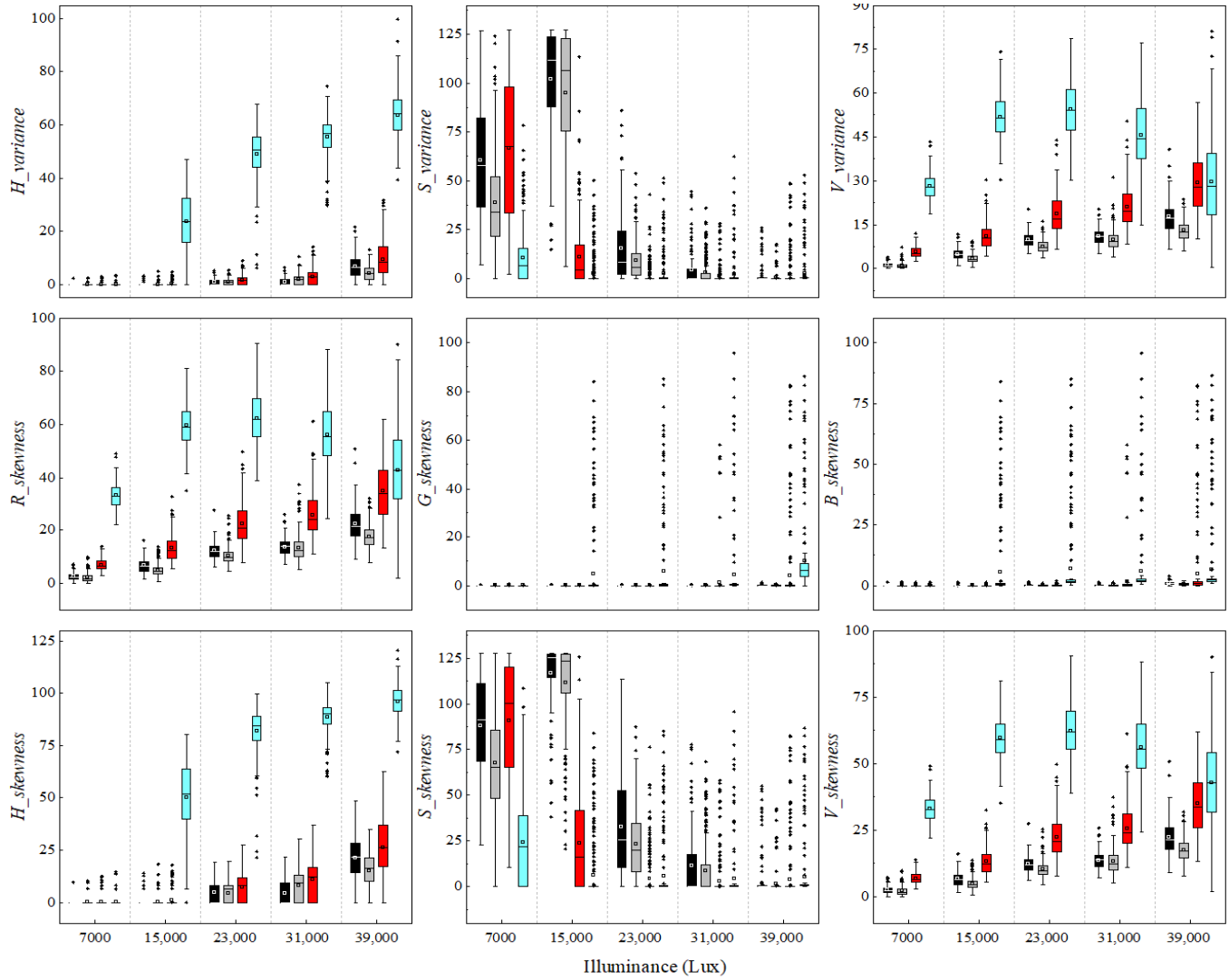


Figure 4. Color characteristics of coal gangue under different light intensities (red light source).

3.2. Analysis of Texture Characteristics

The statistics of texture features for four types of coal gangue under different light sources and illumination intensities (white light source) are presented in Figure 5 and Figure 6, respectively.

Figure 5 reveals the best separation of texture features under the white light source for four types of coal gangue. The full-spectrum characteristics of white light enhance the optical differences in surface microstructures, thus maximizing texture differentiation. Specifically, GG and RC displayed relatively uniform textures with high homogeneity, while WG exhibited complex textures containing impurities, with dispersed color distribution and high contrast. The red light source demonstrated selective enhancement of RG's texture characteristics. Both RC and GG maintained stable low contrast and high ASM under blue, green, and red light sources, with relatively small variation coefficients.

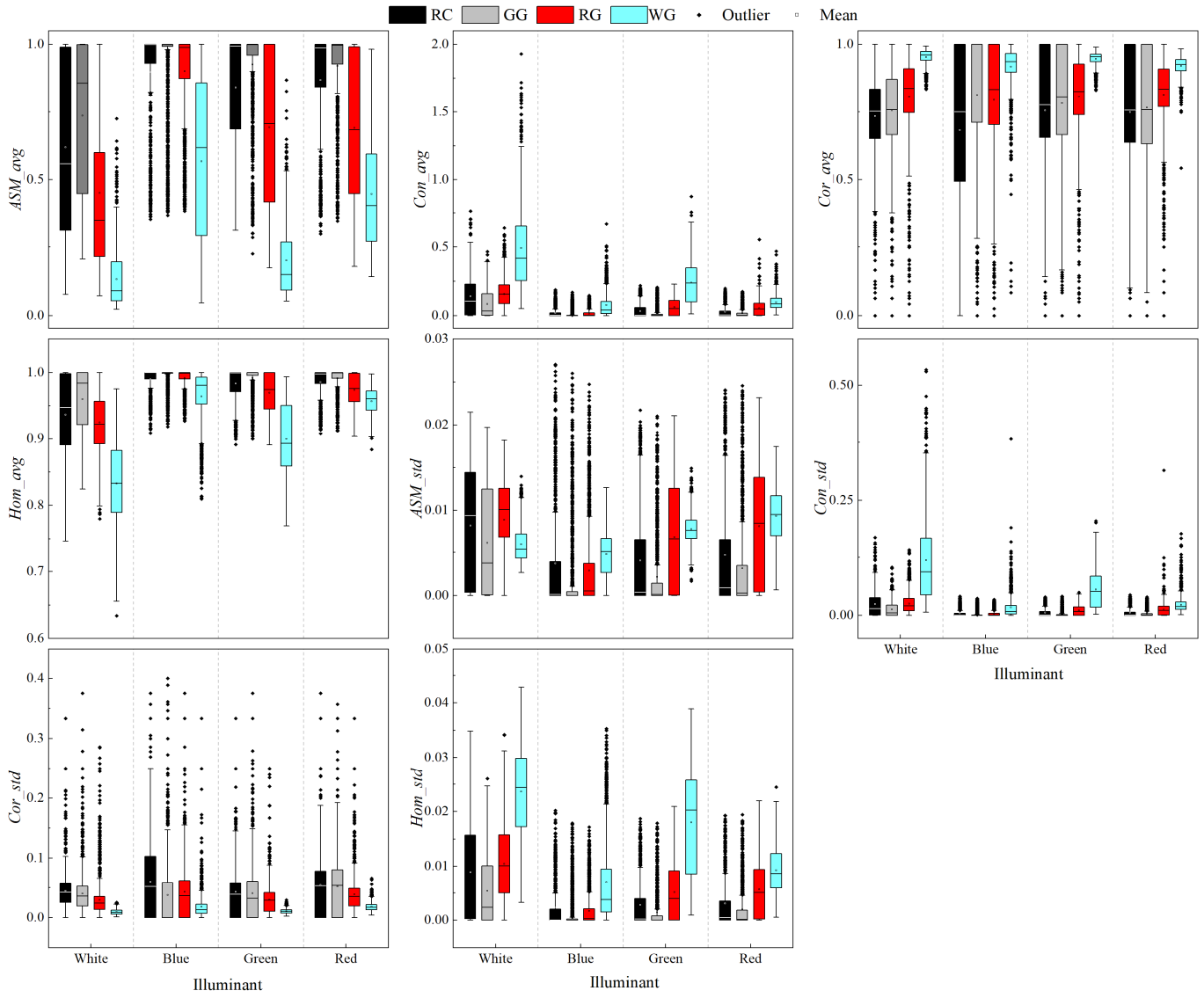


Figure 5. Statistical diagram of texture characteristics of different types of coal gangue under different light sources.

Based on the influences of different light intensities under white light illumination shown in Figure 6, the response relationship between illuminance and texture characteristics of coal gangue was observed. The *ASM_avg* gradually decreased for RC, GG, and RG; only under high illuminance did they display complex and clear textures. The *ASM_avg* of WG exhibited a U-shaped change—initially decreasing and then increasing—with medium illuminance being most conducive to revealing the complexity of surface texture structures. The *Con_avg* values of all coal gangue types exhibited linear growth with increasing illuminance. The trend of *Hom_avg* values resembled that of ASM, while *Cor_avg* values showed no discernible pattern.

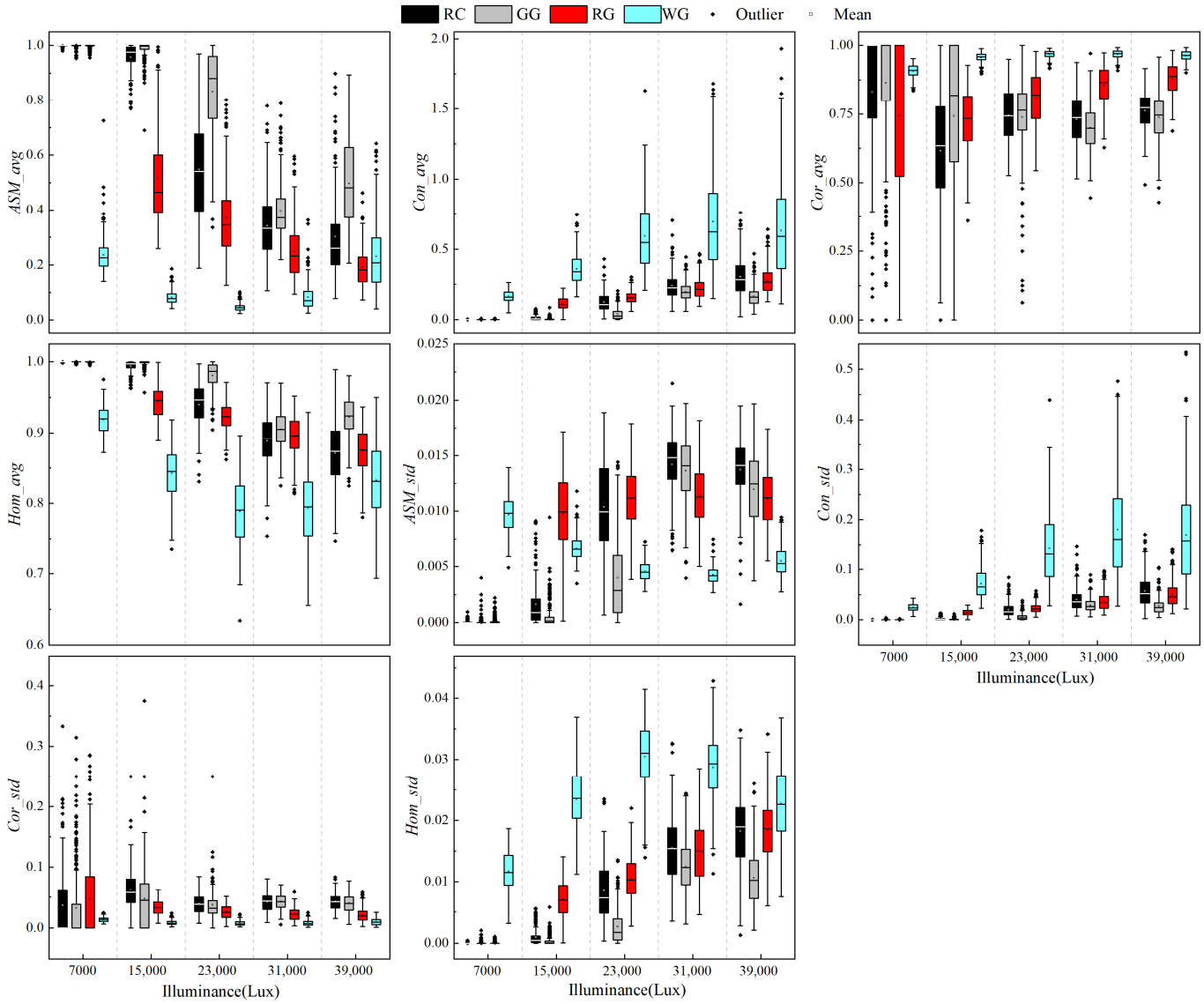


Figure 6. Statistical diagram of texture characteristics of different types of coal gangue under different illumination intensities under white light source.

3.3. Comprehensive Multiclass Classification Prediction of Coal Gangue Based on SVM

In order to further discuss and validate the effect of light source illumination on gangue classification, the widely used classical supervised learning algorithm support vector machine was selected as the classifier. The SVM classifier was implemented using the scikit-learn library in Python. The radial basis function (RBF) kernel was selected due to its capability to handle potential nonlinearities. The key hyperparameters, including the penalty parameter C and the hyperparameter γ, were set as follows: $C = 1.0$ and γ = 'scale', which scales the kernel based on the input feature variance. The weight parameter was set to 'balanced' to automatically adjust class weights inversely proportional to class frequencies, mitigating potential bias due to imbalanced sample distribution. Training and prediction were conducted using images from the Section 2.2 preprocessed image database with varying light source illuminations based on color and texture features (80% training, 20% validation). The F1-Score (the reconciled average of precision and recall) was used as the evaluation metric for predicting each category's accuracy, while Macro-F1 (the arithmetic mean of F1-Scores of each type) served as the overall performance indicator. Figures 7 and 8 demonstrate the prediction results for four types of coal gangue under

different light sources and the classifications under white light with varied luminance intensities.

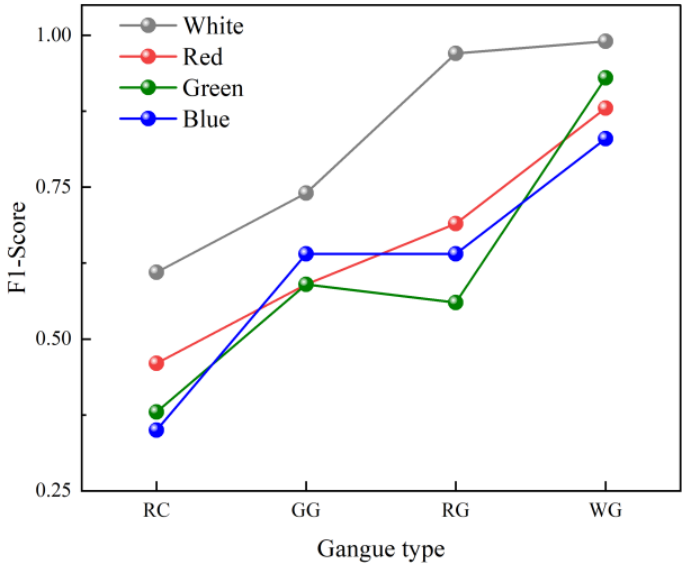


Figure 7. Classification accuracy for different types of coal gangue under different light sources.

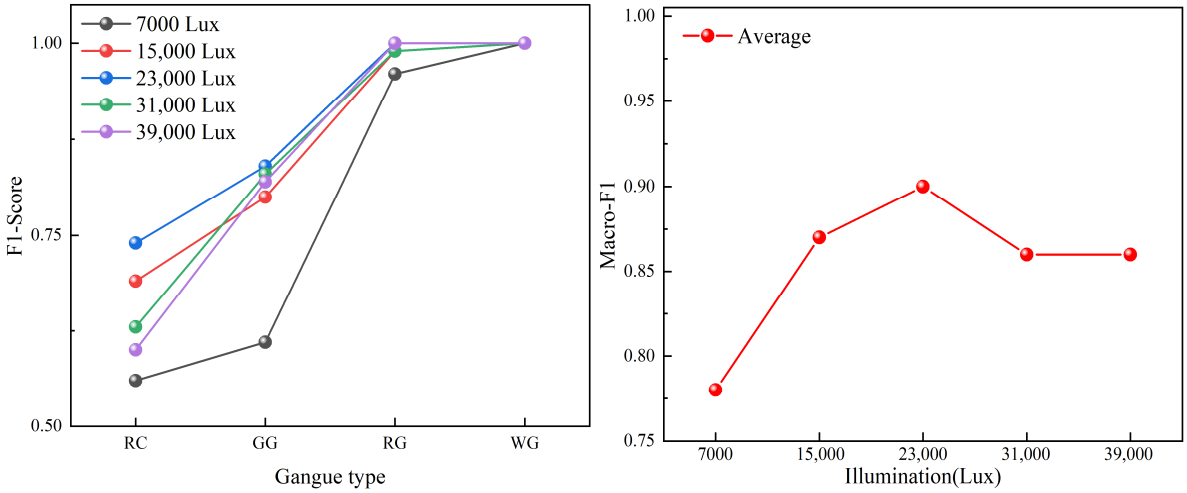


Figure 8. Classification accuracy for various types of coal gangue under different illumination intensities under white light source.

As shown in Figure 7, the selection of the light source significantly impacts the classification performance. The white light source (w) demonstrated overall optimal performance, particularly in distinguishing RG from WG, achieving an F1-Score close to 1. RC proved most challenging, with F1-Scores generally below 0.7, while GG and RG showed intermediate performance. Notably, RG exhibited exceptional classification results under white light sources, followed by red light sources. Therefore, it is recommended to prioritize white light sources for gangue classification. For RC and GG classification, improvements should focus on algorithm optimization or enhanced feature extraction techniques.

As shown in Figure 8, under white light illumination, the overall accuracy of coal gangue classification shows a trend of first increasing and then decreasing with rising illuminance. At low illuminance levels, the classification accuracy for RC and GG is the poorest. Taking the illuminance factor into account significantly improved the classifier's recognition accuracy. At moderate illuminance of 23,000 Lux, the Macro-F1 value reached its peak at 0.90, representing a maximum improvement of 15.38%. This demonstrates that

by fully leveraging the response characteristics of coal gangue under different illuminances, the performance of the SVM classifier was substantially enhanced.

4. Conclusions

(1) The white light source significantly improved the distinguishability of coal gangue color and texture features due to its full-spectrum reflection characteristics, especially in the accuracy of RG and WG classification (F1-Score ≈ 1), and it is superior to other light sources. The red light source can specifically enhance the red channel difference of RG, but the classification of RC and GG still requires algorithm optimization.

(2) The texture features of coal gangue (such as contrast of WG and homogeneity of GG) were optimal under moderate illumination (23,000 Lux), with the overall classification accuracy reaching the maximum (Macro-F1 = 0.90); insufficient illumination led to loss of dark mineral features, while excessive illumination caused overexposure and weakened the texture details.

(3) The multiclass coal gangue sorting system should prioritize the use of a white light source with medium illumination and be combined with a multi-feature fusion algorithm to balance classification efficiency and accuracy.

5. Limitations and Future Work

The proposed method relies on controlled lighting, and its performance may decline in challenging industrial settings with ambient light variations or dust. Although this method is effective for most categories, the identification of residual coal and certain gangue types remains difficult. The use of samples from a single location also limits the generalizability of the findings.

Future work will involve employing deep learning to extract more robust features automatically and exploring hyperspectral imaging to improve accuracy in distinguishing complex categories. We will also expand the dataset to include samples from multiple regions and validate the system under more practical industrial environments.

Author Contributions: C.Z.: methodology, data curation, formal analysis, visualization, writing—original draft, writing—review and editing. Y.X. and W.L.: writing—original draft, validation. X.S., Y.X. and G.W.: data curation, formal analysis, software. J.F.: data curation, supervision. C.Z. and X.S.: funding acquisition, resources, supervision, validation. H.Z.: resources, supervision, validation. C.Z. and H.Z. conceived and designed the study; Y.X. and W.L. collected and analyzed all the data; C.Z. and X.S. wrote the paper. X.S., J.F., G.W. and H.Z. reviewed and edited the manuscript. All authors contributed to the interpretation of results, discussions, and conclusions. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ongoing study.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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